The ACEWEM computational laboratory: An integrated agent-based and statistical modelling framework for experimental designs of repeated power auctions

Daniil Kiose

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STORM, the Statistics Operational Research and Mathematics
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London Metropolitan University

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Abstract

This research work develops a novel framework for experimental designs of liberalised wholesale power markets, namely the Agent-based Computational Economics of Wholesale Electricity Market (ACEWEM) framework. The ACEWEM allows to further understand the effect of various market designs on market efficiency and to gain insights into market manipulation by electricity generators. The thesis describes a detailed market simulations whereby the strategies of power generators emerge as a result of a stochastic profit optimisation learning algorithm based upon the Generalized Additive Models for Location Scale and Shape statistical framework. The ACEWEM framework, which integrates the agent-based modelling paradigm with formal statistical methods to represent better real-world decision rules, is designed to be the foundation for large custom-purpose experimental studies inspired by computational learning.

It makes a methodological contribution in the development of an expert computational laboratory for repeated power auctions with capacity and physical constraints. Furthermore, it contributes by developing a new computational learning algorithm. It integrates the reinforcement learning paradigm to engage past experience in decision making, with flexible statistical models adjust these decisions based on the vision of the future.

In regard to policy contribution, this research work conducts a simulation study to identify whether high market prices can be ascribed to problems of market design and/or exercise of market power. Furthermore, the research work presents the detailed study of an abstract wholesale electricity market and real UK power market.

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I dedicate this thesis to my grandmother who has always believed in me.

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Glossary of Abbreviations

ABM Agent-based Model

ACE Agent-based Computational Economics

ACEWEM Agent-based Computational Economics of Wholesale Electricity Market

BETTA British Electricity Transmission and Trading Arrangement

BM Balancing Mechanism

CAS Complex Adaptive System

CCGT Combined Cycle Gas Turbine

CDF cumulative distribution function

COPF Constrained Optimal Power Flow

CSV comma separated values

DA Day-ahead

DC direct current

DEC Power decrement

GAMLSS Generalized Additive Models for Location Scale and Shape

GenCo Power plant

GUI graphical user interface

ID Intra-day

INC power increment

ISO Independent System Operator

LCOAL Large Coal

LMP Locational Marginal Pricing

LSE load servicing entity

MAPE Mean Absolute Percentage Error

MC Marginal Cost

MCP market clearing price

NETA New Electricity Trading Arrangements

NUC Nuclear

OCGT Open Cycle Gas Turbine

OAP offer acceptance probability

OIL Crude Oil

OPF Optimal Power Flow

OTC Over The Counter Marketplace

PDF probability density function

PR Power Re-dispatch

PS Pumped Storage

PX Power Exchange

RL reinforcement learning

RT Real-time

SPO stochastic profit optimisation

UK United Kingdom

ZP Zonal Pricing

MW Megawatt

Part I

Context and Model Conceptualisation

This part of the thesis overviews the area of study in question and discusses specific problems attributed to it. Moreover it sets the scene for the content in subsequent parts: II, III and IV. Chapter 1 discusses the context of the research problem, as well as aims, objectives and scope. Furthermore, it outlines the methodological approach taken and presents the suggested solution. Chapter 2 introduces the concept of auctions and their implementation in electricity trading. It outlines the specific physical constraints that electricity trading is subject to and overviews the strategic trading behaviour of market participants. Subsequently the discussion enters the case study and overviews the UK wholesale electricity market in detail. An extensive literature review covering the conceptual and technical issues of exiting agent-based models for electricity market is provided to conclude.

1 Introduction

1.1 Introduction

This chapter introduces general prerequisites for initiating this research project and states both the aim and specific research objectives. This is followed by a methodological approach, suggested solution and detailed outline of the thesis.

1.2 Context and the problem

A quarter of a century ago the electricity industry was largely held in hands of vertically integrated monopolies across the world. Utility companies had to pay fixed tariffs set by such monopolies in order to supply electricity to domestic premises. In an attempt to bring rationality and transparency to wholesale electricity pricing, the government in many countries have broken up these monopolies and reorganised electricity industries to form markets (Green, 2005). The first country to introduce power market was Chile in 1978 followed by the wave of deregulations starting in the 1990s with the UK. The emerged liberalised power markets, as a prime example of market competition of daily repeated auctions with capacity and physical constraints, tend to be characterized by: a) an oligopoly of heterogeneous power generators; b) short term inelastic demand (Borenstein et al., 1999); and c) complex (but not necessarily complicated) market mechanisms, which are designed to facilitate both financial and physical trading. Thus, there is potential that these characteristics in conjunction allow the principal market players to manipulate spot market prices upwards. Does this happen? Or, is the process of balancing supply and demand in real time by means of daily repeat auctions, conducted within a framework of known technical constraints, sufficient to ensure that competitive outcomes prevail? From an expert systems perspective, power markets rank among the most complex of all markets operated at present as supply and demand have to be balanced in real time, considering transmission limits and power unit commitment constraints. In other words, power markets exemplify market competition of daily repeated bids/offers of power with capacity and physical constraints. As the result the complexity of a deregulated electricity market resulted in the failure of power market designs. In the US, the Standard Market Design proposal in July 2002 failed due to political, regional and stakeholder pressures and was therefore adapted by the less ambitious Wholesale Power Market proposal (Gross, 2004). The costs of implementing the Standard Market Design proposal were epitomised by the North-east Blackout of 2003 and the Californian electricity market debacle (Tomain, 2011). Also in Europe, electricity market structures were forced to adapt after bearing heavy criticism. UK decided to supersede the Pool's flawed governance structure by the New Electricity Trading Arrangements (NETA) framework but other difficulties arose after doing so. NETA failed to increase either the liquidity of markets or the participation of the true demand side, raised trading costs, and cost over £ 700 million (Newbery, 2004).

In general the main efficiency drawbacks of power markets are related to transmission congestion abuse by a few dominant sellers, poor market designs which invite strategic bidding by suppliers, the lack of customer response to price spikes, capacity shortage caused by demand growth that is not matched by new capacity and thin trading of forward and future contracts that are critical for price discovery and risk management (Maenhoudt and Deconinck, 2010).

This research work attempts to provide a simulation-based solution for key market issues by developing a novel computational model for researchers and policy makers.

1.3 Aims, objectives and scope

1.3.1 Aim

The aim of the proposed research project is to develop a novel computational laboratory, termed here the ACEWEM, for experimental designs of restructured wholesale electricity markets in order to gain insights into the key power market issues considered in objectives of this thesis.

1.3.2 Objectives

The specific research objectives are:

- To develop a reliable tool (the ACEWEM computational laboratory) to serve for engineering of efficient electricity markets.
- To explore the influence of existing pricing mechanisms on wholesale electricity price formation.
- To explore the influence of alternative congestion management schemes on wholesale electricity price formation.
- To explore the emergence and impact of strategic behaviour by power generators on wholesale electricity price formation.
- To explore the impact of transmission grid physical constraints on wholesale electricity price formation and trading behaviour of power generators.

1.3.3 Scope

Wholesale electricity markets are complex adaptive systems. Thus, it is difficult (if not unrealistic) to model all plausible behavioural phenomena arising as a result of the interactions of market participants. Therefore this PhD thesis focuses on the development of a novel and highly flexible model for wholesale electricity markets reflecting on the most important and common features of bidding strategies of wholesale electricity generators while wholesale electricity consumers are assumed to be 'passive'. This is because the short-run price elasticity of demand for electricity is negligible (Yusta and Dominguez, 2002; Faruqui and George, 2002).

Furthermore, the proposed ACEWEM model assumes independence between wholesale electricity generators and wholesale electricity consumers, although a degree of interdependence in terms of behavioural feedback loops might be expected in reality. The ACEWEM model also assumes that electricity generators do not directly communicate in order to coordinate their bidding strategies.

The bidding strategies emerge from bottom-up by means of a bounded rationality stochastic profit optimisation (SPO) algorithm proposed here for the first time.
The ACEWEM model does not include dynamic investment strategies for capacity expansions while the demand for wholesale electricity is specified externally. However, using ACEWEM-based forward-looking scenarios, the implication of alternative investment strategies for wholesale electricity generation and demand profiles can be explored.

1.4 The methodological approach

Three major approaches to power auctions can be distinguished: (cost-based) optimization models, equilibrium models, and (top-down or bottom-up) simulation models (Ventosa et al., 2005). A common application of optimization models in power markets is the capacity expansion planning of public utilities (Simoglou et al., 2014). A limitation of such models is that they do not adequately capture strategic interactions between market participants. In contrast, equilibrium models, which may be viewed as generalizations of cost-based models (Weron, 2014), present generators as entities engaged in a *rational* bidding game for which both the rules of the game and information about rivals are shared among incumbents (Guerci et al., 2010; Weidlich and Veit, 2008). In most cases both these top-down-type models involve high levels of aggregation and over simplification: they are not designed to analyse power markets that are heavily influenced by technical details (*e.g.* transmission network) and strategic player interactions (Sensfußet al., 2007). Taken together, by ignoring strategic player interactions and/or the environment (transmission grid) these models disregard the consequences of learning effects that result from daily repeated auctions conducted within a framework of known technical constraints (Rothkopf, 1999).
While analytical models provide a reasonable representation of power markets under stationary or strong periodicity of dynamic disturbances (Kannan and Zavala, 2011), they struggle representing short-term behaviour (*e.g.* hourly bids/offers) observed in power markets (Bunn and Day, 2009). It is not surprising therefore that the complexities of the power markets drive most analytical modelling methods to their limits.
Asymmetric information, imperfect competition, strategic interaction, collective learning, and the

possibility of multiple equilibria all point to the complexity inherent in power markets.Agent-based Computational Economics (ACE) - a bottom-up simulation-based modelling approach - is a methodology that has the potential to overcome the shortcomings of traditional analytical methods to model complex (power) markets (Tesfatsion (2006) and references therein). In short, ACE models are computational models of micro-agents (*e.g.* power generating companies) operating in an environment (*e.g.* transmission grid), in which they interact repeatedly with other agents over a period of time, thereby permitting the computational study of phenomena as Complex Adaptive Systems (CASs). For Tesfatsion (2006), CASs "include planner units, i.e., units that are goal-directed and that attempt to exert some degree of control over their environment to facilitate achievements of these goals". Voudouris (2011) argues that the development of realistically rendered ACE models offers a better way for the representation and scientific investigation of complex, dynamic phenomena such as energy markets.

An important theme in social and economic science is a move towards bottom-up models for the representation of complex phenomena. Historically, economists have addressed questions about how decisions are made with aggregated models, assuming perfect information and a rational behaviour. In recent years, a disaggregated modelling approach in social and economic science has advanced,see for example the ACE paradigm (Voudouris, 2011). Furthermore, the ACE paradigm, using as a basic tool an Agent-based Model (ABM), have become a widely accepted approach to solving both theoretical and practical problems in energy economics (Weron, 2014).

The key distinction between ACE models (specific models developed based upon the ACE paradigm) and other types of economic modelling is agent *autonomy* and interactions between autonomous agents (see Figure 1.1). Agents in ACE models are decision-making entities capable of reactivity, social communication, goal-directed learning, and - most important of all - self-determinism on the basis of private internal processes such as dynamic profit maximisation. Thus, the agent is modelled as an independent entity that makes decisions and takes actions using the limited share of influence and/or uncertain information (bounded rationality) available to it, similar to how organizations and individuals operate in the real world. A main feature of the ACE models is the repetitive and competitive interactions between the agents - an agent makes publicly available to other interacting agents only a subset of their private information and actions (see Figure 1.1).

Following Voudouris (2011), the other important building block in the ACE paradigm is the representation of the physical and social environment or space within which agents operate (see the different layers of Figure 1.1). Each agent may only observe a subset of the multilayer environment (representing bounded rationality).

The ACE model specifies the initial state of the market by specifying the attributes and methods of each agent and the characteristics of the environment using observational micro-data. The initial attributes of any particular agent might include type characteristics (*e.g.* power generator), structural characteristics (*e.g.* cost function), and initial information about other agents (*e.g.* location on transmissions grids, maximum production capacity). The initial methods might include market protocols (*e.g.* bidding rules), learning modes (*e.g.* reinforcement learning), trading rules (*e.g.* profit maximization), and rules for changing rules (*e.g.* strategy updating of forecasting models based on past performance). The market then evolves over time without further intervention. All events that subsequently occur arise from the historical evolution of agents' interactions (Tesfatsion, 2006; Jennings, 2000).

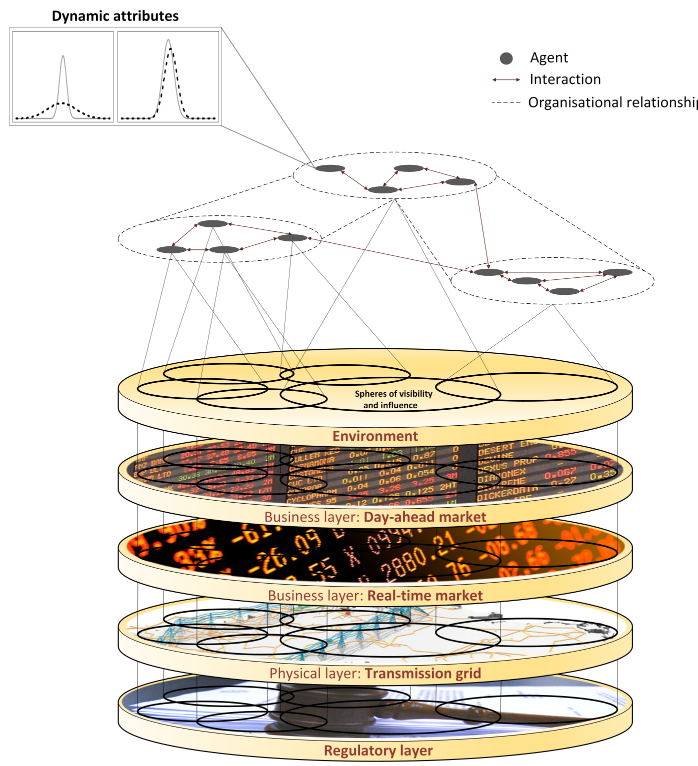

Figure 1.1: Agents, organisation, environment, and interactions (source: Kiose and Voudouris (2014))

ACE models offer three main benefits over other modelling techniques for the representation of wholesale power markets:

- Capturing emergent phenomena, these phenomena result from the interaction of the individual entities.
- Providing a natural description of a complex adaptive system. If the system is composed of behavioural entities (as is the case with power markets), agent-based models are most natural and closer to reality to model these systems.
- Flexibility. This flexibility comes in different dimensions. More agents for instance can be added, and the complexity of the agent, their behaviour, degree of rationality, ability to

learn and evolve can be tuned. This is important when different market designs need to be integrated in the model.

ACE models are useful when:

- the interaction between the agents is complex (see Figure 1.1)
- the agents exhibit complex behaviour, including learning (see Figure 4.4).
- the representation of physical space (*e.g.* transmission grid) is crucial
- the aim is to reveal and explain the complex and aggregate market behaviours that emerge from the interactions of the *heterogeneous* agents (Koritarov, 2004)

However, ACE models are not appropriate when:

- the dynamics of the systems is linear
- the representation of physical space is of marginal utility
- the interactions between the constituent components of the system is limited
- micro-data is not available
- forecasting is the primary focus of the study (although the ACEWEM framework presented here is an important step in addressing this shortcoming by integrating ACE models with formal statistical techniques).

The agent-based approach, due to its advantages over the alternative modelling techniques, is expected to deliver the best insights into research questions of this thesis and therefore is implemented into the following suggested solution.

1.5 The suggested solution

To better represent the characteristics of wholesale power market, this thesis introduces the agent-based Computational Economics of the Wholesale Electricity Market[1] (ACEWEM) framework(see

[1]The ACEWEM software and user guide are available for download from the following source:
https://www.dropbox.com/sh/ha9qk6fn6ol969m/AADoRa5RH_MWaqwJ3vHs4xtJa?dl=0

Figure 1.2). Based on the work of Sun and Tesfatsion (2007b) and Rigby and Stasinopoulos (2005),

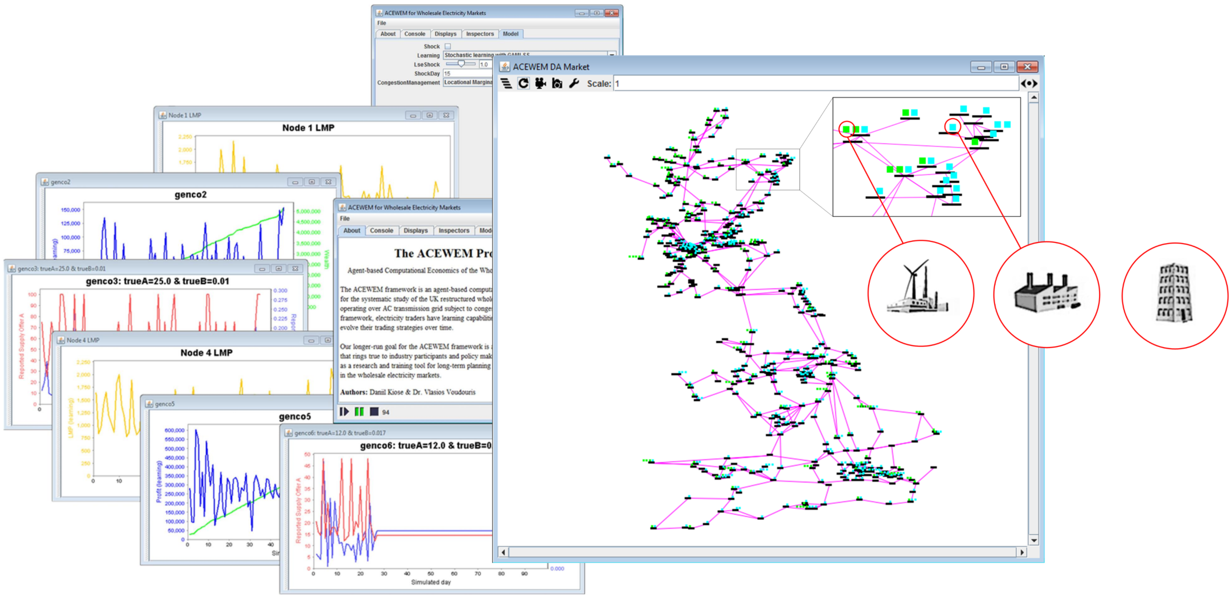

Figure 1.2: ACEWEM graphical user interface

the ACEWEM framework can simulate a wide range of power markets. It contains a variety of key agents (system operator, power generators and wholesale electricity consumers) and other supporting environmental elements (*e.g.* transmission grid). Thus, the ACEWEM framework can represent real-world agents operating over realistically abstracted power grids, in which both economic and physical aspects are taken into account. Specifically, the ACEWEM framework proposed here adds to the literature by:

(a) Suggesting a new decision rule for the strategic offers/bids of the agents competing in repeated power auctions. The agents learn both from past performance of their strategies as well as endogenously estimating a statistical model in order to optimize their strategic bids/offers (see section 4.2.3). Here, it is important to note that the statistical model is developed by selecting the structure of the GAMLSS-based model developed by Rigby and Stasinopoulos (2005) using the RL algorithm of Erev and Roth (1998). This is a distinguishing feature of this research work approach towards realistically rendered ACE models.

(b) Incorporating DA and RT spot markets - see Figure 2.2. This is important because agents might strategically submit bids/offers across different markets as a way of optimizing total profit. Furthermore, physical constraints might not necessarily be taken into consideration in the DA market. In fact, there are market designs where the physical constraints are resolved during the operation of the RT market.

(c) Implementing two congestion management schemes, namely the LMP scheme (Hogan, 1992) and PR scheme (De Vries, 2001) to test the effect of the different congestion management schemes on market dynamics (*e.g.* see Experiment 1 and 3 in Chapter 6).

(d) As a result of (b) and (c), developing a least-cost Constrained Optimal Power Flow (COPF) algorithm so to estimate power outputs from different generators operating in two spot markets under different congestion management schemes.

(e) Implementing two alternative auction designs, namely uniform and discriminatory (pay-as-bid) pricing rules (Klemperer, 2004)

From the modelling perspective, wholesale electricity generators and electricity consumer companies are created based on the firms present in the real-word liberalised power markets. The generation unit portfolio (*i.e.* a number of power plants that belong to power generating firm) and relevant corporate behaviour are configured to match the real-world characteristics. Naturally, these highly active decision-making agents are modelled as heterogeneous (rather than homogeneous) and adaptive (rather than passive) agents. The generation companies 'adaptive' features and decision-rules include the use of i) a RL[2] algorithm to select the best performing strategy from a discrete list of plausible distributions (called action/strategy domain) with ii) advanced statistical models to estimate future electricity prices (and load) at grid nodes or electricity regions (depending on the real-world characteristics of wholesale power market represented). Clearly, prices can be estimated for each one of the spot power markets, such as 1) the DA market and 2) the RT market in which companies sell and buy electricity.

[2]Reinforcement learning was inspired by behaviourist psychology and is an area of machine learning in computer science, concerned with how an agent ought to take actions in an environment so as to maximize some notion of cumulative reward - profit in our case (Gieseler, 2005).

1.6 Detailed outline of the thesis

Part I: Context and Model Conceptualisation

Chapter 1 provides an introduction into the research area. It discusses the background of electricity industry deregulation and overviews the major issues that the liberalised markets are currently facing. This is followed by the research aim, specific research objectives and scope. The subsequent sections on methodological approach and solution justify the contemporary scientific discipline selected for research methods and nominate the simulation framework with which to refer specific market design issues.

Chapter 2 sets the scene for wholesale electricity market by reviewing the theoretical and empirical background for auctions. It also outlines the difficulties of applying a single-unit auction theory to repeated multi-unit auctions and discusses the outcomes gained from empirical studies. This is followed by discussion on the main means for electricity trading, namely through power exchanges and over the counter marketplaces. Subsequent sections present the electricity congestion management methods which are followed by overview of the Optimal Power Flow (OPF) problem. Finally the chapter overviews the UK wholesale electricity market and discusses the peculiarities attributed to it.

Chapter 3 presents a critical survey of the most prominent work conducted in the field of agent-based simulations in power markets modelling.

Chapter 4 discusses in details the model for studying electricity markets developed in this work. In particular it first outlines the overall model structure and characteristics. This is followed by overview of the main agent types presneted in the model, their decision rules and physical infrastructure.

Part II: Model Design

This part of the thesis provides in-depth overview of the proposed model. It presents the overall architecture and graphical user interface. This is followed by detailed discussion on DA and RT markets implementation. This part also overviews the conventional RL algorithm and presents the

Stochastic Profit Optimisation algorithm.

Part III: Model Implementation and Application

This part of the thesis sets an experimental study to address the questions of the current research project. It presents an evaluation and discussion of the results obtained from the simulations performed. In particular Chapter 6 focuses on the abstract wholesale electricity markets while Chapter 7 simulates the real UK power market and outlines the experiments conducted.

Part IV: Discussions and Conclusions

This part of the thesis outlines the regulatory and methodological contributions delivered by this research work, followed by a summary of the main results. It also provides an outlook for further research and a summary statements for the main research outcomes in relation to the objectives set out in the introduction.

1.7 Conclusion

This chapter has presented the rationale for the current research work as well as the aims and objectives. It has been argued that the traditional modelling techniques are rather weak to address the complexity of electricity markets. This complexity however can be well captured by an agent-based modelling paradigm. This chapter has suggested a solution that is based on an agent-based framework integrated with flexible statistical models. The introduction to the concept of wholesale electricity markets is expanded in the subsequent chapter.

2 Wholesale electricity markets

2.1 Introduction

The electricity industry in general can be referred to as a set of specific activities: electricity generation, distribution, transmission, supply and metering. Since its origin the industry was composed of vertically integrated firms. However during the liberalisation initiated process in the 1980s, a number of countries around the world introduced the market concept for electricity trading to unravel the monopolies. It was expected that competition in the industry could lower electricity prices and stimulate emergence of new technologies (Krause, 2005; Weron, 2006).

Electricity trading involves interaction between power generation and retail supply which are subject to competition. On one side generating firms compete for selling electricity to the wholesale market and on the other side, load serving entities compete for buying power from wholesale market to serve their retail customers. Two different establishments exist where trades between electricity generation and the load serving side are settled, Power Exchanges (PXs) and Over The Counter Marketplaces (OTCs) (Lai, 2001; Weidlich and Veit, 2008). PXs and OTCs usually also offer derivative products which allow market participants to hedge their risks.

The rest of the chapter is organized as follows. Section 2.2 presents the concept of auctions and its theoretical and empirical background. It also discusses and compares the main means for electricity trading, namely organised PXs and OTCs. Section 2.3 overviews the most widely implemented congestion management methods. Section 2.4 provides a mathematical description for the linear optimal power flow problem and outlines the electricity market related physical constraints. Section 2.5 looks into the issue of market power exercised by electricity producers. Finally Section 2.6 overviews a design of the UK wholesale electricity market.

2.2 Auctions

Historicallyf auctions were a relatively uncommon way to facilitate exchange of goods or commodities. Nowadays however, it is believed that auctions can lead to economic efficiency and therefore attract a high interest in many industries (*e.g.* telecommunication, natural resources, electricity, finance, *etc*). The study of alternative auction designs generally assumes a benchmark model where bidders:

- are risk neutral;
- have their independent private valuation of the good[1];
- are symmetric;
- make or receive payments as a function of bids alone,
- act in the single-period setting;
- bid for a single unit of an indivisible good.

Thus given these assumptions the Revenue Equivalence Theorem states that the final price achieved is invariant to the auction design selected. In reality, however, the market participants are asymmetric, meet repeatedly to bid for the same commodity and are prone to form oligopolies. Under these circumstances the bidding is unlikely to be competitive, but rather strategic in nature, with auction participants seeking out opportunities to exercise market power. Therefore the parity of auction designs is doubtful and hence it is still an open question as to which auction design is the most efficient.

Among many possible auction designs (see Klemperer (2004)) the two are of a particular interest due to acquired popularity in economic systems, namely first-price and second-price sealed bid auctions (Contreras et al., 2001). In the first-price sealed bid auction each bidder submits a sealed bid (which is hidden from other bidders) to a seller of a single-unit good. The highest bidder

[1]This means that each bidder's private valuation of the auctioned good (*e.g.* 1MW of electricity) is different and independent of peers' valuations.

wins the auction and pays his bid to purchase the good. When the auctioned good is a multi-unit, multiple winners can be established each of which pays his (discriminatory) winning bid. In this case the first-price sealed bid auction design is referred to as 'discriminatory' or 'pay-as-bid', since not all the bidders pay the same price. In the discriminatory price auction the sealed bids are ordered from highest price to lowest. The auction clearing then starts from the highest bid first and moves towards the lowest bid until the supply of multi-unit good is exhausted. Thus depending on multi-unit good supply capacity, the lowest bids may not be reached.

The second-price sealed bid auction is referred to as 'uniform price' and is run likewise, with the exception that the successful bidders all pay the same price regardless of the bids they actually submitted. The uniform price equals to the highest (marginal) bid price accepted.

In early research conducted by Branco and de Portugal (1993) and Maskin et al. (1989) the authors studied multi-unit good auctions, but do not compare discriminatory and uniform price auctions directly. The comparison was conducted by a number of researchers who have argued that discriminatory price auctions are inferior to the uniform price auctions (Bikhchandani and Huang, 1993; Milgrom, 1989). Thus under uniform price auction the bidders would have a lower winner's curse and sellers achieve greater revenues. This conclusion, however was drawn from the assumption that the traded good is a single-unit and as shown by Back and Zender (1993) will no longer apply when the auctioned good is multi-unit. In later work Wang and Zender (2002) model a treasury auction environment considering a multi-unit good, non-competitive bidding and different degrees of price discrimination. They showed that a continuum of equilibria exists for both uniform price and discriminatory auctions however the entire conclusion is still not clear cut on whether one auction design prevails the other. In contrast Maskin and Riley (2000); Kirkegaard (2012) concluded on discriminatory auction superiority over the uniform price design in number of experiments with symmetrical players. Using the identical setting Mares and Swinkels (2014) showed that a well chosen asymmetric second price auction performs better than does the symmetric (or otherwise) first price auction. The authors however assume a single-shot game rather then repeated auction. Note that a number of studies suggest that when bidders meet regularly in the repeated auctions they can easily learn to cooperate to restrain the price from reaching its competitive level. Moreover it is also possible that the bidders cooperation masks the advantage of one auction design over the other which otherwise would be apparent in competitive environment.

Damianov and Becker (2010) in theoretical analysis and later in experimental work (Damianov et al., 2010) compared the uniform price and discriminatory price auctions in an incomplete information setting. They assumed that seller - monopolist, with constant marginal production cost and no capacity constraint, acts strategically and offers multiple units of a good to buyer in two stage game. The seller learns based on the results from stage one and applies its strategic decision during stage two, while the buyers are assumed risk-neutral and face uncertainty about the marginal cost of the seller. The authors conclude that the sellers' strategic behaviour, in respect to supply quantity offered, leads to lower prices under discriminatory price auction and thus generates a lower expected revenue for the seller and a lower trade volume than under uniform price auction. Similar results were achieved in Abbink et al. (2006). The authors studied treasury auctions in a set of laboratory experiments conducted to compare uniform and discriminatory auction designs. They considered a multi-unit good in a series of sequential auctions (75 rounds) with identical set of participants. The main result discovered was that the uniform auction significantly raises the sellers revenue over the discriminatory auction. It is not entirely clear then why, out of 48 countries analysed in Brenner et al. (2009) 24 use discriminatory price while 9 countries use uniform price auctions for government debt. Perhaps the existence of the linked markets (*e.g.* forward markets before treasury auctions and secondary markets) undermine the conclusions derived from studies cited above.

Among many exiting auction markets one particular group which emerged relatively late due to deregulation of electricity industry may give a clear insight into the problem. Electricity markets are of a particular interest since they involve multi-unit bidding and asymmetric market participants (some may have considerable market shares). Also unique for the industry physical constraints require the same market participants to compete daily in order to sell or buy the electricity on the series of linked marketplaces. These marketplaces are distinguished and discussed in following subsection.

2.2.1 Power Exchanges vs Over The Counter marketplaces

In contrast to conventional means for electricity trading that is mainly through Over The Counter contracts, PXs offer centralised, regulated marketplaces at which the standardised electricity contracts can be traded. Centralisation facilitates higher liquidity and delivers essential price and quantities information to the entire electricity industry, while product standardisation makes trading easier, lowers transaction cost and facilitates wholesale price comparability. Trading at PXs is risk-free and anonymous.

On the other hand trading at OTCs is typically unregulated and allows for both standardised and non-standardised products. The products are directly (thus non anonymously) negotiated between parties that usually involves some counter-party risk. As a result OTCs offer a very limited market transparency since contract facts remain hidden from the rest of marketplace participants. Nevertheless, OTCs gained popularity in recent years due to product flexibility and lower operating costs (Feltkamp and Musialski, 2010).

A set of marketplaces with various combination of OTCs and/or PXs form a wholesale electricity market. There is no standard market design around the world. However from the analysis of market models implemented in different countries, it is possible to highlight two main types: a) electricity pooling (centralised market) and b) bilateral trading (decentralised market). The main difference between these two power market designs is that the trading of electricity through a special power exchange (referred as a pool) can be optional - bilateral trading (*e.g.* UK power market, Nord Pool, *etc*) or mandatory - electricity pooling (*e.g.* power market of Spain, Australia, *etc*) (Lai, 2001).

In electricity pooling market design all electricity generators (apart of the smallest ones) are required to sell their electricity output to the Pool at the Pool's Sell Price, similarly the electricity buyers purchase from the Pool at Pool's Purchase Price. All generating plants offer price-quantity pairs to the System Operator. These supply offers all together form an aggregated stepwise supply curve. The offers submitted by generators can be based on predefined variable costs (cost-based pools) or can be any prices the generators choose (price-based pools). Also, the Poolcan be referred as one-sided or two-sided. In one-sided pool the electricity demand is forecast by the system operator, alternately in two-sided pool the demand is recovered from bids submitted by electricity

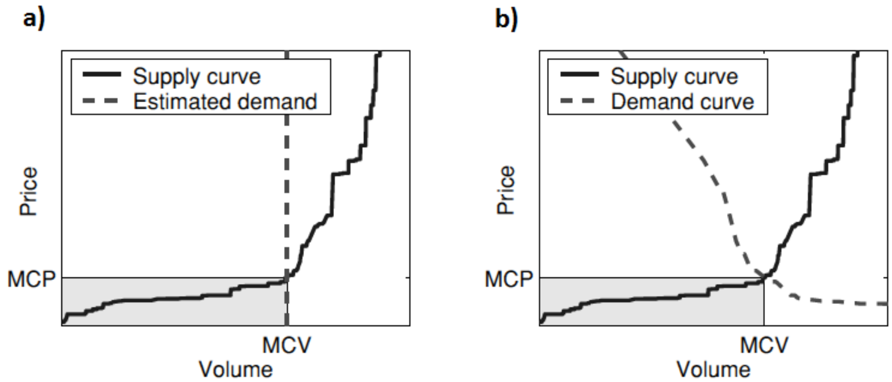

Figure 2.1: Pricing in **a)** one-sided and **b)** two-sided pool (source: Weron (2006))

buyers (Barroso et al., 2005; Surrey, 2013). In general if no generation and transmission constraints are taken into account then the intersection of ranked from highest to lowest demand bids (stepwise bid function), and ranked from lowest to highest supply offers (stepwise supply function), determines the market clearing quantity and price (see Figure 2.1). The pool usually operates on an hourly basis, meaning that bids submitted by buyers and offers submitted by generators are matched (continuously or in discrete points in time depending on the pool's design) for every hour in order to balance the system. The contracts at OTCs in electricity pooling are purely financial and do not entail electricity generators for physical power delivery. Thus OTCs under electricity pooling mainly help market participants manage their risks arising as the result of high electricity price volatility. By setting up a mandatory pool rather than optional the regulator is aiming to achieve high market transparency (Lai, 2001) as it is believed to prevent some large generators from gaining market power. On the other hand the disadvantage is that all market participants have to joint pool which adds to the fixed costs by membership fees, energy fees, *etc*.

In bilateral trading, power generators are allowed to enter into bilateral trades through OTCs with buyers. Parties normally negotiate upon bilateral contracts of any length. These contracts entail physical power delivery and specify the price, amount of wholesale electricity and the period when this electricity dispatch will take place. The generators have to notify the system operator of contract terms and then proceed to self-dispatch when the contract matures. Also in bilateral trading power generators are not obliged to sell their electricity to the pool or any other power exchange.

In general the two market designs can be described by Figure 2.2 as they both comprise a similar set of PXs and/or OTCs. The operational procedures however of a common marketplace can be subject to different rules, which are specific for each market design (e.g. standardised or non-standardised products, anonymous or non-anonymous trading, contacts stipulate physical electricity delivery are allowed or restricted, etc.). One important marketplace for long-term electricity trading is the Forward and Futures market , which we now discuss.

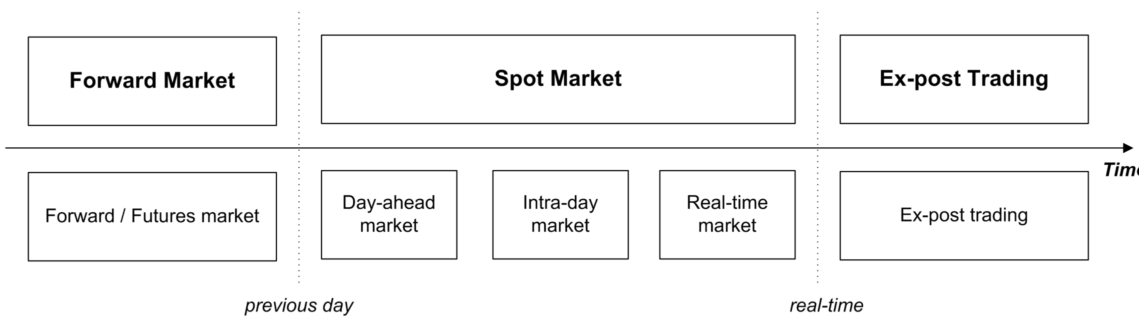

Figure 2.2: General wholesale power market timeline (source: adopted from Petrov and Gore (2009))

Forward and Futures market

In bilateral trading, this market provides an opportunity for generator and buyer to enter into contracts for future electricity supply of contracted quantity and price. This market usually accounts for the majority of electricity traded. In the pool market design the generators and buyers have to buy electricity from pool, thus they cannot contract for the physical delivery. Instead they can hedge against electricity price volatility (contract for differences). The electricity buyer and generator agree on a certain volume and price in the contracts for differences. If on the dispatching day the pool electricity price is higher than the contracted one, the generator pays the buyer the difference and vice versa when the pool electricity price is lower than contracted one.

Futures are standardised and legally binding contracts that obligate electricity sellers for the future power delivery at a specified location, date and quantity. In most cases, however the futures are settled financially between parties on or near the delivery date. Forward contracts also oblige electricity sellers to deliver electricity at specified location, date and quantity. In contrast to futures,

the terms and conditions of forward contracts are not standardised, but negotiated to meet the particular financial or risk management needs of the parties involved. For this reason, they are not traded at PXs, but usually through OTCs (Stoft et al., 1998).
Another important marketplace for contracts that stipulate physical delivery of electricity at a specific time on the following day is referred to as the DA market.

Day-ahead market

Day-ahead market is run in order for the system operator to balance the system and also to determine wholesale electricity prices for the next day delivery based on generation offers[2], predicted demand or demand bids[3], as well as scheduled bilateral transactions. In the case of electricity pooling this is a major market for electricity trading, whereas in bilateral trading the DA market is run independently of the system operator and enables generators and electricity buyers to fine-tune their rolling contract positions as their own demand forecasts improve the closer they get to the RT point of electricity dispatch.

Intra-day market

On the very short term, usually between DA market and an hour prior to real-time dispatch, market participants enter Intra-day (ID) market. Electricity sellers may want to sell spare capacity, or electricity buyers may purchase an additional power in order to be able to react to imperfections in demand forecast or sudden faults in electricity dispatch.

Real-time market

After DA and ID markets closure, the demand and supply of electricity is still not always perfectly balanced due to imperfections in demand forecast, sudden plant outages, or fluctuating renewable electricity production. In both market designs the RT market involves participation of the system operator who continuously levels out imbalances that occur in the system. Thereby the RT is run usually one hour before electricity dispatch where the system operator accepts bids and offers from

[2]An offer is a proposal to increase generation or reduce demand (Harris, 2012).
[3]A bid is a proposal to reduce generation or increase demand (Harris, 2012).

pre-qualified market participants to provide power regulation to counteract energy imbalances detected during the electricity dispatch window (settlement period). The pre-qualification is required to ensure that participating electricity generators meet the specific RT market technical requirements (ramp up rate, maximum start up cycles, *etc.*). Qualified power plants effectively submit two offers: capacity price and incremental power price. Power plants are paid capacity prices for holding the specified electricity generation in reserve (thus losing the opportunity to sell their output elsewhere), and incremental power prices for producing electricity required to balance the system (Weidlich, 2008). Depending on the congestion management method employed (*e.g* PR) the power plants also submit bids: decremental power prices for postponing electricity generation that was contracted at DA or Forward/Futures market. The process of energy balancing on a transmission network at real-time is referred to as frequency control. Unbalanced electricity consumption or injection causes the system's frequency to deviate from its set-point value (commonly 50 Hz) that in turn can damage consuming devices or even cause blackouts.

Ex-post trading or imbalance settlement

Ex-post trading or imbalance settlement is a settlement process for the accepted RT market incremental power offers and bids, and also for recovering the system operator's costs accrued in balancing the system, as well as charging market participants whose contracted positions do not match their metered volumes of electricity.

In a liberalised electricity industry the DA, ID and RT markets are referred to as *spot markets* similar to the markets where commodities are sold and bought for instant delivery, however the use of terminology by some authors might differ slightly (Krause, 2005).

The main market participants are (Harris, 2012):

- *System operator* - a non-commercial organisation that oversees the security of electricity supply, and is neutral and independent with regard to the market participants.
- *Electricity supplier (electricity buyer, load-serving entity)* - purchases a wholesale electricity in order to meet the demand of their end-use customers

- *Electricity generator (electricity seller)* - an electricity generating firm that sells a wholesale electricity, comprises one or more power plants.
- *Non physical trader* - an organisation without a physical demand for electricity, or any means of generating electricity (*e.g.* Banks), to trade electricity

2.3 Congestion management methods

The electricity flow between two nodes is partially governed by the transmission capacity of the line. In practice it may not be possible to deliver the cheapest electricity available if its flow violates the capacity limit of any transmission line. In this case the grid is said to be congested. The cost associated with congestion alleviation can increase dramatically and hence can become a barrier for electricity trading. For this reason the congestion management problem is seen to be critical for the smooth functioning of liberalised electricity markets and subsequently attracted a broad attention within industry and academia (Kumar et al., 2005; Mwanza et al., 2007).

In general the congestion management process comprises four important steps: 1) recognising the current state of transmission physical capacity and existing constraints; 2) allocation of generating capacity; 3) estimation of the level of congestion; 4) alleviation of generating capacity. A variety of congestion management methods exist. Depending on location in the market operation timeline, these methods can be ascribed to capacity allocation or capacity alleviation type. The two most common methods of capacity allocation used in liberalised power markets are:

- *LMP* method also known as *Nodal pricing* found in diverse implementations in New Zealand and parts of United States.
- *Zonal pricing* method is found in Scandinavian market for inter-zonal congestion relief and in Australia.

These methods are applied prior to electricity dispatch. In contrast, capacity alleviation methods are used during electricity delivery and thus are usually referred to as remedial actions. The main methods are:

- *Power Re-Dispatch* method as found in the UK.
- *Countertrade* method as used in Scandinavian power market for intra-zonal congestion relief

Each of these methods of either type maintains energy system security but differs in its influence on the economics of the electricity market. None of these methods can be clearly referred to as dominant (Christie et al., 2000; Krause, 2005; Lo et al., 2000).

Locational marginal pricing (Nodal pricing)

The LMP concept was invented by Schweppe et al. (1988) and later finalised for market application by Hogan (1992). The LMP method is grounded on two key ideas: 1) to set the optimisation task that incorporates technical specifications of generating units, demand elasticities and transmission grid physical constraints; 2) optimise the system in a least-cost generating manner or in other words maximise social welfare. One of the solution output is a price for wholesale electricity at each transmission node. If the least-cost electricity dispatch is impossible without an ensuing power congestion, in this case electricity prices vary across the nodes. This is seen to have a positive effect since price variation provides the correct investment signals to generators and loads. Thus LMP as methodology comprehends that in addition to the necessity of electricity production it also has to be delivered to a particular node. Under LMP method generators and electricity buyers do not explicitly contract for transmission capacity. The capacity is allocated rather implicitly through the bids and offers submitted (from particular nodes) to the market. The LMP method is usually used in pool-based market designs where the system and transmission operator is a single body responsible for clearing the market while respecting transmission constraints.

Zonal Pricing

The Zonal Pricing (ZP) congestion management method is used within the Scandinavian DA electricity market (Krause, 2005) in order to manage large and long-lasting constraints (Bjorndal et al., 2003). Similar to LMP, ZP method determines electricity prices for different locations of the transmission grid. However in the congested networks the distinct prices are established not for each individual node but rather for a group of nodes referred to as zones. This concept is usually used when the system operator anticipates that parts of the transmission grid can be potentially congested. Independent System Operator (ISO) splits the system into two price areas located on the both sides of the 'bottleneck' and notifies market participants. Market participants have to submit separate bids and offers to price areas in which they have generating or loading facilities. These price areas are settled separately at the prices which satisfy transmission grid constraints. Zones with excess generation will have lower prices than those with excess load. The price difference is paid to the system operator and later on used to reduce the capacity fee[4]. If the market is not congested then only uniform electricity price is established as no price areas exist.

Power Re-Dispatch

For congestion relief in Sweden, Denmark, Finland, UK and smaller internal congestions in Norway, the PR method is adopted along the RT market operation. In particular the ISO clears the DA market based on supply and demand information received, and by treating the entire transmission grid as 'copper plate' as no physical transmission constraints exist. Subsequently when the system timeline enters the RT market, ISO adds physical transmission constraints to the optimisation problem. By solving it the ISO defines the nodes where the power injection has to be increased or decreased in order to relieve the congestion. The INC and DEC are obtained through bilateral contracts between the ISO and market participants and thus remain closed for the public (Sioshansi, 2011). Subsequently each contracted participant will be instructed to either increase or decrease their power output at the node and also reimbursed for the service provided according to contract specifications.

Countertrade

Countertrading is a modified form of PR and is referred to as more market-oriented (De Vries, 2001). In contrast to the PR method the ISO buys and sells electricity at prices determined by bidding process at power exchange. Only market participants which satisfy specific technical requirements are allowed to trade at RT market. In the case of the offered capacity not being enough

[4]Capacity fee is applied to electricity generators and electricity buyers and it based on maximum MW consumed (for buyers) or maximum MW produced (for generators) (Christie et al., 2000)

to resolve the congestion, the ISO can add a shape to contracted positions (at Forward/Futures or/and DA markets) by accessing the spinning reserve[5] available to it.The costs that the system operator is subject to (when buy and resell the power) are distributed among market participants as fixed charges of the transmission grid tariff (Christie et al., 2000).

2.4 Optimal Power Flow

The objective of an OPF algorithm is to find a steady state solution of electricity dispatch which minimises the loss in power transportation and total generation cost while satisfying limits of real and reactive power production, transmission constraints, output of compensating devices, and etc. (Pandya and Joshi, 2008). In practice, the alternating current power flow problem is typically approximated by a more tractable direct current (DC) OPF (Wood and Wollenberg, 1996; Sun and Tesfatsion, 2007a) that focuses exclusively on real power constraints in linearised form under several assumptions (Kirschen and Strbac, 2004):

- The voltage angle[6] difference across each branch is sufficiently small (close to zero) in magnitude
- The voltage magnitudes at each node are assumed to be constant
- The resistance for each branch is negligible compared to the reactance[7] and can therefore be set to 0
- There is a reference node on the transmission grid that has voltage angle normalized to 0

These assumptions allow the creation of a model which is a reasonable first approximation for the real energy system. Such a model is very advantageous for computer calculations and also has some beneficial properties such as 1) *Linearity* - if the amount of power (Megawatt (MW)) in transaction between nodes is doubled, the corresponding power flow will double as well 2) *Superposition* - the

[5]Spinning reserve characterises an unloaded generation that is synchronized and ready to serve additional demand (Hirst, 2002)
[6]Voltage angle is a phase angle between voltage and current (Parker, 2003).
[7]Reactance is an opposition of inductance and capacitance to alternating current. Capacitance in tern is the property of electric conductor to accumulate electric charge. Inductance the physical property of an electric conductor that causes an electromotive force to be generated by a change in the flowing current (Parker, 2003).

power flows on the transmission lines can be broken down into a sum of components (Christie et al., 2000). By taking all the assumptions listed above into account, the power flow P_{nm} on the branch connecting node n and node m is calculated by:

$$P_{nm} = \frac{1}{R_{nm}} \Delta\varphi_{nm} \tag{2.1}$$

where, R_{nm} - branch reactance in per unit, φ_n and φ_m - phase angles at nodes n and m respectively. The DC OPF objective can be represented as a minimisation of total generation cost and energy losses as follows:

Minimise

$$\sum_{i \in I} C_i(P_{G_i}) + \sum_{nm \in \Omega} \Delta\varphi_{nm}^2 \tag{2.2}$$

With respect to

$$P_{G_i} \text{ and } \Delta\varphi_{nm}$$

where, $C_i(P_{G_i})$ characterises generator's i cost of production which is a function of its electricity output; $\Delta\varphi_{nm}$ is a phase angles difference at the nodes adjacent from both sides to branch nm. The solution of (2.2) delivers the optimal output level by generators required to meet the system load at the lowest possible cost and least energy loss. However this solution does not guarantee that certain generating and transmission grid physical specifications will be respected in order to serve the power in a robust and reliable manner to the end user. Depending on the congestion pricing method employed the set of constraints may vary (see Grundy et al. (1996) for extended list of physical constants), however it is possible to define the crucial ones underlying most of congestion pricing approaches.

Real power balance constraint for each node. The power plants are coupled together by the transition grid in such way that the rotors of all generators are in synchronised rotation. However the synchronisation may be lost due to variations in load and power generation, short circuits, disconnections of power transmission lines, and similar causes. In order to avoid blackouts the system frequency stability has to be properly managed at every instant. In particular the frequency stability across the network is provided by respecting the total power balance at each node. Thus the total power flowing to the node n plus the power generated at node n must be equal to total power withdrawn from node n:

$$\sum_{i \in I_n} P_{G_i} + \sum_{nm \in \Omega} \frac{\Delta\varphi_{nm}}{R_{nm}} = \sum_{k \in K_n} P_{L_k} \tag{2.3}$$

where, P_{G_i} is an electricity output by generator i at node n, P_{L_k} is an amount of electricity withdrawn by load k and node n, R_{nm} is reactance of branch nm.

Real power thermal constraint for each branch. All transmission lines are made from materials of finite resistance, thus running electric current will cause them to heat up, which in order can damage the ability of wires to conduct a power. Thus thermal capacities of the transmission lines have to be properly managed. Notationally the constraint can be expressed as following:

$$\left| \frac{\Delta\varphi_{nm}}{R_{nm}} \right| < T^U_{nm} \tag{2.4}$$

where, T^U_{nm} is a thermal limit for real power flow on branch nm.

Real power production constraint for each generator. Every distinct generating technology has unique technical specifications attributed to it. This particular constraint highlights the fact that each generating technology usually has lower and always upper production limits[8]:

$$P^L_{G_i} \leq P_{G_i} \leq P^U_{G_i} \tag{2.5}$$

where, $P^L_{G_i}$ and $P^U_{G_i}$ are lower and upper production limits accordingly of generator i

Voltage angle setting at reference node. Overall the DC OPF problem is set by z number of equations with $z + 1$ number of variables. Computationally this system does not have an unique optimal solution, unless number of unknowns and number of equations are equal. For this reason

[8]For example a peak generator can usually produce from just above 0 MW, however a nuclear power plants starts producing at well above 0 MW level

the angle at a random node (referred as the reference node) is explicitly set to 0, thus a power injection at the reference node is simply the negative sum of all other node injections in the system.

$$\varphi_1 = 0 \tag{2.6}$$

In addition to the physical constraints listed above the phenomenon called 'Loop flows' is also incorporated into DC OPF implicitly. The dispatched power flow is governed by the First Kirchoff's Law[9], and thus some portions of it are also distributed into other branches that are adjacently connected. The loop flow is defined as a difference between the scheduled power transaction and actual load of the line.

Consider the 3-bus network in Figure 2.3 using two generators(2000 MW and 1000 MW) and a load of 3000 MW. Generator at bus 1 is required to dispatch a total power of 2000 MW to the load at bus 3. But in actual practice, only 70% (1400 MW) of the dispatched power flows from bus 1 to bus 3. The remaining 30% (600 MW) of power will flow along the non-contract paths 1-2 (from bus 1 to bus 2) and 2-3 (from bus 2 to bus 3). This remaining flow is known as loop flow.

[9]First Kirchoff's Law: a current flows uniformly in a circuit. Electrons do not bunch up. At any node (connection of 2 or more wires) the sum of the currents flowing into the node is exactly equal to the sum of currents flowing out of the node (University of Texas at Austin, 2012).

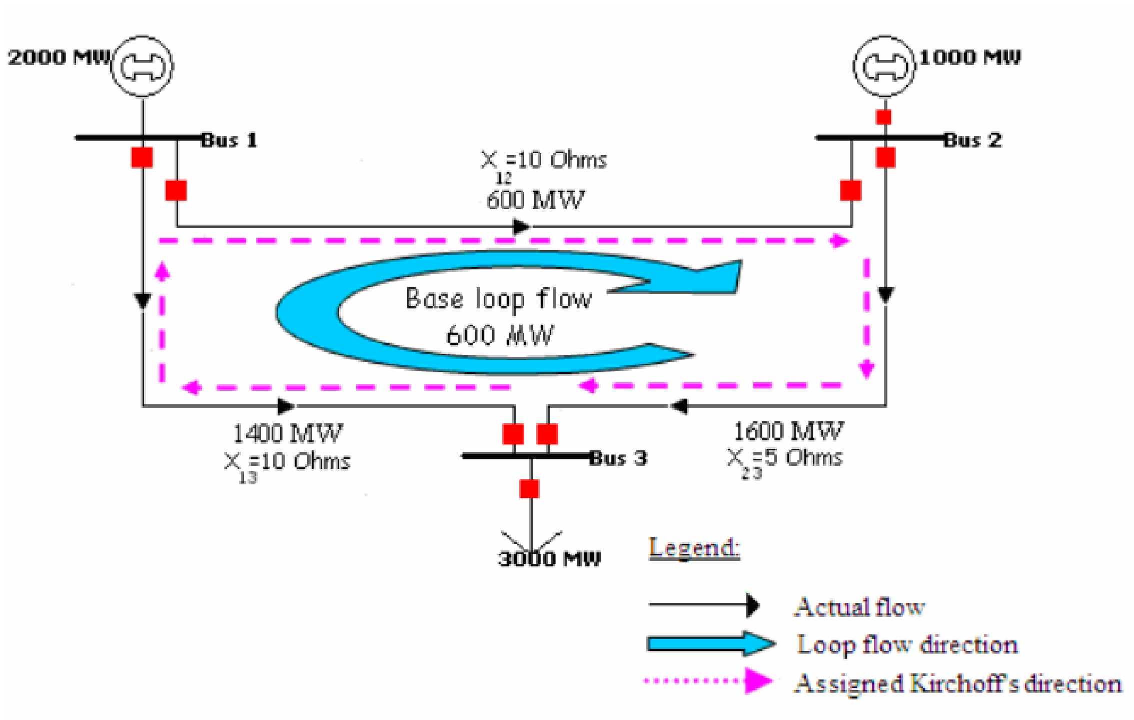

Figure 2.3: Demonstration of Loop flow (source: Chin, 2006)

2.5 Trading behaviour of electricity producers

All the established markets in general can be referred to as competitive, oligopoly or monopoly (Frezzi, 2008). The competitive market comprises numerous buyers and sellers of homogeneous good with negligible individual market share. Thus each market participant cannot affect the aggregate supply, demand or price and hence referred as a price taker (Makowski and Ostroy, 2001). Moreover the competitive market does not impose barriers for entry and does not impede the capital flow between economic sectors. In contrast the pure monopoly is characterised by only one producer that offers inelastic good. This market type has high price levels, supply constraints, and usually excessive barriers to entry (Pindyck and Rubinfeld, 2001). The intermediate between both market structures is oligopoly. The oligopoly is distinguished by a group of domination producers each of which controls a considerable marker share. Uncompetitive bidding in an oligopoly may dramatically influence the market price leading to high pay-offs and hence abnormal profits. This structure better represents the electricity industry and given its background (used to be organised as vertically integrated monopolies) implies that a perfect competitive market model cannot be achieved (Maiorano et al., 1999).

After liberalisation the electricity industries across the globe are characterized by a move toward oligopolistic competition (Boroumand, 2015). Furthermore in electricity markets, firms trade repeatedly interacting on daily basis hence there is an opportunity to develop subtle communication and collusive strategies (Borenstein et al., 2002). Moreover the concept of electricity market unties some specific attributes that favour firms' collusion such as 1) an inability to store electricity efficiently; 2) demand inelasticity in response to price change; 3) electricity flows in the system according to physical laws through the path that is not necessary an economically efficient. Empirical evidence suggests that the generators have been able to raise prices well above competitive levels (Borenstein and Bushnell, 2000; Joskow and Kahn, 2001).

Broadly speaking there are three common types of the strategic behaviour in electricity markets (Twomey et al., 2005; Younes and Ilic, 1998):

- *Capacity withholding* involves generators reporting reduced production capacity, or power

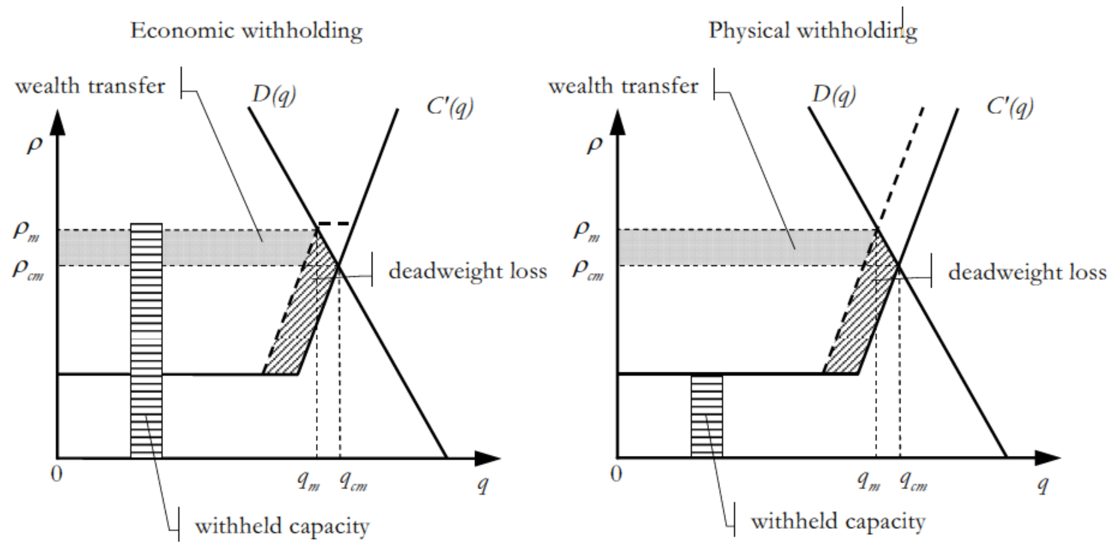

Figure 2.4: Illustration of economic and capacity withholding (source: Frezzi (2008))

plant outages, in order to create a deficit for power and thus to rise the market prices for electricity (see Figure 2.4).

- *Economic withholding* involves reduction in generator's output when it offers into the market the prices above competitive ones (see Figure 2.4).
- *Transmission related strategies* creating new or enhancing the existing power congestions with the purpose of increasing prices for electricity in certain zones or nodes. Can be a result of capacity or economic withholding.

According to Figure 2.4 the impacts from alternative strategic behaviours on market efficiency are similar. Thus by exercising either strategy the electricity price increases from its competitive level of ρ_{cm} to ρ_m and the quantity of power produced decreases from q_{cm} to q_m. The deviation of market clearing results from their competitive positions leads to the following consequences:

- *Wealth transfer* - when the power producers exercise market power[10] the wealth[11] shifts from consumers to the strategic players.

[10]Market power - the unilateral or coordinated ability of market participants to profitably increase prices above competitive levels for a significant period of time (Garcia, 2007).
[11]Wealth - the total value of the accumulated assets owned by an individual, household, community, or country (Deardoff, 2006).

- *Deadweight loss* - the increase of market price diminishes the benefits to consumers in comparison to the raise of producers' profits, causing an inefficiency to the society.
- *Price volatility* - the exercise of market power causes considerable price fluctuations especially when the electrcity demand is price inelastic.
- *Supply shortage* - strategic behaviour can lead to shortage of power supply, particularly in periods of peak demand.
- *Distortion of price signals* - when the market power is exercised for a long time it could lead to false price signals and as the result to distortion of operating and investment decisions.

Moreover the applied strategies of various types can be classified as static or dynamic. By adopting the static class strategies the firm attempts to maximise its profits without taking into account subsequent evolution of market variables and the competitors' behaviour as a response to its strategic action. In contrast, when dynamic class strategies are employed, the firm anticipates the responses of other market participants (also strategic players). Firms are said to collude when they all simultaneously reach an equilibrium in their long-term profit maximisation actions. Through collusion the market participants coordinate their strategies in order to maximise individual profits. In the electricity market there are, in general, two ways of reaching a collusion among power producers, 1) tacitly or 2) explicitly. Tacit collusion does not involve a communication between power producers, they individually analyse market prices and respond with their own bidding strategies. These strategies are negotiated across power producers when they collude explicitly (Ivaldi et al., 2003).

Market power concerns are probably the most difficult and controversial challenges faced by power market regulators worldwide. On the one hand, electricity prices have to reflect the scarcity of resources used for power generation and thus are expected to be high, however they should not be accelerated by strategic behaviour of market participants. There is always a trade-off between interests of consumers in low electricity prices and incentives for power generators (Garcia and Reitzes, 2007).

Research into market design is very important. It can help to 1) reveal the aspects that contribute to the market power exertion by trading parties and 2) establish market rules that improve market efficiency. One of the most prominent power market designs that have been influencing the way electricity is traded in many countries is implemented in the UK. The UK power market design is discussed in the following section.

2.6 UK wholesale electricity market

In 1990 the radical reforms introduced by the Governmet allowed for the liberalisation of the electricity industry in the UK and the establishment of a new wholesale electricity market design referred as the Pool. The Pool implementation has delivered the following changes to the existing back then electricity industry (Green and McDaniel, 1998; Newberry, 2002):

- Unbundling four distinct functions of the electricity industry (generation, transmission, local distribution, and retail services)
- Privatising generation and retail services
- Establishing a compulsory electricity pool for physical power exchange and financial market for contracts for differences
- Introducing an independent system operator to manage the transmission system (*e.g.* dispatch power plants, maintain system reliability)

The first results of liberalisation were two generating firms controlling over 80% of total capacity. In the course of the following 10 yeas these companies were broken up and subsequently none of the firms among existed on the market had more than 25% of total generating capacity (Green and McDaniel, 1998). It is noteworthy that after liberalisation the electricity prices did not actually fall, in fact 7 years later they were 35% higher than in the winter of 1990/1991 when market trading began (OFFER, 1998). Also, evidence confirms that market power exploitation persisted as generators manipulated prices (by *e.g.* capacity withholding, bidding strategies) (Green and McDaniel, 1998; Wolfram, 1999). Overall the failure of pool-base market design is prescribed to a) market power arising from few sellers, b) poor market design that allows for strategic bidding,

c) little demand response to price changes and d) absence of information on forward trading for price discovery (Woo et al., 2003).

In an attempt to reduce the wholesale electricity prices and introduce demand side bidding, the UK regulator proposed a bilateral model for market design named NETA. NETA came into force in 2001 followed by a drop in wholesale electricity prices (Giulietti et al., 2010). Later in 2005 the concept of NETA was extended to include Scotland and is currently referred as British Electricity Transmission and Trading Arrangement (BETTA).

In BETTA the daily power demand is split on 48 half hour chunks called Settlement Periods. Thus the electricity is considered to be traded, generated, transferred, and consumed in these half hour portions. For each half hour electricity buyers estimate the energy demand and contract these volumes in advance with electricity generators in the Forward market or/and Futures market. The Forward and Futures markets allow the contracts to be struck up starting from years ahead down to an hour before contracted energy dispatch. This barrier is referred as Gate Closure and illustrated in Figure 2.5 as dashed line under 'Gate Closure' notch on electricity market timeline.

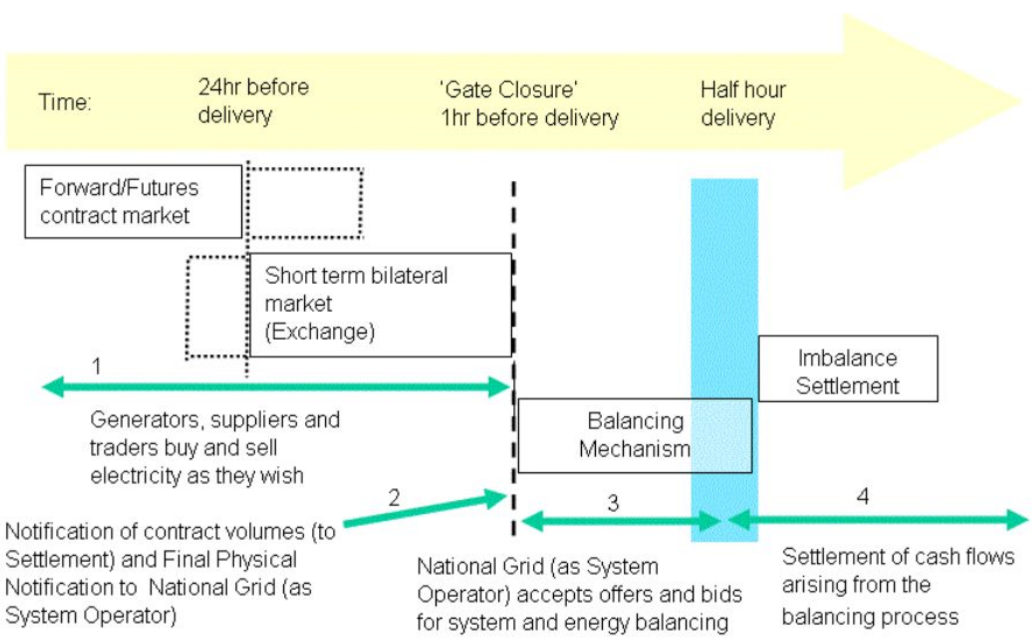

Figure 2.5: Overview of the wholesale electricity market of Great Britain (source: Harris (2012))

The dashed line under the '24hr before delivery' notch on the market yellow timeline is symbolic and does not represent a compulsory border between Forward/Futures and Exchange markets. During period 1 (green arrow 1 in Figure 2.5) market participants buy and sell electricity as they wish. The only difference is that the contract terms (volume and price) at Forward market are not standardised and negotiated directly between trading parties (see Section 2.2.1). In contrast in the Futures market the contracts are standardised and the price determined by market clearing mechanism based on bids and offers received from trading parties (see Section 2.2.1).

At the Gate Closure market participants have to notify (by means of Final Physical Notification) the system operator about individual contracted positions, namely the amount of electricity each party is contracted for as the result of Forward market and Futures markets operations. If the market participant is flexible enough on either demand or supply side and satisfies the specific requirements by the system operator it can offer or bid additional power to the BM by including its proposition into the Final Physical Notification. This stage is depicted by green arrow 2 in Figure 2.5.

The blue stripe (see Figure 2.5) represents the energy dispatch period (half hour window) during which the generators are expected to deliver the contracted amount of electricity to the system. At the same time electricity buyers are expected to withdraw the contracted electricity from the system. The generators that overproduce/underproduce are penalised at the Imbalance Settlement (green arrow 4 in Figure 2.5) by selling/buying electricity at system sell/buy price. The system sell and buy prices are designed in a way that market participants have no incentive to deviate from their contracted positions. The Imbalance Settlement is a closed monetary system in that all the profits or deficits obtained by the system operator during the Imbalance Settlement are distributed proportionally amongst all parties. The ISO can buy or sell the electricity ahead of Gate Closure if it believes that an extra amount of electricity will be needed during the settlement period. These contracts are called a Pre-Gate Closure BM Unit[12] Transactions. They specify the electricity volumes required in a minute by minute basis across the settlement period.

[12]BM Unit contains either a generating unit or a consumption unit that is comprised of a collection of consumption meters. All BM Units are the smallest smallest generating or consumption units that can be independently controlled Harris (2012)

2.7 Conclusion

This chapter has outlined the main attributes of wholesale electricity markets, and overviewed the most widely adopted congestion management methods. It provided detailed specifications of the UK power market design. It also showed that power markets comprise a set of interrelated marketplaces for trading electricity and related products. These marketplaces are usually daily repeated auctions. This gives potential to trading parties to learn bidding strategies and subsequently exercise market power.

3 Survey of agent-based models in electricity

3.1 Introduction

The electricity industry is a complex economic system that adopts specific real-world aspects such as asymmetric information, imperfect competition, strategic interaction, collective learning, and the possibility of multiple equilibria (Amman et al., 2006). In order to address these real-world aspects and get an insight into market interdependencies, many researchers have developed agent-based electricity market models. The diversity in implementation approaches makes it difficult for the new entrant to overview the field. Therefore the literature review in Section 3.2 describes the key contributions to methodology of Agent-Based Computational Economics to study wholesale electricity markets. The conclusive summary in Section 3.3 highlights the key similarities and differences between existing agent-based electricity models.

3.2 Literature survey

The first agent-based models in electricity were tailored for a specific design of the wholesale electricity market and often developed real-world approximations for the bidding strategies. Thus the work by Bower and Bunn (2001) developed an agent-based simulation model for the electricity market of England and Wales, with particular focus on two structural aspects: uniform price auction versus discriminatory price auction. The model simulates a daily repeated market with two combinations of trading (daily and hourly bidding) and two combinations of settlement arrangements (uniform and discriminatory pricing). Each autonomous adaptive agent represents a generating firm that owns a number of electricity plants characterised by capacity, fuel type, efficiency, marginal production costs and availability. The load agents are modelled as price takers with no ability to influence the market through strategic behaviour. There is no transmission grid. As a result the model does not account for physical transmission constraints and the cost of transmission is assumed to be zero. Depending on the market design of choice, each agent at the DA market submits to the system operator one (daily bidding) or 24 (hourly bidding) bids and offers all available generating capacity for each plant in his portfolio. The strategic capacity withholding is not concerned within the model. The generating firms submit strategically increased marginal generating costs and learn the best performing strategies with the help of the RL algorithm. This allows the agents to select a bidding strategy that simultaneously 1) maximises profit and 2) enables reaching a target utilisation rate on plant portfolio. The supply offers are submitted by generators daily according to the following decision rule:

- if on the previous trading day the target rate of utilisation was not met across the portfolio, then a percentage is subtracted from the bid price for each plant in the portfolio.
- if on the previous trading day any plant sold output for a lower price than other plants across the portfolio, then the bid price is raised of that plant to the next highest bid price submitted.
- if on the previous trading day the total profit did not increase across the portfolio, then a percentage is randomly added or subtracted from the bid price for each plant in the portfolio.
- if on the previous trading day profit and utilisation objectives are achieved across the portfolio, then the decision is repeated.

Moreover the plant with the higher marginal cost of production must always bid higher prices than the plant, in the same portfolio, with lower cost of production. Finally a generating agent is allowed to utilise the successful bidding strategy across all the plants within his portfolio. It is assumed that agents have a comprehensive knowledge of their own portfolio of plants (bids, output levels, profits), but know nothing about their rivals. The authors impose various limits for capacity utilisation rate for each generating technology. The average target utilisation rate across plant portfolios is set to 60%. However for all power plants with closed-cycle gas turbine (CCGT) technology, nuclear power plants and inter-connectors, the target utilisation rate is set to 100%

as these plants, in general, trade almost fully contracted. These assumptions are made in order to avoid explicit modelling of the forward market but still have it implicitly incorporated. At the same time the model does not capture the interaction between the DA trading and the balancing mechanism.

The work by Bunn and Oliveira (2001) presents a model for the UK power market primarily focusing on possible market equilibria. In contrast to the model discussed above, here authors introduce an active demand side (strategic load agents) and interaction between the DA market and the balancing mechanism. Each load agent is characterised by: market share, balancing mechanism exposure, retail price, prediction error, and search propensity. The prediction error reflects the capability of the agent to predict its own demand while search propensity is a numerical identifier of how the agents search for the best pay-off and transform past experience into future policies. The agents of both types 1) markup at DA market based on previous trading day results and 2) explore DA market outcomes in order to markup at subsequent balancing mechanism. All trading agents aim to 1) maximise total daily profits and 2) minimise the difference between preferred and actual exposure to the balancing mechanism. Similar to the model developed by Bower and Bunn (2001), each generating agent represents a firm that owns a number of electricity plants. Each electricity plant is characterised by the number of cycles per day it can operate, capacity, availability, preference for balancing mechanism exposure, marginal production cost, and search propensity. Whilst equal generating technologies are assumed to have identical marginal, start-up, and no-load costs, the last two are not considered by agent explicitly during decision making process. The authors also imposed some additional rules for the generating agents in order to avoid inconsistent behaviour during the learning process:

- within plant portfolio the generator with higher or equal number of cycles will never undercut the offers by another plant with equal or less number of cycles;
- the base-load plants (one cycle plants) may run with no profits in certain hours of the day.
- one cycle plants do not run without profit at the beginning or at the end of the day or do not run at all if the price is to low.

- multi-cycle plants (peak plants) do not offer prices below marginal cost
- All power plants never bid (offer) above (below) the previous system buy price (system sell price).
- All power plants never pay more than the marginal cost for speculative DEC of electricity which the system operator buys in order to balance the system.

It is noteworthy that none of the agents actually learn the absolute bidding strategies, instead they learn how to choose the markups on the previous day offers and bids, thus the model benefits from strategies which are unbounded. The entire learning process implemented here can be describes as sequence of the following actions:

1. For the markups used, each agent determines new expected daily profit (3.1) and acceptance rate (3.2):

$$E(\Pi_{tj}) = E(\Pi_{t-1j}) + \alpha * [\Pi_{t-1j} - E(\Pi_{t-1j})] \tag{3.1}$$

$$E(A_{tj}) = E(A_{t-1j}) + \alpha * [A_{t-1j} - E(A_{t-1j})] \tag{3.2}$$

   where, Π_{tj} and A_{tj} is a total profit and acceptance rate at day t of the markup j.

2. Given these values each agent calculates the expected reward for each markup:

$$E(R_{tj}) = E(\Pi_{tj}) * E(A_{tj}) \tag{3.3}$$

3. Each agent calculates the perceived utility of each markup:

$$U_j = u * \left(\frac{S-n}{S}\right)^{Rank(j)-1} \tag{3.4}$$

   where, $u = 1000$ for each agent, $n = 3$, and S is search propensity parameter that defines agent's exploration capability.

4. Finally the agent defines a policy that represents a set of probabilities with each value attached to a certain markup. The probability of selecting a particular markup equal the ratio

of that markup perceived utility and the sum of perceived utilities of all markups:

$$P_j = \frac{U_j}{\sum_k U_k} \tag{3.5}$$

In order to model the balancing mechanism the authors had to adopt several simplifications:

- Absence of transmission grid, and as the result lack of the regional imbalances and transmission constraints.
- Load profile is fixed to a typical day.
- The continuous nature of trading at DA market and balancing mechanism is simplified and presented as two sequential one-shot markets.
- Assumed independence between generators and suppliers.

To overcome the issues related to computational time when simulating the real scale power market the authors utilised a single call auction developed by Cason and Friedman (1997), while adopting it to reflect trading principles of the real UK power market. Market operations flow is best described by Figure 3.1. The trading starts at the DA market where the load agents forecast the demand and place the bids accordingly, while aiming to buy electricity at the lowest possible prices. At the same time power agents build up generating portfolios by deciding on which power plants to run given their technical specifications. They also decide on the percentage of capacity to withhold for trading at the balancing mechanism. After the DA market clears, the agents bid/offer to balancing mechanism. The system operator clears the balancing mechanism and calculates imbalance prices. This is followed by the agents' learning stage and subsequently the market enters a new trading day thus the process repeats.

Another distinctive work was conducted by Visudhiphan and Ilic (2003) where the authors explored three different learning algorithms employed by strategic agents, namely:

- Mixed strategy algorithm formulated in Auer et al. (2003)
- Mixed strategy algorithm based on the Boltzman distribution

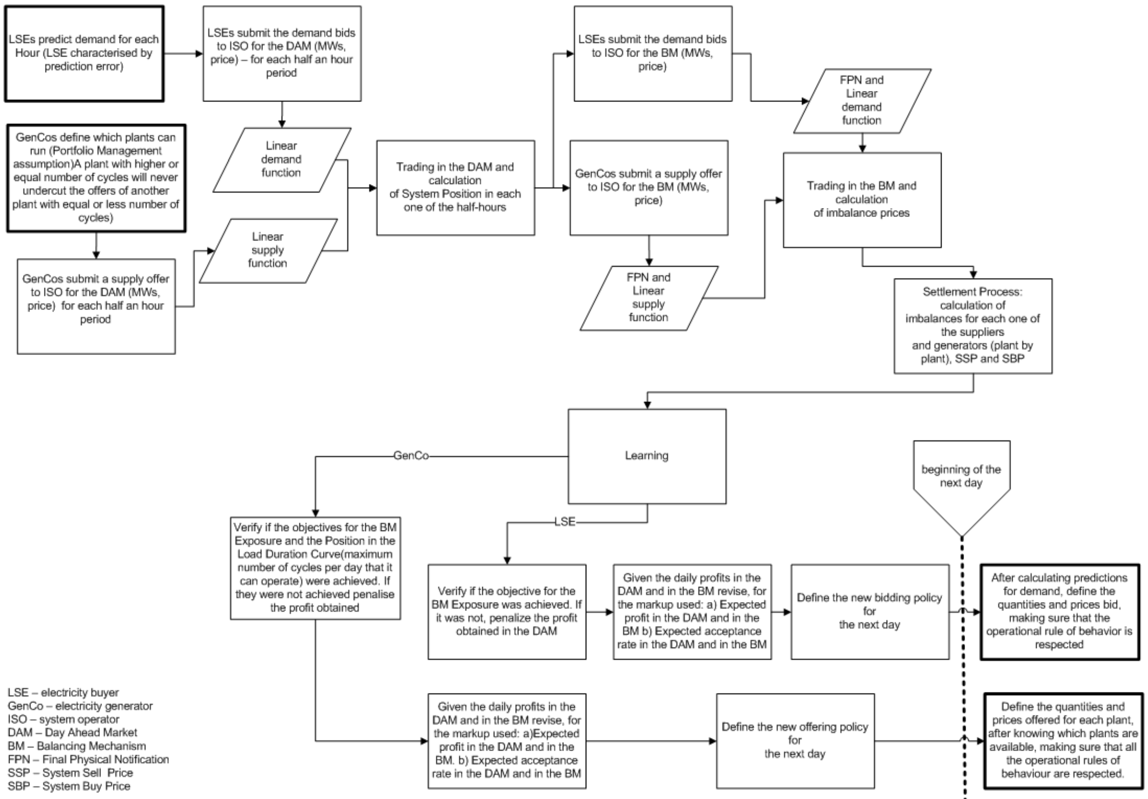

Figure 3.1: Electricity market model flow chart developed by Bower and Bunn (2001)

- The algorithm developed by the authors

The first learning algorithm assigns probability $p_t(i)$ to each strategy $i \in K$. This probability is a function of a uniform distribution $\frac{\gamma}{K}$ and the weight factor $w_t(i)$ associated with each strategy i:

$$p_t(i) = (1-\gamma)\frac{w_t(i)}{\sum_{j=1}^{K} w_t(j)} + \frac{\gamma}{K} \tag{3.6}$$

where

$$\gamma = \min\left\{\frac{3}{5}, 2\sqrt{\frac{3}{5}\frac{KlnK}{T}}\right\} \tag{3.7}$$

The weight $w_t(i)$ is adjusted every trading day based on the rewards received from the actions selected:

$$w_{t+1}(j) = w_t(t) * \exp(\frac{\gamma}{3K}(\hat{x}_t(j) + \frac{\alpha}{p_t(j)\sqrt{KT}}) \tag{3.8}$$

where T is a total number of market operational days set by the user,

$$\alpha = 2\sqrt{ln(KT/\delta)} \tag{3.9}$$

and δ is a probability error,

$$\hat{x}_t(j) = \begin{cases} \frac{x_t(j)}{p_t(j)}, & \text{if } j = i_t \\ 0, & \text{if } j \neq i_t \end{cases} \tag{3.10}$$

here $x_t(j)$ is reward for the chosen action j in day t. This algorithm is used by agents to learn the best performing strategies.

In the second algorithm based on the Boltzman distribution the probability of choosing the action j is defined as:

$$p_t(j) = \frac{\exp\{R_t(j)/\tau\}}{\sum_{h=1}^{K} \exp\{R_t(h)/\tau\}} \tag{3.11}$$

where $R_t(j)$ is the reward obtained due to strategy $j \in K$ at day t, τ is a positive parameter referred as temperature. It affects the degree to which an agent makes use of propensity values in determining its strategy choice probabilities. The $R_t(j)$ value is updated every day in the following way:

$$R_{t+1}(j) = \begin{cases} (1-\alpha)R_t(j) + \alpha * \Pi_t(j) & \text{if } j = i_t, \\ R_t(j) & \text{if } j \neq i_t, \end{cases} \tag{3.12}$$

where Π_t is an average of profits associated with action j in the day t and α is a step-size parameter $(0 < \alpha < 1)$ Similar to the first algorithm the agents here also learn how to strategically manipulate price-quantity pairs in order to maximise the profits.

In the learning algorithm developed by the author the stratigic agents build the historical record of the market outcomes in a way that every new market outcome is associated with a discrete load range, so the agent memory represents a matrix with columns and rows corresponding to the market outcomes and load ranges respectively. Each agent utilises one of six following strategies when deciding on the offer price:

- the price is set to the maximum of historic prices

- the price is set to the mean of historic prices
- the price is set to the minimum of historic prices
- the price is set to the sum of weighted historic prices
- the price is set to the the last bid price plus the difference between the last market price and the last bid price weighted by a constant β
- the price is set to the target price plus the absolute value of the difference between the last market price and this target price, weighted by a constant β (represents the success in the previous trading day)

Unfortunately, no conclusion from the paper can be withdrawn regarding superiority of one learning algorithm over the others.

Nicolaisen et al. (2000) presented a model of a double auction wholesale electricity market. The model benefits from a fully connected transmission grid with electricity generators and electricity buyers located at the nodes. Each transmission line has limited capacity thus the model is able to address the congestion problem. Every electricity buyer is characterised by a maximum amount of electricity it can consume per hour, linear marginal revenue and fixed costs. Similar, each generating plant is characterised by the maximum amount of power it can generate per hour, linear marginal and fixed costs. Both types of agents trade with the objective of maximising their profits. The whole trading process is split into market rounds (same as days in the models above). At every round, electricity generators and buyers submit price-quantity pairs to clearing-house. Bids and offers are limited by explicitly imposed price caps. The clearing-house matches bids and offers in a least-cost manner. It starts with selecting the generator with the lowest offer and the buyer with the highest bid and sets the price to the mean of the offer-bid spread. Finally the volume of contracted electricity is determined by the tightest constraint, namely a) maximum generating capacity of the power producer, b) maximum volume of electricity that the load agent can consume or c) maximum volume of electricity that the transmission line can handle. The distinctive feature of this model is an implementation of the genetic algorithm which allows the agents to search for the best bid/offer prices. Each strategy is associated with a number in the interval $[0, 1)$ with step 2^{-10}, thus there are about 2^{10} strategies available to each agent. At the end of every round the performance of each agent is reassessed based on the earned profits, whilst no outcomes from other preceding rounds are taken into account. The authors argue that by implementing this modelling approach they were unable to find convincing evidence that the market power of electricity buyers/generators is negatively/positively related to their relative capacity. They also concluded that changes in relative concentration have negligible effects on market power, especially for the electricity buyers.

In the later work of Nicolaisen et al. (2001) the authors substituted the genetic algorithm for a modified Roth-Erev method (Erev and Roth, 1998). In the original Roth-Erev algorithm the agent j at the end of the n^{th} trading round updates its action propensities $q_{jk}(n)$ in order to select feasible action k based on earned profits:

$$q_{jk}(n+1) = (1-r)q_{jk}(n) + E(j,k,k',n,K,e) \tag{3.13}$$

where, r is a value of recency parameter, k' is previously submitted feasible action, K is a total number of feasible actions, e is a value of experimentation parameter, $E(j,k,k',n,K,e)$ is an update function which reflects the experience gained from past trading activity, it takes the form of:

$$E(j,k,k',n,K,e) = \begin{cases} R(j,k',n)(1-e), & k = k' \\ R(j,k',n)\frac{e}{K-1}, & k \neq k' \end{cases} \tag{3.14}$$

According to the specified algorithm the submitted action k' is reinforced or discouraged based on the earned profits $R(j,k',n)$. Finally given the estimated propensities $q_{jk}(n+1)$ the choice probabilities are updated according to the following expression:

$$p_{jk}(n+1) = \frac{q_{jk}(n+1)}{\sum_{m=1}^{K} q_{jm}(n+1)} \tag{3.15}$$

The authors however argue that the Roth-Erev method described above has two shortcomings, namely a) parameter degeneracy and b) lack of probability updating in response to zero profits. They suggest replacing the original recency parameter r with $r* = (r - \frac{e}{K-1})$, thus the degeneracy will no longer occur for $e = \frac{K-1}{K}$ and as the market progresses the agent will be moved away from zero profit actions. In a number of experiments the authors compared the performance of the two learning algorithms. They argued that each learning algorithm lead to the similar results and thus the preference cannot be established.

Krause and Andersson (2006), with help of agent-based model, compared thee different congestion management methods for the abstract wholesale electricity market with transmission grid constraints. Thus the authors studied a) LMP, 2) Zonal pricing and 3) Flow-based market coupling. Figure 3.2 illustrates the modelled network where the dashed lines separate the zones used for the zonal pricing simulation. The authors assume only lines from nodes 2-5 and 3-4 have a limited transfer capacity (100 MW and 150 MW respectively), all other lines are not restricted.

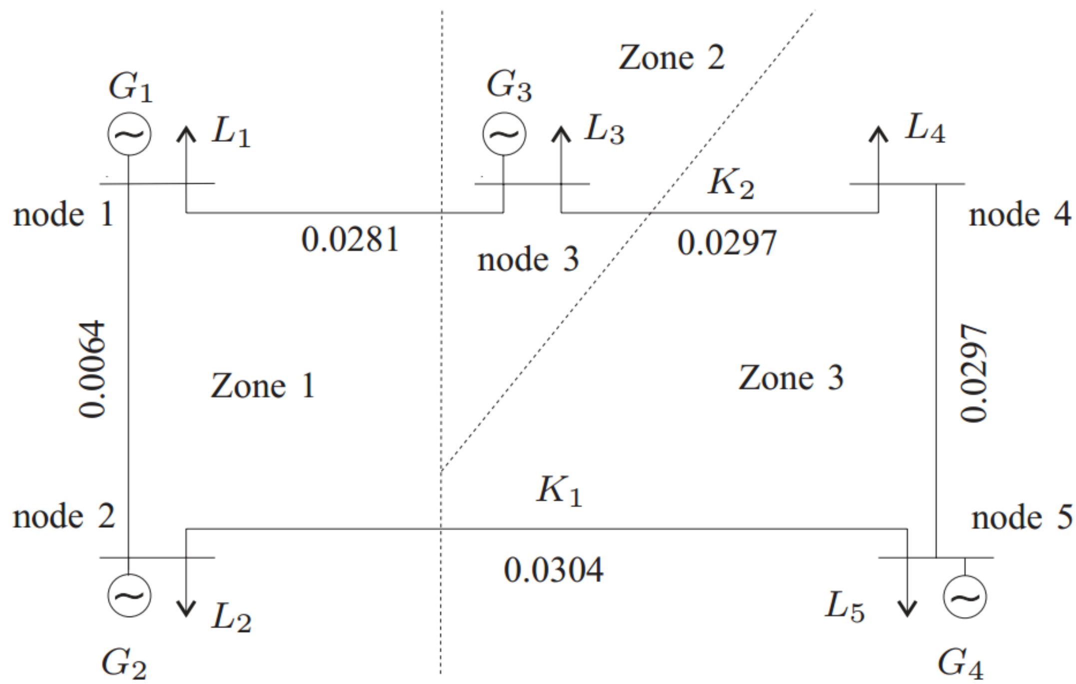

Figure 3.2: Experimental electricity network (source: Krause and Andersson (2006))

Section 2.3 describes the specifics of LMP and zonal pricing methods in detail. According to the flow-based market coupling algorithm the electricity prices are determined by topological simplifications of the transmission grid, thus a) each country is represented as copperplate as no transmission constraints exist and b) all country to country interconnections aggregated into equivalent line. Subsequently the country represents one super-node and therefore the LMP scheme can be used to solve flow-based market coupling problem. These simplifications transform Figure 3.2 into Figure 3.3

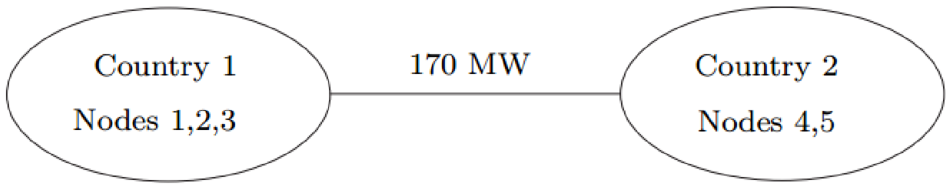

Figure 3.3: Flow-based market coupling representation of the experimental network in Figure 3.2 (source: Krause and Andersson (2006))

The authors assume that generating agents can deviate from their true marginal costs when looking for the most profitable supply offer with the help of the RL algorithm. The agents maximise their pay-offs by a) altering the slope s_{G_i} of the marginal cost function, or b) altering the intercept ic_{G_i} by setting a specified markup mup_{G_i} as illustrated in Figure 3.4.

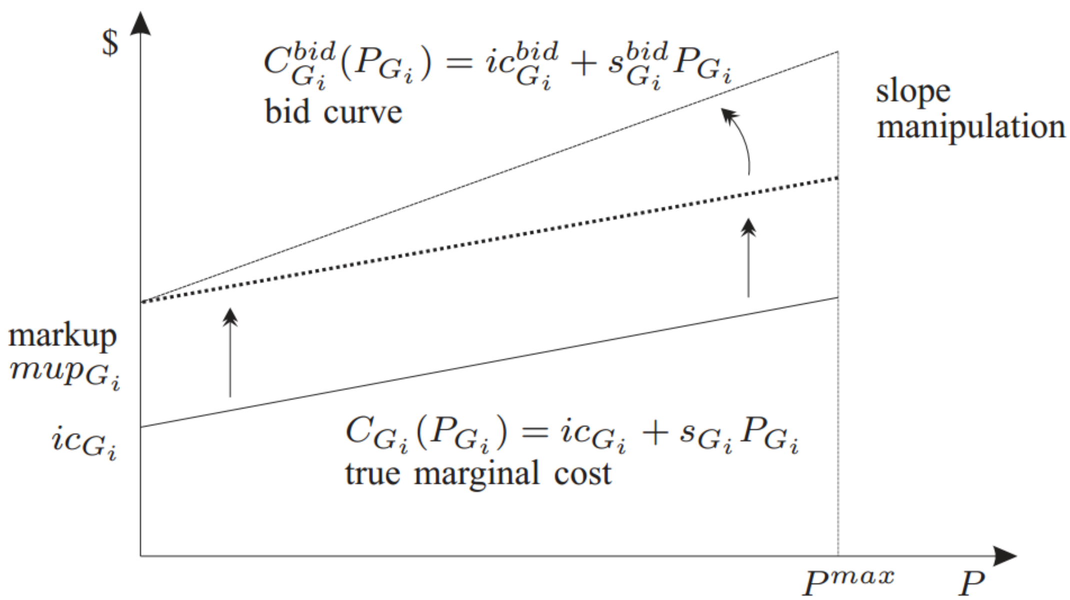

Figure 3.4: True Marginal Cost and Strategic Choices (source: Krause and Andersson, 2006)

The model benefits from an elastic demand side, therefore electricity buyers reduce electricity consumption or switch to partial self-supply in order to respond to increases in market prices. The experimental results suggested different allocations of market power for the different congestion management schemes. Given these results the authors argued that the distribution of social welfare as well as market power have to be assessed in conjunction with the specific market design, implying that general conclusions cannot be made.

Perhaps one of the most prominent works was done by Sun and Tesfatsion (2007b). The authors developed an open-source agent-based framework called AMES to address the specifics of the Wholesale Power Market Platform proposed by U.S. Federal Energy Regulatory Commission for adoption by US wholesale power markets. The AMES benefits from an explicitly modelled transmission grid and incorporates three main types of market participants, namely the system operator (oversees the security of electricity supply and clears the market), load servicing entities (electricity consumers) and power generators (electricity sellers). The AMES employs the LMP congestion management method with uniform pricing auction design and assumes an absence of demand and supply shocks. Thus all the trading and congestion alleviation is done during the DA market without need to rebalance the system at RT market.

In AMES the load agents are modelled as price takers, so they always place their bids without strategic consideration. In contrast the power producers in AMES implement the RL algorithm (similar to the algorithm discussed in Nicolaisen et al. (2001)) and try to reveal the best bidding strategy by a trial and error approach based on the profits earned. Each generating agent is characterised by marginal production cost, generating capacity, learning capabilities and initial wealth. However AMES power producers do not incur start-up, shut-down and no-load costs and also do not face ramping constants. The authors assume a linear marginal generating cost of the following form:

$$MC_i = a_i + 2 \cdot b_i \cdot P_{G_i} \tag{3.16}$$

[1] where, a_i is an intercept and b_i is a slope parameter for the marginal cost of the generator i, P_{G_i} is an electricity output by the generator i. In AMES, generating agents exercise market power by altering the reported marginal cost curve coefficients and production capacity. This is schemati-

[1]Note, the marginal cost is: $MC_i = \frac{dTC_i}{dP_{G_i}}$, where the total cost is: $TC_i = a_i \cdot P_{G_i} + b_i \cdot P_{G_i}^2$

cally depicted in Figure 3.5. Note the bottom line $l_i u_i$ illustrates the true marginal cost curve of generator i, while all the above curves iteratively are offered to the market and have higher intercept and/or slope parameter. In the daily repeated market the agent i, based on the learning parameters specified, is likely to converge to the single profit maximising strategy out of the set of available reported marginal cost curves.

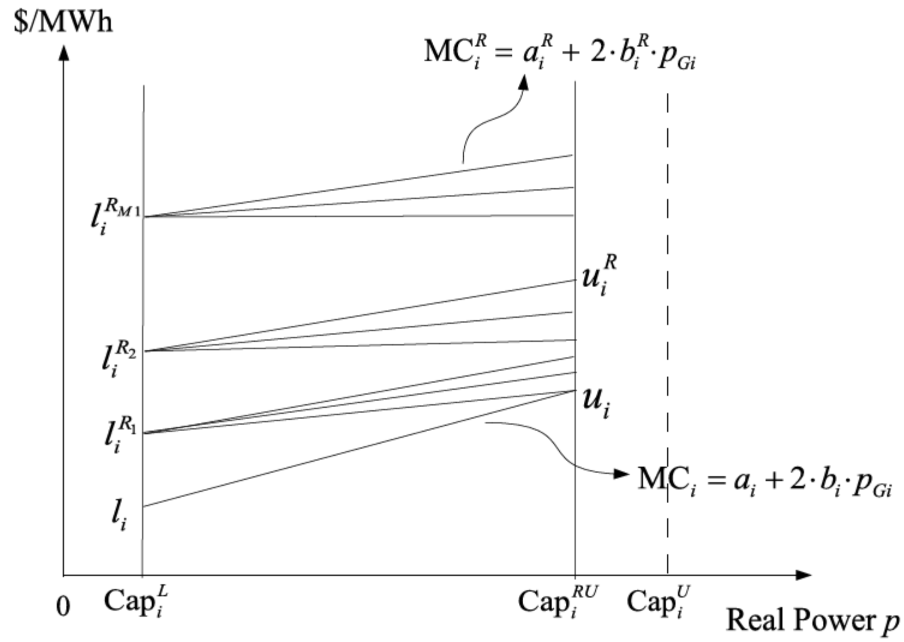

Figure 3.5: Marginal cost modification by AMES generating agent (source: Sun and Tesfatsion (2007b))

Another prominent work has been conducted by the team at Argonne National Laboratory (Conzelmann et al., 2005). The authors developed a full-scale agent-based simulation model called EMCAS to test the market design and reliability of existing power systems. EMCAS incorporates a great number of agents of different types, specifically power generation, electricity transmission, distribution and load companies, system operator, regional transmission organisations and regulators. EMCAS addresses the pool market design for electricity trading and also incorporates three explicitly modelled ancillary services markets, namely power regulation (balancing mechanism), spinning reserve[2] and contingency reserve market[3]. Figure 3.6 illustrates the decision rule of the EMCAS generating agent. The upper part of Figure 3.6 shows that each generating agent uses

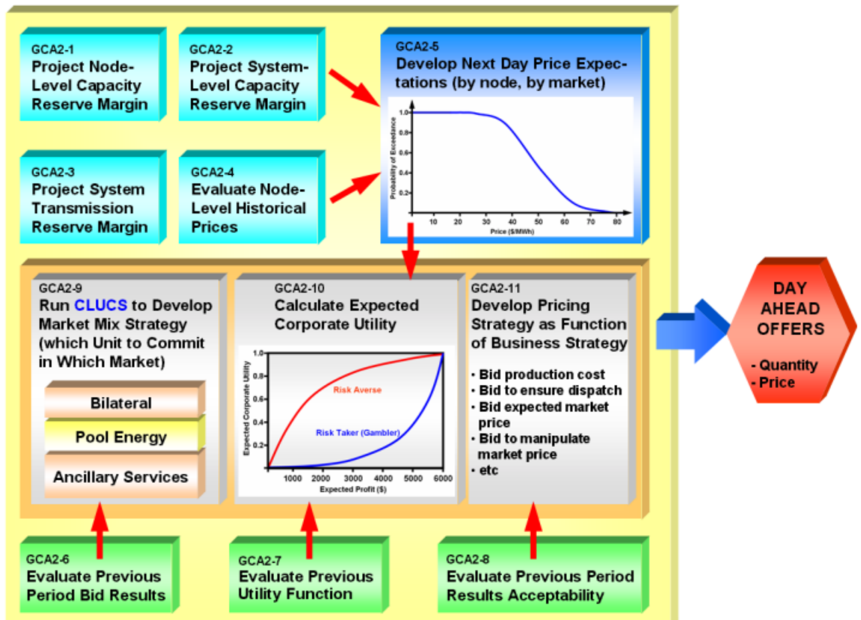

Figure 3.6: Decision rule of EMCAS generating agent (source: North et al. (2002))

its own historical record and publicly available information to build the projected market clearing price distribution at node for each of the markets. Furthermore the agent determines the optimal combination of generating units that bid to some or all available markets. Subsequently it constructs the expected utility function based on personal attitude to risk and one or several simultaneous objectives (*e.g.* maximise profits, or minimise the risk). This is illustrated by the middle section of Figure 3.6. Finally the strategic agent determines and submits price-quantity pairs that optimise its corporate utility. Overall, at every step the generating agents alter the strategies based on anticipated market conditions. The strategies are assessed based on performance in respect to the corresponding objectives.

In the paper by Young et al. (2014) the authors attempt to discover whether an agent-based modelling paradigm can be used to accurately forecast electricity market prices in the New Zealand

[2]Spinning reserve is a back-up generation capacity which is unconnected from the system but can be brought on-line within ten minutes (Hirst, 2002)

[3]Contingency reserve is a power provided by generators that require a longer start-up (typically from 30 to 60 minutes) (Hirst, 2002)

electricity market. The model proposed by authors benefits from an explicitly modelled transmission grid that is a 19-node simplification of the 244 node New Zealand grid. The demand side is modelled as price inelastic while the generating agents can trade electricity strategically by analysing the market with the help of the RL algorithm. Some power plants are specified as 'must-run', with a predefined maintenance schedule. The generating capacity of each power plant is reduced by 12% to account for contracted power at the reserves market which is not modelled explicitly. The authors conclude that the proposed agent-base model can actually predict the market clearing prices with high degree of accuracy. This in turn serves as proof for an agent-based concept that is able to reconstruct market prices from fundamental market data.

van der Veen et al. (2012) developed an agent-based model to analyse the impact of various imbalance pricing mechanisms on the performance of a European type balancing market. In the model, the balance responsible parties are modelled as strategic agents that consume and produce electricity in order to balance the system. The agents forecast their power commitments with an error drawn from the Normal distribution with zero mean and user-specified standard deviation (unique for each agent). The agents employ the RL algorithm to make a choice at each step from the action domain of one intentional imbalance option that represents a level of over or under-contracting. Overall the authors analyse six alternative pricing mechanisms and conclude that single pricing[4] approach leads to the highest social welfare.

3.3 Conclusion

The literature review conducted highlights the high research activity in utilisation of agent-based models to study electricity markets. The analysis of different articles shows that 1) the majority of models do not incorporate the transmission grid and thus disregard grid congestion concerns, 2) in most of the models the demand side is reduced to fixed load-profiles, 3) the strategic learning in majority of the models concerns economic withholding by manipulation of prices, capacity withholding usually is not considered, 4) the majority of models rely on the RL algorithm and its com-

[4] In the single pricing methods the agents with a surplus receive a specific price, and agents with a shortage pay this price (van der Veen et al., 2012).

binations, whilst the genetic algorithm is very rarely applied but is not completely abandoned, and none of the papers analysed explicitly integrates flexible statistical models into the agents' learning algorithm to better address firms' real-world behaviour, 5) the most popular research question is the comparison between discriminatory and uniform price auction designs. The overall conclusion is that agents report higher marginal costs under discriminatory pricing, however, in general, the electricity prices are higher under uniform pricing.

4 The ACEWEM model: A mathematical description

4.1 Introduction

This section outlines a detailed description of the agent-based electricity market model that is developed to support the aims of this research. The model is very flexible in the sense that is not fixed to a particular market design. It can be initialised with either a uniform or discriminatory pricing rule with option of alternative congestion management methods. The model benefits from a realistically rendered transmission grid which is fully customisable and can be extended up to the scale of realistic wholesale electricity markets. The adaptive market participants are generating agents that learn the bidding behaviour of the other participants from available information and determine their strategies in response to the others. These agents employ a realistic learning algorithm which is a combination of forward looking with statistical modelling and past experience addressed by the RL algorithm. The demand side is assumed to be inelastic of a price in the short-term, thus the load agents bid only fixed load profiles. The following section describes the characteristics of the generating agents, the demand, and the market rules used in the model.

4.2 The ACEWEM from inside

4.2.1 Overview of the ACEWEM Framework

Agent-based Computational Economics of Wholesale Electricity Market (ACEWEM) is a simulation software framework designed to support research objectives of this thesis. It is mainly

JAVA-based with option of calling R and Matlab methods which can offer higher degree of computational robustness, speed or solution optimality. It employs the MASON multi-agent simulation library (Luke et al., 2005) developed for large custom-purpose JAVA simulations in social sciences. The ACEWEM framework can simulate different designs of existing wholesale power markets and operates over a high-voltage alternating current transmission grid starting from hour 0 of day 1 to a user-specified number of days (for example 365 days). It incorporates a variety of key power market participants (agents), namely:

- The ISO, who oversees the security of electricity supply
- Power plants (GenCos), which produce and sell electricity
- Load servicing entities (LSEs), which are the wholesale electricity consumers (electricity buyers).

These market participants, whose key operations are discussed below, act within different power markers such as the DA and RT market. Both RT and DA markets are explicitly modelled by ACEWEM framework. The contracted power is assumed to be delivered without failure from generating agents, thus the bids and offers accepted at the RT market are only used to resolve transmission grid congestion according to a PR congestion management scheme. As the result the DA market is cleared without accounting for transmission grid constraints. During the RT market, transmission constraints are taken into account by accepting electricity bids (for DEC) and offers (for INC) in order to respect transmission grid congestions. The ACEWEM framework also employs the LMP congestion management method. Based upon the LMP approach, the overall transmission grid congestion is resolved at the DA market by solving a least cost optimisation problem (see Section 4.2.2).

The sequence of actions performed (under PR congestion management scheme) during daily trading is depicted by UML diagram in Figure 4.1. A trading day starts with the ISO calling for supply offers from GenCos and demand profiles from LSEs for the DA market. The GenCos randomly choose a DA price distribution (thus more profitable distributions will have a higher probability to be selected) from the RL algorithm (specific for DA market) and proceed with fitting the two

GAMLSS models sequentially, first for the DA wholesale electricity price and second for DA power commitment (for power commitment GenCos use predefined by user reasonable distribution). The first model is used to determine a predictive PDF for the DA electricity price while the second model outputs a point forecast for DA power commitment (the mean of power commitment predictive PDF). This information enters the expected profit optimisation algorithm which is used to estimate the best reported MC coefficients to hit the highest expected profit. Finally the estimated MC coefficients along with actual generating capacity are reported by each GenCo to ISO as DA supply offer. At the next step ISO clears the DA market in a least-cost manner without accounting for thermal branch constraints. The market clearing results are sent back to all GenCos who subsequently update their own DA reinforcement learners based on the profits achieved. At this stage ISO enters the RT market and calls for RT supply offers (for INC) and bids (for DEC). The GenCos randomly choose a RT INC price distribution from the RL algorithm (specific for RT INC) and proceed with fitting the two GAMLSS models sequentially, first for RT INC market clearing price and second for RT INC power commitment. Similar to DA market operation, each GenCo forecasts the RT power increment and estimates the predictive PDF for RT INC market clearing price. A subsequent expected profit optimisation routine uses this information and outputs the best MC coefficients which along with available uncontracted capacity (a difference between total and contracted at DA capacity) form RT market supply offers. Supply bids are formed in a similar manner. The GenCos randomly[1] choose a RT DEC price distribution from the RL algorithm (specific for RT DEC) and proceed with fitting the two GAMLSS models sequentially, first for RT DEC market clearing price and second for RT DEC power commitment. Each GenCo forecasts the RT DEC and estimates the predictive PDF for RT DEC market clearing price. Given this information the expected profit optimisation routine optimises for the best MC coefficients. The coefficients along with available DEC capacity (which is effectively the contracted at DA capacity) form a RT market supply bid. The offers and bids are reported to ISO who proceeds with clearing the RT market in a least-cost manner. At this stage the ISO also accounts for thermal branch constraints. The RT market clearing results are sent back to all GenCos who subsequently update

[1] The randomness is required to guarantee that all the distributions and not only the best performing ones are iteratively selected. However the best performing distributions will have a higher propensity to be chosen.

own RT INC and RT DEC reinforcement learners accordingly based on the profits achieved. Then all the agents enter the following day and the process described above repeats for a number of user specified days. Note that in LMP implementation the agents do not enter RT market as the possible congestions are resolved by the DA market clearing mechanism.

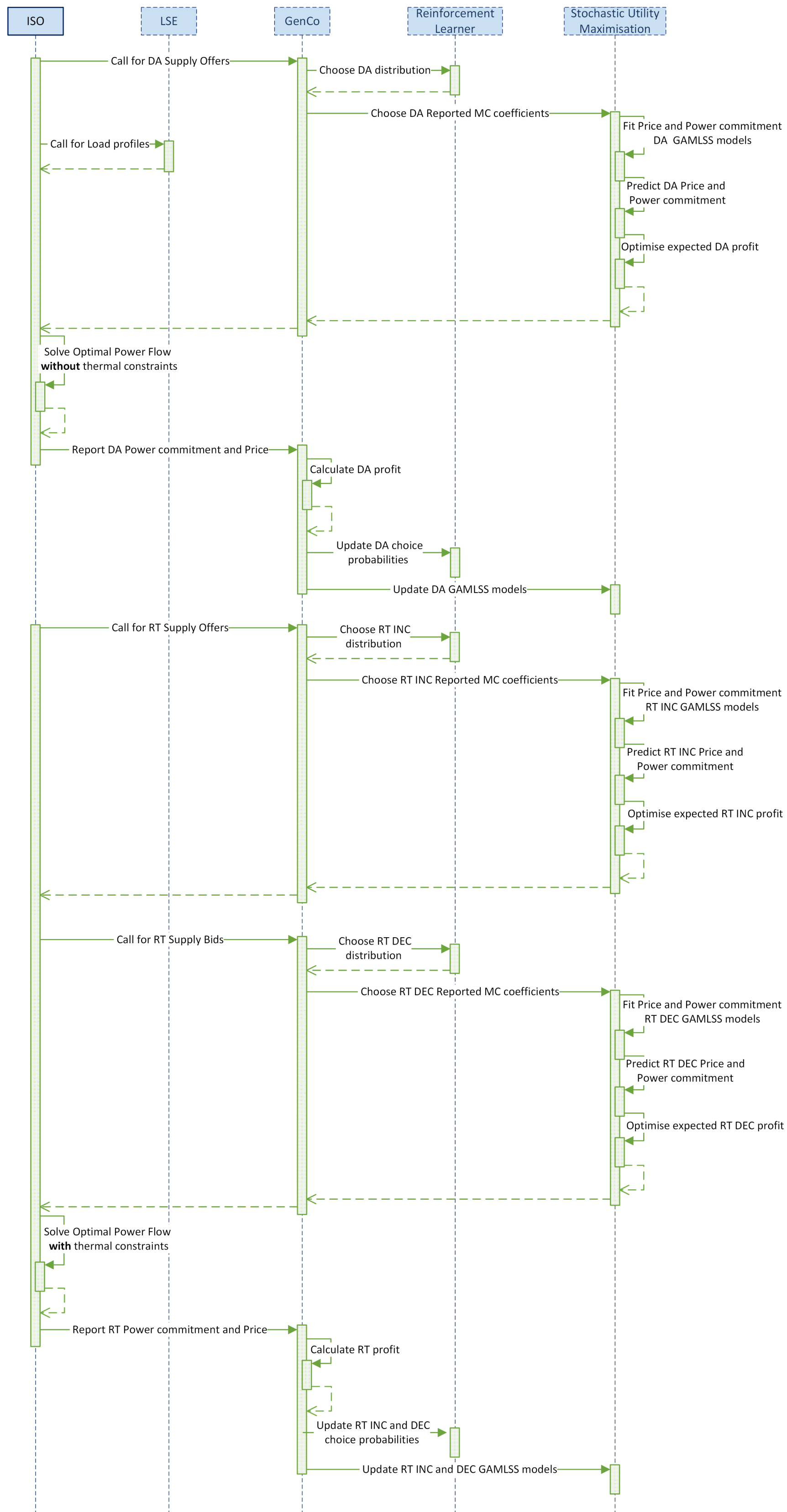

Figure 4.1: ACEWEM sequence UML diagram of the daily trading process

4.2.2 ACEWEM Independent System Operator

With the objective of minimising the aggregate power generating cost, the ISO operates the DA and RT market. It solves a least-cost constrained optimal power flow (COPF) problem to determine the power output from different power generators in order to fulfil the system's electricity demand. Within the ACEWEM framework, the formulation of DC COPF differs with respect to the selected congestion management method. Therefore when an ACEWEM model is launched with the LMP scheme, the ISO with the help of quadratic programming algorithm implemented in JAVA, R or MATLAB solves the following DC COPF problem during the DA market (Sun and Tesfatsion, 2007b):

Minimise the total variable cost reported by GenCos:

$$\sum_{i=1}^{I}\left[a_i{}^{DA}P_i^{DA} + b_i{}^{DA}(P_i^{DA})^2\right] + \eta\left[\sum_{nm\in\Omega}(\varphi_n - \varphi_m)^2\right] \tag{4.1}$$

subject to:

a) Real power balance constraint for each node n=1, ...,N:

$$\sum_{k\in K_n} P_{L_k} - \sum_{i\in I_n} P_i^{DA} + \sum_{nm \text{ or } mn\in\Omega} P_{nm} = 0 \tag{4.2}$$

where

$$P_{nm} = \frac{V_0^2(\varphi_n - \varphi_m)}{R_{nm}}$$

b) Real power thermal constraints for each branch nm $\in \Omega$*:*

$$|P_{nm}| \leq P_{nm}^U \tag{4.3}$$

c) Reported energy generation constraints for each GenCo i=1,...,I:

$$Cap_i^{RL} \leq P_i^{DA} \leq Cap_i^{RU} \tag{4.4}$$

d) Voltage angle setting at reference node 1:

$$\varphi_1 = 0 \tag{4.5}$$

where, ${a_i}^{DA}$ and ${b_i}^{DA}$ are the *reported* to DA market marginal cost curve coefficients of the generator i, η is a soft penalty weight on the sum of squared voltage angle differences ($\eta > 0$), φ_n is a voltage angle at node $n \in \Omega$ - set of all distinct branches nm, P_{L_k} is a power withdrawn by k'th LSE, $k \in K_n$ - total number of LSEs at node n, V_0 is a base voltage (kV), R_{nm} is a reactance (Ohm) for nm ($R_{nm} = R_{mn}, nm \in \Omega$), Cap_i^{RL} and Cap_i^{RU} lower and upper reported generating capacities of the GenCo i.

When the PR congestion management scheme is selected, the DC COPF problem for the DA market is similar except occurrence of branch thermal constraints, thus implying transmission grid with infinite capacity. When the DA market is cleared, the ISO accepts bids and offers in order to alleviate a possible transmission grid congestion at the RT market. Thus, the ISO with the help of quadratic programming algorithm implemented in JAVA, R or MATLAB solves the following DC COPF problem (note the constraint 4.10):

Minimise the total variable cost reported by GenCos:

$$\sum_{i=1}^{I}\left[VariableCost_i^{INC} + VariableCost_i^{DEC}\right] + \eta\left[\sum_{nm\in\Omega}(\varphi_n - \varphi_m)^2\right] \tag{4.6}$$

where

$$VariableCost_i^{INC} = {a_i}^{INC}P_i^{INC} + {b_i}^{INC}(P_i^{INC})^2 \tag{4.7}$$

$$VariableCost_i^{DEC} = ({a_i}^{DA} - {a_i}^{DEC})P_i^{DEC} + ({b_i}^{DA} - {b_i}^{DEC})(P_i^{DEC})^2 \tag{4.8}$$

subject to:

a) Real power balance constraint for each node n=1, ...,N:

$$\sum_{k \in K_n} P_{L_k} - \sum_{i \in I_n} P_i^{DA} + \sum_{i \in I_n} (P_i^{DEC} - P_i^{INC}) + \sum_{nm \text{ or } mn \in \Omega} P_{nm} = 0 \tag{4.9}$$

where

$$P_{nm} = \frac{V_0^2(\varphi_n - \varphi_m)}{R_{nm}}$$

b) Real power thermal constraints for each branch nm ∈ Ω:

$$|P_{nm}| \leq P_{nm}^U \tag{4.10}$$

c) Power increment and decrement constraints for each GenCo i=1,...,I:

$$Cap_i^{RL} \leq P_i^{INC} \leq Cap_i^{RU} - P_i^{DA} \tag{4.11}$$

$$0 \leq P_i^{DEC} \leq P_i^{DA} \tag{4.12}$$

d) Voltage angle setting at reference node 1:

$$\varphi_1 = 0 \tag{4.13}$$

here, P_i^{INC} and P_i^{DEC} is a INC and DEC of GenCo i at RT market; a_i^{INC}, b_i^{INC}, a_i^{DEC} and b_i^{DEC} are the marginal cost curve coefficients reported for power increment (index INC) or power decrement (index DEC) by GenCo i.

The decision rule of ISO is illustrated by Figure 4.2. This decision rule is mainly influenced by the user selection upon the congestion management scheme. See section 4.2.1 for the sequence of ISO actions.

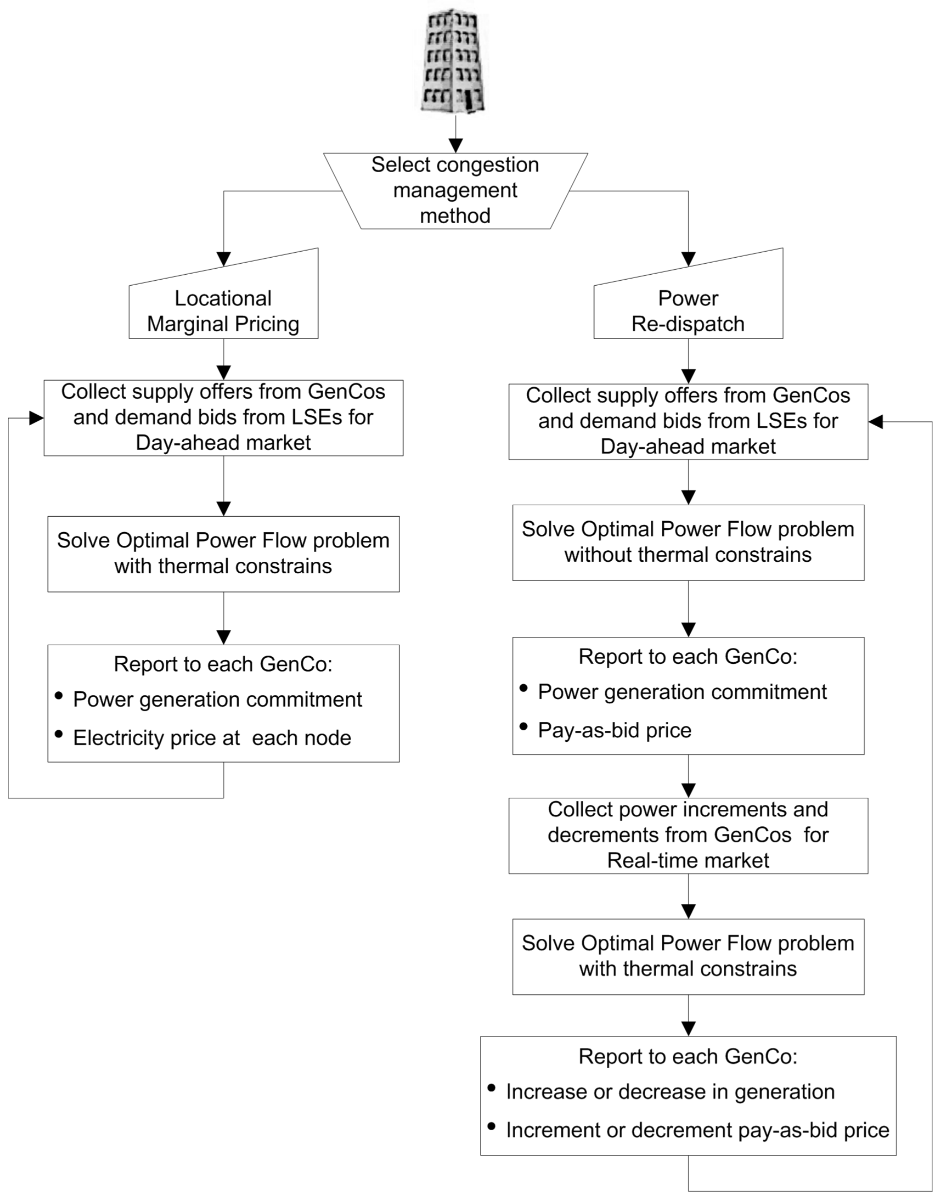

Figure 4.2: Decision rule of ISO

4.2.3 ACEWEM Generating Agents

Within the ACEWEM framework, each GenCo represents an individual power plant with the objective of maximising the daily profit. The overall decision rule of GenCo is illustrated in Figure 4.3. The different building blocks [*e.g.* estimation of reported marginal cost curves MC, estimation of the forecasted probability density function ($\mathcal{D}$), use of the RL algorithm to select the most profitable probability density function] of the decision rule are detailed below.

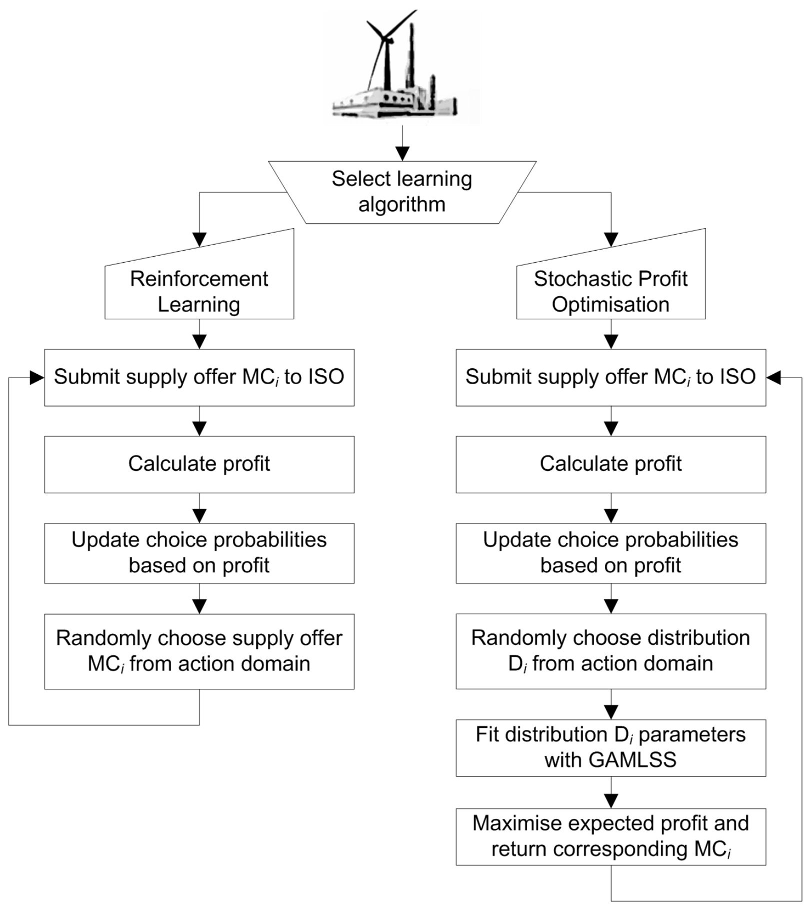

Figure 4.3: Decision rule of GenCo, $i \in$ (DA MC, RT INC MC or RT DEC MC)

At the beginning of each day, every GenCo submits a supply offer to the ISO in the form of a linear marginal cost curve:

$$MC_i^{DA} = a_i + 2b_i Cap_i \tag{4.14}$$

where a_i and b_i are the marginal cost curve coefficients and Cap_i is generating capacity of GenCo i available for the DA market. Each generating agent is able to submit the 'true' marginal cost curve coefficients (*e.g.* a_i^T , b_i^T) or a 'higher' marginal cost curve coefficients in strategic attempt to increase its daily profits:

$$MC_i^{DA} = a_i^{DA} + 2b_i^{DA}Cap_i^T \tag{4.15}$$

where a_i^{DA} and b_i^{DA} ($a_i^{DA} \geq a^T$, $b_i^{DA} \geq b^T$) are the *reported* marginal cost curve coefficients. These coefficients are not chosen randomly but are selected as a result of the Stochastic Profit Optimisation algorithm proposed here. Specifically, the Stochastic Profit Optimisation algorithm estimates the expected profit given the predictive probability density function (PDF) of the wholesale power price and power commitment. Each agent estimates the predictive PDF of the wholesale power price and power commitment by building a statistical model using the GAMLSS framework first proposed by Rigby and Stasinopoulos (2005).

The particular model for wholesale power prices implemented by each generating agent is as follows:

$$\begin{aligned} M_t|\mu_t^M, \sigma_t^M, \nu_t^M, \tau_t^M &\sim \mathcal{D}_M(\mu_t^M, \sigma_t^M, \nu_t^M, \tau_t^M) \\ g_1(\mu_t^M) &= \mathbf{X^M}_1\boldsymbol{\beta^M}_1 \\ g_2(\sigma_t^M) &= \mathbf{X^M}_2\boldsymbol{\beta^M}_2 \\ g_3(\nu_t^M) &= \mathbf{X^M}_3\boldsymbol{\beta^M}_3 \\ g_4(\tau_t^M) &= \mathbf{X^M}_4\boldsymbol{\beta^M}_4 \end{aligned}$$

Effectively, each distribution parameter (μ,σ,ν and τ) at time t is a linear function of explanatory variables encapsulated in design matrix $\mathbf{X^M}$. Here $g_1(.)$, $g_2(.)$, $g_3(.)$ and $g_4(.)$ are the link functions appropriately selected for the $\mathcal{D}_M$ distribution. Similarly, the model for power commitment is defined as follows:

$$
\begin{aligned}
P_t|\mu_t^{MW}, \sigma_t^{MW}, \nu_t^{MW}, \tau_t^{MW} \sim \mathcal{D}_{MW}(\mu_t^{MW}, \sigma_t^{MW}, \nu_t^{MW}, \tau_t^{MW}) \\
g_1(\mu_t^{MW}) = \mathbf{X^{MW}}_1 \boldsymbol{\beta^{MW}}_1 \\
g_2(\sigma_t^{MW}) = \mathbf{X^{MW}}_2 \boldsymbol{\beta^{MW}}_2 \\
g_3(\nu_t^{MW}) = \mathbf{X^{MW}}_3 \boldsymbol{\beta^{MW}}_3 \\
g_4(\tau_t^{MW}) = \mathbf{X^{MW}}_4 \boldsymbol{\beta^{MW}}_4
\end{aligned}
$$

The GAMLSS algorithm, which has been implemented in ACEWEM framework estimates the distribution parameters (given the information available to market participants) in order to be used by the agents to realistically address the strategic bidding. In particular as parts of the agents learning, the statistical models are applied to the bid offer strategy selection process driven by the agent's profit optimisation objective. Thus, each agent not only develops regression-type of models for the distribution parameters μ, σ, ν and τ but also selects the best performing (in terms of received profits) distribution $D(\theta^i)$ for the regression model based upon the RL algorithm (discussed below). The agents are incentivised to use different forecasting models (used by the Stochastic Profit optimisation algorithm) to better represent their own information sets, thus allowing for a high degree of heterogeneity.

Reinforcement learning is a learning algorithm that probabilistically selects a strategy m (*i.e.* a distribution in our case), while the full set of strategies form the action domain AD of the GenCo ($m \in AD$). Specifically the GAMLSS framework incorporates a set of flexible distributions which are selected by the RL algorithm using the realised daily profit as the key criterion. This is to say that the probability $p_m(t)$ of choosing a particular distribution m depends on the realised profit obtained by using the distribution m within the Stochastic Profit Optimisation algorithm.

Mathematically, the RL algorithm for the selection of the agent-specific model to be used for the selection of the optimal offer/bid to sell/buy electricity is given by:

$$p_m(t) = \frac{\exp(\frac{q_m(t)}{T})}{\sum_{j=1}^{n} \exp(\frac{q_j(t)}{T})} \tag{4.16}$$

with

$$q_m(t) = [1 - r]q_m(t-1) + R_m(t-1)$$

$$R_m(t-1) = \begin{cases} [1-e] * Z_{m'}(t-1), & \text{if } m = m' \\ e * q_m(t-1)/[AD^c - 1], & \text{if } m \neq m' \end{cases}$$

where m' denotes the distribution that was actually selected at time $t-1$, $p_m(t)$ is the probability of selecting distribution m by generating agent at time t, $q_m(t)$ is the propensity of the agent to select the distribution m and $Z_{m'}$ is the realised profit of agent at time $t-1$ obtained as the result of m' strategy selection. Note AD^c is the cardinality of the action domain AD (strategies repository). T is a *temperature parameter* that affects the degree to which the agent makes use of propensity values in determining its choice probabilities $p_m(t)$. The recency parameter r affects the growth of the propensities over time. The experimentation parameter e allows for spillover effects (see Sutton and Barto 1998 for details with respect to the RL algorithm).

The Stochastic Profit optimisation algorithm is employed by each adoptive agent i and used to estimate the best reported marginal cost curve coefficients given the agent's objective. In mathematical terms this algorithm for DA market can be described as follows:

$$E(\Pi_i^{DA}) = [MC_i^{DA} * P_F^{DA} - TotalCost_i] * \mathcal{D}_U[MC_i^{DA}] \tag{4.17}$$

and if PR congestion management method is selected, then the Stochastic Profit optimisation algorithm is used to optimise bidding strategies by optimising the expected profit at RT market. It is described as follows:

$$E(\Pi_i^{INC}) = [MC_i^{INC} * P_F^{INC} - TotalCost_i] * \mathcal{D}_U[MC_i^{INC}] \tag{4.18}$$

and

$$E(\Pi_i^{DEC}) = [TotalCost_i - MC_i^{DEC} * P_F^{DEC}] * \mathcal{D}_L[MC_i^{DEC}] \tag{4.19}$$

where P_F^{DA}, P_F^{INC} and P_F^{DEC} are the forecast power commitments at DA and RT for INC and DEC (mean parameters of corresponding power commitment distributions). $\mathcal{D}_U[MC_i^{DA}]$, $\mathcal{D}_U[MC_i^{INC}]$ and $\mathcal{D}_L[MC_i^{DEC}]$ are the cumulative distribution functions (CDFs) of the GAMLSS-based models. These CDFs are used to estimate the reported marginal costs MC_i^{DA}, MC_i^{INC} and MC_i^{DEC} at the DA and RT markets and characterise the probability of bid/offer acceptance (the chance to sell or buy electricity at the desired price). Note that subscripts $_U$ and $_L$ at $\mathcal{D}$ characterise *Upper* (right) and *Lower* (left) distribution tails.

To summarise, given the CDFs of the wholesale power prices and power commitments, each generating agent estimated the probability of acceptance of different MCs (forward looking inn Figure 4.4). It is important to note that at the DA and RT markets (for INC) the lower reported MC, which might lead to lower profits, has a higher probability of acceptance. Alternatively for DEC at RT market, the lower reported MC corresponds to a lower probability of acceptance. Effectively, the optimisation algorithm maximises the expected profit [$E(\Pi_i^{DA})$, $E(\Pi_i^{INC})$ and $E(\Pi_i^{DEC})$] as a function of the reported marginal cost curve coefficients [(a_i^{DA} and b_i^{DA}), (a_i^{INC} and b_i^{INC}) and (a_i^{DEC} and b_i^{DEC})] (output decision in Figure 4.4) by taking into account the GAMLSS-based models (*e.g.* $\mathcal{D}_U[MC_i^{INC}]$). The PDF for use by the GAMLSS-based model is selected based upon the RL algorithm discussed above.

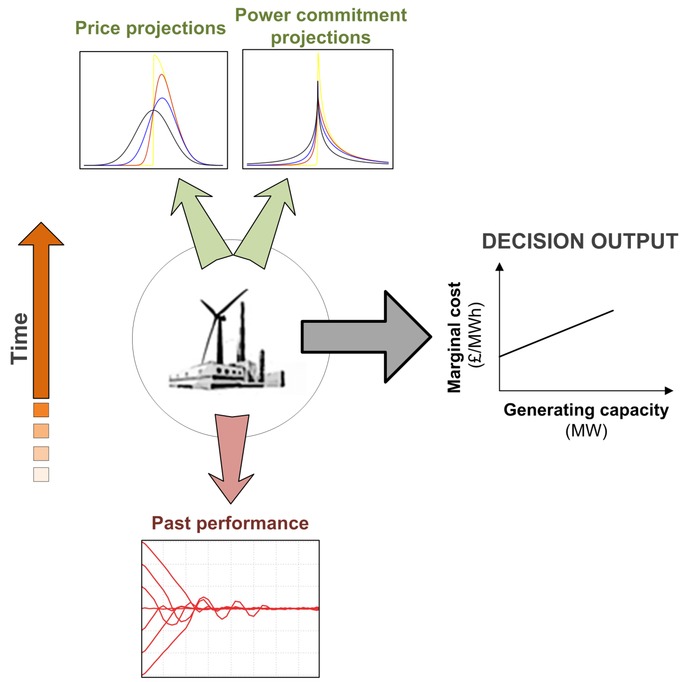

Figure 4.4: Overview of GenCo agent

4.2.4 ACEWEM Load Agents

The load agents purchase wholesale power to serve end users in retail electricity markets. It is assumed that the load agents do not engage in production. They only purchase electricity from the generating agents. The overall decision rule of load agents is illustrated by Figure 4.5.

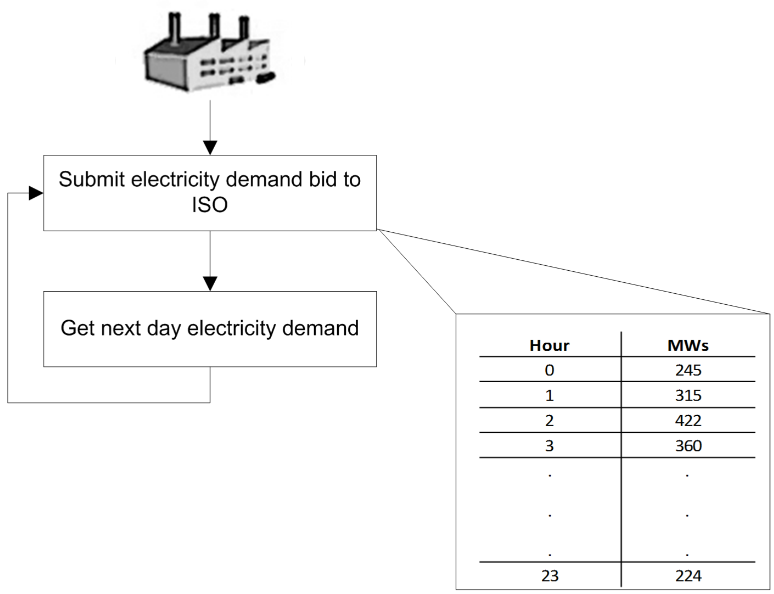

Figure 4.5: Decision rule of LSE

It is important to note that the currently implementation of the ACEWEM framework assumes that the load agents bid their 'true' load profiles, thus they do not exercise strategic bidding. One justification for this is that empirical evidence suggests that electricity demand does not fall in response to a short-term price increase (Yusta and Dominguez, 2002; Faruqui and George, 2002). Nevertheless daily stochastic demand shocks are allowed in order to test the dynamics of the market. The load agents also do not enter the RT market regardless of the congestion management scheme used.

4.2.5 ACEWEM Transmission Grid

The ACEWEM transmission grid is modelled as a balanced three-phase network with a number of nodes and branches determined by the user. The reactance of each branch is an absolute branch reactance, and not a reactance per a unit of length. Phase angle shifts of all generators are assumed to be zero and the tap ratio[2] of each transformer is assumed to be 1, thus the voltage magnitude of output electricity from a power plant remains constant over time. This is required by the setting

[2]The ratio of the number of turns in a secondary winding of a transformer to the number of turns in the primary winding (Parker, 2003).

of COPF problem discussed in the section 4.2.2. It is also assumed that temperature change does not effect branch properties and that charging current[3] is zero. The ACEWEM transmission grid has no isolated nodes or branches, every pair of nodes is connected by a linked path consisting one or more branches. If two nodes are directly connected by multiple branches, these multiple branches are modelled as a single branch incorporating the aggregate properties of all sub-branches according to the physical rules. For example if two branches with reactances $R1$ and $R2$ directly connect a pair of nodes the reactance of aggregate simulated branch is $R_G = \frac{R1R2}{R1+R2}$. No complete connectivity is assumed, hence two nodes are not necessary in direct connection by a single branch. It is also assumed that the power flows of the ACEWEM transmission grid are governed by Kirchoff's current law, meaning that real and reactive power must be balanced at each node regardless of the fact that the real power must be also balanced across the entire transmission grid, so lost and consumed energy must be injected.

4.3 Conclusion

In this chapter, the architecture of ACEWEM model was outlined in detail, containing both its advantages and disadvantages. The advantage is that ACEWEM provides a high flexibility in formulating the agents and the market rules. The agents can be modelled to have different marginal production costs, capacities, objectives, and learning algorithms. Also the market design sets the agents' operational environment and can be modelled as a uniform or discriminatory pricing auction while applying a variety of congestion management schemes. The obvious model disadvantage lies in reliance on the quality of input data, which is usually commercially sensitive and thus not available for public access or just simply does not exist in the required form or quality. As the result, this renders model verification a difficult task. This will be addressed in the subsequent Chapter 7 of this thesis.

[3]Charging Current is a current produced when a d-c voltage is first applied to conductors of an unterminated cable. It is caused by the capacitive reactance of the cable, and decreases exponentially with time (Parker, 2003)

Part II

Model Design

This part overviews the entire structure of the ACEWEM model in detail. The discussion is guided by the ACEWEM class diagram where the model's main building blocks such as learning, optimisation and data fitting algorithms are discussed individually. The chapter also describes the ACEWEM graphical user interface and comments on input data specification.

5 The ACEWEM model: Logical level

5.1 Introduction

Current agent-based economics research can be divided into the four threads: descriptive thread, normative thread, theory postulation and methodology advancement (Amman et al., 2006). The descriptive thread attempts to understand how the applied macro-level policies affect micro-level agents behaviour. In the normative research the modellers use computational laboratories in order to test the designs of an economic system and establish the best performing polices given the environment of adaptive agents. In theory postulation the main emphasis is on experimental study of potential dynamics of an economic system subject to alternative initial conditions. This is expected to clarify why certain global outcomes have evolved and what is also important why the others have not. Finally the researchers constantly seek to improve existing methodology and agent-based tools in order to achieve a higher degree of realism of simulated economic systems. Most research in electricity is related to the normative thread, thus aiming to develop a reliable and competitive market design that eliminates the opportunity for participants to exercise market power.

One important attribute inherited by adaptive agents is heterogeneity. Heterogeneous agents may differ from one another by unique preferences, attitude to risk, wealth, behavioural rules, learning capabilities, *etc* (Axtell, 2005). During the simulation agents are engaged in strategic interaction, they follow their individual decision rules based on private objectives, acquired success and anticipated market outcomes, while none of the agents has a complete information about the state of global system. On this basis each agent develops unique strategies to maximise its profit when competes with the rest of market players.

Adaptation and learning is an evident attribute of human behaviour and it is also central feature of

ACEWEM agents. The subsequent sections discuss the employed and developed methodologies in this research work to empower agents' heterogeneity and adaptivity.

5.2 Overall ACEWEM architecture

Implementing the principles of the agent-based computational economics ACEWEM incorparates autonomous agents. All the agents in ACEWEM (three main types: ISO, GenCos and LSEs) implement *Steppable* class. By being steppable, the agents can be placed on the actions schedule by the simulation engine to have their *step()* functions called (sequentially or in random order) at various times in the future. Additionally, GenCos and LSEs extend *SimplePortrayal2D* class in order to be optionally portrayed on the dynamic transmission grid. The *ACEWEMmodel* class incorporates DA and RT markets and extends *SimState* class which contains an important item :

- A discrete event schedule which is a simulation engine. Effectively it wakes up the agents at various times so they can perform the actions according to their own rules

The ACEWEM class diagram is illustrated by Figure 5.1. It sketches all the main JAVA classes that are used to support ACEWEM operation.

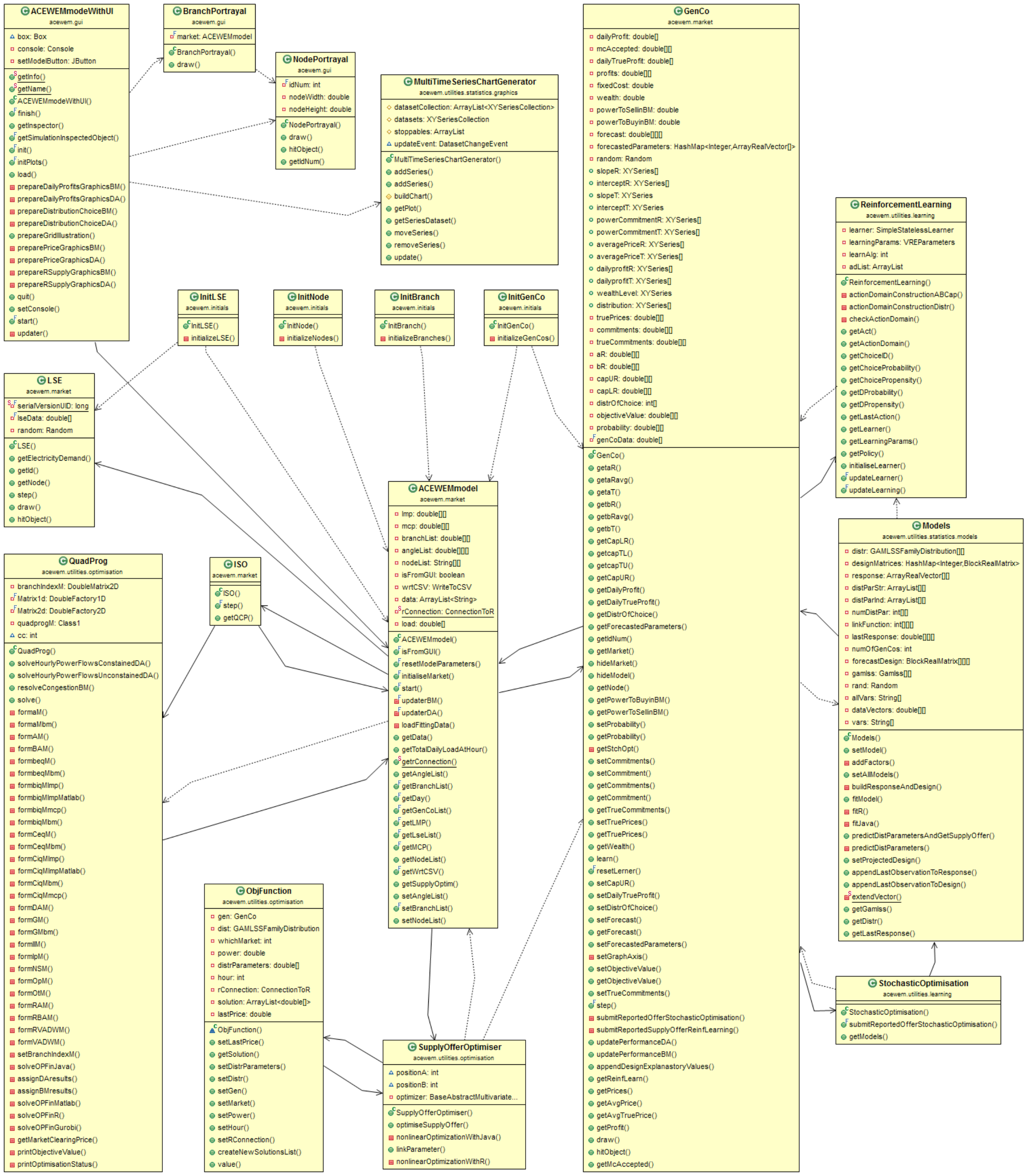

Figure 5.1: ACEWEM class diagram

ACEWEMmodeWithUI class encapsulates the visualization in ACEWEM and does not affect the simulation model's logic. In particular the methods of this class specify fields and visual elements reflected by ACEWEM displays.

BranchPortrayal and *NodePortrayal* classes extend *SimpleEdgePortrayal2D* and *SimplePortrayal2D* accordingly and are used to draw nodes and branches of the simulated transmission grid on the ACEWEM display

MultiTimeSeriesChartGenerator class produces time series charts for variables determined by market clearing.

InitBranch, *InitGenCo*, *InitLSE* and *InitNode* classes load the data from CSV files and initialise corresponding objects with parameters adjusted according to supplied data. All initialised objects are assembled by types and stored in the main model repository.

ACEWEMmodel class is the main model repository and also the main class that controls the simulated market designed logic. It extends $SimState$ which provides a discrete event scheduler that fires various types of agents in a certain order and time frequency according to simulated market design rules.

ISO class represents the ACEWEM system operator agent that oversees security of electricity supply, accepts bids and offers and clears the markets. It implements *Steppable* interface and thus can be placed on the schedule by scheduler to have its *step(.)* method called at various times in the future.

LSE class represents the ACEWEM load agent type that bids electricity demands to the market for each settle period. It implements *Steppable* interface and thus can be placed on the schedule by scheduler to have its *step(.)* method called at various times in the future.

GenCo class represents the ACEWEM generating agent type that generates electricity and can strategically exercise market power in order to maximise profits. It implements *Steppable* interface and thus can be placed on the schedule by scheduler to have its *step(.)* method called at various times in the future.

QuadProg class includes the methods for setting up and solving the optimal power flow problem by one of three implemented in ACEWEM quadratic linear programming optimisers from JAVA, R and Matlab.

SupplyOfferOptimiser class holds the methods for setting up and solving the SPO problem for each GenCo by one of two implemented in ACEWEM non-linear optimisers from JAVA and R.

ObjFunction class sets the non-liner objective function for the SPO problem which subsequently is maximised by non-liner optimisers from *SupplyOfferOptimiser* class.

ReinforcementLearning class realises a backward looking feature of each generating agent by providing methods for constructing action domain and also for learning the best performing distributions applied by agent.

StochasticOptimisation class realises a forward looking feature of each generating agent by providing methods for specifying the GAMLSS regression model for electricity price and power commitment.

Models class comprises the methods used to modify the fitting data for the GAMLSS use and estimate predictive distribution parameters.

All aforementioned classes jointly form the framework for DA and real-time market operations. These markets implementation in ACEWEM is discussed in subsequent sections.

5.3 The Day-ahead market

In ACEWEM different realisations of the DA market have been implemented. One implementation embodies the aspects attributed to the PR congestion management method. Thus the DA market is cleared with no transmission grid thermal constraints taken into account and the single market clearing price is established. Another implementation addresses the specifics of the LMP congestion management scheme. Thus the DA OPF problem incorporates thermal branch constraints and solution establishes a set of nodal prices rather than a single price. Moreover the DA market can be executed as a uniform price or discriminatory price auction. This differentiates whether the generating agents are paid with uniform price (equal to the marginal cost of the most expensive generator scheduled for electricity dispatch) or with pay-as-bid price (own reported marginal cost) regardless of what the market clearing price is. At the DA market the agents, upon the user's preference, can also submit a strategic offer for the entire market day or for each settlement period (they are usually 24 or 48 per day). Effectively the DA market is represented by the sequence of simple call markets for every electricity delivery settlement period of the following day. It is assumed that each generating agent offers his full available capacity to the DA market (pre-multiplied by a capacity availability factor which is unique and constant for each generating technology). Nevertheless the GenCos in ACEWEM can randomly offer reduced production capacity when the simulation study intends to incorporate supply shocks. The user can optionally set the location, frequency and magnitude of these shocks or avoid them completely. In cases where electricity supply is less than electricity demand the market clearing price is set to the maximum possible price and no power volumes are traded.

The optimal supply offer (a pair of MC coefficients) is determined by a non-linear maximisation routine. This algorithm optimises the expected profits (see Section 4.2.3) by determining the right balance between probability of bid/offer acceptance and the magnitude of possible profits to be earned. The marginal cost coefficients are continuous values, withdrawn from the set of numbers limited by:

$$
\begin{aligned}
0.5 * a_i^T &< a_i^R < 1000 * a_i^T \\
0.5 * b_i^T &< b_i^R < 1000 * b_i^T
\end{aligned}
\tag{5.1}
$$

where, a_i^T and b_i^T are the true intercept and slope parameter for the marginal cost curve of GenCo i, a_i^R and b_i^R are the reported marginal cost parameters output by expected profit optimisation routine. It is assumed that agents can actually submit offers below their true marginal cost. In some rare cases the generators can be better off by paying for the electricity produced rather than being exposed to the no load costs (EDF Energy department representatives, 2013).

The demand side of the DA market is represented by LSE agents. The total load at the DA market is recovered from the fixed profiles of LSE agents. Nevertheless the LSE agents in ACEWEM can deviate from fixed loads and randomly bid higher or lower demands when the simulation study intends to incorporate demand shocks and test the reliability of the system. The user can optionally set the location, frequency and magnitude of these shocks or avoid them completely.

5.4 The Real-time market

The RT market implemented in ACEWEM provides the means for the system operator to balance the congested transmission grid according to PR congestion management method. The power balance is regulated by the system operator accepting bids and offers from generating agents. Depending on the settings specified the agents can bid/offer one reported marginal cost for the entire market day or a set of marginal costs for the each market settlement period. The maximum capacity that GenCo i can offer to RT for INC is calculated as follows:

$$Cap_i^{INC} = Cap_i^{T} - Cap_i^{DA} \tag{5.2}$$

similarly the maximum capacity that power plant can bid to RT market for DEC is calculated as follows:

$$Cap_i^{DEC} = Cap_i^{DA} \tag{5.3}$$

where, Cap^{INC} is the maximum capacity that can be offered to RT for INC by GenCo i, Cap_i^{DEC} is the maximum capacity that can be bid to RT for DEC by GenCo i, Cap_i^{T} is a total generating capacity of GenCo i and Cap_i^{DA} generating capacity contracted at DA market. The reported marginal cost coefficients offered for INC at RT market are limited by:

$$\begin{aligned} 0.5 * a_i^{T} &< a_i^{INC} < 1000 * a_i^{T} \\ 0.5 * b_i^{T} &< b_i^{INC} < 1000 * b_i^{T} \end{aligned} \tag{5.4}$$

similarly the reported marginal cost coefficients bid by GenCos for DEC at RT market are limited by:

$$\begin{aligned} 0.001 * a_i^{T} &< a_i^{DEC} < 2 * a_i^{T} \\ 0.001 * b_i^{T} &< b_i^{DEC} < 2 * b_i^{T} \end{aligned} \tag{5.5}$$

The upper and lower limits in (5.4) and (5.5) are arbitrary and introduced here to avoid optimisation algorithm searching for solutions within extremely small and large numbers. It is assumed that total system load at RT market does not change from its DA market level.

5.5 Stochastic profit optimisation algorithm

In stochastic optimisation problems the optimal solution is determined given the uncertainty in influential events or outcomes (Gutjahr, 2012). Usually this uncertainty is addressed by predictive probability density function (PDF). In expected profit optimisation for example, each generating agent decides on the offer price for his generating capacity. This decision highly depends on the agent's expectation regarding the future market clearing price and its own power commitment. In particular the agents estimate the predictive probability density functions (PDFs) for market clearing price and power commitment by building statistical models.

When the market clears, the generating agents receive profits that can be represented mathematically by:

$$f(MC_i^R, \Pi_i(M))$$

where, MC_i^R is the decision (or alternately the marginal generating cost) that GenCo i offers to the market, $\Pi_i(M)$ is the profit earned as the result of submitted MC_i^R, and M is the market clearing price that determines a realisation of the profit $\Pi_i(M)$. Therefore the ordinary stochastic optimisation problem that maximises the expected profit can be written as:

$$\begin{aligned} max \quad & \mathbb{E}\left[f(MC_i^R, \Pi_i(M))\right] \\ s.t. \quad & a_i^R \in A, b_i^R \in B \end{aligned} \tag{5.6}$$

where, E is expectation operator, and A and B are the sets of feasible solutions for intercept and slope parameters of reported marginal cost function. However, expression (5.6) does not lead to meaningful solutions yet as it ignores the risk. To quantify the risk associated with the decision a measure addressed by a cumulative distribution function is employed. Subsequently the problem to maximise the expected profit can be stated as:

$$\begin{aligned} max \quad & E\left[f(MC_i^R, \Pi_i(M)) * \mathcal{D}^M(MC^R)\right] \\ & s.t. \quad a_i^R \in A, b_i^R \in B \end{aligned} \tag{5.7}$$

or

$$E(\Pi_i) = [MC_i^R * P_i^F - TotalCost_i] * \mathcal{D}^M[MC_i^R] \tag{5.8}$$

where

$$MC^R = a_i^R + 2b_i^R P_i^F$$
$$TotalCost_i = a_i^T P_i^F + b_i^T (P_i^F)^2$$

here, P_i^F is a forecast power commitment by GenCo i, a_i^T and b_i^T are the true marginal cost curve parameters of GenCo i and $\mathcal{D}^M[MC_i^R]$ is a cumulative distribution function of forecasted market price distribution.

Figure 5.2 well explains the SPO algorithm proposed here. In order to maximise expected profit the GenCo has to offer a higher marginal cost, however by offering it too high the agent can become out of merit by having its offer positioned rightwards from the demand curve intersection on the generating stack (see Figure 5.2). This means that the agent will not be scheduled for electricity generation and thus no profit will be made. The risk of falling into the out of merit side is addressed by entire forecasted market price PDF. Thus a very high offered marginal cost will correspond to the right tail of forecasted price distribution and thus will have a low acceptance probability for electricity generation. Similarly a very low offered marginal cost will correspond to the left tail of forecasted price distribution and thus have a high acceptance probability for electricity generation. To summarise, the SPO algorithm optimises the expected profit and estimates the reported marginal cost given the predictive PDF of the wholesale power price and power commitment. Each agent estimates the predictive PDF of the wholesale power price and power commitment by building a statistical model using the GAMLSS framework first proposed by Rigby and Stasinopoulos (2005). Specifically the GAMLSS framework incorporates a set of flexible distributions which are selected by the RL algorithm (discussed below in Section 5.6) using the realised daily profit as the key criterion. The agents might have different forecasting models by altering the distributions to better represent their own information sets - allowing for a high degree of heterogeneity.

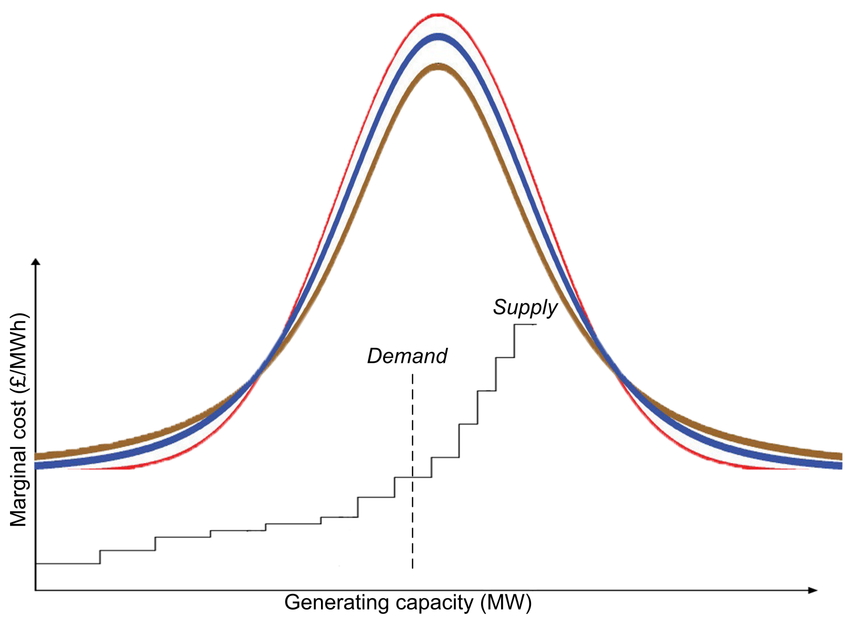

Figure 5.2: Merit order generating stack

5.6 Reinforcement learning algorithm

Reinforcement learning is a trial and error type algorithm. The goal-oriented agents adopt RL algorithm to perceive the best strategies through repeated interaction with dynamic environment (Kaelbling et al., 1996). In other words in the RL algorithm each agent explores all the available strategies and gradually converge to the best performing ones given his objective. Thus the agents tend to repeat the actions that give them the best rewards.

There are various modifications of the RL algorithm in the literature (see for example Wiering and van Otterlo (2012)). This research, however, is grounded in the three parameter RL algorithm proposed by Erev and Roth (1998). The development of this algorithm was inspired by psychological findings about human learning. These findings are primarily related to Law of Effect and Power Law of Practice. According to Law of Effect the behaviour of choice is probabilistic. Thus the choice (with a good outcome in the past) will be selected again with higher probability than the choice that led previously to worse outcomes (Thorndike, 1898). The Power Law of Practice principle states that the learning effect is stronger just after the event occurred and gradually dissolves as the time passes (Blackburn, 1936). In a simulation study the parameters called *experimentation* and *recency* account for Law of Effect and Power Law of Practice accordingly. The parameter called *propensity* is assigned to every possible action that agent can choose from his action domain and represents the likelihood for that action to be selected randomly in the future. At the beginning of simulation all the propensities attached to the agent's actions are assumed to be equal as if the agent had no experience. This is shown in Figure 5.3. The set of distributions (upper blocks from $D1$ to $D10$) represent the agent's action domain with choice probabilities equal across all the distributions. In order to adopt negative pay-offs this work relates the choice propensities with choice probabilities through the Gibbs-Boltzmann distribution with a positive *temperature* parameter:

$$p_{D_3}(t) = \frac{\exp(\frac{q_{D_3}(t)}{T})}{\sum_{j=1}^{n} \exp(\frac{q_j(t)}{T})} \tag{5.9}$$

where, $p_{D_3}(t)$ is the probability of selecting distribution D_3 by the agent at time t, $q_{D_3}(t)$ is the propensity of the agent to select the distribution D_3, T is a temperature parameter that determines a degree to which the agent concentrates on actions with high propensities. Usually temperature parameter is used as leverage to allow for more exploration at the beginning of simulation and allow a focus on exploitation later on. The propensity parameter is calculated according to the following expression:

$$q_{D_3}(t) = [1 - r]q_{D_3}(t - 1) + R_{D_3}(t - 1)$$

where, $R_{D_3}(t - 1)$ is a reward obtained as the result of selecting distribution D_3 at time $t - 1$. The reword is determined as follows:

$$R_{D_3}(t-1) = \begin{cases} [1-e] * Z_{D_3}(t-1), & \text{if } D_3 = D_{t-1} \\ e * q_{D_3}(t-1)/[AD^c - 1], & \text{if } D_3 \neq D_{t-1} \end{cases}$$

where D_{t-1} denotes the distribution that was actually selected at time $t-1$, Z_{D_3} is the realised profit of agent at time $t-1$ obtained as the result of D_3 distribution choice. Note AD^c is the cardinality of the action domain AD (distributions repository). Thus as shown in Figure 5.3 and according to the algorithm discussed above, if any distribution performs particularly well in terms of profits its probability of choice will be increased in each successful round. Moreover if such good performance is frequent enough so that the recency effect is relatively low, it is expected that the agent converges at some point in time to the best performing distribution.

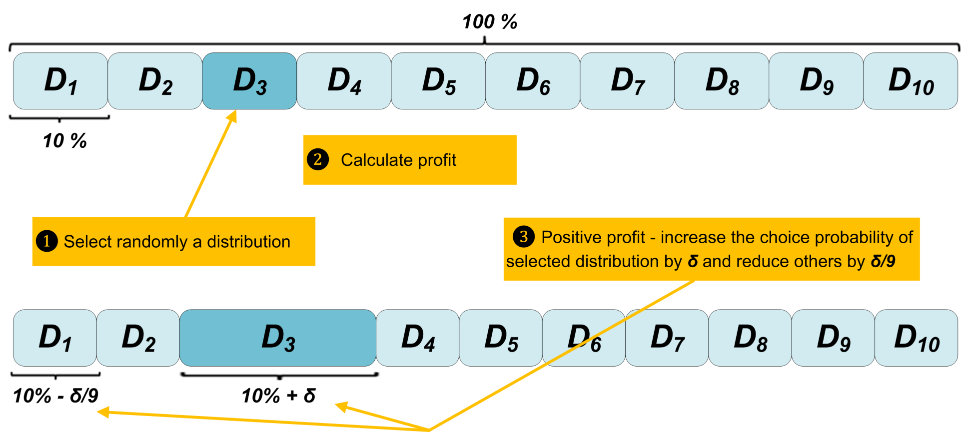

Figure 5.3: Graphical illustration for the RL algorithm

Erev and Roth highlight the advantage of using this RL algorithm rather than static equilibrium models based on forecast results from twelve different experimental games. The authors also argue that the proposed RL algorithm performs better than the other learning models they developed. Many agent-based modellers with primarily research in the electricity industry often apply this learning algorithm or its modifications.

5.7 The GAMLSS tool

Generalized Additive Models for Location, Scale and Shape framework was introduced by Rigby and Stasinopoulos (2005) to overcome limitations associated with Generalized Linear Models (McCullagh and Nelder, 1989) and Generalized Additive Models (Hastie and Tibshirani, 1990). In the GAMLSS framework the exponential family distribution assumption for the response variable y (for example DA electricity price or system load) is relaxed and replaced by a general distribution family, including highly skew and/or kurtotic discrete and continuous distributions. In particular this makes GAMLSS a preferred choice amongst other tools when modelling price or load since historically these variables exhibit high positive and negative peaks. This dynamic requires highly flexible distributions in order to be captured. The required flexibility is achieved by the GAMLSS capability of modelling not only the mean (location parameter) but other parameters of the distribution of y as linear parametric and/or additive non-parametric (smooth) functions of explanatory variables (for example historic and forecast weather data, social events, price in preceding hour/day/year). GAMLSS model integrated to ACEWEM implies the independence of response variable y_i observations (*e.g.* DA electricity price, power commitment) distributed with probability density function $f(y_i|\theta^i)$ conditional on the vector of distribution parameters $\theta^i = (\theta_{i1}, \theta_{i2}, ..., \theta_{ip})$ where each p'th distribution parameter is related to explanatory variables (*e.g.* historic and forecast weather data, price in preceding hour/day/year). The GAMLSS allows for modelling of up to four distribution parameters, for exmple mean (μ), standard deviation (σ), skewness (ν) and kurtosis (τ), where two first parameters are mostly characterised as scale parameters, and other two as shape parameters.

In particular, each agent assumes that, for $i = 1,2,...,n$ observations of the response variable Y_i (wholesale electricity price/power commitment) have probability density function $f_Y(y_i|\theta^{\mathbf{i}})$ conditional on $\theta^i = (\mu_i, \sigma_i, \nu_i, \tau_i)$, which is a vector of four distribution parameters, each of which can be a function of explanatory variables. This is denoted by:

$$Y_i|\theta^i \sim \mathcal{D}(\theta^{\mathbf{i}}) \tag{5.10}$$

i.e. $Y_i|(\mu_i, \sigma_i, \nu_i, \tau_i) \sim \mathcal{D}(\mu_i, \sigma_i, \nu_i, \tau_i)$ independently for $i = 1, 2, \ldots, n$, where $\mathcal{D}$ represents the distribution of Y_i. Let $\mathbf{Y}^\top = (Y_1, Y_2, \ldots, Y_n)$ be the n length vector of wholesale electricity prices/power commitments of the generating agent. For $k = 1, 2, 3, 4$, let $g_k(.)$ be a known monotonic link function relating the distribution parameter θ_k to predictor η_k:

$$g_k(\theta_k) = \eta_k = X_k\,\beta_k, \tag{5.11}$$

i.e.

$$\begin{aligned} g_1(\mu) &= \eta_1 = X_1\,\beta_1 \\ g_2(\sigma) &= \eta_2 = X_2\beta_2 \\ g_3(\nu) &= \eta_3 = X_3\,\beta_3 \\ g_4(\tau) &= \eta_4 = X_4\,\beta_4 \end{aligned}$$

where μ, σ, ν and τ are the distribution parameters - vectors of length n; X_1, X_2, X_3 and X_4 are design matrices of independent variables for each one of distribution parameters; $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \boldsymbol{\beta}_3$ and $\boldsymbol{\beta}_4$ are the unknown parameters to be estimated.

The parameter vectors β_k with $k = 1, 2, 3, 4$ are estimated within the GAMLSS framework by maximising the penalised log likelihood function l_p defined by:

$$l_p = \sum_{i=1}^{n} l_i \tag{5.12}$$

where, l_p is the log likelihood function of the data and l_i is the log likelihood function of observation y_i (*e.g.* electricity spot price, power commitment or system load). This is achieved using the fitting algorithms described in Rigby and Stasinopoulos (2005) and implemented in JAVA (Kiose and Voudouris, 2014). The Rigby and Stasinopoulos (RS) algorithm requires the first (and optionally observed or expected second) derivatives of the log likelihood with respect to the parameters μ, σ, ν and τ.

Figure 5.4 shows a flowchart of the GAMLSS fitting algorithm with RS. The fitting process is initialised by the user specifying the formula to model parameters of distribution as functions of the explanatory variables (*e.g.* using linear, non-linear or smoothing terms). The user also provides data comprising of observations for response (*e.g.* spot electricity prices) and explanatory variables (*e.g.* weather data, social events, price in preceding hour/day/year) with distribution of choice.As noted above, the fitting algorithm uses the first (and optionally observed or expected) second derivatives of the log likelihood with respect to the distribution parameters and is based on the algorithm used for the fitting of the MADAM models proposed by Rigby and Stasinopoulos (1996). If the user chooses to model the distribution parameters as linear parametric or non-parametric (smooth) functions of the explanatory variables the model fitting enters the backfitting cycle to estimate β_k, h_{jk} and λ_{jk}. When the fitting process passes all the internal cycles it returns the fitted values for each modelled parameter of the distribution specified.

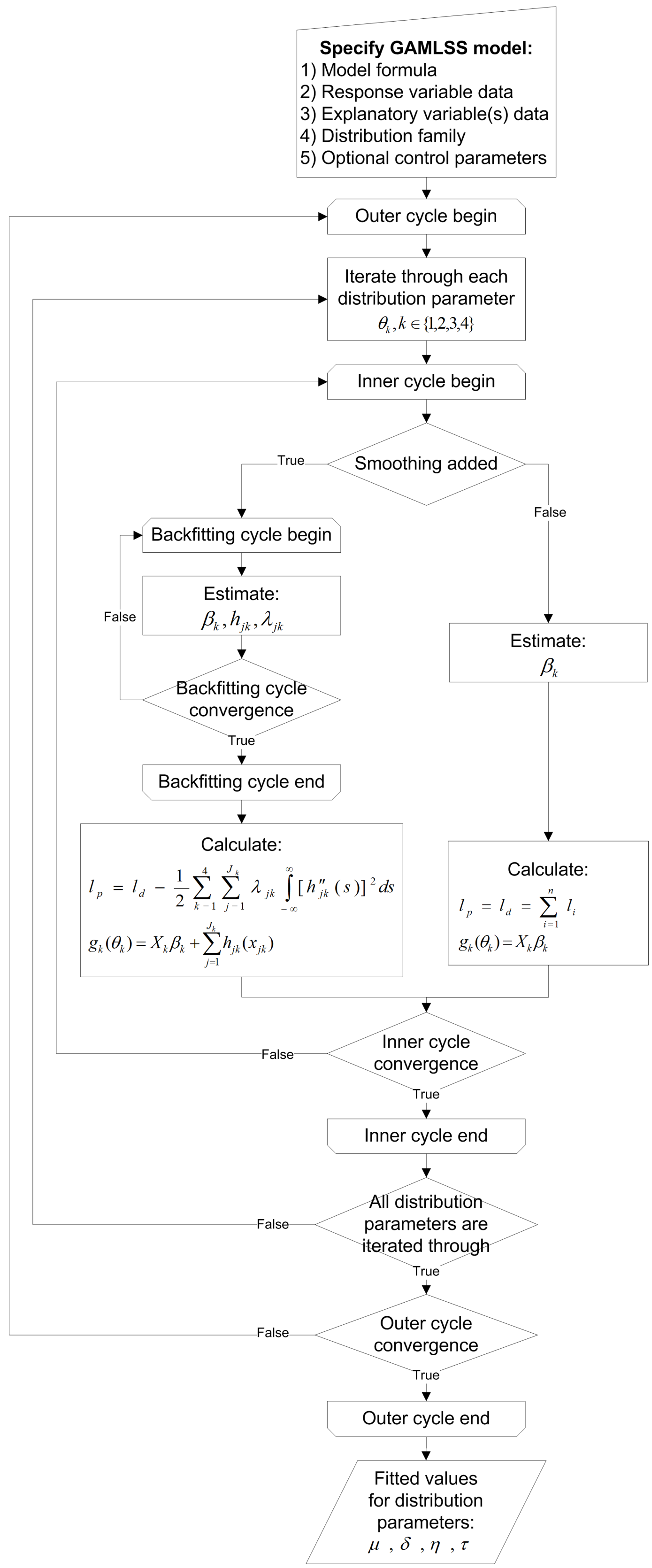

Figure 5.4: Flowchart of the GAMLSS fitting algorithm

5.7.1 GAMLSS Model Selection

Based on the work of Voudouris et al. (2012), this section describes the model selection strategies adopted in this research project. In the search for an appropriate GAMLSS-based model for electricity spot prices or power commitments, three components have to be specified as objectively as possible namely, 1) the distribution of choice, 2) the link functions and 3) explanatory variables for each distribution parameter modelled.

In ACEWEM the selection of the appropriate distribution is not affected by the user, instead it is purely a result of an agent evolution process. It is reasonably assumed that the most profitable model is the one that better than others captures the market dynamics. Thus by trial and error the agent explores all available[1] distributions and with help of the RL algorithm and converges to the most appropriate one. The selection of the link function is usually determined by the range of parameters in hand, thus for example for electricity prices and power commitments the log link function would be a natural selection to ensure that values remain on the positive side (important for power commitments as these values can be close to zero). For any response variable distribution the selection of terms for all distribution parameters is done using a stepwise GAIC procedure with two alternative strategies:

- The *Strategy A* is described by Figure 5.5. This strategy iterates through one parameter at the time by fixing the others in forward and backward GAIC procedures. The algorithm determines a set of explanatory variables that respond to the lowest GAIC criteria. These variables are then included to the predictor and the algorithm proceeds with defining the best set of variables for other distribution parameter while keeping the rest of the parameters fixed. This GAIC minimisation procedure is performed forward (where it adds terms to the parameter) and backward (where it withdraws terms from the parameter), thus after strategy execution the remaining terms meet the lowest GAIC criteria
- The *Strategy B* is described by Figure 5.6. This strategy forces all the distribution parameters to have the same explanatory variable. Thus the variable is selected if its inclusion to the

[1] Six suitable for the current study distributions, namely NO, TF, TF2, PE, SST and JSU were shortlisted to be used by agents in forecasting models

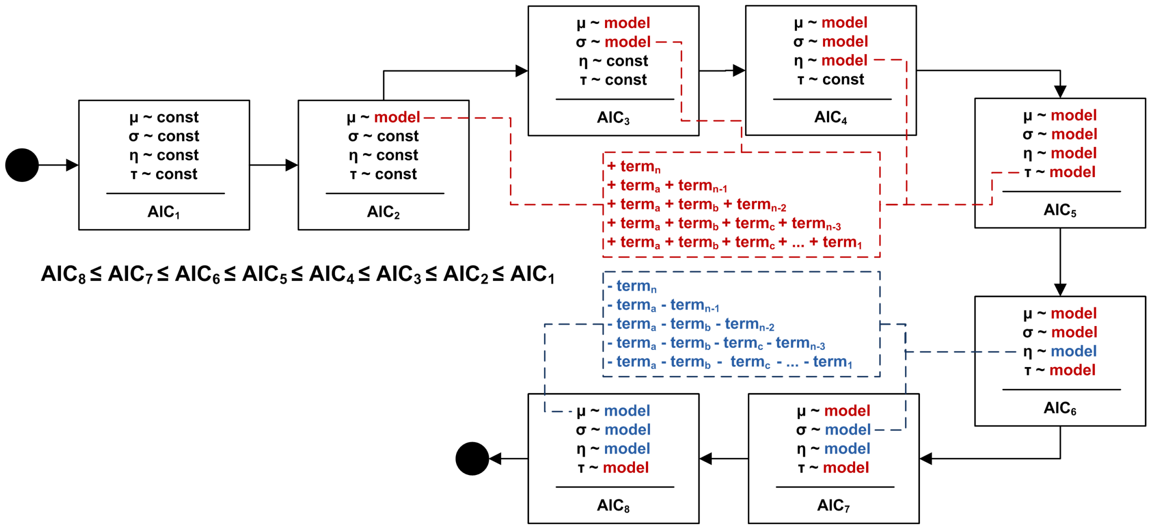

Figure 5.5: Flowchart of the model selection strategy A

predictor in all distribution parameters improves the GAIC

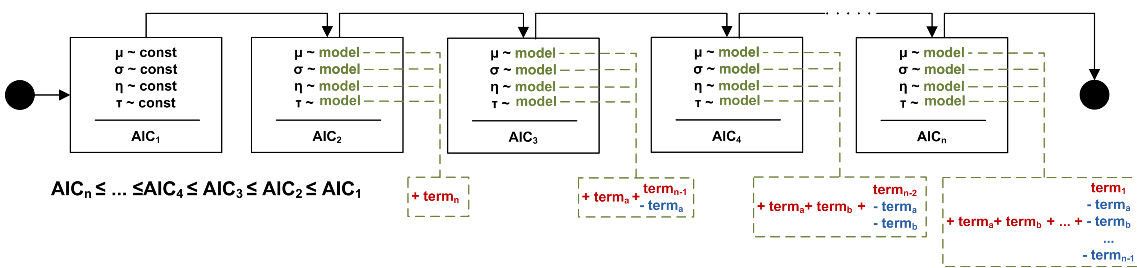

Figure 5.6: Flowchart of the model selection strategy B

Both strategies were applied to select appropriate models for the electricity market prices and power commitments. Overall strategy A and strategy B highlighted the similar set of explanatory variables for both models. Note however it was found sufficient to develop the model only for the mean distribution parameter (see Section 7.3.4), while the other parameters were estimated only by constants. This allowed to dramatically reduce computational timing while providing reasonable results.

5.8 The Graphical User Interface

In order to facilitate the use of ACEWEM by prospective researchers and decision makers a graphical user interface (GUI) has been developed. The GUI (see Figure 5.7) allows for easy access and control of simulation settings. It also delivers plots and graphics that illustrate a transmission grid (in the dynamic mode) and simulation outcomes. The simulation input data is supplied by means of comma separated values (CSV) files that are located in the ACEWEM software root folder. The set of supplied CSV files consists:

- NODE.csv specifies the code and the coordinate location for each of the simulated transmission grid:

Node Code	X Coordinate	Y Coordinate
Node1	42.4268	27.46372581
...	...	...

- BRANCH.csv specifies the positioning between the nodes and also the branch physical parameters such as Reactance (% of apparent power in MVA) and Capacity (MW):

From Node	To Node	Reactance	Capacity
Node1	Node5	0.021438	625
...	...	...	...

- LSE.csv specifies the LSE code, locations on the transmission grid at node and the percentage of total system energy demand the LSE withdraws from the network for each of the market settlement periods:

LSE Code	At Node	Demand
LSE1	Node3	0.0075
...	...	...

- GENCO.csv specifies the GenCo code, locations on the transmission grid at node, true marginal cost parameters, total generating capacity, generating technology and capacity availability factor:

GenCo Code	At Node	Intercept	Slope	Total Cap	Technology	Cap Factor
Gen1	Node3	130.04	0.025	440	Pumped Storage	0.4
...	...	...	...	...	...	...

- DATA.csv specifies the historical and projected data (*e.g.* system load, market outcomes such as electricity prices, power commitments or days of the week, settlement periods) used for initialisation of the GAMLSS fitting models and subsequently for the forecasting of market prices and power commitments:

Date	WDay	SP	Load	MCP	LMP1	-	LMPN	Gen1 MW	-	GenI MW	Etc.
14/02/12	3	1	33256	42	41	...	57	311	...	563	...
...	...	...	...	...	...	...	...	...	...	...	...

Figure 5.7: ACEWEM graphical user interface

The Model tab illustrated by Figure 5.8 allows for selecting a learning algorithm for the GenCos (RL algorithm or SPO algorithm) and congestion management scheme (LMP or PR). It also allows the user to introduce a negative or positive shock in electricity demand by specifying the shock magnitude and the occurrence day.

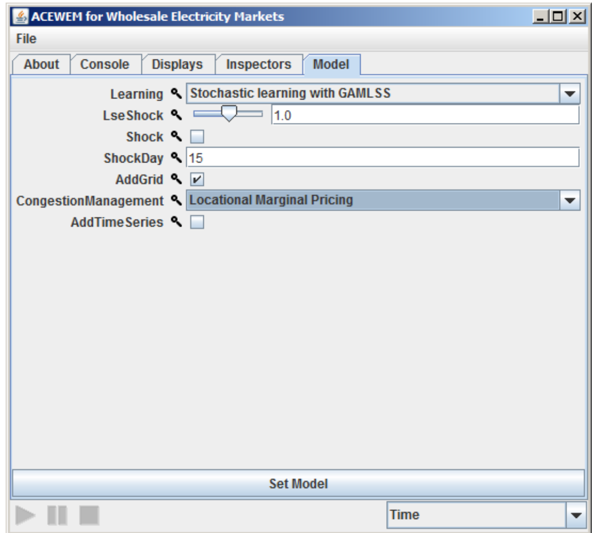

Figure 5.8: ACEWEM graphical user interface: Model tab

The Displays tab (see Figure 5.9) incorporates the time-series plots for quick visualisation of the market performance. The plots illustrate the dynamics of key market variables (*e.g.* electricity prices, GenCos supply offers) which can be shown individually or jointly for side-by-side comparison. It also incorporates display panels that visualise the entire transmission grid in dynamic mode for DA and RT markets, in particular the congested branches are coloured with tints of red proportional to the ratio of electricity flow to branch capacity. Fully congested branches are marked in black colour.

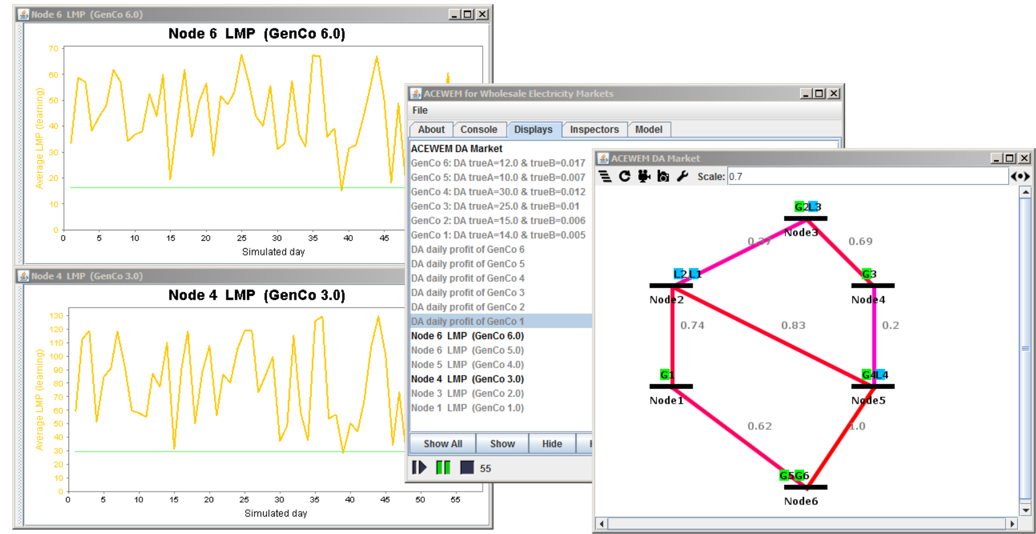

Figure 5.9: ACEWEM graphical user interface: Displays tab

5.9 Conclusion

This chapter described the main characteristics of the ACEWEM model design and illuminated its main components interlinkage. The economic modelling principle to keep models as simple as possible is respected. The ACEWEM structure may seem complex but the emphasis was not to make it complicated. The entire learning algorithm can be split into two components: backward looking and forward looking. The backward looking part adopts the well established and broadly used RL algorithm, whereas forward looking algorithm is based on the SPO procedure introduced for the first time by this research work. Also the elegant solution in linking these two components allowed the constitution of a novel computational learning algorithm that is very promising in capturing the realistic decision marking. This conclusion follows from analysis of experimental results discussed in subsequent chapters.

Part III

Model Implementation and Application

In the following part a simulation study is conducted for an abstract and the real UK power markets. It analyses the impact of specific changes in the market design and auction rules. The simulation study results are expected to deliver important insights for policy makers and market regulators in the electricity industry. The effect of different market designs and pricing rules on electricity trading outcomes, especially on electricity price dynamics, is assessed through specific experiments and compared to the benchmark scenario. Thus the differences in the experimental results can be unilaterally referred to the changes between simulation scenarios.

6 Application example: Abstract market

6.1 Introduction

According to an agent-based paradigm the emerging events are driven solely by agent interactions once initial conditions have been specified (Amman et al., 2006). For this reason the conclusions drawn from simulation study of an abstract market can be far more general compared with modelling of the real system. In the abstract market the initial state of the system is strictly known to the modeller, while the imperfections of estimation techniques can be passed into the simulation model when the aim is to simulate a real economic system. For example the information on electricity production costs is commercially sensitive and thus is not publicly available. Therefore the imperfections in these costs estimation can make it difficult to explain real market outcomes by simulation study. Thus this chapter analyses the abstract wholesale electricity market initialised under different market designs in a number of experiments.

6.2 Abstract six-node electricity market

The ACEWEM framework can be initialised with real-world data to explore plausible strategies by competing electricity generators in repeated electricity auctions. In practise, the daily strategies of generating utilities are not entirely based on the individual marginal cost of production, but also depend on daily strategies of their competitors. Clearly, the 'collective' strategies are reflected in the 'emergent' price (the price that emerge from the individual profit maximising offers/bids) of the wholesale power market.

To get an insight into the plausible strategies of competing market participants, the ACEWEM framework is used to simulate a realistically-rendered abstract wholesale power market with six electricity generating agents and four load agents with known features/properties. For example, the 'true' marginal cost curve coefficients and generating capacity (see Table 6.1) for each generating agent are assumed to be known so that conclusions can be drawn.

Table 6.1: Input parameters for power generating agents

ID	*Capacity (MW)*	*MC intercept (a^T)*	*MC slope (b^T)*
GenCo1	110	14	0.005
GenCo2	100	15	0.006
GenCo3	520	25	0.01
GenCo4	200	30	0.012
GenCo5	600	10	0.007
GenCo6	430	12	0.017

The market participants are distributed across a six-node transmission grid (as illustrated by Figure 6.1). Specifically the locations of agents are as follows: GenCo1 is located at Node1, LSE1 and LSE2 at Node2, GenCo2 and LSE3 at Node3, GenCo3 at Node4, GenCo4 and LSE4 at Node5, GenCo5 and GenCo6 at Node6. The ISO agent operates the wholesale power market from outside the network. All nodes are sequentially joined by branches that have their physical parameters reported by Table 6.3. There are 24 call auctions within a single trading day.

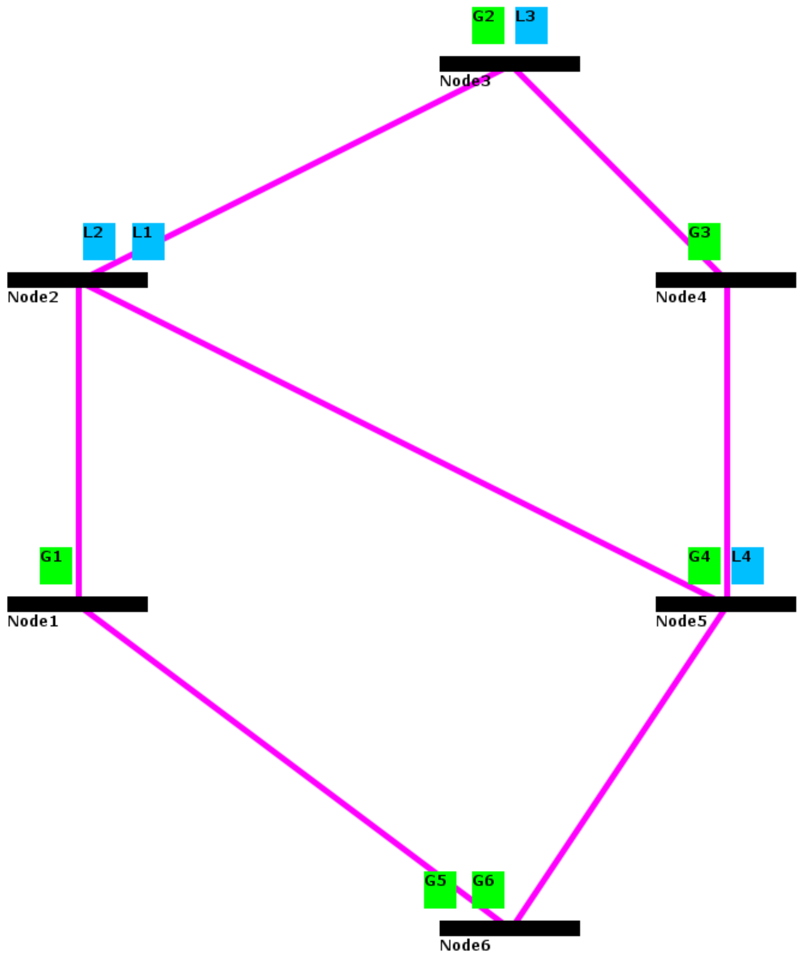

Figure 6.1: Transmission grid illustration for abstract market (ACEWEM graphical user interface)

The transmission grid base values are presented in Table 6.2. Base apparent power is three-phase apparent power common to the entire transmission grid and is a product of its base voltage and current measured in the unit of Volt-Amps (VA). Base voltage is a nominal rated voltage of the entire transmission grid, set to 10 kV.

Table 6.2: Transmission grid base values

Base apparent power (MVA)	*Base voltage (kV)*	*Soft penalty weight*
100	10	0.005

Table 6.3: Physical parameters for transmission grid branches

From	*To*	*Capacity (MW)*	*Reactance (% on base apparent power)*
Node1	Node2	450	2.81
Node2	Node5	250	3.04
Node2	Node3	400	0.64
Node3	Node4	450	1.08
Node4	Node5	340	2.97
Node5	Node6	340	2.97
Node6	Node1	360	3.15

Daily load profiles for all load agents represent a typical winter day (see Figure 6.2) reaching a minimum in electricity demand from 3 till 6 o'clock and maximum from 16 till 19 o'clock.

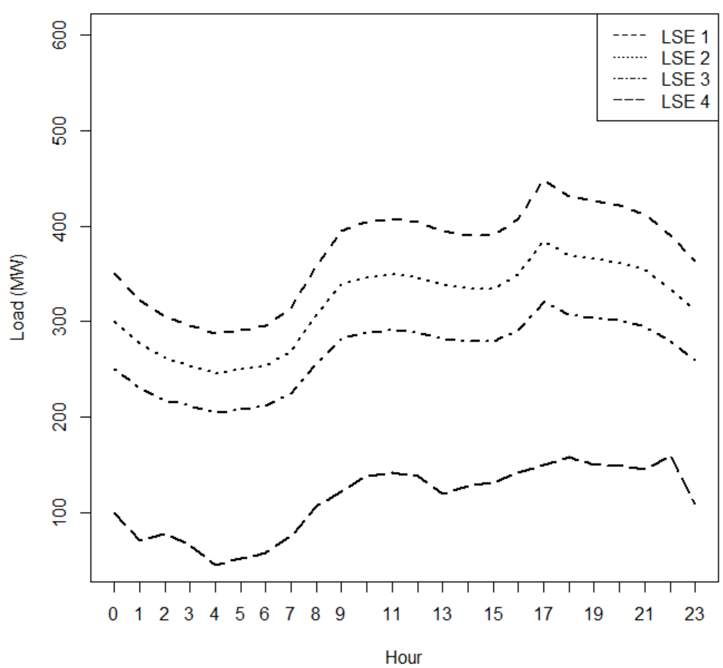

Figure 6.2: 24-hour electricity demand profiles of the load agents

Having specified the settings for the realistically-rendered abstract market, the experiments for different congestion management schemes (LMP and PR) may be conducted. This will enable us to explore the plausible daily strategies of the market participants and the price dynamics of wholesale power markets - important building blocks for electric utilities operating in the real-world power markets.

6.2.1 Benchmark

In the 'benchmark' experiment, the generating agents do not exercise market power. In particular the agents do not optimise their strategies and thus report only true marginal costs and true production capacities (see Table 6.1). The results reported here are based upon: a) the LMP congestion management scheme with uniform price auction design (see Table 6.4) and b) the PR congestion management method with discriminatory price auction design(see Table 6.5).

Table 6.4: Benchmark case results for LMP congestion management scheme

Power generating agent	*Marginal cost curve intercept*	*Marginal cost curve slope*	*Average nodal price (Unit/MWh)*	*Average power commitment (MW/h)*	*Daily profit (Unit/day)*
GenCo1	14	0.005	22.50	110	20992.10
GenCo2	15	0.006	28.55	100	31084.46
GenCo3	25	0.01	29.30	215	13390.78
GenCo4	30	0.012	31.37	75	2456.53
GenCo5	10	0.007	16.22	444	33162.12
GenCo6	12	0.017	16.22	124	6287.94

Table 6.4 shows that on the 'benchmark' market (absence of strategic bidding by generating agents) cleared under LMP congestion management scheme, all the GenCos are scheduled daily for power

generation by the ISO. GenCo1 and GenCo2 sell all their generating capacity at every hour. While GenCo3, GenCo4, GenCo5 and GenCo6 sell (on average) 41%, 38%, 74% and 29% of generating capacity accordingly. Overall all generating agents accumulate non-zero daily profits calculated by:

$$\Pi_i^{DA} = \sum_{h=0}^{23} \left[NP_i^{DA_h} P_i^{DA_h} - (a_i^T + b_i^T P_i^{DA_h}) P_i^{DA_h} \right] \tag{6.1}$$

where $NP_i^{DA_h}$ is the nodal price at GenCo's i node at hour h; a_i^T and b_i^T are the true marginal cost curve coefficients and $P_i^{DA_h}$ is the power commitment at hour h.

It is noteworthy that the average nodal prices differ across the nodes. This points out the presence of transmission grid congestion. This suggests that it is not always possible to dispatch the cheapest generator due to branch thermal constraints even when the generating agents offer true marginal costs.

Table 6.5 shows that under thePR congestion management scheme GenCo1 and GenCo2 sell all their generating capacity at every hour. GenCo4 sells zero MWs and GenCo5, GenCo6 and GenCo3 sell 95%, 66% and 2% of generating capacity. Note that the power commitments of GenCo3, GenCo4, GenCo5 and GenCo6 differ under the LMP congestion management scheme (see Table 6.4). This is because under the PR congestion management scheme, electricity congestion does not affect the order of the least-cost power dispatch (see section 4.2.2). The DA market clearing price at hour h equals the marginal cost of the last generating agent scheduled for power production to fulfil at total electricity demand. According to discriminatory price auction the profits are calculated here based upon the pay-as-bid price:

$$\Pi_i^{DA} = \sum_{h=0}^{23} \left[PAB_i^{DA_h} P_i^{DA_h} - (a_i^T + b_i^T P_i^{DA_h}) P_i^{DA_h} \right] \tag{6.2}$$

where $PAB_i^{DA_h}$ is pay-as-bid price received by GenCo i that equals to his reported marginal cost.

After the DA market is cleared, the ISO operates the RT market in order to alleviate the possible electricity congestion. For the RT market, the ISO resolves the transmission grid congestions by solving the COPF problem with added branch thermal constraints (see section 4.2.2). The ISO estimates the least-cost optimal dispatch per hour. The daily profits (for GenCo3 and GenCo4) at RT market are calculated according to:

$$\Pi_i^{INC} = \sum_{h=0}^{23} \left[PAB_i^{INC_h} P_i^{INC_h} - (a_i^T + b_i^T P_i^{INC_h}) P_i^{INC_h} \right] \tag{6.3}$$

where $PAB_i^{INC_h}$ is the pay-as-bid price. This price equals to marginal cost reported by GenCo i to the RT market for INC.

The daily profits (for GenCo5 and GenCo6) at the RT market are calculated according to:

$$\Pi_i^{DEC} = \sum_{h=0}^{23} \left[(a_i^T + b_i^T P_i^{DEC_h}) P_i^{DEC_h} - PAB_i^{DEC_h} P_i^{DEC_h} \right] \tag{6.4}$$

where $PAB_i^{DEC_h}$ is the pay-as-bid price. This price equals to marginal cost reported by GenCo i to the RT market for DEC. Note that in order to avoid negative profits at the RT market for DEC, the slope parameter of the reported marginal cost curve by GenCo i equals to $b_i^T/2$. The market clearing price at hour h for RT INC/DEC equals to the marginal cost of the last generating agent scheduled for power dispatch.

Table 6.5: Benchmark case results for the PR congestion management scheme

Power generating agent	*Market*	*Marginal cost curve intercept*	*Marginal cost curve slope*	*Average power commit-ment (MW / h)*	*Average market clearing price (Unit / MW)*	*Daily profit (Unit / day)*
GenCo1	DA	14	0.005	110	21.64	1452
GenCo2		15	0.006	100		1440
GenCo3		25	0.01	8		89
GenCo4		30	0.012	0		0
GenCo5		10	0.007	567		54536
GenCo6		12	0.017	284		37473
GenCo1	RT INC	14	0.005	0	32.58	0
GenCo2		15	0.006	0		0
GenCo3		25	0.01	170		8907
GenCo4		30	0.012	107		4191
GenCo5		10	0.007	0		0
GenCo6		12	0.017	0		0
GenCo1	RT DEC	14	0.0025	0	11.37	0
GenCo2		15	0.003	0		0
GenCo3		25	0.005	0		0
GenCo4		30	0.006	0		0
GenCo5		10	0.0035	196		0
GenCo6		12	0.0085	81		0

Moving away from the idealised Benchmark market reported above, the experiments conducted below assume that the agents build a GAMLSS-based forecasting model in order to strategically develop their bids/offers. Thus, the agents are not forced to submit their bids and offers based upon their true costs of production. In particular, each GAMLSS model is used by the agents to estimate the forward-looking PDF of the price and power commitment, given the information at time t. For this particular reason we have simulated the price and power commitment process for the first 365 days based upon the Normal (NO) distribution in order to 'control' for the best forecasting model that the agents can use to develop their strategic bids/offers. This will also enable us to control for information symmetry/asymmetry in the market. Thus, we will be in a position to draw some conclusions with respect to the repeated nature of the daily power auctions.

6.2.2 Information symmetry under the LMP congestion management scheme: Experiment 1

In Experiment 1, the generating agents employ the same structural forecasting models for the nodal price and the power commitment of the DA market.

The structure of the model for the estimation of the predictive PDF of nodal price is given by:

$$\begin{aligned} M_t|\mu_t^M, \sigma_t^M &\sim NO_M(\mu_t^M, \sigma_t^M) \\ \mu_t^M &= \beta_{0_1}^M + \beta_{1_1}^M * M_{t-1} \\ log(\sigma_t^M) &= \beta_{0_2}^M + \beta_{1_2}^M * M_{t-1}. \end{aligned} \tag{6.5}$$

While the structure of the model for the estimation of the predictive PDF of power commitment is given by:

$$\begin{aligned} P_t|\mu_t^{MW}, \sigma_t^{MW} &\sim NO_{MW}(\mu_t^{MW}, \sigma_t^{MW}) \\ \mu_t^{MW} &= \beta_{0_1}^{MW} + \beta_{1_1}^{MW} * P_{t-1} \\ log(\sigma_t^{MW}) &= \beta_{0_2}^{MW} + \beta_{1_2}^{MW} * P_{t-1} \end{aligned} \tag{6.6}$$

These are two autoregressive type models where distribution parameters are the linear functions of the preceding day price (model (6.5)) and preceding day power commitment (model (6.6)). Note that since the same structural model is utilised by every agent, there is no forecasting asymmetry among the agents. In other words, the market dynamics observed in this experiment are not affected by information asymmetry.

Figure 6.3 shows that agents with different cost of production exhibit different dynamics with respect to their offers over time. In particular, the two least expensive power plants expect to sell their full capacity. It is of note that the risk assumed by the agents is characterised by the probability of acceptance for the reported MCs, which is discussed in section 4.2.3 and illustrated by Figure 6.4. Therefore GenCo1 and GenCo2 effectively select a risk averse strategy by offering marginal costs that have a high (about 90%) probability of acceptance (see Figure 6.4). Also note that the marginal costs are higher by factor of 1.4 (for GenCo1) and 1.7 (fro GenCo2) compared with the true marginal production costs. GenCo3, GenCo4, GenCo5 and GenCo6 are the most expensive power plants. They find it optimal to take a higher risk and offer their production capacity close to the expected nodal price at about 50% probability of acceptance (see Figure 6.4)). Observed behaviour confirms the risk-taking strategy of the 'expensive producers', which is also seen in the real markets as some power produces tend to make offers with a lower probability of acceptance but with higher returns, thus making strategic offers based upon predicted peak prices during the DA market.

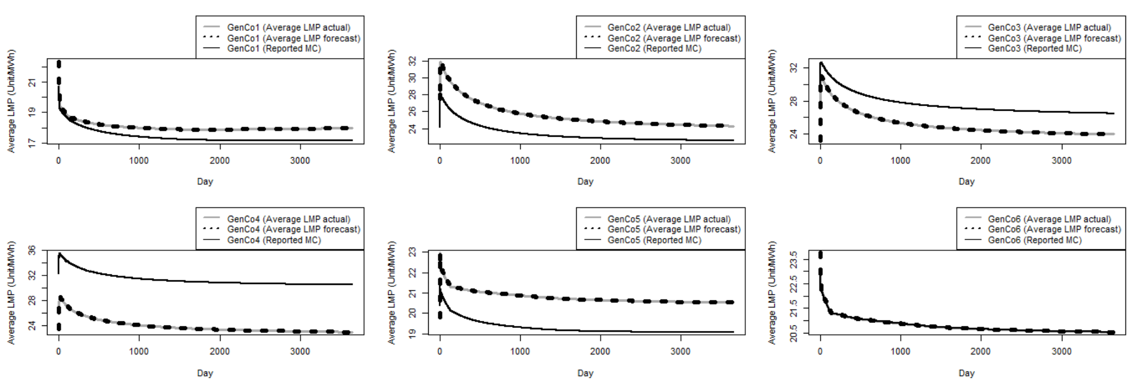

Figure 6.3: Reported MC, true MC, forecast average nodal prices and actual average nodal prices in Experiment 1

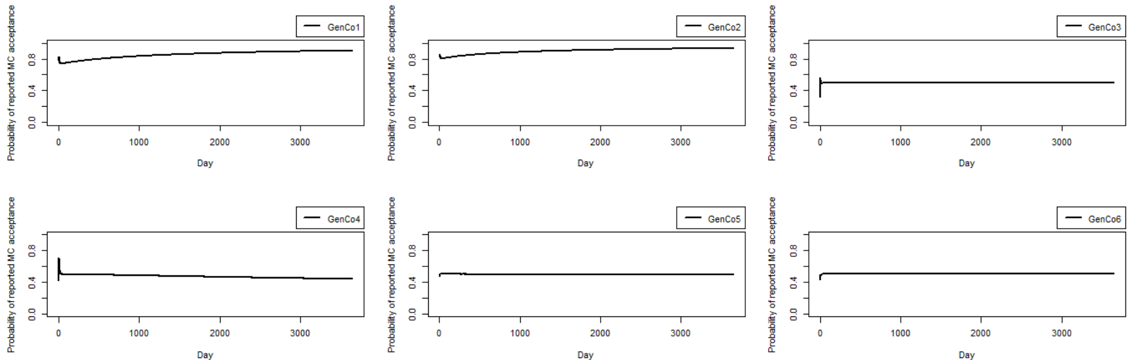

Figure 6.4: Probability of acceptance for reported MC in Experiment 1

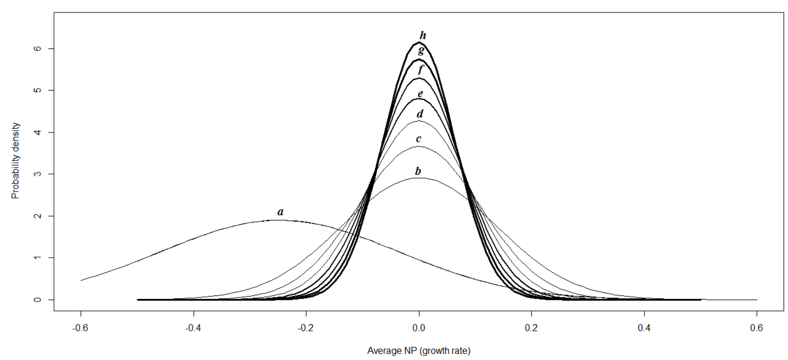

Figure 6.5: Probability density function of the average nodal price in Experiment 1: a - day 1; b - day 500; c - day 1000; d - day 1500; e - day 2000; f - day 2500, g - day 3000, h - day 3500

An interesting observation relates to the dynamics of the nodal prices. Figure 6.3 clearly shows that the volatility of the average nodal prices decreases over time (each simulation step represents a trading day). This can be explained by examining the daily predictive probability density function of the nodal price of the DA market which is showed by Figure 6.5.

Figure 6.5 illustrates that the predictive PDF of the average nodal prices with 500 days interval (from day 500 to day 3500). It is clear from the figure that the predictive PDF of the average nodal prices at day 500 (PDF with the symbol α) is 'fatter' in the middle of the distribution than other PDFs illustrated. This indicates that during the first 500 days there is a higher degree of uncertainty compared with uncertainty around the expected nodal prices at day 3500 (note the predictive PDF of the average nodal prices at the day 3500 - PDF with the symbol *h*). This indicates that the information used to form the offers for the DA market is more precise. Thus, information symmetry and better information over time cause the emergence of competitive markets out of individual profit maximisation actions. These results contradict the conclusions suggested by Bunn and Day (2009): the repeated nature of the daily power auction with a substantial amount of information in common, gives rise to a continuous evolution of learning with no evidence of convergence to a stationary solution.

An interesting question is whether the emergence of competitive markets out of individual profit maximisation actions is also observed when the system is characterised by frequent supply and demand shocks. This is addressed in the experiment below.

6.2.3 Information symmetry with shocks under the LMP congestion management scheme: Experiment 2

In Experiment 2, the repeated random positive shocks in demand and random negative shocks in supply are introduced. By simulating contingency in the load and generating capacity we aim a) to test system reliability and b) to access electricity price variability at certain nodes. Two agents were selected, namely GenCo5 (for shocks in electricity production) and LSE4 (for shocks in electricity demand). The shock mechanism is as follows:

- The upper generating capacity of GenCo5 submitted to ISO is pre-multiplied daily by the random number withdrawn from the set $X = \{x : 0.3 \leq x \leq 1.0; x \in R\}$. This represent a generation outage up to 70% of agent's capacity.

- The hourly electricity demands submitted by LSE4 to ISO are pre-multiplied daily by the random number withdrawn from the set $X = \{x : 1.0 \leq x \leq 1.2; x \in R\}$. This represents a random load increase up to 20% of LSE4 total demand.

Figure 6.6 shows the dynamics of node electricity prices and reported marginal costs by the generating agents. First the reader is advised to focus on the average electricity price at Node6 (location of GenCo5 and GenCo6), the higher volatility compared with the Experiment 1 can be observed. The increased price volatility is reflected by the scale of the PDF modelled by GenCo6 (see Figure 6.7). This suggests that GenCo6 has a higher probability of acceptance for extreme offers compared with Experiment 1. This also explains the enhanced exercise of market power by GenCo6. Thus the average reported marginal cost by GenCo6 in Experiment 2 is 1.3 times higher compared with the average reported marginal cost in Experiment 1.

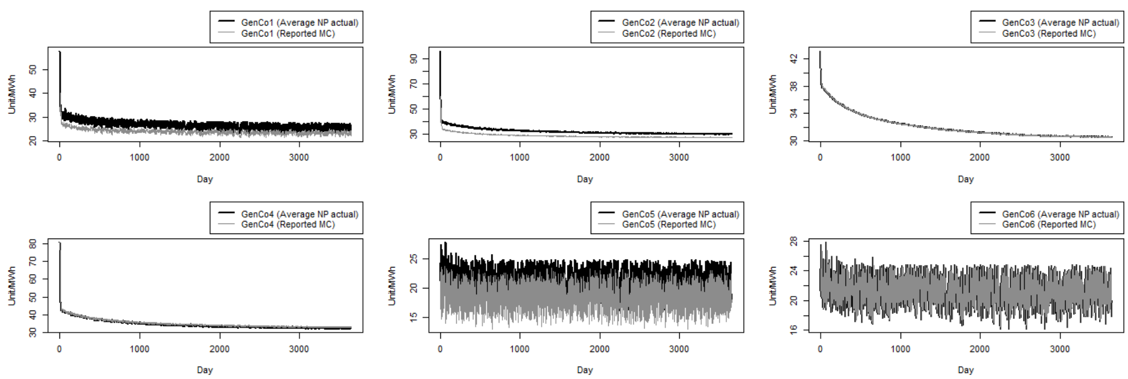

Figure 6.6: Reported MC and actual average nodal prices in Experiment 2

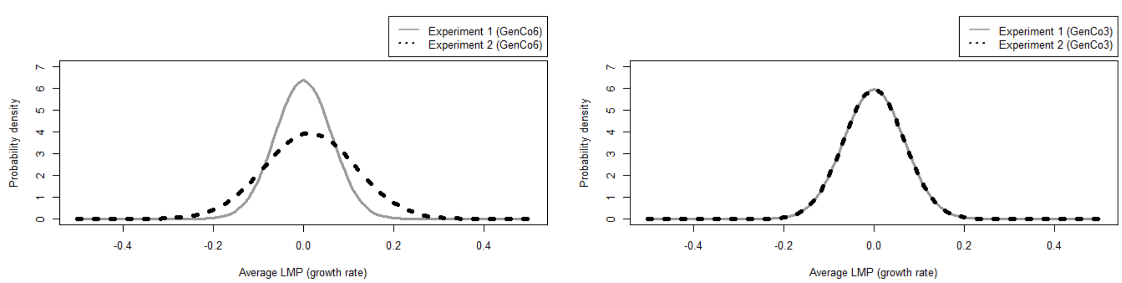

Figure 6.7: Probability density function of GenCo6 and GenCo3 for the average nodal prices in Experiments 1 and 2 on 3500th day of market operation

The results of Experiment 2 show that demand/supply shocks can intensify the strategic behaviour of some generating agents (note the different dynamics compared with the nodal price of the reported MCs by GenCo 5 and GenCo 6) by increasing the volatility of the power price under the LMP congestion management scheme. In order to test the effects of the different congestion management methods, the experiment below reproduces Experiments 1 and 2 under thePR congestion management scheme.

6.2.4 Information symmetry under the PR congestion management scheme: Experiment 3

In Experiment 3, every generating agent employs the GAMLSS model to forecast the average MCP and the average daily power commitment. Power congestion, unlike Experiments 1 and 2, is resolved here according to PR congestion management scheme. Therefore each generating agent forecasts the price and commitments both for the DA market and RT market (for INC and DEC). Figures 6.8, 6.9 and 6.10 illustrate the reported MC, true MC, forecast average MCP and market average MCP for DA, RT (for INC) and RT (for DEC) markets. The figures show that agents with different costs of production exhibit different dynamics with respect to their offers and bids over time. In the long run (DA market - see Figure 6.8), we observe the MCP falling below true MC for GenCo3 and GenCo4. This indicates that in order to fulfil the total electricity demand in a least-cost manner, these power plants are not required for power generation. Note, this is possible since the solution of DA COPF under the PR congestion management scheme does not account for transmission grid thermal constraints (see Section 4.2.2). This behaviour also confirms the risk-taking strategy of the more expensive 'peak producers', which base their strategic bids/offers upon predicted peak prices during the DA market. On the other hand, less expensive power generators (GenCo1, GenCo2, GenCo5 and GenCo6) maximise their expected profit when offering below the expected MCR with a 90% probability of acceptance. This behaviour confirms the strategy of the 'base load producers'.

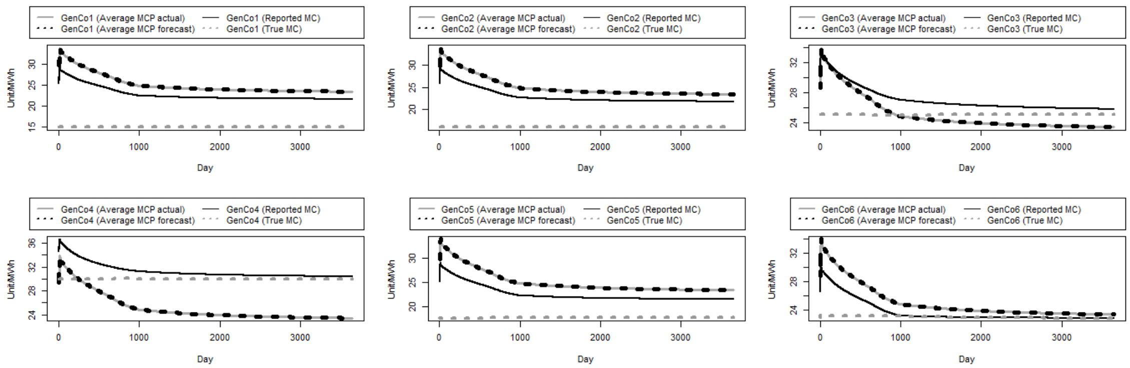

Figure 6.8: Reported MC, true MC, forecast average MCP and actual average MCP in Experiment 3 (DA market)

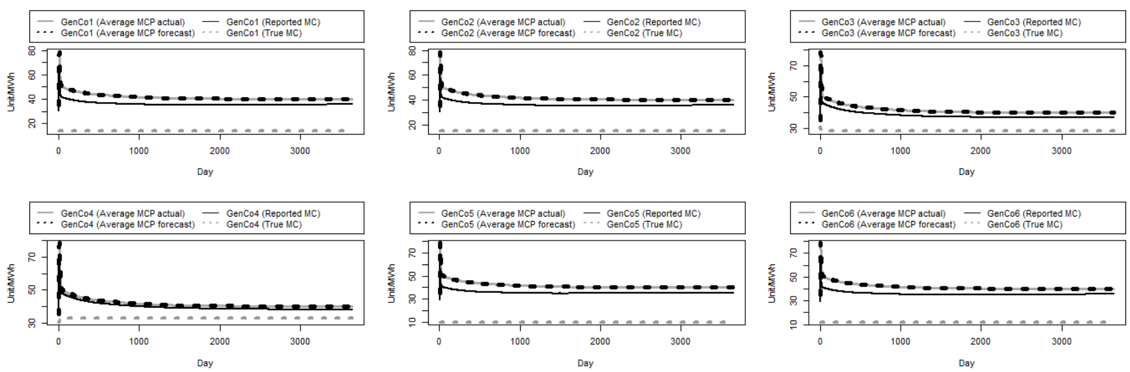

Figure 6.9: Reported MC, true MC, forecast average MCP and actual average MCP in Experiment 3 (RT market for INC)

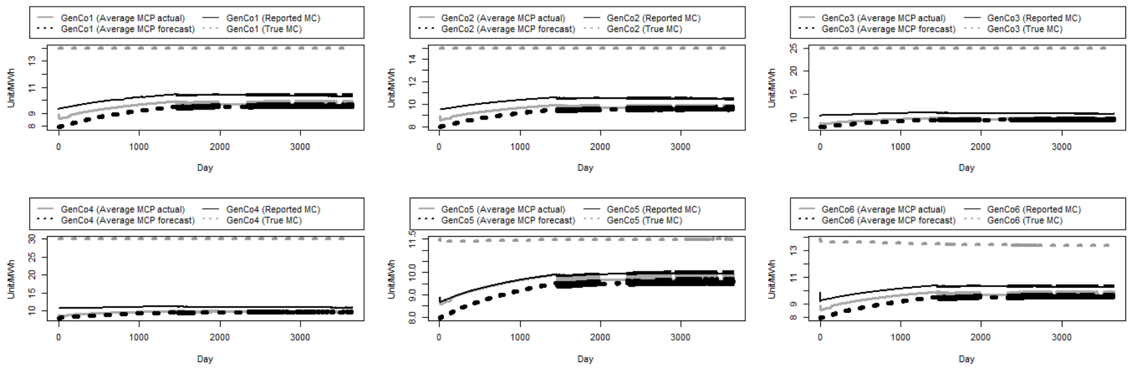

Figure 6.10: Reported MC, true MC, forecast average MCP and actual average MCP in Experiment 3 (RT market for DEC)

The RT market is cleared accounting for branch thermal constraints (see Section 4.2.2). Furthermore, the clearing of the RT market takes into account the total generating capacity contracted at DA market. As a result, GenCo3 and GenCo4 are the only power producers that have commitments to produce power. This means that the MCP at RT market for INC is considerably higher compared with the DA market. It is interesting to observe that the other 'cheaper' power plants submit their offers just below the offers of 'expensive' producers, namely GenCo3 and GenCo4. This is a clear indication of the emergence of collective learning in repeated auctions with capacity and physical constraints.

At RT market, the ISO also accepts bids from GenCos in order to balance the congested system. We observe that the ISO only schedules GenCo5 and GenCo6 for DEC to alleviate the electricity congestion. Note that strategic behaviour by each agent here is to bid below its 'true' MC. It is noteworthy that the other power plants submit their bids close to bids of GenCo5 and GenCo6.

To summarise, information symmetry causes the emergence of competitive markets (cleared according to PR congestion management method) out of individual profit maximisation actions. It is also interesting to observe how the agents' competitive behaviour changes when the system is characterised by frequent supply and demand shocks and when the market is cleared based upon the PR congestion management scheme. This is addressed in the experiment below.

6.2.5 Information symmetry with shocks under the PR congestion management scheme: Experiment 4

In Experiment 4, random positive shocks in demand (LSE4) and random negative shocks in supply (GenCo5) are introduced for the DA market. The contingency mechanism is described in the section 6.2.3.

Figure 6.11 illustrates the average MCP dynamics at DA market (left), RT market for INC (middle) and RT market for DEC (right). It suggests that when the system is subject to power shocks, the average MCP undergo a series of frequent peaks with the RT market for INC expressing higher volatility.

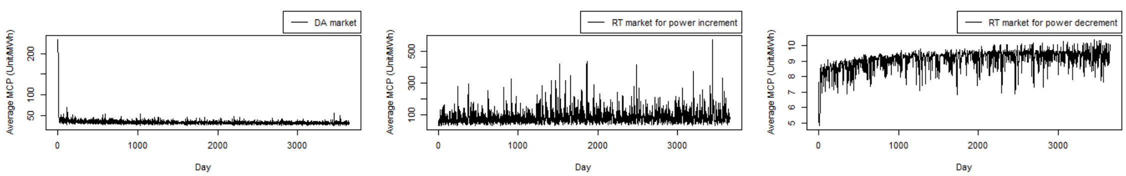

Figure 6.11: Average MCP at DA market (left), RT market for INC (middle) and RT market for DECt (right) in Experiment 4

Note that since the generating agents implement an identical GAMLSS model (4.16) to forecast MCP, the predictive PDFs are identical across all agents. Figure 6.12 compares the predictive PDF of the MCP between Experiments 3 and 4 at the DA market (left figure), the RT market for INC (middle figure) and the RT market for DEC (right figure). It is clear that the scale of the PDFs of Experiment 4 is higher compared with the scale of the PDFs in Experiment 4. This suggests higher market volatility. As argued earlier, a higher market volatility can intensify strategic behaviour since extreme bids/offers have higher probability of acceptance. Indeed, the agents report offers (compared with Experiment 3) at the DA market higher by a factor of 1.2, at the RT market for INC higher by a factor of 1.9 and bids at the RT market for DEC lower by a factor of 1.1.

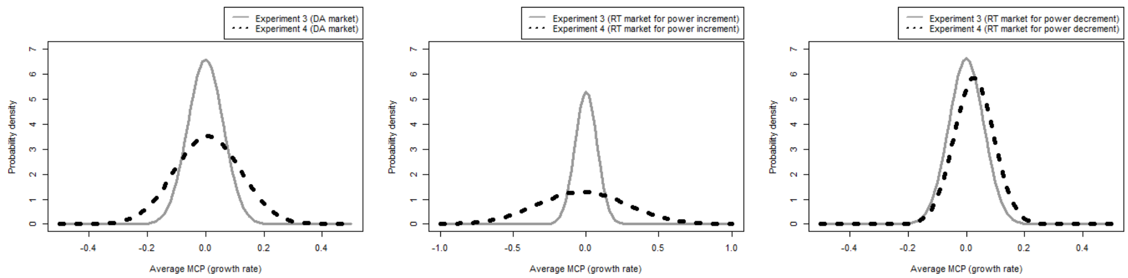

Figure 6.12: Probability density function of each generating agent for the average MCP in Experiments 3 and 4 on 3500th day of market operation

6.3 Conclusion

From an expert systems perspective, this thesis proposes a detailed computational model for repeated power auctions operating across realistically rendered transmission grids that are subject to congestion.

To get an insight into the plausible strategies of competing market participants, an ACEWEM framework is used, simulating a model wholesale power market with six electricity generating agents and four load servicing agents with known features/properties. In particular, this research work explores two market designs:

- Market design 1: The wholesale power market is managed according to a LMP congestion management scheme.
- Market design 2: The discriminatory price wholesale electricity market is managed according to the PR congestion management scheme.

The results reported are of significant practical value to market participants and regulators. The key practical insights from the experiments are:

- Enhanced dissemination of information (leading to information symmetry) and either the LMP or PR congestion management scheme leads to competition over time, even when market participants are heterogeneous (in terms of production costs, capacity and technology).

- ’Expensive’ power producers tend to exhibit risk-taking behaviour when compared with the behaviour of ’less expensive’ power producers - reflecting presciently behaviour observed in real-world liberalized power markets.
- Overall, the PR congestion management scheme seems to result in higher market prices compared with the LMP congestion management scheme. This points to the importance of the market participants in understanding the rules of the daily repeated auctions.
- Unexpected supply or demand shocks lead to the likelihood of market power being exercised, particularly under the PR congestion management. Thus, advanced information about ’power outages’ will curtail this from happening.
- Incumbent costs of production structures affect their ability to participate in DA or RT markets, with high cost producers more active in RT markets.

Finally, apart from the success which this model demonstrates as an application of agent-based computational laboratory for liberalised power markets, and the behavioural insights which emerged, its practical value is considerable. Unravelling conditions under which collusive pricing is observed as a manifestation of conduct rather than market structure has been an elusive task in many business and policy circles. This is because it requires an estimate of what the profit-maximizing prices should be in the perfect market (the benchmark experiment). The computational technique presented here does achieve that, notwithstanding the various simplifications involved in any modelling specification, and can thereby provide a baseline from which to compare both market structure (*e.g.* LMP congestion management scheme) or market conduct (*e.g.* strategic submission of offers).

7 Application example: UK market

7.1 Introduction

This chapter presents a realistic model of the UK wholesale electricity market. The heterogeneous agents that represent UK power plants of various generating technologies, implement the SPO algorithm proposed by this research work. The following sections of this chapter introduce a novel methodology for estimating marginal generating costs of UK power producers based on the GAMLSS framework and information recovered from real bidding data. Also presented is the overall structure of the model and the detailed data on the UK market participants and physical infrastructure. Validated model and simulation experiments with various market design scenarios are then carried out. Concluding remarks from these experiments are outlined in the final section of this chapter.

7.2 Estimating the marginal cost of electricity generation in the UK

The marginal concept in power generation refers to the rate at which the cost of electricity production changes with respect to extremely small increases in generating output. Even when the concept of marginal cost is completely agreed in principle, its estimation involves far more than calculations founded upon a set of rules. Since none of the existing methods have proved to be optimal, the thesis proposes a new marginal cost estimation technique based on analysis of real bidding data with flexible GAMLSS models. Fitting a GAMLSS parametric distribution to the bidding data often results in a model that agrees well with the data in high density regions, but poorly in areas of low density. For unimodal distributions, such as the normal (NO) or Student's t (SST), these regions are known as the 'tails' of the distribution. One reason why a model might fit poorly in the tails is that by definition, there is less data in the tails on which to base a choice of model, and so models are often chosen based on their ability to fit data near the mode. Another reason might be that the distribution of bidding data is often more complicated than the usual parametric models. The entire GAMLSS distributions family was developed as a package that can model tails of a wide variety of distributions, based on theoretical arguments. One approach to distribution fitting that involves the marginal cost is to use a non-parametric fit (the empirical cumulative distribution function, for example) in regions where there are many observations, and to fit the marginal cost to the tail(s) of the bidding data.

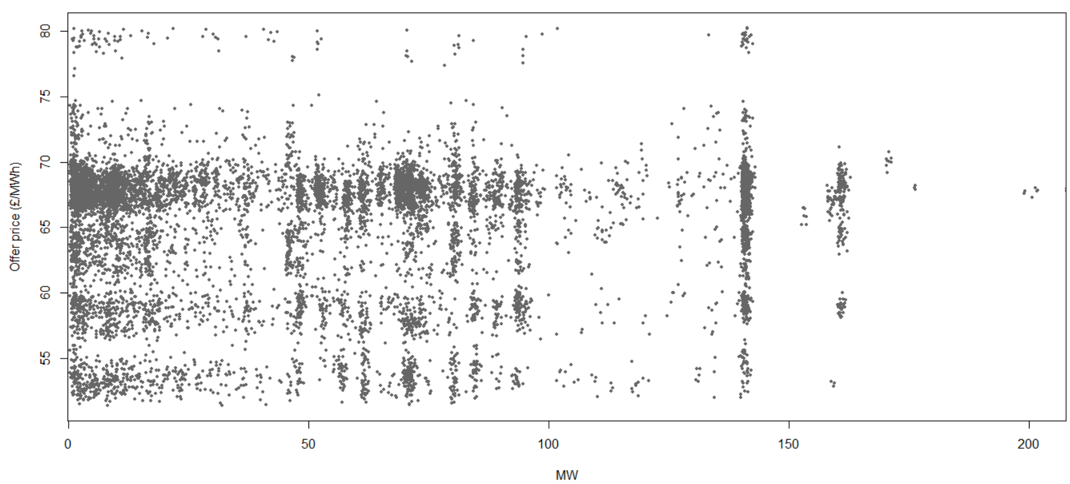

Figure 7.1: Offers to Balancing Mechanism accepted by National Grid Operator for power generation (example of Grain CCGT power station)

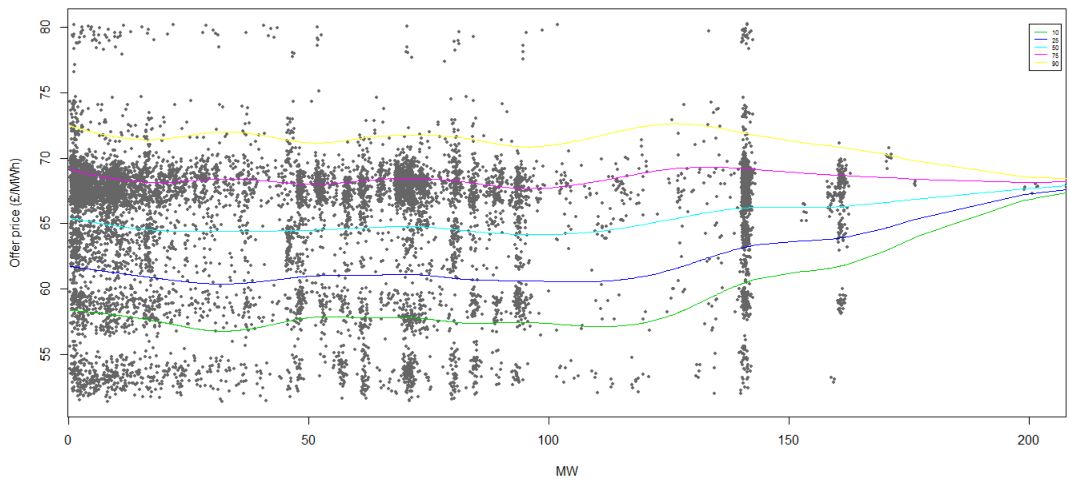

Figure 7.2: GAMLSS estimated smoothed centile curves

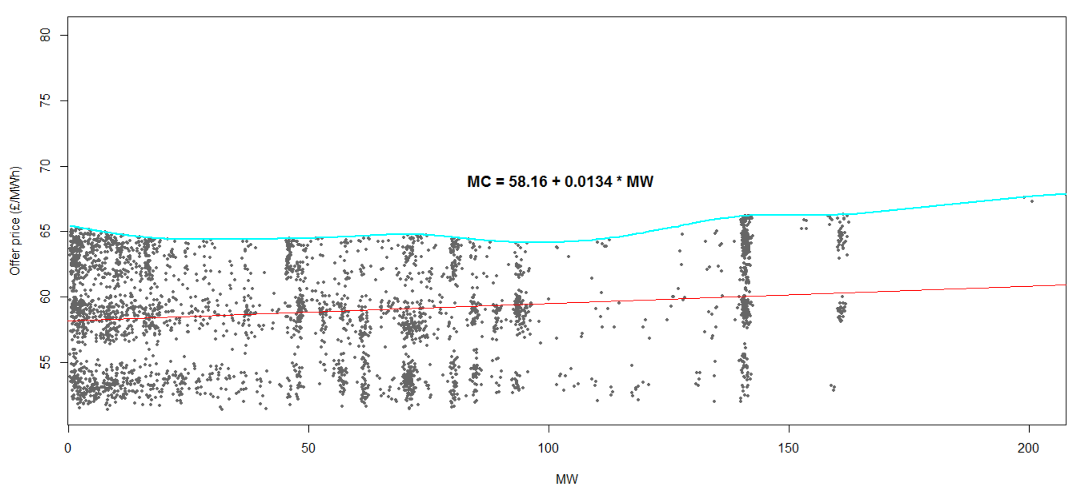

Figure 7.3: Estimated marginal cost curve with truncated distribution

Figure 7.1 illustrates the real UK bidding to Balancing Mechanism data for Grian CCGT power plant. It is noteworthy that market participants regularly bid resources at prices in excess of marginal costs (Borenstein et al., 2002; Joskow and Kahn, 2001). The industry expertise suggests that bidding above the true marginal cost takes place in about 50% cases (EDF Energy department representatives, 2013). Therefore given the full scatterplot of bids the GAMLSS semi-parametric model is used to estimate centile curves (see Figure 7.2) and truncate the bidding data above 50% (see Figure 7.3). Presumably the remaining bidding data holds the information on the true marginal cost of the power producer. Since in ACEWEM the marginal generating costs are assumed to have a linear form, Figure 7.3 purposely illustrates linear approximation of 50% centile curve. A priori we expect the line parameters to be clearly positive to have an economic sense that is also confirmed by the results achieved. The estimated marginal cost curve (see Figure 7.3) has a positive intercept value (58.16) and slope parameter (0.0134). An identical approach has been applied to other power plants located in UK and estimated marginal costs are reported in the Table 1.

7.3 UK electricity market model

The ACEWEM framework is used to simulate the UK wholesale electricity market and analyse the impact of specific changes in the market design on the market performance. It is also used to get an insight into strategies of competing market participants. Figure 7.4 illustrates the UK transmission grid modelled by the ACEWEM framework. The locations of GenCos and LSEs on the transmission grid are coloured in green and blue accordingly. The nodes are connected by branches and coloured in black. Table 1 and Table 2 presents the actual and estimated characteristics of UK GenCos and LSEs accordingly. The LSEs do not act strategically and are price takers with demands characterised by the fixed percentage (see Table 2) of the total system's load illustrated by Figure 7.5. It is assumed that based load power plants(*e.g* Nuclear, Coal) do not act strategically and thus always bid/offer true generating costs. Moreover it is assumed that there is no error in demand estimations by load agents, thus they bid only to DA market while electricity congestions at BM are resolved only by bids and offers accepted from generating agents.

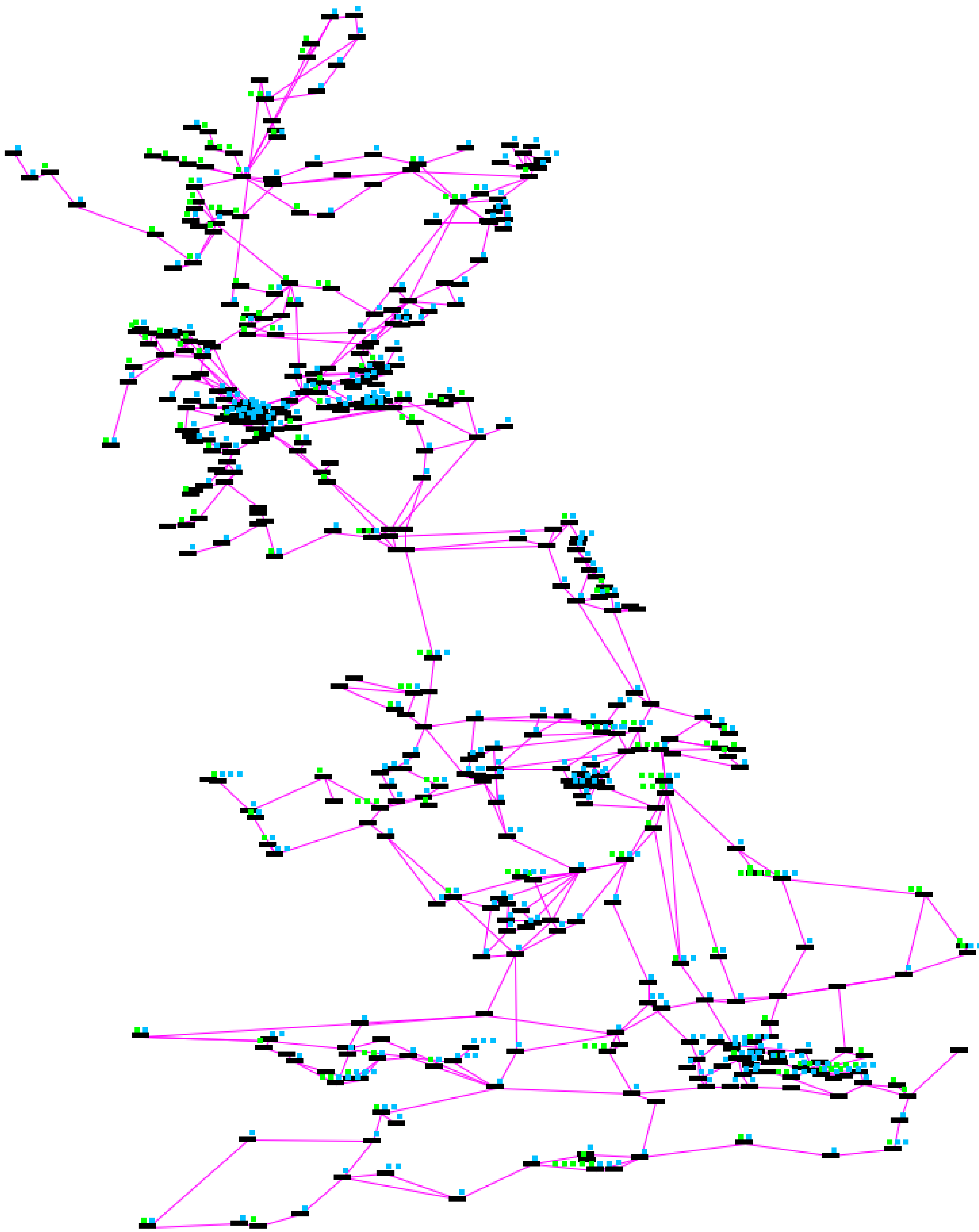

Figure 7.4: UK transmission grid in ACEWEM

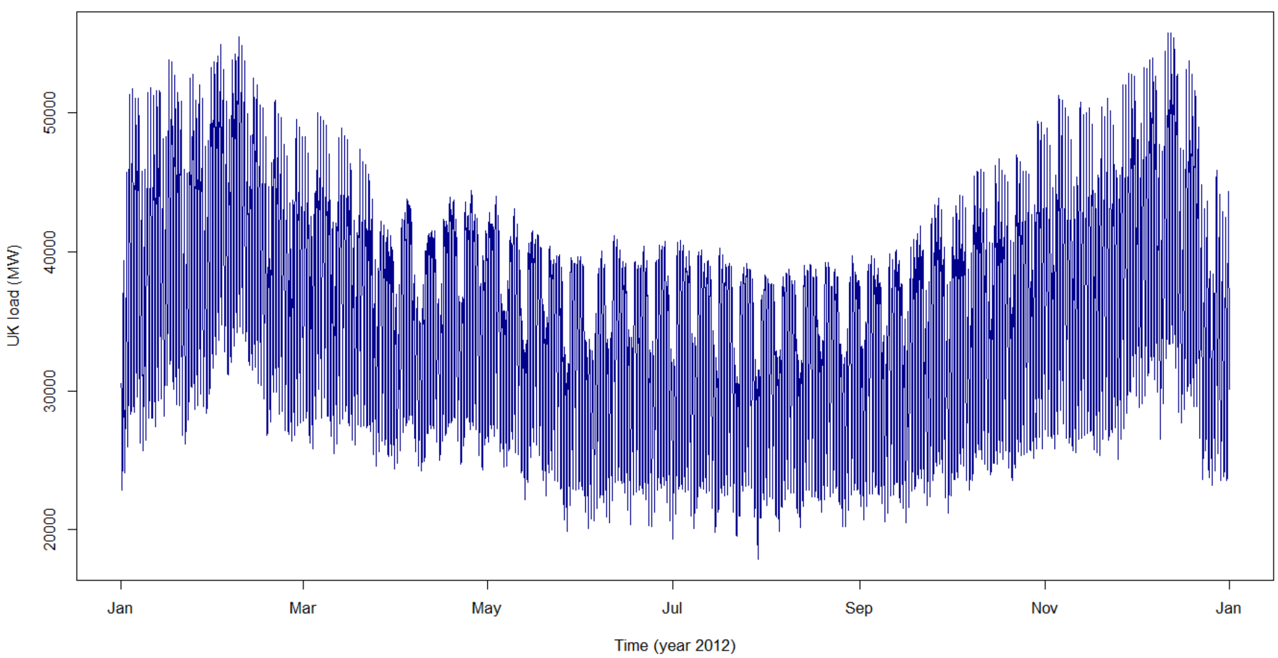

Figure 7.5: UK electricity load during year 2012 (measured every half-hour)

7.3.1 Model validation

According to Law (2006) a valid simulation system can be used to draw conclusions about the real one.Two approaches will be used for comparing real and simulated systems including 1) correlated inspection approach and 2) calculation and alysis of Mean Absolute Percentage Error (MAPE). According to the first approach, in the validation process for the proposed UK market model it is graphically assessed whether the simulated price dynamics on the DA market corresponds to the observed one in the real UK power market. The price dynamics accessed by converting prices to growth rates:

$$m_t^h = \frac{ln(M_t^h)}{ln(M_{t-1}^h)}$$

here, M_t^h and M_{t-1}^h current and previous day wholesale electricity price at settlement period h. The ACEWEM simulation model is run with input data that characterises the UK electricity industry during the year 2012. Figure 7.6 illustrates the dynamics of real and simulated market clearing prices. It is remarkable that the real price dynamics (but not the real price itself) can be well reproduced by simulation model. This result supports the model validity.

In the simulated model the load variability plays an important role in price formation. The GenCo availability is assumed to be constant over the year. This is a simplification, whereas in reality a percentage (2% - 10%) of total generating capacity, depending on the time of the year, is off for planned maintenance (OFGEM, 2012). Moreover in a simulated model the renewable energy availability is also assumed to be constant over the year whereas in reality water levels and wind energy vary considerably throughout the year, month and even day. Due to the simplifications above the model cannot serve as electricity price forecasting tool (it is also not the research aim), the ACEWEM is expected to provide deeper insights into the market operation.

The quantified measure of whether the model can be validated follows from the MAPE approach. This approach measures an accuracy of simulated data as a percentage of the error, and is defined by the formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - S_t}{A_t}\right| \tag{7.1}$$

where A_t is a vector of actual price observations, S_t is a vector of simulated price observation and n is a total number of observations. The MAPE of the real and simulated DA price is approximately equal to 20%. This means that about of 80% of the real DA electricity prices were accurately simulated by ACEWEM. Overall this validates the model to be able to realistically simulate the UK wholesale electricity market. The 20% loss in accuracy can be associated with the events in the real market that are not accounted for in ACEWEM (*e.g.* power plant outages, unavailability of renewable generation *etc.*).

To summarise, it has been shown that agents behaviour and interaction on the micro level is able to generate the price dynamics at macro level. The micro level behavior has been validated qualitatively by domain experts (EDF Energy department representatives, 2014). The macro level data have been validated by comparing statistical properties of output electricity prices from the model with statistics of the real-world system.

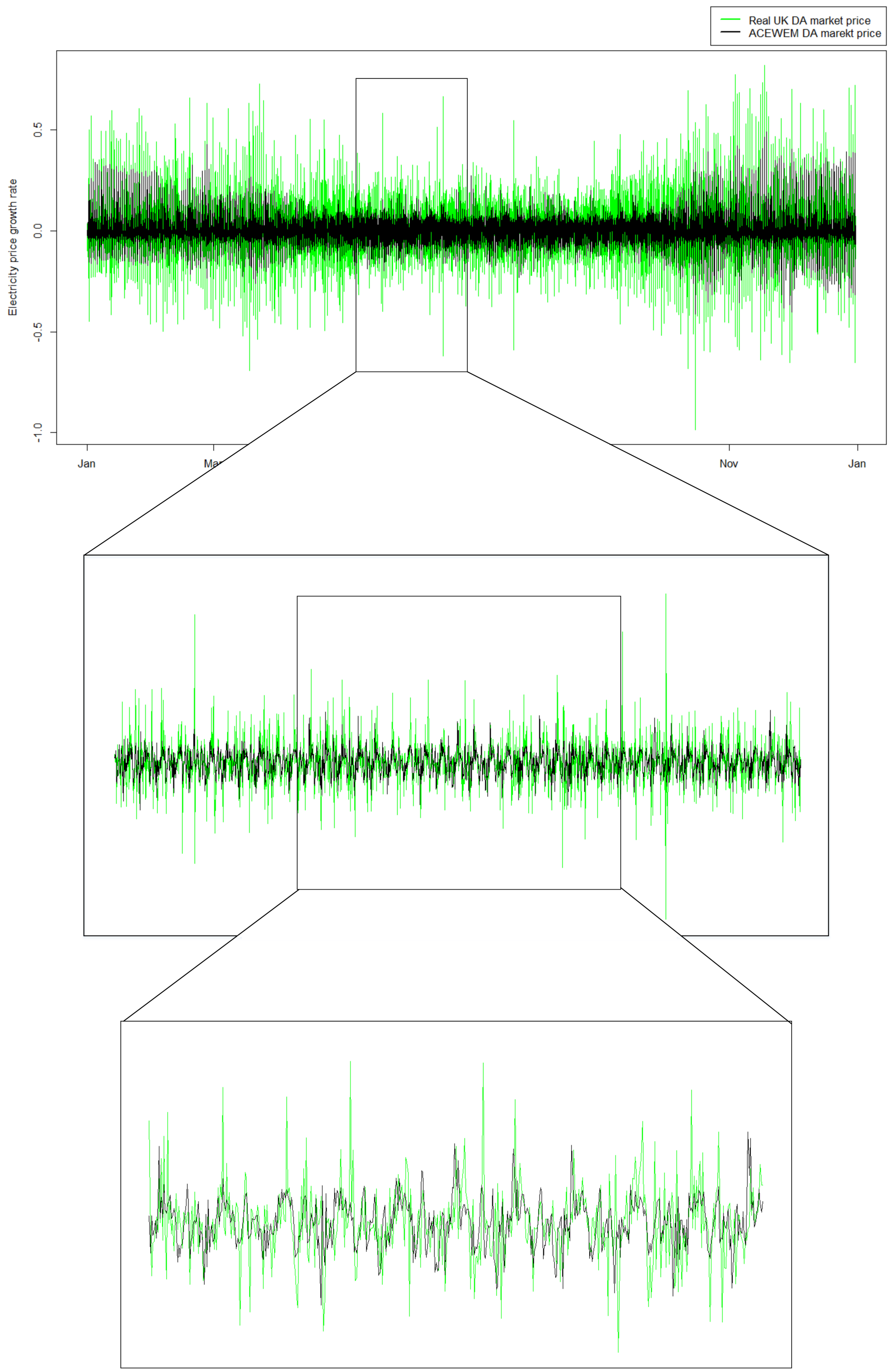

Figure 7.6: UK real and simulated price dynamics

7.3.2 Conventional reinforcement learning

This simulation is set to analyse the performance of the conventional RL algorithm (Erev and Roth, 1998). In particular here the GenCos do not build statistical models to find the optimal strategies, instead they employ RL algorithm and select the marginal cost parameters directly from corresponding action domain based on the profits earned. Thus the agents do not build predictive models and only make their decisions based on the former performance. Figure 7.7 illustrates the real and simulated (with reinforcement learning) UK DA market clearing price. Overall the

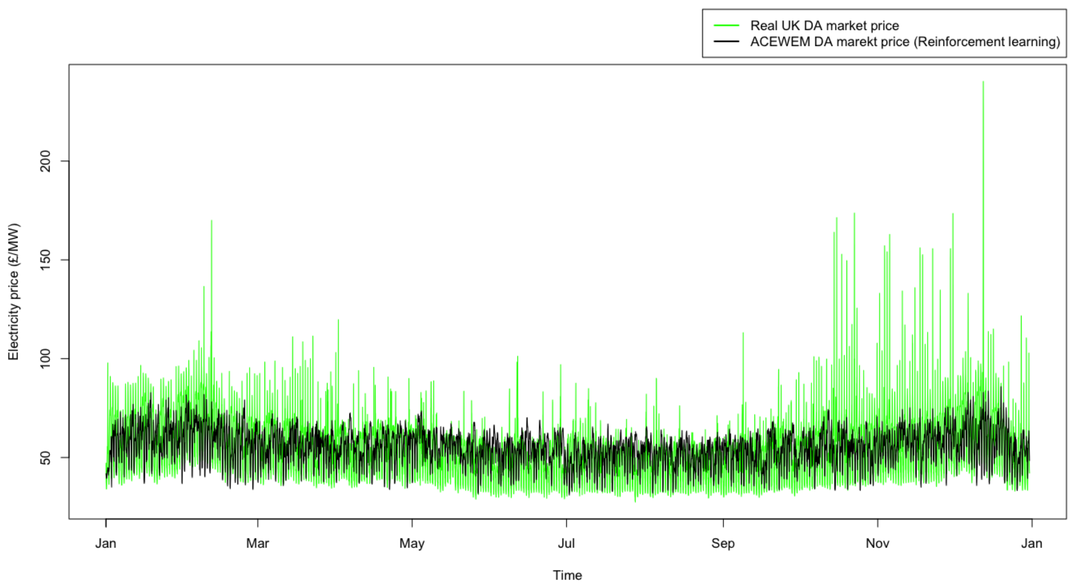

Figure 7.7: DA market clearing price year 2012

simulated price dynamics can be seen as reasonable, however according to Figure 7.8 the RL algorithm performance is rather poor in the case of low and high demand hours. Thus for example the SPO algorithm performs considerably better (see Figure 7.8) as the marginal costs offered by agents result in more realistic market clearing prices. This example effectively shows the limitation of the conventional learning algorithm to address the behaviour observed in the real UK power market. Whilst the RL algorithm is grounded solely on experience acquired by strategic agents, this simulation study however suggests that in the real UK power market the generators take into account future anticipated market clearing prices and power commitments when deciding on the

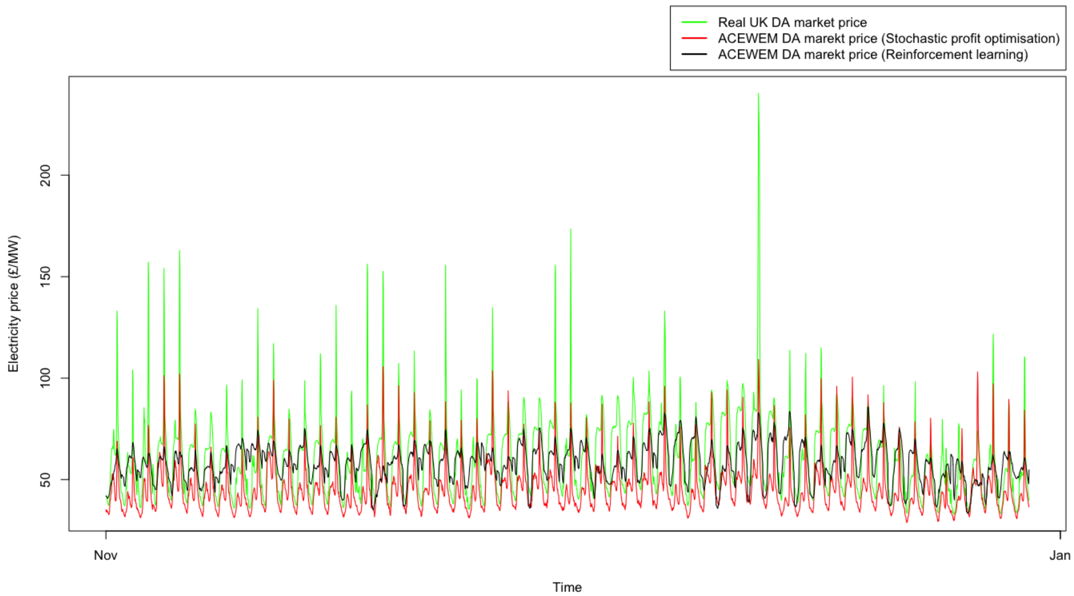

Figure 7.8: DA market clearing price November - January 2012

marginal costs to report.

7.3.3 Benchmark

Under the 'benchmark' experiment, GenCos do not exercise market power. In particular the agents do not optimise their strategies and thus report only true marginal costs and true production capacities (see Table 1). The results reported here are based upon: a) the LMP congestion management scheme with uniform price auction design and b) the PR congestion management method with discriminatory price auction.

Figure 7.9 illustrates the average nodal prices at various GenCos locations. Note that these electricity prices vary across the nodes, which indicates that the system is congested and therefore cannot be cleared in the least-cost manner. Another important observation relates to the fact that the UK transmission grid is actually unable to provide the least-cost electricity dispatch given the highest market efficiency (the power producers report only true marginal costs and production limits, thus they do not even attempt to exercise market power, which is unlikely to occur in reality).

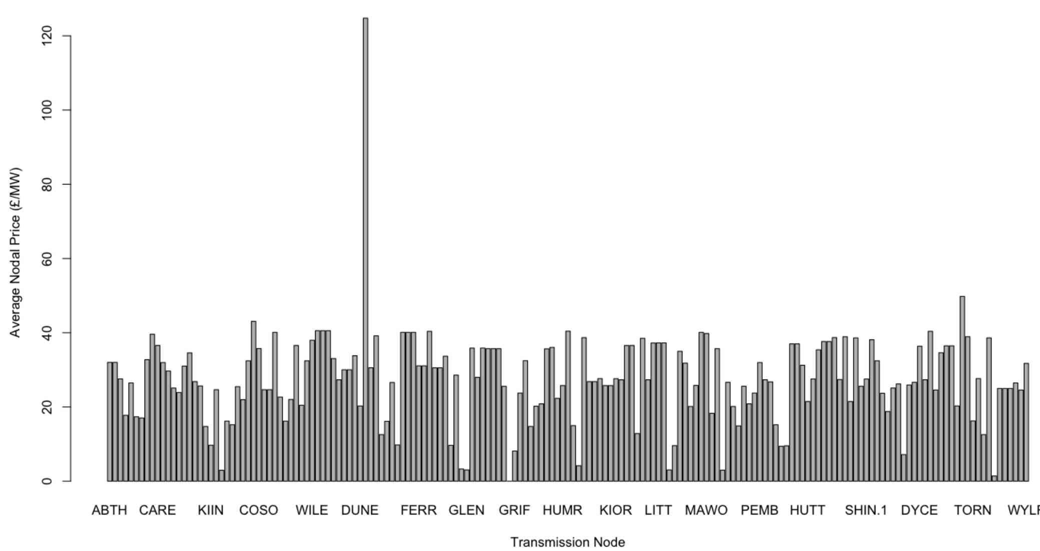

Figure 7.9: Average nodal prices across the UK transmission nodes

The average power commitments by generating technology are illustrated in Figure 7.10. It shows that on the efficient market the most expensive power producers receive zero (see Oil and OCGT) or negligible (Pumped Storage) capacity allocation, while the total demand is fulfilled mainly by base load and renewable generation. Figure 7.10 illustrates average power commitments by generating technology.

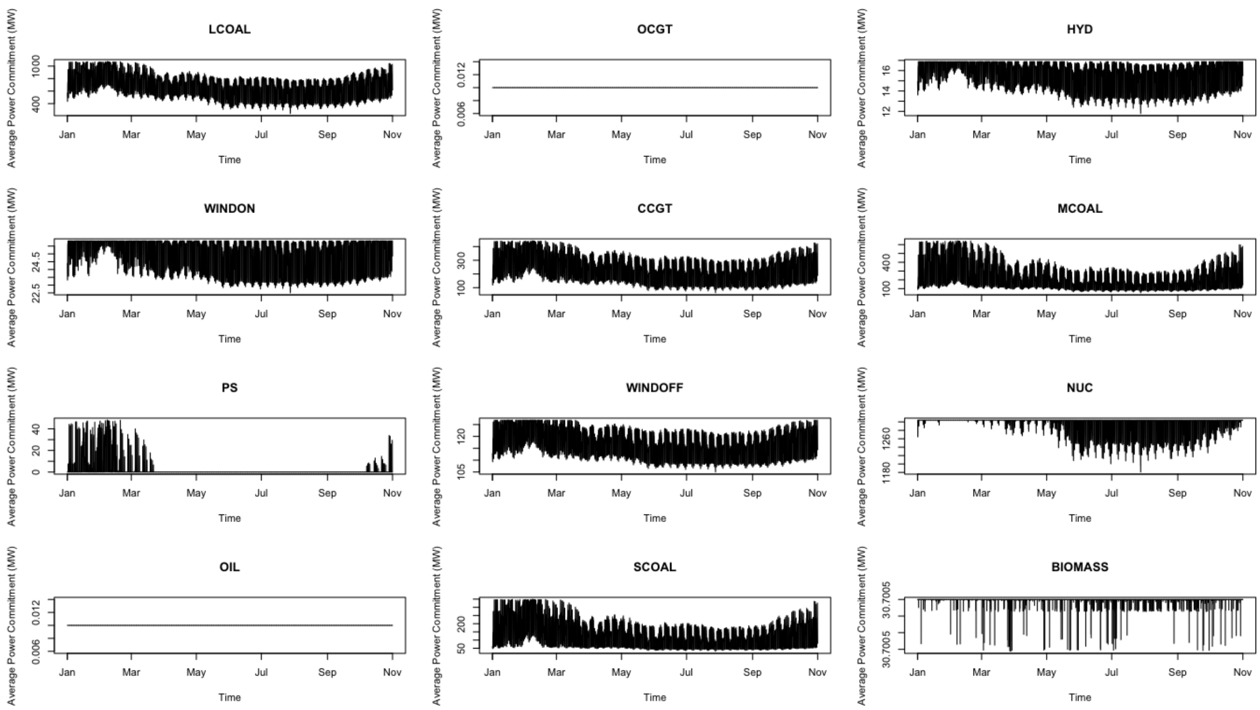

Figure 7.10: Average power commitments by generating technology allocated by LMP congestion management clearing mechanism

Figure 7.11 illustrates the real UK DA wholesale electricity price and the DA market clearing price determined by the PR congestion management clearing mechanism on the perfectly competitive market. This plot outlines an extension that the actual strategic bidding takes on the real UK wholesale electricity market. This also confirms the importance of the UK power market research towards more efficient market design since the main issue is clearly evident.

The average DA power commitments by generating technology are illustrated in Figure 7.12. Similar to LMP congestion management clearing results, the most expensive power producers (OCGT and Oil technologies) remain idle during entire 2012 period. Note that according to PR methodology, no account is made for transmission capacity at DA market. Thus the power output from Pumped Storage technologies is partially substituted by a cheaper electricity source. Also, this experiment points out a limited branch capacity between wind farms and transmission grid. Thus

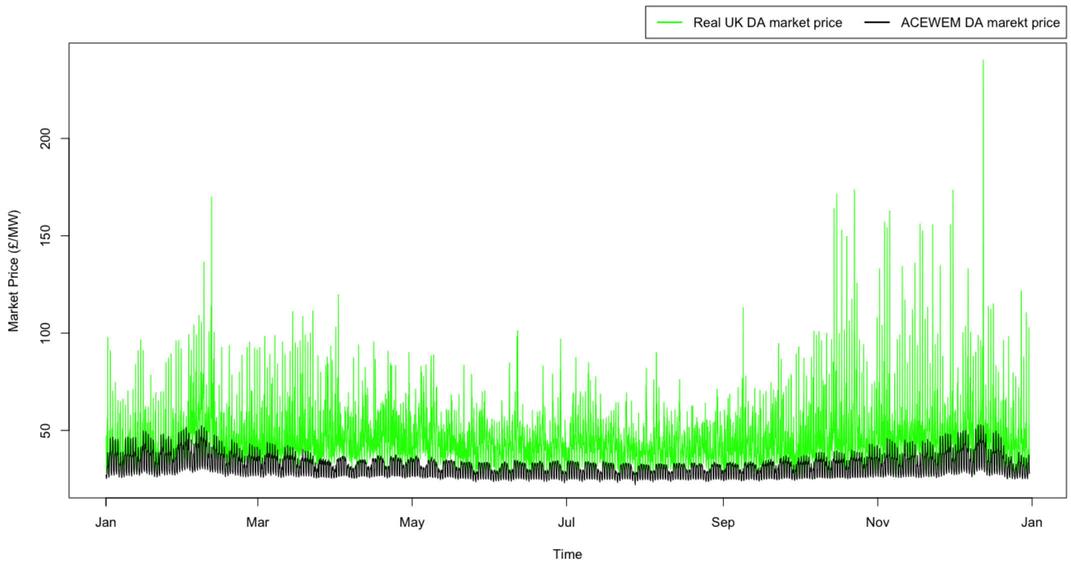

Figure 7.11: DA market clearing price

unlike the LMP case, here wind farms both onshore and offshore are constantly dispatched up to full available capacity. Nevertheless, similar to the LMP method, the total electricity demand is also fulfilled mainly by base load and renewable generation.

Figure 7.13 illustrates BM (INC) and BM (DEC) market clearing prices. The price for INC undergoes two peaks over the year. These peaks highlight the fact that more expensive generation is required to fulfil higher demand levels observed during the winter months (see Figure 7.5). Indeed, Figure 7.14 shows that PS generating technology was dispatched few times over the winter months which influenced two high price jumps. Moreover Figure 7.14 reports that mostly renewable generation is regulated to withhold the electricity output in order to balance the system throughout the year. This in turn explains the particular price dynamics observed at BM (DEC) market. Flat line indicates that no other technology apart from renewable generation sets the market clearing price. This price equals the true marginal production cost of renewable electricity producers which is negligible (close to zero).

The average BM INC and DEC by generating technology are illustrated in Figure 7.14. Here the ISO rebalances the system by incorporating the transmission capacity constraint into the market clearing algorithm. Due to congestions, the relatively cheap electricity from renewables is cut off

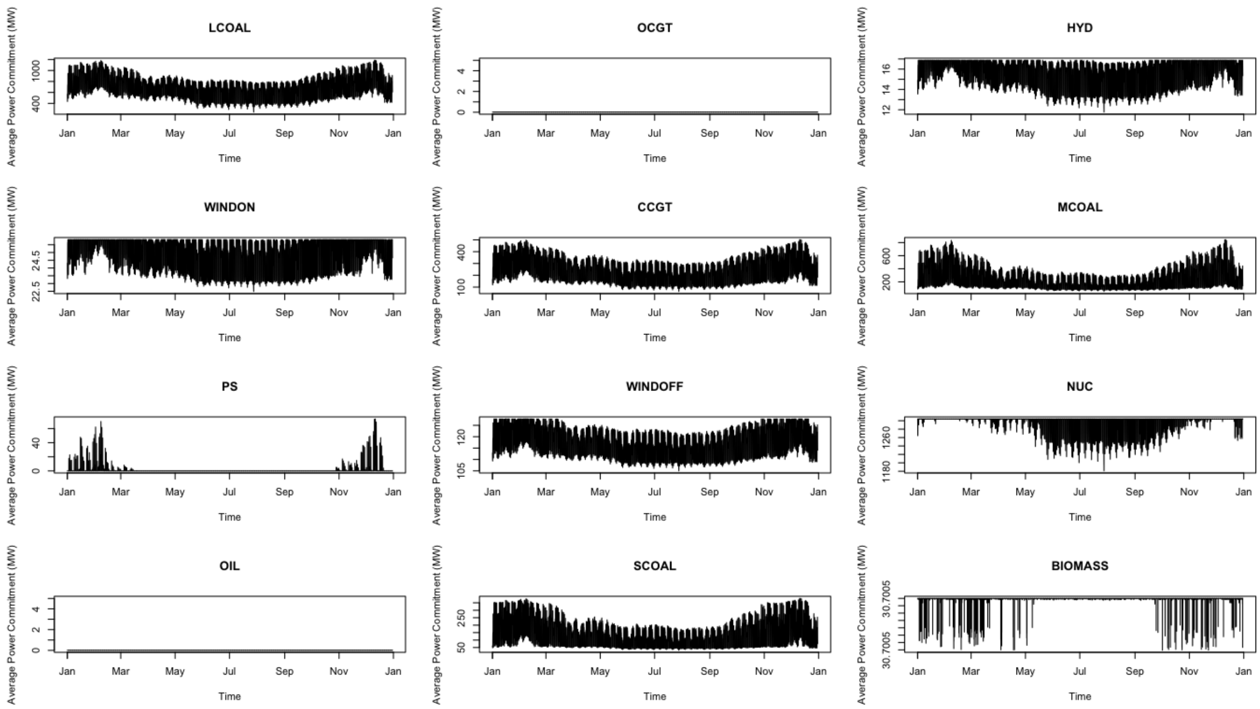

Figure 7.12: Average power commitments by generating technologies (PR scheme, DA market)

and replaced by power produced from more expensive generators (Combined Cycle Gas Turbine (CCGT), Pumped Storage (PS)). It is interesting to note that on the efficient market with no strategic bidding the Open Cycle Gas Turbine (OCGT), Crude Oil (OIL) and most of PS technologies are not engaged in the generation schedule over entire 2012 year. Presumably these technologies exist to provide the means for ISO to balance sudden demand shocks and unpredicted generation outages which are not modelled in this experiment.

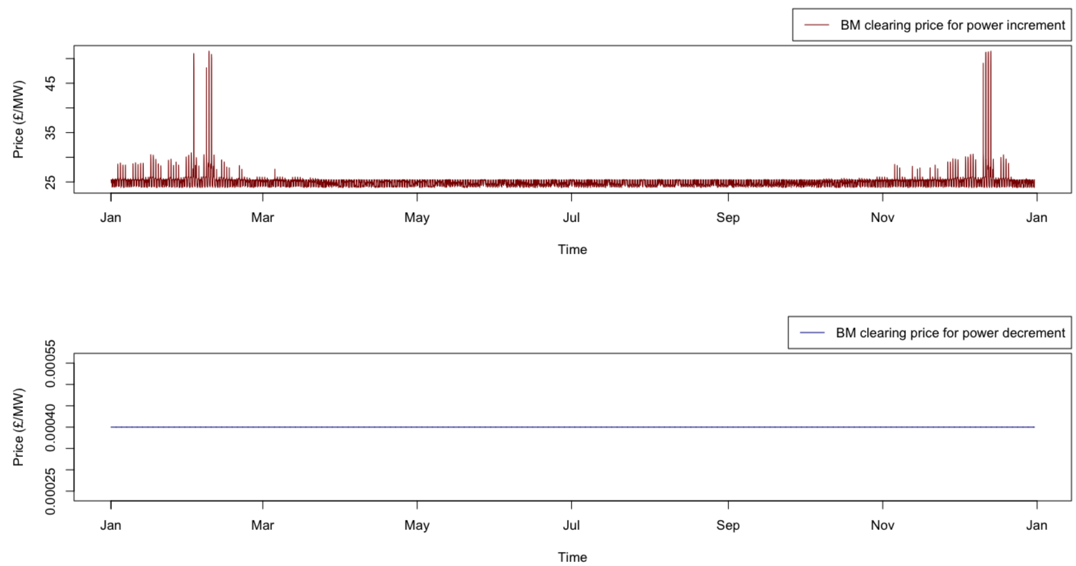

Figure 7.13: Market clearing price for INC and DEC (PR congestion management scheme, BM market)

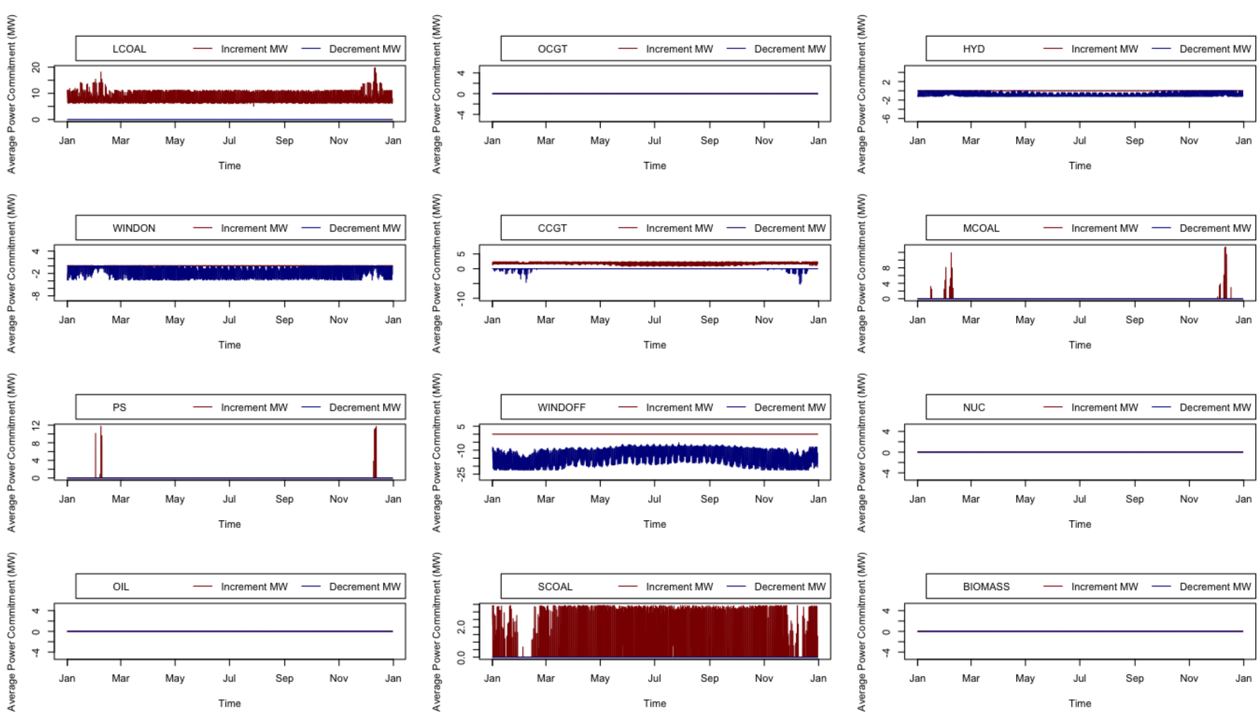

Figure 7.14: Average BM INC and DEC by generating technology allocated by power the PR congestion management clearing mechanism

7.3.4 Information asymmetry under the LMP congestion management scheme: Experiment 1

In Experiment 1, each generating agent selects a structural forecasting model for the DA nodal power price and DA power commitment with the RL algorithm based on model performance (profits earned) over the preceding days. A structure of the model for the estimation of the predictive PDF of DA nodal price is given by (Serinaldi, 2011):

$$\begin{aligned} M_t|\mu_t^M, \sigma_t^M, \nu_t^M, \tau_t^M &\sim \mathcal{D}_M(\mu_t^M, \sigma_t^M, \nu_t^M, \tau_t^M) \\ g_1(\mu_t^M) = \beta_{0_1}^M + \beta_{1_1}^M WD + \beta_{2_1}^M SP + \beta_{3_1}^M M_{t-1} + \beta_{4_1}^M M_{t-2} + \beta_{5_1}^M M_{t-7} &+ \beta_{5_1}^M M_{t-1}^{min} \\ g_2(\sigma_t^M) &= \beta_{0_2}^M \\ g_3(\nu_t^M) &= \beta_{0_3}^M \\ g_4(\tau_t^M) &= \beta_{0_4}^M \end{aligned} \tag{7.2}$$

While the structure of the model for the estimation of the predictive PDF of power commitment at DA is given by:

$$\begin{aligned} P_t|\mu_t^{MW}, \sigma_t^{MW} &\sim \mathcal{NO}_{MW}(\mu_t^{MW}, \sigma_t^{MW}) \\ \mu_t^{MW} = \beta_{0_1}^{MW} + \beta_{1_1}^{MW} WD + \beta_{2_1}^{MW} SP + \beta_{3_1}^{MW} LOAD_t &+ \beta_{4_1}^{MW} P_{t-1} \\ log(\sigma_t^{MW}) &= \beta_{0_2}^{MW} \end{aligned} \tag{7.3}$$

where, WD is a week days categorical variable; SP is a settlement period categorical variable; M_{t-1}, M_{t-2} and M_{t-7} are the nodal electricity prices lagged by 1,2 and 7 days accordingly; M_{t-1}^{min} is a minimal electricity nodal price observed on the preceding day; $LOAD_t$ is a day t total system load anticipated by generating agent; P_{t-1} is a preceding day power commitment; $\mathcal{D}_M$ is the distribution selected by the agent with corresponding set of link functions $g1(.)$,...,$g4(.)$ from the RL algorithm's action domain. The action domain is supplied with distributions subject to condition that μ parameter should be an exact mean of response variable. These distributions are: NO, TF, TF2, PE, SST and JSU.

Figure 7.15 illustrates the average nodal prices at the UK DA market. It is noteworthy that the price spread across the nodes is considerably lower compared to the benchmark case. This can be explained by the fact that generating agents implicitly perceive the electricity congestion through the nodal price forecasting.It is interesting to observe that the collective learning actually equalises the prices across the nodes while elevating the overall price level in the system. This follows on directly from the fact that power producers lift the reported marginal costs in order to optimise the expected profits. This is addressed by Figure 7.16 which shows that the agents of different

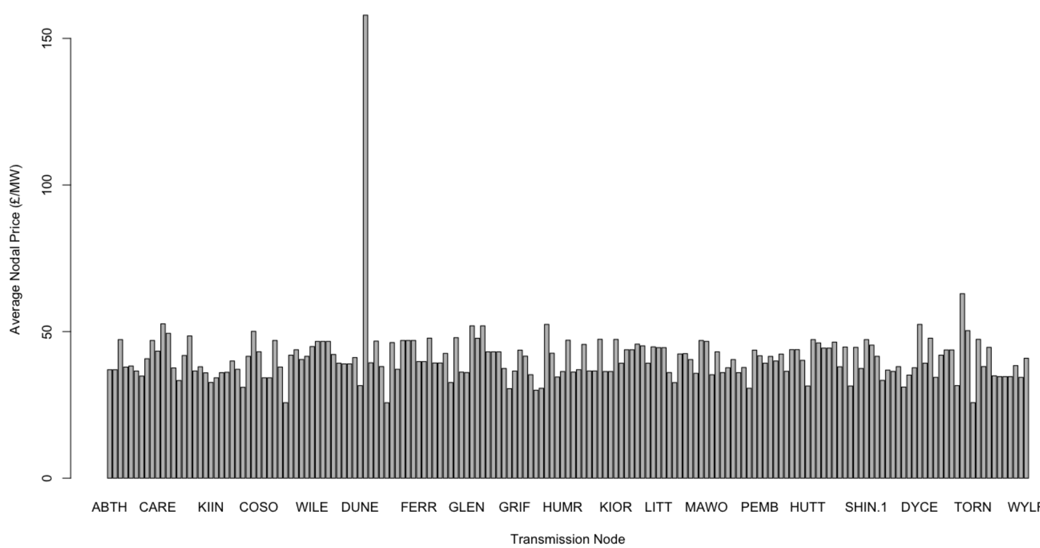

Figure 7.15: Average nodal prices across the UK transmission grid nodes

generating technologies exhibit different dynamics with respect to their offers over time but overall often report marginal costs above their true levels. Note that the risk assumed by the agents is characterised by the probability of acceptance of the reported marginal costs (see Table 7.1). Thus on average the OCGT, Pumped storage and OIL generating technologies are willing to take a high risk and offer their reported marginal costs below 50% probability of acceptance. As the result these reported marginal costs are considerably higher than anticipated market price. The remaining technologies effectively select a risk averse strategy by offering marginal costs that have a high probability of acceptance (see Table 7.1). The observed behaviour confirms the risk-taking strategy of the 'expensive producers', which is also seen in the real markets as some power producers tend

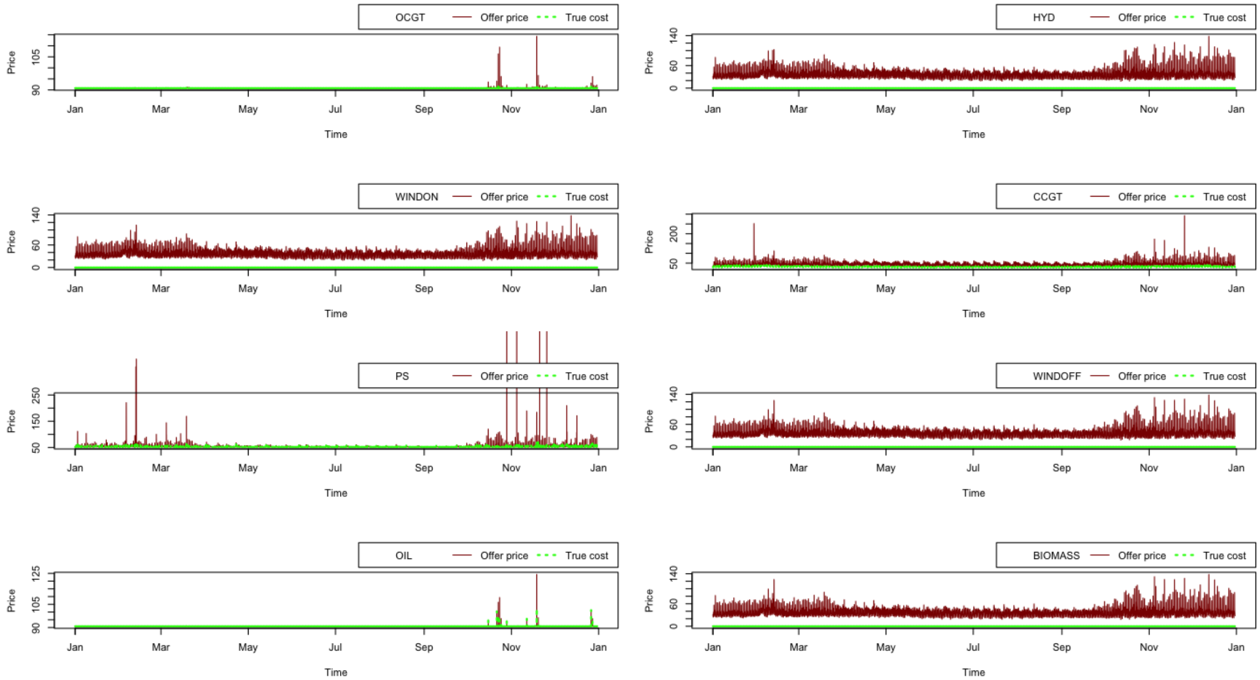

Figure 7.16: Average offer price and true marginal cost of production across generating technologies (LMP scheme, DA market)

to make offers with a lower probabilities of acceptance but with higher returns - making strategic offers based upon predicted peak prices during the DA market.

Generating Technology	*Average OAP*
OCGT	0.2404
HYD	0.8728
WINDON	0.8728
CCGT	0.6274
PS	0.3991
WINDOFF	0.8728
OIL	0.2016
BIOMASS	0.8728

Table 7.1: Average OAPs selected by various generating technologies

Figure 7.17 illustrates average power commitments by generating technologies. Note that throughout the entire year the total system demand is mainly fulfilled by renewable, base load and partially peak generation. OIL and OCGT mostly produce only during the winter months when total load reaches its maximum values.

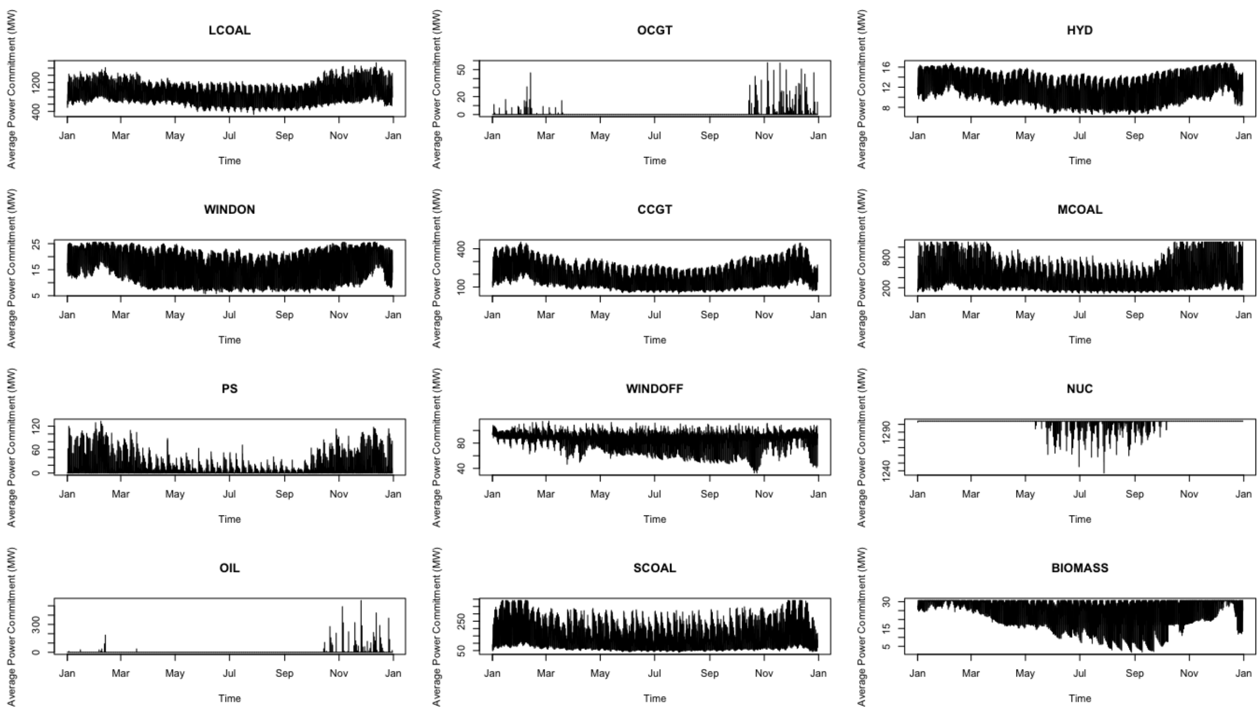

Figure 7.17: Average power commitments by generating technologies (LMP scheme, DA market)

Figure 7.18 illustrates the dynamics of average distribution parameter values across all electricity generators. It is noteworthy that during time period from November to January both μ and σ parameters reach their highest values. This causes a higher degree of uncertainty around the expected price and hence intensifies the strategic behaviour by power producers. In particular, during the November - January period (see Figure 7.16), the agents submit higher reported marginal costs compared to preceding months. This behaviour confirms the implicit collective learning by GenCos without direct collusion, as they substantially inflate reported marginal costs just by analysing market outcomes.

There is an open discussion on the choice of auction design that facilitates better the efficiency of the UK power market. Generally in the electricity industry, two auction designs are commonly

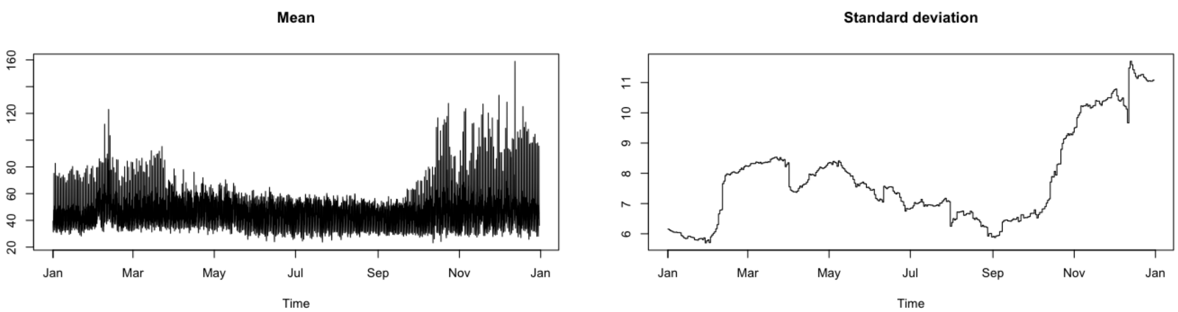

Figure 7.18: Average mean and standard deviation parameters of selected distribution by generating agents

employed 1) uniform pricing and 2) discriminatory pricing. In uniform pricing a single market clearing price is determined (in case of LMP congestion management method this is a single price per node). This price is usually the most expensive offer accepted by the ISO for electricity generation which is paid to all scheduled generators. In contrast, under discriminatory pricing a single market clearing price is also established, however power producers are paid their offer prices. It is still an open discussion as to which auction design is best for UK.

Some authors favour the uniform price design. For example Kahn et al. (2001); Bunn and Oliveira (2001) argue that uniform pricing reinforces the competition and lowers the market inefficiencies. In contrast, the outcomes from several studies, for example Xiong et al. (2004); Bin et al. (2004); Bakirtzis and Tellidou (2006); Cincotti et al. (2006) reveal that in discriminatory price auctions the agents offer higher marginal costs, however social welfare is respected better comparing to uniform pricing.

Binmore and Swierzbinski (2000) explore the empirical studies that analyse the uniform and discriminatory price auctions. Thus some studies suggest that discriminatory pricing contributes to higher sellers' revenues more than the uniform pricing. Others suggest the opposite. The conclusions from theoretical considerations are rather confusing; therefore this thesis attempts to shed a light on the problem by conducting a simulation study on UK market cleared with LMP congestion management method under the discriminatory and uniform pricing rules. The advantage of one design against the other is best assessed through the estimation of excessive profits earned by power plants. Thus Figure 7.19 illustrates the difference between profits earned under discriminatory and uniform price auctions across different generating technologies. Overall the profits earned under

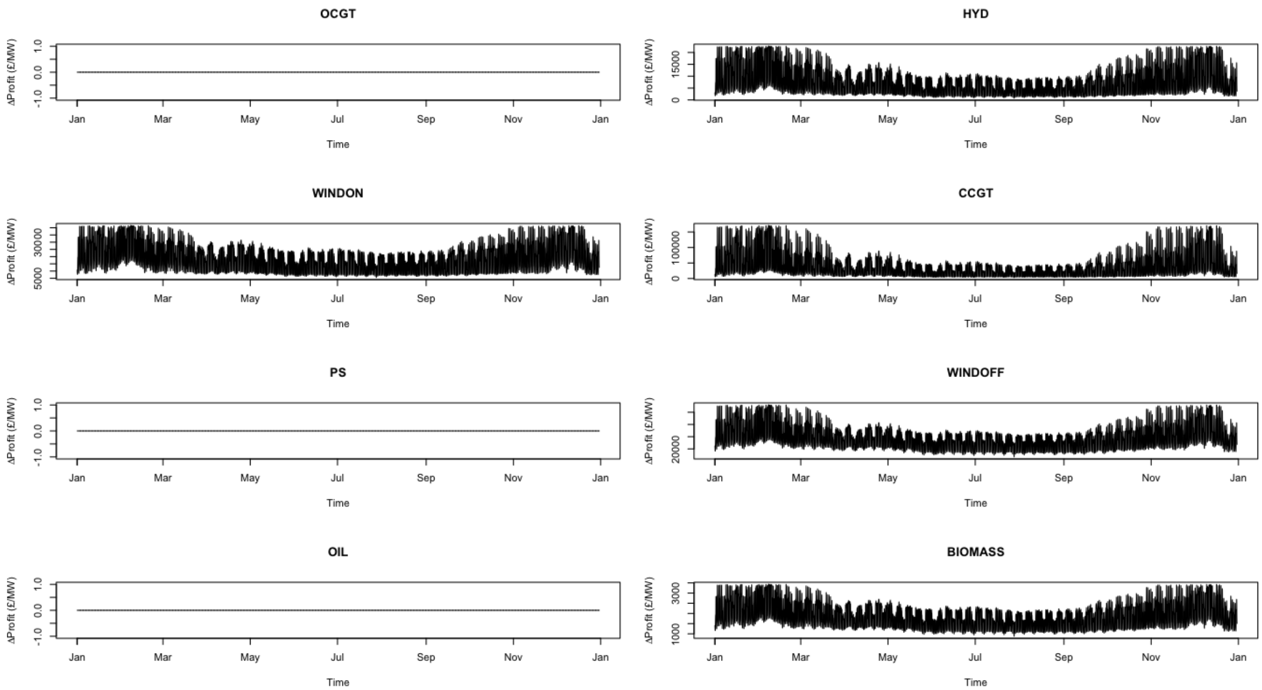

Figure 7.19: The profit difference across generating technologies under discriminatory and uniform price auction design (LMP scheme)

the uniform price auction are considerably higher for infra-marginal power plants. Peak power plants (OCGT, PS and OIL) are usually marginal producers (the ones that set the market clearing price) and therefore are indifferent with respect to auction design.

7.3.5 Information asymmetry under the PR congestion management scheme: Experiment 2

In Experiment 2 every generating agent employs the GAMLSS model to forecast the market clearing price and the power commitment (see model 7.3 and model 7.2 in Section 7.3.4). Power congestions, unlike in Experiments 1, are resolved here according to the PR congestion management scheme. Therefore each generating agent forecasts the price and commitments both for the DA market and BM (separately for INC and DEC). Figure 7.20 illustrates the electricity price dynamics at DA market and BM for INC and DEC. It can be seen that electricity prices are considerably

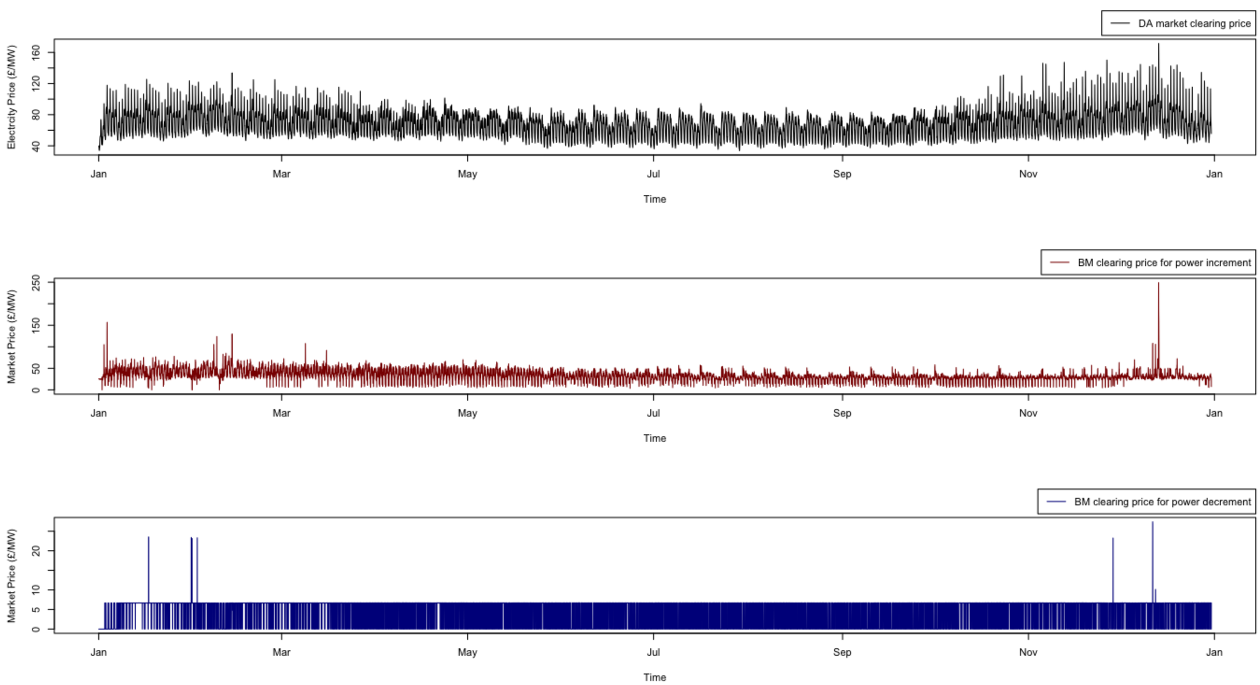

Figure 7.20: Wholesale electricity price (PR scheme, DA, BM (INC) and BM (DEC) markets)

higher in this experiment compared to the benchmark case (see Section 7.3.3). This follows directly from profit-maximising behaviour of power producers that exercise market power by reporting inflated marginal costs. Note that the strategic behaviour of electricity producers at BM for DEC is to bid below their 'true' MC. Figure 7.22 suggests that unlike the benchmark case, the DEC price at BM is mainly set by two generating technologies, namely renewable and base-load, which justifies the observed price dynamic. The base-load generation by model assumption bids electricity prices without strategic consideration (and thus does not manipulate the electricity prices), while renewables have very limited space for decreasing their reported marginal costs. Note, true marginal generating costs of renewable electricity producers are close to zero.

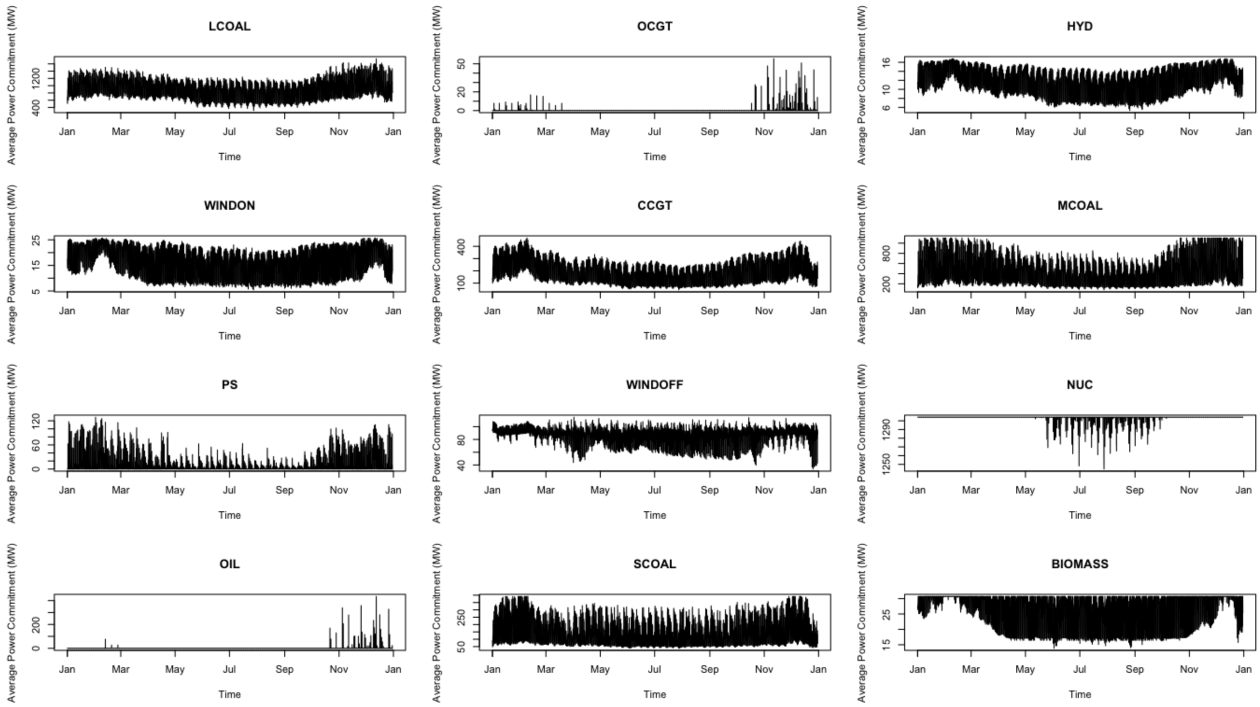

Figure 7.21: Average power commitments by generating technologies (PR scheme, DA market)

The average reported marginal costs across generating technologies offered to the DA market are illustrated by Figure 7.23. Note that renewable technologies offer above their true MC throughout the entire year, while peak producers (*e.g.* OIL, PS, OCGT) exercise market power mainly during the winter months when the electricity demand reaches its highest values (see Figure 7.5).

Figure 7.21 illustrates average power commitments across generating technologies allocated by the DA clearing mechanism. Similar to results of Experiment 1 (where the market was cleared according to the LMP scheme) the system demand throughout the entire year is mainly fulfilled by renewables, base-load and partially by peak generation. OIL and OCGT technologies are scheduled for electricity dispatch during the winter months only.

Overall the capacity allocation at the DA market cleared by two presented congestion management

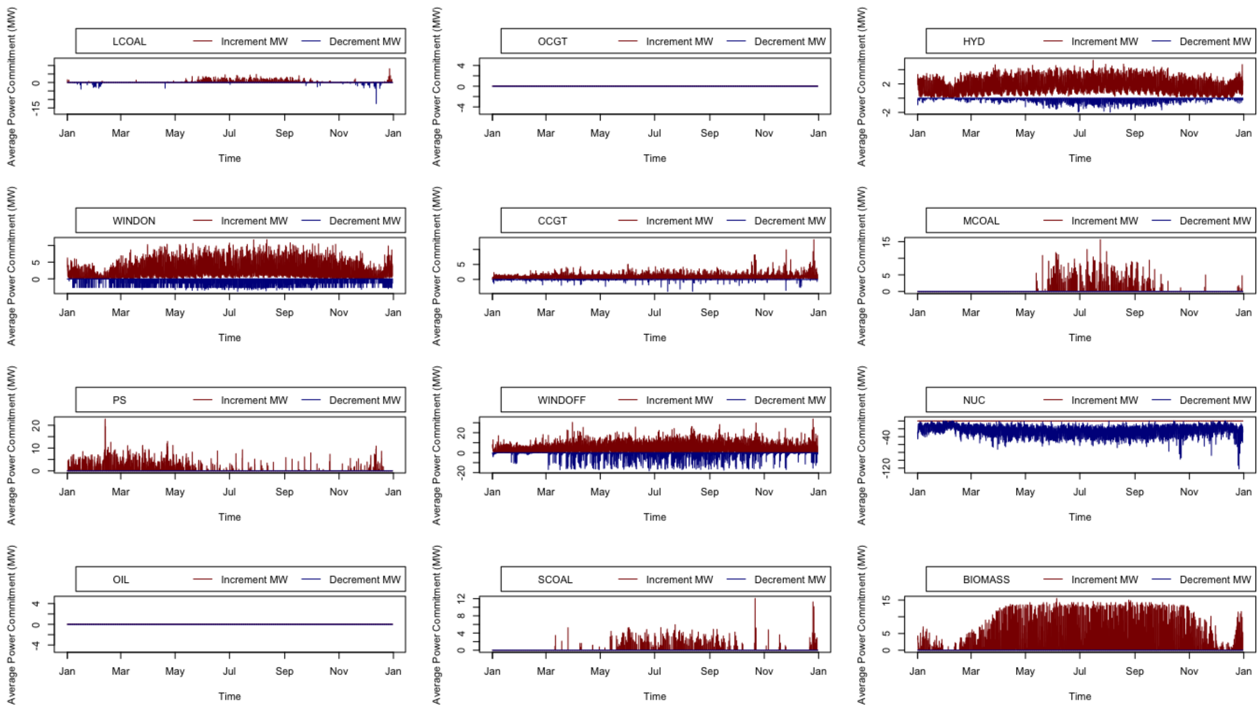

Figure 7.22: Average BM INC and DEC by generating technology (PR scheme, BM market)

schemes undergoes similar dynamics. Note that PR scheme COPF problem does not account for transmission thermal constraints while LMP scheme COPF problem does. This suggests that generally there are no severe electricity congestions in the system. In this sense the UK transmission grid is sufficiently developed to facilitate the least cost electricity dispatch.

Figure 7.24 illustrates average reported marginal costs across generating technologies offered to the BM market for INC. Similar to the DA market, majority of generating technologies offer above their true MC with exception for OCGT and OIL generators. According to Table 7.2 the offer acceptance probabilities for the marginal costs reported by OCGT and OIL technologies are very low. This suggests that these generating technologies are too expensive (even when they offer true marginal costs) to run.

Thus according to results obtained, the economic existence of peak OCGT and OIL technologies on the UK transmission grid can be difficult to justify. Perhaps the capacity allocation share of these peak producers is replaced by a cheaper base-load generation that in the real-world is restricted from participation of the BM market due to its technical specifications. Nevertheless the

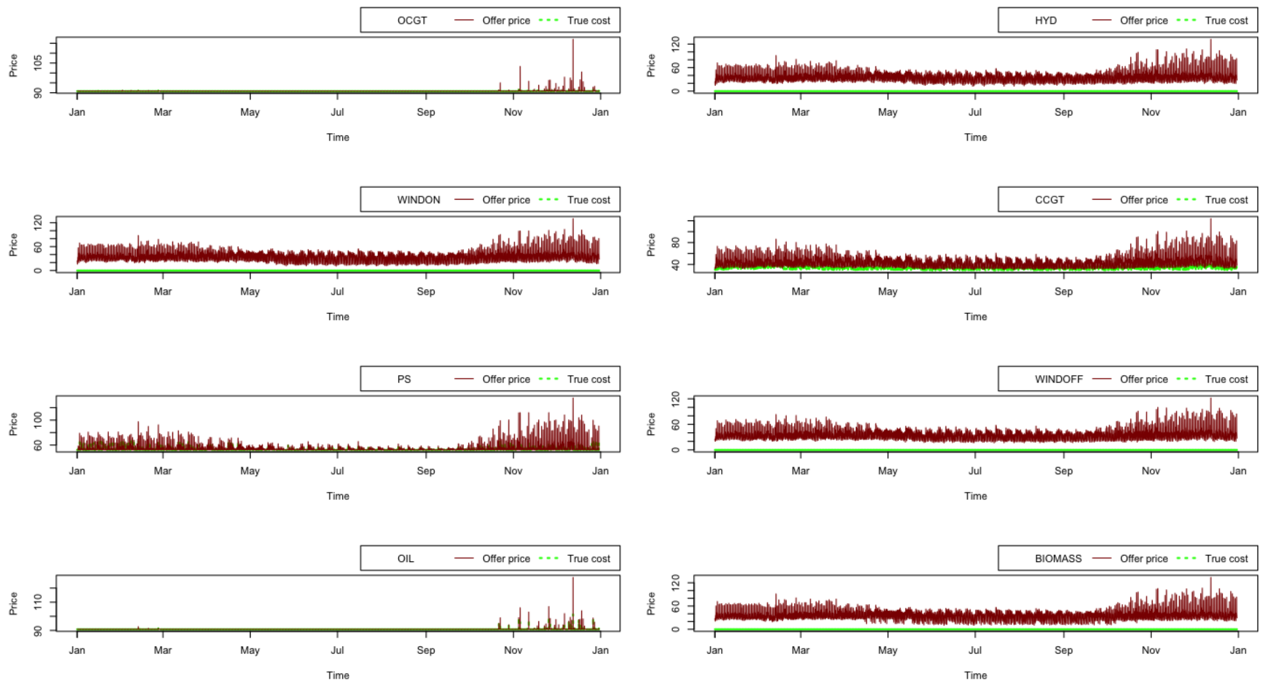

Figure 7.23: Average offer price and true marginal cost of production across generating technologies (PR scheme, DA market)

proposed model allows for bids and offers from base-load generation at the BM market. This is done to address specific aims of this research, in particular to allow for the tantamount comparison of alternative congestion management schemes. Note, the proposed model does not simulate contingency in electricity demand or generation output, thus the BM market is integrated only for the purpose of congestion alleviation.

Figure 7.25 illustrates average marginal costs across generating technologies bid for DEC at the BM market. It is interesting to observe that all generating technologies, apart from CCGT, bid exactly or close to their true marginal costs. First of all, the strategic OCGT, PS and OIL producers bid the lowest prices they can for the provision of DEC. This could be seen as attempt to become competitive in the market and earn some (at least negligible) profits. Note however that throughout the entire year these technologies remain idle for providing DEC at the BM market (see Figure 7.22). In fact from the least-cost production perspective, without taking system reliability into account, these electricity producers should be dispatched first for DEC. The reason why this is

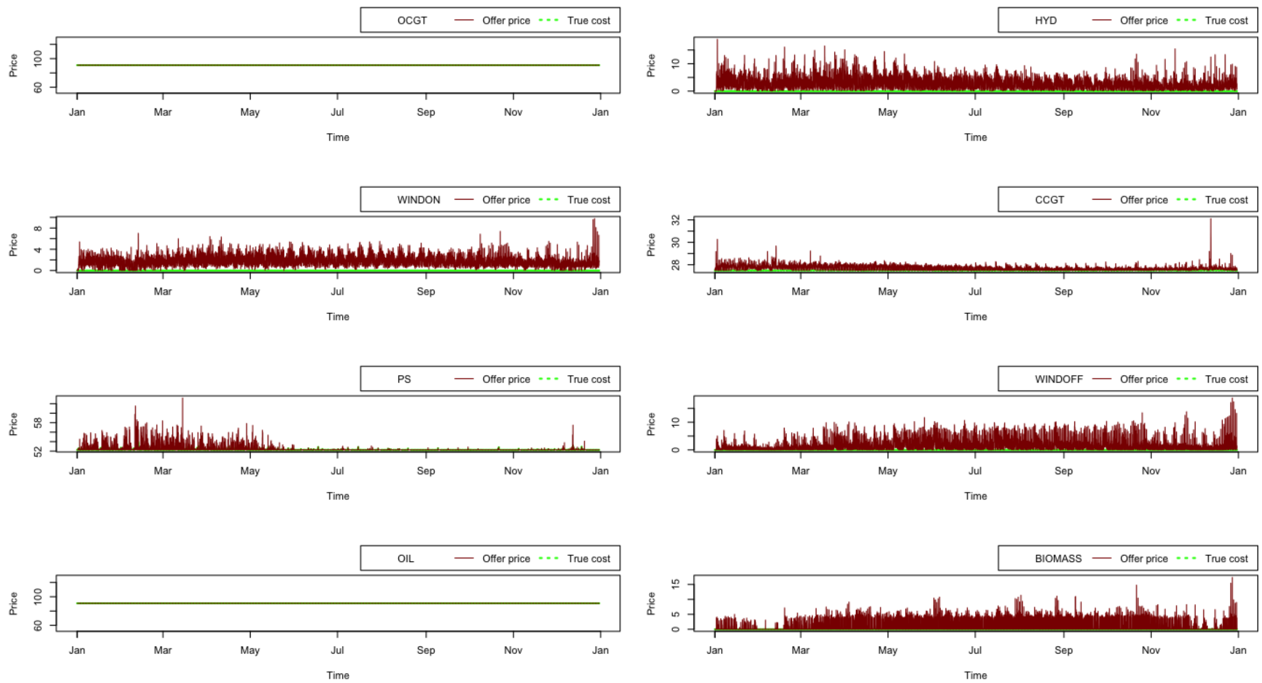

Figure 7.24: Average offer price and true marginal cost of production across generating technologies (PR scheme, BM market for INC)

not the case is because the system is congested and mainly renewable generation (expensive in this case) and base-load is required to provide the means (*e.g.* DEC) for congestion alleviation. The renewable electricity producers are also strategic, however they choose to bid true marginal costs as a way to address their risk concerns (see Table 7.2) and maximise the expected profit. In fact the bids submitted by renewables are extremely unlikely to be accepted according to their expectation of the forthcoming market clearing price (see Table 7.2). Nevertheless renewables benefit from their strategic offers due to scarce transmission capacity between nodes they are located on and the rest of the UK transmission grid.

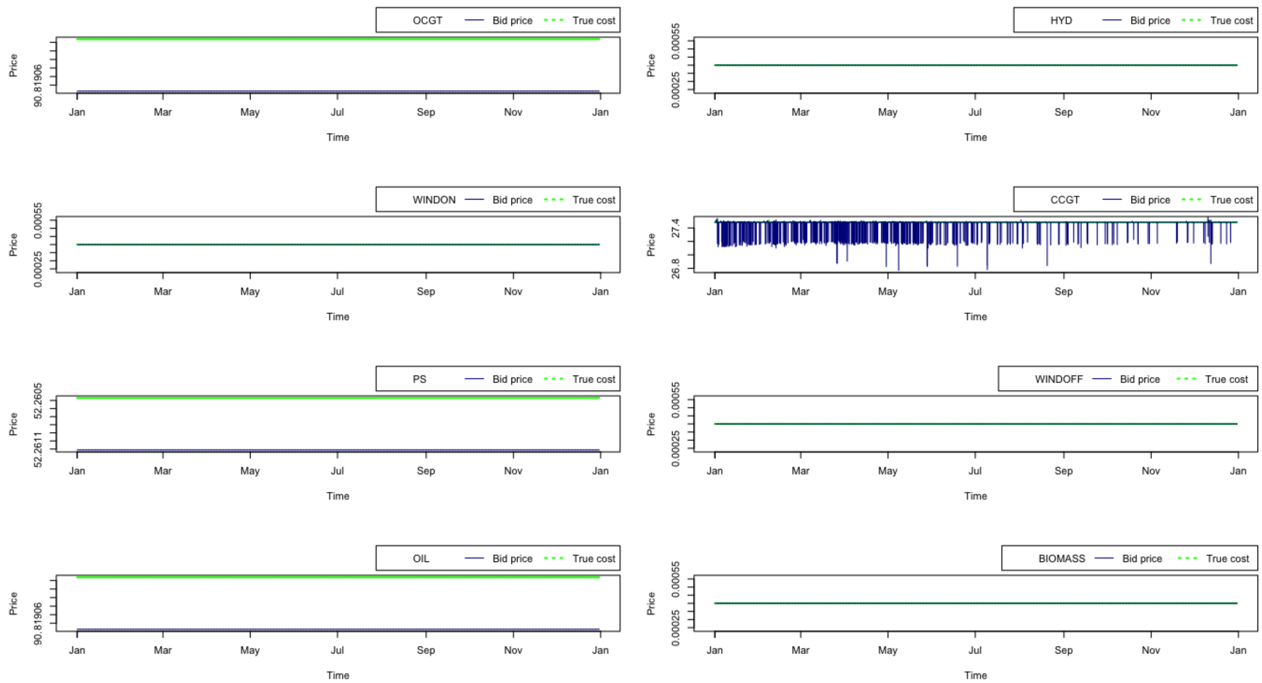

Figure 7.25: Average offer price and true marginal cost of production across generating technologies (PR scheme, BM market for DEC)

Generating Technology	*Average OAP DA*	*Average OAP BM for INC*	*Average OAP BM for DEC*
OCGT	0.00411479	0.000554403	1
HYD	0.876204495	0.993315635	0.174197158
WINDON	0.876204497	0.992496848	0.174197158
CCGT	0.583800091	0.700363626	0.998981436
PS	0.204787773	0.113858747	0.999826109
WINDOFF	0.87620449	0.988298698	0.174197158
OIL	0.002669161	0.000168187	1
BIOMASS	0.876204497	0.991016735	0.174197158

Table 7.2: Average OAPs selected by various generating technologies (PR congestion management scheme)

The comparison of two alternative pricing rules (uniform pricing vs and discriminatory) reveals that social welfare is maximised under discriminatory price auction design. This is addressed by the profit differences illustrated by Figure 7.26.

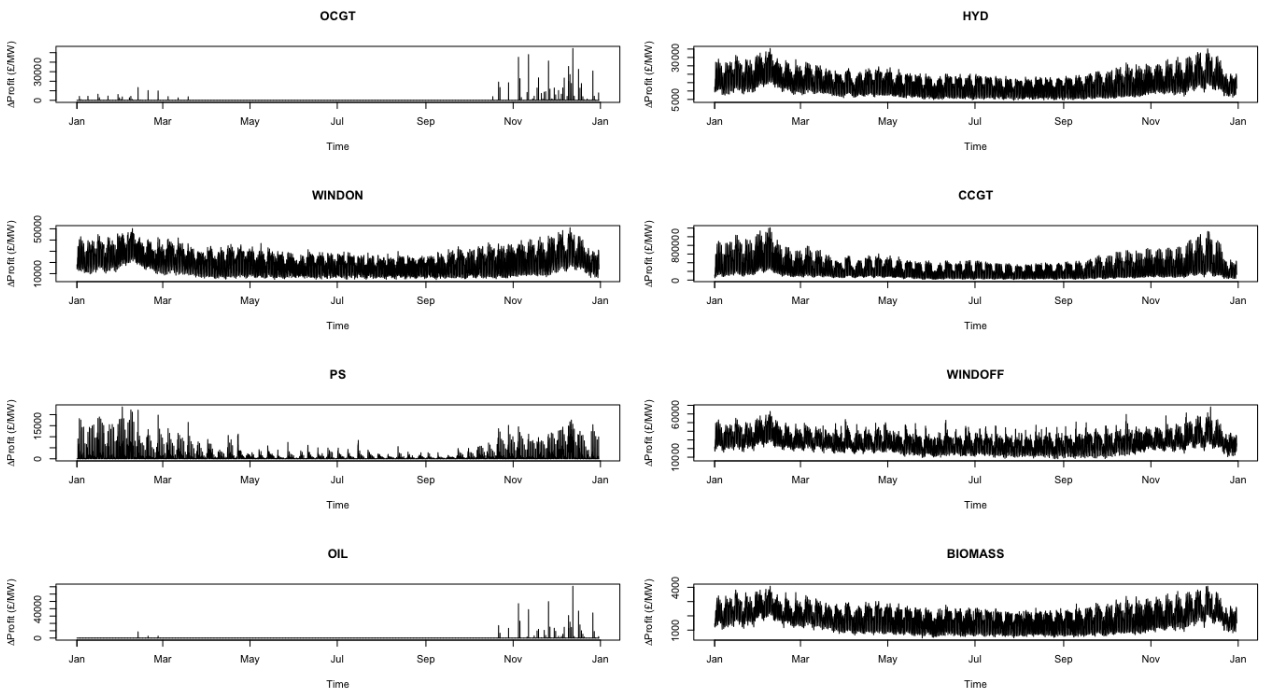

Figure 7.26: The profit difference across generating technologies under discriminatory and uniform price auction designs (PR scheme)

7.4 Conclusion

In order to gain insight into the real power market operation the ACEWEM framework is used to simulate the UK wholesale electricity market. The simulated market comprises 173 electricity generators with known physical parameters and estimated marginal costs, and 356 load servicing entities with known demand profiles. All these market participants are distributed across the simulated UK transmission grid that comprise 471 nodes which are connected by branches with known physical parameters. Four market designs with different congestion management methods and auction pricing rules were explored. These were, namely, the PR and LMP schemes for congestion management with uniform or discriminatory price auction rule. This study attempts to analyse the extent to which these market designs permit and even contribute to the exercise of market power by UK power producers through strategic reporting of marginal generating costs.

It has been shown in Section 7.3.1 that the simulated electricity market efficiently replicates the real UK market price dynamics. Thus the proposed computational approach inspired by the integration of the agent-based modelling paradigm with formal statistical models, appears to be useful in reflecting well the type of behaviour observed in the real UK power market. Also Section 7.3.2 compares the performance of the SPO algorithm against conventional RL and highlights the superiority of the former.

In Experiment 1 the simulated UK market is cleared under the LMP congestion management scheme. The experiment reveals the fact that the higher electricity market price variability intensifies the strategic bidding by power producers. It also confirms that the expensive generating technology producers express a risk taking behaviour and report their marginal costs well above anticipated nodal prices. The comparison of different auction price rules shows that discriminatory pricing employed by the UK market design lowers the excessive profits earned by electricity producers while the uniform pricing lowers the social welfare.

In Experiment 2 the simulated UK market is cleared under the PR congestion management scheme. The obtained results confirm the key findings from Experiment 1. Thus the peak power producers as the result of profit-maximising behaviour tends to select the strategies with higher acceptance risk. Alternately the profit-maximising strategy for base load power plants is to offer low profit marginal costs but with high acceptance probability. The comparison of two auction designs also indicates that discriminatory pricing rule contributes to the higher social welfare comparing to uniform pricing rule. Therefore this confirms the rationality of switching from uniform pricing to discriminatory pricing that was done by the UK market regulator at 2001. Note that for 10 years from 1991 to 2001 the UK power market was run under uniform price auction design.

The outcomes from both experiments indicate the absence of major electricity congestions within the UK transmission grid that would dramatically affect the least-cost electricity dispatch. The minor congestions however arise in the branches connecting the renewable generation. Most of the renewable electricity producers entered the UK generation mix only in the recent few years. Therefore these experiments reveal that the transmission capacity is lagging behind the current renewable electricity expansion in the UK.

Simulation study of an abstract power market (see Chapter 6) reveals that the LMP congestion management scheme delivers a higher social welfare and therefore is superior to PR congestion management scheme. This conclusion, however, does not hold for the real UK power market simulation results. Figure 7.27 illustrates the difference between profits earned (average for uniform and discriminatory price auction designs) across generating technologies under LMP and PR congestion management schemes. In this case it is hard to highlight the most efficient congestion management scheme for the UK, as on average, the corresponding profits earned by power producers are very close to each other. According to experimental results above, in the UK transmission grid electricity congestions primarily arise in the branches connecting the renewable generation. Thus in order to re-balance the system it is the renewable generation that is regulated for the DEC (where it has a very limited space for exercising market power due to negligible true marginal generating costs) and non-strategic base-load for the INC at the BM market. For this particular reason there are no excessive profits earned by market participants at the BM market. Effectively, only the DA market remains the main scene for strategic price manipulation under both congestion management schemes. In this case none of the alternative congestion management schemes is clearly dominant.

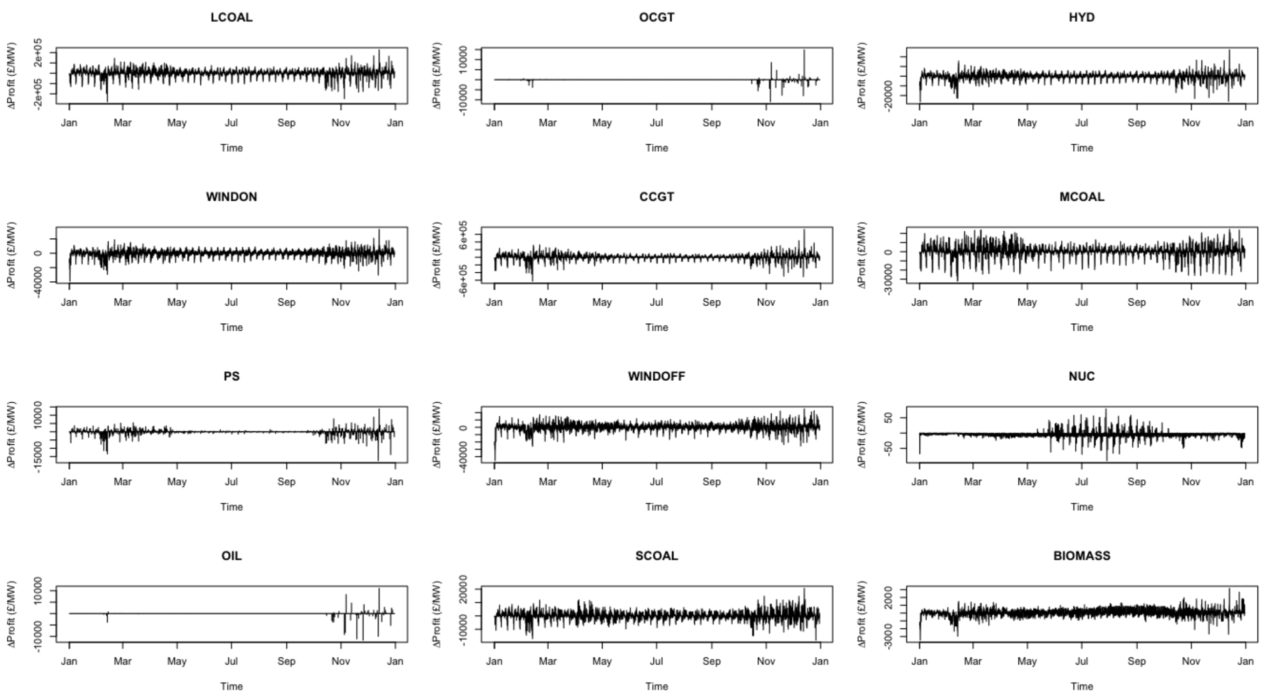

Figure 7.27: The profit difference across generating technologies under LMP and PR congestion management schemes (average for uniform and discriminatory price auction designs)

Part IV

Discussions and Conclusions

This final part of the thesis seeks to outline the main regulatory and methodological contributions delivered by this research work. It also provides summary statements for the main research outcomes in relation to the objectives set out in the introduction. This part is completed with directions for future research, followed by a general research conclusion.

8 Discussion, context and consequences

8.1 Introduction

In this thesis the agent-based electricity market model called ACEWEM has been developed and applied to study the research questions. The model incorporates alternative market designs comprising the DA market for trading the electricity contracts and RT market for balancing the system. The model comprises three types of market participants, namely the independent system operator, load entities and asymmetric electricity generators. The load agents are specified with fixed demand profiles while the generating agents have learning capabilities represented through the SPO algorithm. This learning algorithm has been proposed by this thesis and extends the conventional RL algorithm by introducing the forward looking feature of agents based on flexible statistical models. The model has been run to simulate two markets, first the abstract six-node case with pre-simulated data and second the UK power market with data for year 2012 from the UK electricity sector. The resulting model price dynamics are compared to prices observed at the real UK power market. The developed simulation model delivers the realistic daily and seasonal patterns of UK electricity prices on the DA and RT market. The model therefore can be used to support decision making by engineers and policy makers in the electricity sector.

The major contributions that have been achieved through the current research work are summarised in Section 8.2. This is followed by summary on the main research outcomes in Section 8.3. The suggestions for future research work in the studied field are formulated in Section 8.4.

8.2 Contributions

The contributions of the current research work are rather spread across two levels:

- At regulatory level the contributions are the gained insights into the operation of wholesale electricity markets under alternative auction designs and congestion management schemes with an application to abstract (six-node case) and realistic (UK power market) systems.
- At methodological level the developed simulation model has added to advancement of agent-based electricity modelling technique.

Contributions to market regulatory

Part III shows that the agent-based paradigm can provide strong insights into the pricing and strategic behaviour in the power markets. The assumption that strategic market players do not only assess past results but also forecast future market outcomes (this is addressed in the SPO learning algorithm) allowed the replication of the real market price dynamics to a high degree. This presents a detailed study of a six-node abstract case and the real UK power market. Furthermore this research provides insights into the application of alternative market designs and pricing rules. This aspect is especially important for existing power markets since the minor changes in design regulation can cause serious undesirable events both in electricity supply reliability and capital expenditure. The experimental study conducted in Part III analyses the impact of alternative market designs and pricing rules on overall market efficiency. Moreover it provides insights into emergence of strategic trading and reasons for its intensification. Therefore it can help the regulator to prevent market power manipulation by market participants through providing the means to discover a suitable market design.

Methodological contributions

Part II outlines the agent-based computational framework for electricity trading that accounts for the learning behaviour of market participants in the repetitive auctions by using the SPO algorithm. It represents an improvement on the models discussed in the literature review (see Section 3) by providing a far more realistic decision rule based on the flexible statistical models. The developed model is a first merger of an agent-based paradigm with the statistical GAMLSS framework (Rigby and Stasinopoulos, 2005) for electricity market modelling. The important contribution here is that the agents do not withdraw the discrete strategies from an action domain (likewise it is done in the RL algorithm). Instead the agents fine-tune their decisions (outputs from profit optimisation routine) by trying on the distributions from the GAMLSS family as part of forecasting model selection process with the RL algorithm. This way the agents are insured against bidding the strategies that they never apply in the real markets. It has been shown that the SPO algorithm is superior to conventional reinforcement learning (see Section 7.3.2) as it leads to better simulation results in terms of replicating the real-world price dynamics. Also, the model was validated based on 1) graphical verification with the real-world price dynamics and 2) statistical confidence interval technique (see Section 7.3.1). This indicates a high model potential to serve as a comprehensive simulation tool for the future industry research.

8.3 Evaluation of research objectives

Objective 1: To develop a reliable tool (the ACEWEM computational laboratory) to serve for engineering of efficient electricity markets.

This thesis has developed a novel framework for experimental designs of liberalised wholesale power markets, namely the ACEWEM computational laboratory. The ACEWEM is not prescribed to any particular market design and size and therefore is highly customisable. Moreover it is mainly written in JAVA computer language that makes the ACEWEM easily extensible. Also all the libraries it integrates are proved to be reliable and free of charge to use.ACEWEM can simulate large power systems which until recently could only be handled by commercial softwares. Therefore ACEWEM can be used without limitations by prospective researchers, industry professionals and policy makers.

Objective 2: To explore the influence of existing pricing rules on wholesale electricity price formation.

It has been confirmed that discriminatory price auction design currently employed by the UK power market lowers the prices paid to power producers. Thus it delivers a higher social welfare comparing to uniform price auction design (see Chapter 7).

Objective 3: To explore the influence of alternative congestion management methods on wholesale electricity price formation.

Two different simulated markets (abstract electricity market and UK electricity market) were initialised with alternative congestion management schemes. First with LMP congestion management scheme (from capacity allocation type methods) and second with PR congestion management scheme (from capacity alleviation type methods). In the simulated abstract power market it has been revealed that the LMP scheme lowers the excessive profits earned by power producers and thus delivers a higher social welfare. This conclusion, however, is not a clear cut given the structure of the real UK power market. Both congestion management schemes perform similar in terms of maximising social welfare and none of them can be clearly referred as dominant for the UK electricity industry.

Objective 4: To explore the emergence and impact of strategic behaviour by power generators on wholesale electricity price formation.

It has been shown that peak power producers are willing to take a high risk when selling their electricity. Moreover this trading behaviour does not simply emerge as agents collusively offer high marginal costs to lift market clearing price. It rather follows from individual expected profit maximising strategies based on each agent's anticipation regarding future market clearing outcomes. Similarly the risk averse behaviour by base-load generating technologies also follows from individual expected profit maximising strategies. Overall the exertion of market power considerably increases market clearing prices.

Another important research finding relates to the intensification of strategic behaviour by power producers. It has been shown that increasing market clearing price variability intensifies the strategic bidding by all generating technologies. Therefore the regulator should seek for the means to keep price variability low to support market efficiency.

Objective 5: To explore the impact of transmission grid physical constraints on wholesale electricity price formation and trading behaviour of power generators.

It has been shown that generating agents implicitly perceive the electricity congestion through price forecasting. Thus the results of Experiment 1 (see Section7.3.4) reveal that collective learning equalises the prices across the nodes while raising the overall price level in the system.

Another interesting research outcome relates to the UK transmission grid. It was observed that there are no severe congestions in the UK transmission grid to dramatically effect least cost generation dispatch. The minor congestions however persist in the low capacity branches that connect the renewable generation (mainly wind farms) to the UK transmission grid. In this instance the UK transmission grid operator should improve the congested branches to allow for 100% renewable energy utilisation.

8.4 Prospective research work

The proposed agent-based simulation model can be enhanced in several ways. First in the current state, the model does not account for interconnection capacities with neighbouring countries. To improve the simulation outputs the model needs to adopt implicitly or explicitly the electricity systems around the UK. Thus the ACEWEM framework needs to be extended to allow the representation of coupled wholesale power markets. This is particularly important when different market mechanisms and structures need to be integrated (*e.g.* EU power markets).

The experimental study has highlighted the importance of transmission grid physical constraints in the electricity price formation process in the UK. It is noteworthy that the market clearing mechanism implemented in the model assumes quadratic objective function linear in parameters with linear constraints. This simplification might be relaxed in future work and replaced by a constrained non-linear optimisation routine in order to better account for the branch resistance and the harmonic nature of voltage and current. While the focus of this research was mainly placed over the market design issue it would be also interesting to analyse implications from altering market structures or the effect of various regulatory interventions (for example to promote a certain generating technology) on market dynamics. A set of other improvements to the model developed can be introduced. For example the development of specialised GUI so that appropriate visualisations can support the design and exploration of alternative experiments of real-world power markets by domain experts - to conduct controlled computational experiments of real-world power markets using the ACEWEM framework. Also to enhance the ecology of the decision rules to include in future alternative business strategies (*e.g.* bid to ensure dispatch, bidding based on corporate utilities with different attitudes to risk). Finally to develop an endogenous investment strategy for capacity decommissioning/expansion.

8.5 Conclusion

Aside from the methodological claims made in this work (see Section 8.2) and the practical insights it yields, this thesis draws attention to the conditions under which collusive pricing is observed. This is a finding that has important policy implications. In setting out to provide a computational laboratory that can be used for controlled computational experiments of wholesale power markets, the approach adopted here provides a fertile basis for evaluating the interactions between policy makers, politicians, business executives and key consumers.

In designing a simulation framework to model a large scale system the very first dilemma faced by the researcher is a trade-off between the level of disaggregation and behavioural analysis. The agent-based paradigm, along with constantly improving computational power, provide the potential for the good balance between two options thus allowing modelling of a detailed market structure with complex behaviour rules in repeated auctions. The model outlined in Part II of this thesis benefits from interaction between different marketplaces, an explicitly modelled transmission grid, differentiation between generating technologies, advanced learning algorithm based on flexible statistical models and composite strategies offered daily by generating agents (the bidding strategy decision by agent is unique for each individual settlement period). This research propagates the concept of bounded rationality to address the way people or firms learn and make decisions. To improve the performance of the conventional RL algorithm (which does not address forecasting capabilities of agents) this thesis develops the SPO algorithm based on flexible statistical models. Nevertheless it still requires several assumptions to be imposed on the agent's rationality. First of all the algorithm implies that market players adapt true optimality to their decision making, this assumes that market participants possess strong reasoning capabilities. However this can be relaxed if the modeller finds this assumption inadequate. Moreover the algorithm assumes that the agent can infer the strategy output without actually trying it. Nevertheless this learning algorithm is expected to reasonably address the key aspects of the way the strategic power producers behave. Also due to the high degree of simlarity between simulated and real market electricity prices the model can be qualified to represent a real-world power market to a great extent. It is truly hoped that the simulation model demonstrated here can be built upon in order to be transformed from exciting academic practise into complete computational laboratory that can be actively used by future researchers and policy makers.

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Appendices

UK generation database

Power plant	*Node*	*Plant Type*	*Capacity*	*Available*	*MC intercept*	*MC slope*
Aberthaw B	ABTH	LCOAL	1586	1	23.0321	0.0049
Aberthaw GT	ABTH	OCGT	51	1	90.8188	0.0122
Aigas	AIGA	HYD	20	0.458	0.0004	0
An Suidhe	ANSU	WINDON	19	0.286	0.0004	0
Andershaw	LINM	WINDON	45	0.286	0.0004	0
Ardkinglas	ARDK	WINDON	19.25	0.286	0.0004	0
Arecleoch	AREC	WINDON	120	0.286	0.0004	0
Baglan Bay	BAGB	CCGT	552	1	19.2273	0.0219
Barking	BARK	CCGT	1000	1	30.5678	0.0219
Barry	CARE	CCGT	245	1	33.68	0.0188
Beinn an Tuirc 2	CAAD	WINDON	38	0.286	0.0004	0
Beinn Tharsuinn	ALNE	WINDON	29	0.286	0.0004	0
Black Law	BLLA	WINDON	121	0.286	0.0004	0
Bowbeat	KAIM	WINDON	33	0.286	0.0004	0
BP Grangemouth	GRMO	CCGT	120	1	23.5743	0.0219
Braes of Doune	BRAC	WINDON	74	0.286	0.0004	0
Brigg	KEAD	CCGT	260	1	79.8535	0.0004
Caledonian Paper Mill	MEAD	CCGT	20	1	23.5743	0.0219

Carraig Gheal Wind Farm	FERO	WINDON	46	0.286	0.0004	0
Cashlie (Killin Cascade)	KIIN	HYD	11.12	0.458	0.0004	0
Cottam Development Centre Limited	COTT	CCGT	395	1	23.5743	0.0219
Ceannacroc	CEAN	HYD	20	0.458	0.0004	0
Clachan	CLAC	HYD	40	0.458	0.0004	0
Clunie Cascade	CLUN	HYD	61.2	0.458	0.0004	0
Clyde North ; South ; Central	CLYS	WINDON	348	0.286	0.0004	0
Cockenzie	COCK	MCOAL	1102	1	20.0032	0.0196
Connahs Quay	DEES	CCGT	1380	1	25.1655	0.0036
Corby	GREN	CCGT	401	1	23.5743	0.0219
Coryton	COSO	CCGT	800	1	23.1805	0.0227
Cottam	COTT	LCOAL	2000	1	19.3217	0.0005
Cottam	COTT	CCGT	395	1	23.5743	0.0219
Cowes	FAWL	OCGT	145	1	97.8282	0.0019
Crauchan	CRUA	PS	440	0.4	52.0167	0.0253
Crystal Rig 2 Stage 1	CRYR	WINDON	138	0.286	0.0004	0
Culligran	CULL	HYD	19.1	0.458	0.0004	0
Damhead Creek	KINO	CCGT	805	1	20.1433	0.0219
Deanie	DEAN	HYD	38	0.458	0.0004	0
Deeside	DEES	CCGT	515	1	21.3356	0.0324
Derwent	WILE	CCGT	228	1	27.7228	0.0957
Didcot A	DIDC	LCOAL	2058	1	22.9853	0.0196
Didcot A GTs	DIDC	OCGT	100	1	97.7591	0.0385
Didcot B	DIDC	CCGT	1550	1	21.9402	0.0332

Dinorwig	DINO	PS	1644	0.4	51.4701	0.1328
Docking Shoal Wind Farm	WALP	WINDOFF	500	0.377	0.0004	0
Drax	DRAX	LCOAL	3894	1	20.8033	0.0175
Drax	DRAX	OCGT	30	1	90.8188	0.0122
Dungeness B	DUNG	NUC	1081	1	6.6324	0.0001
Dunlaw Extension (Dun Law)	DUNE	WINDON	29.75	0.286	0.0004	0
Edinbane Wind (Skye)	EDIN	WINDON	41.4	0.286	0.0004	0
Eggborough	EGGB	LCOAL	1932	1	20.8014	0.0196
Enfield (Brimsdown)	BRIM	CCGT	408	1	25.7484	0.0074
Errochty	ERRO	HYD	75	0.458	0.0004	0
Fallago	FALL	WINDON	144	0.286	0.0004	0
Farr Wind Farm (Tomatin)	FAAR	WINDON	92	0.286	0.0004	0
Fasnakyle	FASN	HYD	138	0.458	0.0004	0
Fawley	FAWL	OIL	1000	1	90.8188	0.0122
Fawley	FAWL	OCGT	65	1	90.8188	0.0122
Fawley CHP (Cogen)	FAWL	CCGT	158	1	23.5743	0.0219
Ferrybridge	FERR	LCOAL	1960	1	20.1433	0.0196
Ferrybridge	FERR	OCGT	21	1	90.8188	0.0122
Ffestiniog	FFES	PS	360	0.4	57.6606	0.0599
Fiddlers Ferry	FIDF	LCOAL	1987	1	20.3104	0.0051
Fiddlers Ferry	FIDF	OCGT	21	1	90.8188	0.0122
Fife Energy	WFIE	CCGT	123	1	23.5743	0.0219
Finlarig	FINL	HYD	16.5	0.458	0.0004	0
Foyers	FOYE	PS	300	0.4	47.892	0.0385
Glendoe	GLDO	HYD	100	0.458	0.0004	0

Glenmoriston Hydro Group Stage 1 (Moriston Cascade)	GLEN	HYD	37	0.458	0.0004	0
Glens of Foudland Wind (SRO)	KINT	WINDON	26	0.286	0.0004	0
Gordonbush Wind	GORW	WINDON	70	0.286	0.0004	0
Gordonstown Hill Wind Farm	KINT	WINDON	12.5	0.286	0.0004	0
Grain (Stage 1)	GRAI	OIL	1300	1	90.8188	0.0122
Grain (Stage 1)	GRAI	OCGT	55	1	90.8188	0.0122
Grain (Stage 2;3)	GRAI	CCGT	1290	1	58.1621	0.0134
Great Yarmouth	NORM	CCGT	420	1	22.2444	0.042
Greater Gabbard Offshore Wind Farm Stage 1	LEIS	WINDOFF	500	0.377	0.0004	0
Griffin Windfarm (near Aberfeldy)	GRIF	WINDON	204	0.286	0.0004	0
Grudie Bridge	ORRI	HYD	22	0.458	0.0004	0
Gwynt Y Mor Offshore Wind Farm Stage 1	GWYN	WINDOFF	39	0.377	0.0004	0
Hadyard Hill	HADH	WINDON	117	0.286	0.0004	0
Hartlepool	HATL	NUC	1207	1	6.6324	0.0001
Heysham	HEYS	NUC	2408	1	6.6324	0.0001
Hill of Towie	KEIT	WINDON	48.3	0.286	0.0004	0
Hinkley Point B	HINP	NUC	1261	1	6.6324	0.0001
Hunterston	HUER	NUC	1074	1	6.6324	0.0001
Immingham Stage 1	HUMR	CCGT	1218	1	22.7148	0.0773

Indian Queens	INDQ	OCGT	140	1	87.9179	0.0025
Inverawe	TAYN	HYD	25	0.458	0.0004	0
Invergarry	INGA	HYD	20	0.458	0.0004	0
Ironbridge	IRON	LCOAL	964	1	21.4014	0.0196
Keadby	KEAD	CCGT	735	1	23.7035	0.0026
Keadby GT	KEAD	OCGT	25	1	73.7237	0.0306
Kilbraur	STRB	WINDON	67	0.286	0.0004	0
Killingholme	KILL	CCGT	900	1	50.7649	0.0424
Killingholme 2	KILL	CCGT	665	1	26.2032	0.0083
Kilmorack	KIOR	HYD	20	0.458	0.0004	0
Kings Lynn A	WALP	CCGT	340	1	23.5946	0.0064
Kingsnorth	KINO	LCOAL	1940	1	21.3809	0.0287
Kingsnorth	KINO	OCGT	26	1	90.8188	0.0122
Kinlochleven	KILO	HYD	20	0.458	0.0004	0
Langage	LAGA	CCGT	905	1	21.3187	0.011
Lincs Offshore Wind Farm	WALP	WINDOFF	250	0.377	0.0004	0
Little Barford	EASO	CCGT	665	1	23.5743	0.0219
Littlebrook	LITT	OIL	1370	1	90.8188	0.0122
Littlebrook	LITT	OCGT	105	1	97.8011	0.0066
Livishie	GLEN	HYD	15	0.458	0.0004	0
Lochay	LOCH	HYD	47	0.458	0.0004	0
London Array	CLEH	WINDOFF	630	0.378	0.0004	0
Longannet	LOAN	LCOAL	2284	1	27.4002	0.0696
Luichart	LUIC	HYD	34	0.458	0.0004	0
Lynemouth	BLYT	SCOAL	420	1	21.4014	0.0196
Lynes Common	FAWL	OCGT	49.9	1	90.8188	0.0122
Marchwood	MAWO	CCGT	900	1	22.2331	0.004

Mark Hill Wind Farm	MAHI	WINDON	56	0.286	0.0004	0
Medway	GRAI	CCGT	700	1	24.6466	0.0073
Millennium Wind	MILW	WINDON	65	0.286	0.0004	0
Minsca	CHAP	WINDON	37.5	0.286	0.0004	0
Mossford	MOSS	HYD	18.66	0.458	0.0004	0
Nant	NANT	HYD	15	0.458	0.0004	0
Neilston	NEIL	WINDON	80	0.286	0.0004	0
Ormonde	HEYS	WINDOFF	150	0.377	0.0004	0
Orrin	ORRI	HYD	18	0.458	0.0004	0
Pembroke	PEMB	CCGT	2100	1	22.6968	0.012
Peterborough	WALP	CCGT	405	1	64.6223	0.0219
Peterhead	PEHE	CCGT	1180	1	22.0257	0.0047
Pitlochry	CLUN	HYD	15	0.458	0.0004	0
Quoich	QUOI	HYD	18	0.458	0.0004	0
Rannoch	RANN	HYD	45	0.458	0.0004	0
Ratcliffe on Soar	RATS	LCOAL	2000	1	20.2676	0.0113
Ratcliffe on Soar	RATS	OCGT	21	1	93.9989	0.0026
Rocksavage	ROCK	CCGT	810	1	21.2009	0.0219
Roosecote	HUTT	CCGT	229	1	89.7722	0.0219
Rosehall	SHIN	WINDON	25	0.286	0.0004	0
Rothes Bio-Plant	GLRO	BIOMASS	52	0.633	0.0004	0
Rugeley	RUGE	LCOAL	996	1	20.6766	0.0094
Rugeley	RUGE	OCGT	22	1	91.3042	0.0122
Rye House	RYEH	CCGT	715	1	25.5785	0.0125
Saltend	SAES	CCGT	1100	1	20.3361	0.0129
Seabank	SEAB	CCGT	1234	1	25.2069	0.0219
Sellafield Stage 1	HUTT	CCGT	155	1	23.5743	0.0219
Severn Power	USKM	CCGT	850	1	23.71	0.028

Sheringham Shoal Offshore Windfarm	NORM	WINDOFF	315	0.377	0.0004	0
Shin	SHIN	HYD	18.62	0.458	0.0004	0
Shoreham	BOLN	CCGT	420	1	24.434	0.0026
Shotton	DEES	CCGT	210	1	24.434	0.0026
Sizewell B	SIZE	NUC	1207	1	6.6324	0.0001
Sloy	SLOY	HYD	153	0.458	0.0004	0
South Humberbank	SHBA	CCGT	1285	1	24.4656	0.0006
Spalding	SPLN	CCGT	880	1	23.9968	0.0042
St Fillans	SFIL	HYD	16.8	0.458	0.0004	0
Staythorpe	STAY	CCGT	1700	1	23.1301	0.0889
Stevens Croft	CHAP	BIOMASS	45	0.633	0.0004	0
Stoneywood Mills (Wiggins Teape Stoneywood)	DYCE	CCGT	12	1	23.5743	0.0219
Sutton Bridge	WALP	CCGT	819	1	15.3361	0.0001
Taylors Lane	WISD	OCGT	144	1	95.8302	0.0122
Teesside	TODP	CCGT	1875	1	23.5743	0.0219
Thanet Offshore Windfarm	CANT	WINDOFF	300	0.377	0.0004	0
Tilbury	TILB	MCOAL	1104	1	21.4014	0.0196
Tilbury	TILB	OCGT	26	1	90.8188	0.0122
Toddleburn Wind Farm	DUNE	WINDON	27.6	0.286	0.0004	0
Tongland	TONG	HYD	33	0.458	0.0004	0
Tormywheel	BAGA	WINDON	32.4	0.286	0.0004	0
Torness	TORN	NUC	1215	1	6.6324	0.0001

Torr Achilty (Beauly Cascade)	BEAU	HYD	15	0.458	0.0004	0
Tummel	TUMB	HYD	34	0.458	0.0004	0
Uskmouth	USKM	SCOAL	363	1	22.7928	0.0485
Walney	STAH	WINDOFF	364	0.378	0.0004	0
West Burton	WBUR	LCOAL	1972	1	19.7003	0.0009
West Burton	WBUR	OCGT	15	1	81.2061	0.0025
West Burton B	WBUR	CCGT	1370	1	23.5743	0.0219
Whitelee	WLEE	WINDON	592	0.287	0.0004	0
Wilton Stage 2	TODP	CCGT	99	1	23.5743	0.0219
Wylfa	WYLF	NUC	980	1	6.6324	0.0001

Table 1: UK generation database

UK load servicing entities database

LSE	*Node*	*Load (% total UK load)*
Anglesey Aluminium	WYLF	0.005597418
BOC	TEMP	0.000492187
British Energy	DUNG	0.00013511
British Energy	EGGB	0.000772058
British Energy	HEYS	0.002219666
British Energy	HINP	0.000458409
British Energy	SIZE	7.72E-05
British Nuclear Group	DUNG	3.86E-05
British Nuclear Group	HINP	1.93E-05
British Nuclear Group	IROA	6.43E-05
British Nuclear Group	OLDS	3.22E-05
British Nuclear Group	SIZE	3.86E-05

British Nuclear Group	TRAW	1.93E-05
British Nuclear Group	WYLF	0.001910843
Celsa	TREM	0.001833637
Central Networks East (EMEB)	BESW	0.007079768
Central Networks East (EMEB)	BICF	0.003057348
Central Networks East (EMEB)	CHTE	0.009955684
Central Networks East (EMEB)	COVE	0.009195207
Central Networks East (EMEB)	DRAK	0.003543745
Central Networks East (EMEB)	ECLA	0.006888685
Central Networks East (EMEB)	ENDE	0.0097839
Central Networks East (EMEB)	GREN	0.013072866
Central Networks East (EMEB)	RATS	0.010689138
Central Networks East (EMEB)	WALP	0.004705692
Central Networks East (EMEB)	WBUR	0.005288595
Central Networks West (Aquila)	BISW	0.008899894
Central Networks West (Aquila)	BUSH	0.002924168
Central Networks West (Aquila)	BUST	0.006846221
Central Networks West (Aquila)	CELL	0.009652651
Central Networks West (Aquila)	ECLA	0.001273895
Central Networks West (Aquila)	FECK	0.004838871
Central Networks West (Aquila)	IROA	0.001199263
Central Networks West (Aquila)	KITW	0.007720577
Central Networks West (Aquila)	NECH	0.006794107
Central Networks West (Aquila)	OCKH	0.002264059
Central Networks West (Aquila)	OLDB	0.001864519
Central Networks West (Aquila)	OLDS	0.000599631
Central Networks West (Aquila)	PENN	0.005854127
Central Networks West (Aquila)	RUGE	0.004387218

Central Networks West (Aquila)	WIEN	0.002653948
Centrica	ABTH	0.000138005
Centrica	CARE	6.90E-05
CORUS	ALDW	0.003783083
CORUS	RAVE	9.65E-05
CORUS	STSB	0.001351101
CORUS	TEMP	0.000231617
CORUS	TINP	0.001138785
CORUS	WHSO	0.001863168
Drax Power Limited	DRAX	0.001775733
E.ON (UK) plc (Powergen)	COTT	0.000772058
E.ON (UK) plc (Powergen)	GRAI	0.000887866
E.ON (UK) plc (Powergen)	IRON	0.000321691
E.ON (UK) plc (Powergen)	KINO	0.000772058
E.ON (UK) plc (Powergen)	RATS	0.000829962
E.ON (UK) plc (Powergen)	SHRE	0.000160845
Eastern Power Networks	AMEM	0.001235811
Eastern Power Networks	BARK	0.001880033
Eastern Power Networks	BRFO	0.010340178
Eastern Power Networks	BRIM	0.004535165
Eastern Power Networks	BURW	0.004983994
Eastern Power Networks	EASO	0.00408721
Eastern Power Networks	ELST	0.001656119
Eastern Power Networks	GREN	0.001860142
Eastern Power Networks	MILH	0.003952946
Eastern Power Networks	SUND	0.009258559
Eastern Power Networks	TILB	0.003324481
Eastern Power Networks	TOTT	0.005231453

Eastern Power Networks	WALP	0.008438124
Eastern Power Networks	WARL	0.004243469
Eastern Power Networks	WATS	0.00380024
Eastern Power Networks	WISD	0.000860549
Eastern Power Networks	WTHU	0.000646379
EDF (Formerly LPN)	BARK	0.003090639
EDF (Formerly LPN)	BRIM	0.002339002
EDF (Formerly LPN)	CITR	0.016722493
EDF (Formerly LPN)	HACK	0.00679433
EDF (Formerly LPN)	LITT	0.001874404
EDF (Formerly LPN)	MILH	0.000481938
EDF (Formerly LPN)	NEWX	0.005383364
EDF (Formerly LPN)	REBR	0.002531234
EDF (Formerly LPN)	SJOW	0.013635046
EDF (Formerly LPN)	WHAM	0.011134799
EDF (Formerly LPN)	WIMB	0.002551166
EDF (Formerly LPN)	WISD	0.006261152
EdF Energy	WBUR	0.001158086
Exxon Mobil	SFEM	0.000413051
Fellside Heat and Power	HUTT	0.000414981
First Hydro	DINO	0.011580865
First Hydro	FFES	0.02316173
Ineos (Innovene) Grangemouth	GRMO	0.001443748
International Power	RUGE	0.000579043
National Grid	GRAI	0.001190899
National Grid	SFEG	0.000965072
Northern Electric	BLYT	0.003256067
Northern Electric	FERR	0.003456606

Northern Electric	FOUR	0.000329033
Northern Electric	HARM	0.001814274
Northern Electric	HAWP	0.002079936
Northern Electric	LACK	0.004283508
Northern Electric	NORT	0.009210198
Northern Electric	OFFE	0.001399571
Northern Electric	OSBA	0.005596337
Northern Electric	POPP	0.000972507
Northern Electric	SALH	3.49E-05
Northern Electric	SPEN	0.004505062
Northern Electric	SSHI	0.001022741
Northern Electric	TYNE	0.003593992
Northern Electric	WBOL	0.005265207
NORWEB (UU)	BRED	0.006559669
NORWEB (UU)	CARR	0.004907835
NORWEB (UU)	HUTT	0.002007284
NORWEB (UU)	KEAR	0.012722001
NORWEB (UU)	MACC	0.000903349
NORWEB (UU)	PADI	0.003840315
NORWEB (UU)	ROCH	0.001708436
NORWEB (UU)	SMAN	0.005940766
NORWEB (UU)	STAH	0.001066763
NORWEB (UU)	STAL	0.007639486
NORWEB (UU)	WASF	0.003038441
NORWEB (UU)	WHGA	0.005704637
Railtrack	BARK	0.000714153
Railtrack	ELST	0.000250919
Railtrack	LEIB	0.000289522

Railtrack	PAFB	0.000337775
Railtrack	POPP	0.00011272
Railtrack	RUGE	0.000350321
Railtrack	SELL	0.000714153
Railtrack	SING	0.000714153
Railtrack	WYMO	0.00019784
RWE Npower plc (Innogy)	ABTH	0.000424632
RWE Npower plc (Innogy)	CARE	0.000212316
RWE Npower plc (Innogy)	FAWL	0.000386029
RWE Npower plc (Innogy)	LITT	0.000295955
RWE Npower plc (Innogy)	TILB	0.000424632
Saltend	SAES	0.001930144
SEEBOARD Power Networks	BEDD	0.013389583
SEEBOARD Power Networks	BOLN	0.016815015
SEEBOARD Power Networks	CHSI	0.010350326
SEEBOARD Power Networks	KEMS	0.001490625
SEEBOARD Power Networks	KINO	0.003086285
SEEBOARD Power Networks	LALE	0.001371374
SEEBOARD Power Networks	LITT	0.00011581
SEEBOARD Power Networks	NFLE	0.003570861
SEEBOARD Power Networks	NINF	0.008060876
SEEBOARD Power Networks	WIMB	0.003619282
SEEBOARD Power Networks	WWEY	0.006576533
Sembcorp (Formerly ICI)	TODP	0.000386029
SHELL	MOSM	0.000453584
SHEPD	ABNE	0.000823786
SHEPD	ALNE	0.000723804
SHEPD	ARBR	0.000762407

SHEPD	ARMO	0.000550091
SHEPD	BEAU	0.000574797
SHEPD	BOAG	0.000613786
SHEPD	BRAC	0.000752177
SHEPD	BRID	0.000650459
SHEPD	BROA	0.000252849
SHEPD	BROR	0.000225827
SHEPD	BUMU	0.001016028
SHEPD	CAAD	0.000497977
SHEPD	CASS	4.25E-05
SHEPD	CEAN	5.64E-05
SHEPD	CHAR	0.000652389
SHEPD	CLAY	0.001009465
SHEPD	COUA	0.000619576
SHEPD	CRAI	0.000660109
SHEPD	DOUN	0.000154412
SHEPD	DUBE	0.000279871
SHEPD	DUDH	0.000745036
SHEPD	DUGR	0.000123529
SHEPD	DUNO	0.000360937
SHEPD	DYCE	0.000741175
SHEPD	ELGI	0.001142645
SHEPD	FASN	7.72E-06
SHEPD	FAUG	7.82E-05
SHEPD	FIDD	0.000499907
SHEPD	FRAS	0.000519209
SHEPD	FWIL	0.001205182
SHEPD	GLAG	0.000511488

SHEPD	GRUB	0.00026829
SHEPD	INNE	0.00133759
SHEPD	KEIT	0.001366542
SHEPD	KIIN	5.79E-05
SHEPD	KILO	7.72E-05
SHEPD	KINT	0.00134338
SHEPD	LUNA	0.001374263
SHEPD	LYND	0.000654319
SHEPD	MACD	0.000445863
SHEPD	MILC	0.001048068
SHEPD	MYBS	0.000291259
SHEPD	NAIR	0.000793289
SHEPD	PEHG	0.000555881
SHEPD	PERS	0.000943068
SHEPD	PORA	0.000276976
SHEPD	REDM	0.000768197
SHEPD	SFEG	0.000297242
SHEPD	SFIL	5.79E-06
SHEPD	SHIN	7.72E-05
SHEPD	SLOY	6.18E-05
SHEPD	STLE	0.000233547
SHEPD	STRI	0.000384099
SHEPD	TARL	0.000488326
SHEPD	TAYN	0.000400119
SHEPD	THSO	0.000497977
SHEPD	TUMB	0.000251498
SHEPD	WIOW	0.000909098
SHEPD	WOHI	0.000876285

Southern Electric	AMEM	0.001168749
Southern Electric	AXMI	0.002374388
Southern Electric	BOTW	0.003523095
Southern Electric	BRLE	0.004262737
Southern Electric	CHIC	0.001152398
Southern Electric	COWL	0.014173553
Southern Electric	EALI	0.004631746
Southern Electric	FAWL	0.001451698
Southern Electric	IVER	0.009791244
Southern Electric	LALE	0.004340904
Southern Electric	LOVE	0.012667148
Southern Electric	MANN	0.013548184
Southern Electric	MELK	0.007621884
Southern Electric	MITY	0.006413727
Southern Electric	NHYD	0.004270747
Southern Electric	NURS	0.008370379
Southern Electric	TYNE	0.000133521
Southern Electric	WISD	0.002756839
SP Distribution	BAGA	0.001233362
SP Distribution	BAIN	0.000868565
SP Distribution	BERW	0.000631157
SP Distribution	BONN	0.001623251
SP Distribution	BRAE	0.000773988
SP Distribution	BROX	0.001115623
SP Distribution	CATY	0.001198619
SP Distribution	CHAP	0.000912958
SP Distribution	CHAS	0.001847148
SP Distribution	CLYM	0.001329869

SP Distribution	COAT	0.00173713
SP Distribution	COCK	0.000849263
SP Distribution	COYL	0.000710293
SP Distribution	CROO	0.001262314
SP Distribution	CUMB	0.000851194
SP Distribution	CUPA	0.001291266
SP Distribution	CURR	0.000252849
SP Distribution	DEVM	0.000858914
SP Distribution	DEVO	0.001231432
SP Distribution	DEWP	0.002053673
SP Distribution	DRCR	0.000413051
SP Distribution	DRUM	0.001511303
SP Distribution	DUMF	0.001594299
SP Distribution	DUNB	0.000976653
SP Distribution	DUNF	0.000775918
SP Distribution	ECCL	0.000826102
SP Distribution	EERH	0.001947515
SP Distribution	EKIL	0.001314428
SP Distribution	EKIS	0.000679411
SP Distribution	ELDE	0.001036487
SP Distribution	ERSK	0.000494117
SP Distribution	GALA	0.000685201
SP Distribution	GIFF	0.001586578
SP Distribution	GLLU	0.000386029
SP Distribution	GLNI	0.000494117
SP Distribution	GLRO	0.000872425
SP Distribution	GORG	0.000712223
SP Distribution	GOVA	0.000810661

SP Distribution	GRMO	0.001264244
SP Distribution	HAGR	0.000914888
SP Distribution	HAWI	0.000528859
SP Distribution	HELE	0.000453584
SP Distribution	HUNF	0.000169853
SP Distribution	INKE	0.001019116
SP Distribution	JOHN	0.000922609
SP Distribution	KAIM	0.001748711
SP Distribution	KIER	0.001428307
SP Distribution	KILB	0.000901377
SP Distribution	KILS	0.000683271
SP Distribution	KILT	0.001721689
SP Distribution	KILW	0.00039568
SP Distribution	LEVE	0.000828032
SP Distribution	LING	0.001362682
SP Distribution	LINM	0.000750826
SP Distribution	MAYB	0.000461304
SP Distribution	NEAR	0.001522884
SP Distribution	NETS	0.000283731
SP Distribution	PAIS	0.000907168
SP Distribution	PART	0.000943841
SP Distribution	POOB	0.001980328
SP Distribution	PORD	0.001683086
SP Distribution	RAVE	0.000567462
SP Distribution	REDH	0.00093612
SP Distribution	SACO	0.001312498
SP Distribution	SANX	0.000772058
SP Distribution	SHRU	0.001078951

SP Distribution	SIGH	0.002071045
SP Distribution	SPAV	0.000820311
SP Distribution	STHA	0.001057719
SP Distribution	STIR	0.00160974
SP Distribution	STLE	0.001057719
SP Distribution	TELR	0.000633087
SP Distribution	TONG	0.00054044
SP Distribution	WFIE	0.000573253
SP Distribution	WGEO	0.001713968
SP Distribution	WHHO	0.001250733
SP Distribution	WISH	0.00161167
SP MANWEB	BIRK	0.005157669
SP MANWEB	CAPE	0.004831529
SP MANWEB	CARR	0.002205916
SP MANWEB	CELL	0.003382134
SP MANWEB	FIDF	0.005231263
SP MANWEB	FROD	0.001476836
SP MANWEB	KIBY	0.007016112
SP MANWEB	LEGA	0.006521955
SP MANWEB	LISD	0.007152665
SP MANWEB	PENT	0.004031574
SP MANWEB	RAIN	0.0076307
SP MANWEB	SWAN	0.00100593
SP MANWEB	TRAW	0.001459095
SP MANWEB	WYLF	0.001241231
SSE Generation Ltd	FERR	0.000443933
UPM KYMMENE	MEAD	0.000842894
WPD (formerly SWALEC (Infralec))	ABTH	0.003979262

WPD (formerly SWALEC (Infralec))	CARE	0.001989631
WPD (formerly SWALEC (Infralec))	PEMB	0.004030867
WPD (formerly SWALEC (Infralec))	PYLE	0.00248946
WPD (formerly SWALEC (Infralec))	RASS	0.004567376
WPD (formerly SWALEC (Infralec))	SWAN	0.011554571
WPD (formerly SWALEC (Infralec))	UPPB	0.005535657
WPD (formerly SWALEC (Infralec))	USKM	0.005243482
WPD(formerly SWEB)	ABHA	0.004932097
WPD(formerly SWEB)	ALVE	0.00413186
WPD(formerly SWEB)	AXMI	0.002038811
WPD(formerly SWEB)	BRWA	0.004054268
WPD(formerly SWEB)	EXET	0.006091149
WPD(formerly SWEB)	INDQ	0.008959922
WPD(formerly SWEB)	IROA	0.006306553
WPD(formerly SWEB)	LAND	0.005306932
WPD(formerly SWEB)	OLDS	0.003153276
WPD(formerly SWEB)	SEAB	0.006504393
WPD(formerly SWEB)	TAUN	0.002323315
Yorkshire Electricity	BRAW	0.009261688
Yorkshire Electricity	CREB	0.008299515
Yorkshire Electricity	DRAX	0.000570595
Yorkshire Electricity	ELLA	0.00622968
Yorkshire Electricity	FERR	0.009680696
Yorkshire Electricity	GRIW	0.003204663
Yorkshire Electricity	JORD	0.001294007
Yorkshire Electricity	KEAD	0.005797836
Yorkshire Electricity	KIRK	0.005649304
Yorkshire Electricity	NEEP	0.001475142

Yorkshire Electricity	NORL	0.001212591
Yorkshire Electricity	PITS	0.002141726
Yorkshire Electricity	SAEN	0.001982183
Yorkshire Electricity	SHEC	0.001917559
Yorkshire Electricity	SKLG	0.012368547
Yorkshire Electricity	THUR	0.003253269
Yorkshire Electricity	WIBA	0.000721245
Yorkshire Electricity	WMEL	0.013815155

Table 2: UK load servicing entities database

UK transmission grid database

From	*To*	*Reactance (% on base apparent power)*	*Capacity (MW)*
ABEW	ERRO	0.0057	264
ABEW	GRIF	0.016595	264
ABHA	EXET	0.005118213	2780
ABHA	LAGA	0.002722	2780
ABNE	CHAR	0.0566	132
ABNE	GRIF	0.0999	132
ABTH	COWT	0.005449	935
ABTH	PYLE	0.014523	935
ABTH	TREM	0.021438	625
ABTH	UPPB	0.00575494	1725
AIGA	KIOR	0.00594	111
ALDW	BRIN	0.007628	625
ALDW	WMEL	0.003891	955
ALNE	MOTA	0.0014	458
ALVE	INDQ	0.009688996	2780

ALVE	TAUN	0.00766875	2780
AMEM	ECLA	0.003523	3400
AMEM	IVER	0.002015	3400
ARBR	DENS	0.0337	183
ARBR	TEAL	0.0527	183
ARDK	INVE	0.021	132
ARDK	SLOY	0.0233	132
ARDR	BEAU	0.01826	535
ARDR	STRB	0.02796	535
AREC	MAHI	0.01349	214
ARMO	DUGR	0.0394	83
AUCH	MAHI	0.00809	690
AUCW	HADH	0.0388	140
AUCW	MAYB	1.00E-04	140
AXMI	CHIC	0.00687	2780
AXMI	EXET	0.006293	2770
AYR-	COYW	0.00192	1910
BAGA	BONN	0.019517492	292
BAGA	DRCR	0.007145	292
BAGB	MAGA	0.005468	875
BAGB	SWAN	0.00783	875
BAIN	BONN	0.007497259	228
BARK	BARP	5.77E-04	1700
BARK	REBR	0.002222997	2470
BARK	WHAM	9.87E-04	4020
BARK	WTHU	0.001579	4020
BEAU	CULL	0.0328	111
BEAU	DOUN	0.06143	702

BEAU	FAAR	0.035125	264
BEAU	FASN	0.029973978	252
BEAU	INNE	0.01795	252
BEAU	KIOR	0.0029	111
BEAU	KNOC	0.003435	1870
BEAU	MOTA	0.03397	252
BEDD	CHSI	0.003778727	1705
BEDD	ROWD	5.65E-04	2160
BEDD	WIMB	0.001933714	1855
BERW	ECCL	0.024304999	264
BESW	COVE	0.0039505	1910
BESW	FECK	0.015095	955
BESW	HAMH	0.010067	820
BICF	SPLN	0.00355	3160
BICF	WALP	0.006488	3190
BICF	WBUR	0.0056295	6660
BIRK	CAPE	0.0034195	1910
BIRK	LISD	0.002978	750
BISW	FECK	0.009633	955
BISW	KITW	0.005297726	1910
BISW	PENN	0.012726	1040
BLHI	DAAS	0.01381	525
BLHI	KEIT	0.001	1090
BLHI	KINT	0.01105	1050
BLHI	KNOC	0.03756	525
BLHI	PEHE	0.03576	1090
BLLA	WISH	0.01917	705
BLYT	HEDD	0.002583677	2200

BLYT	STEW	0.006948988	1360
BLYT	TYNE	0.003576993	2480
BOAG	FAAR	0.035125	264
BOAG	GLFA	0.04957	126
BOLN	LOVE	0.005633	5550
BOLN	NINF	0.0044705	5560
BONB	BONN	0.024949599	252
BONN	CUMB	0.010294811	270
BONN	LAMB	0.01495	795
BONN	LOAN	0.00915	840
BONN	STIR	0.012935	366
BOTW	FAWL	0.001509	3820
BOTW	LOVE	0.00252	3820
BRAC	BONB	0.01115	252
BRAC	ERRO	0.06705	264
BRAE	BRAP	0.00256	250
BRAE	GOVA	0.001195	250
BRAE	PAIS	0.00745	268
BRAI	BRFO	0.008395	2780
BRAI	PELH	0.011469	2780
BRAI	RAYL	0.002870749	5560
BRAP	ERSK	0.00719604	204
BRAP	PAIS	0.00986	274
BRAW	ELLA	0.007134	760
BRAW	KIRK	0.00855	760
BRAW	MONF	0.018824	1200
BRAW	PADI	0.011321	1000
BREC	BRID	0.00605	224

BREC	DENS	0.0633	112
BREC	FIDD	0.0726	112
BRED	MACC	0.008305	950
BRED	SMAN	0.004604	850
BRED	STAL	0.006374	1090
BRFO	NORM	0.012896	1590
BRFO	PELH	0.012053	2780
BRFO	SIZE	0.002509103	8340
BRIM	TOTT	8.08E-04	4360
BRIM	WALX	6.30E-04	4360
BRIN	CHTE	0.004135178	2135
BRIN	JORD	0.005918	555
BRIN	NORL	0.006085	420
BRIN	TEMP	5.85E-04	1910
BRIN	THOM	0.003158	5040
BRIN	THUR	0.002384	625
BRIN	TINP	6.71E-04	1370
BRLE	DIDC	0.00336075	5060
BRLE	FLEE	0.0015265	5560
BRLE	MELK	0.008163	2780
BRLE	WWEY	0.004748	4400
BROA	EDIN	0.09963	83
BROA	QUOI	0.1487	83
BROR	DUBE	0.0901	126
BROR	SHIN	0.0799	126
BROX	CURR	0.011935	264
BUMU	CHAR	0.0976	132
BUMU	GRIF	0.0684	132

BURW	PELH	0.003680489	6130
BURW	WALP	0.00439575	6200
BUSB	GIFF	6.70E-04	552
BUSB	NEIL	0.0082	1090
BUSB	STHA	0.00642	750
BUSH	DRAK	0.016016	955
BUSH	PENN	0.009078	1040
BUSH	WIEN	0.003404	760
BUST	DRAK	0.006361496	2400
BUST	NECH	0.001631	1450
CAAD	PORA	0.07265	198
CAFA	KEOO	0.00584	132
CANT	SELL	0.0025975	3860
CAPE	DEES	9.92E-04	7160
CAPE	FROD	0.001459492	5560
CARE	COWT	0.014488	680
CARE	USKM	0.010362	680
CARR	DAIN	1.54E-04	4390
CARR	KEAR	0.002574	2100
CARR	PEWO	0.011179	2170
CARR	SMAN	0.002202997	1670
CASS	LAIR	0.0675	111
CATY	DALM	0.001225	190
CEAN	MILW	0.0086	111
CELL	DAIN	0.010314	3100
CELL	DRAK	0.004354839	4360
CELL	MACC	0.006068	3100
CHAP	DUMF	0.028524957	342

CHAP	ECCF	0.007439987	144
CHAP	GRNA	0.014625	264
CHAP	HAKB	0.03472	132
CHAR	BIHI	0.004255	458
CHAR	GLAG	0.0023	252
CHAR	LYND	0.00225	252
CHAS	DALM	3.25E-04	372
CHIC	EXET	0.013205	2780
CHIC	MANN	0.00469524	6140
CHSI	WWEY	0.003117497	2640
CHTE	HIGM	0.009015477	2760
CILF	IMPP	0.004396	2780
CILF	RASS	0.004679	2780
CILF	SWAN	0.003540882	8740
CILF	UPPB	0.001476	1500
CILF	WHSO	0.006151	2780
CITR	SJOW	2.87E-04	2820
CITR	WHAM	3.88E-04	2820
CLAC	INVE	0.0195	126
CLAC	SLOY	0.033	132
CLAY	REDM	0.0014	240
CLAY	WIOW	0.0012	120
CLEH	CANT	0.00282	3100
CLEH	KEMS	0.00259	3100
CLUN	COUA	0.0444	252
CLUN	ERRO	0.018	252
CLYM	DALM	9.25E-04	1390
CLYM	EERH	0.00321	1500

CLYM	EKIL	0.001095	2240
CLYM	LOAN	0.01917	1500
CLYN	ELVA	0.00174	476
CLYS	ELVA	7.90E-04	291
COAL	ELVA	0.00507	2010
COAL	LINM	0.007592479	268
COAL	STHA	0.00413	2010
COAT	NEAR	0.0013	352
COCK	ECCL	0.006565	2180
COCK	KAIM	0.00756	1090
COCK	SMEA	0.00396	1090
COSO	RAYL	0.002785	2010
COSO	TILB	0.002476	2210
COTT	EASO	0.011771239	5560
COTT	GREN	0.025548	2010
COTT	KEAD	0.003352483	4420
COTT	STAY	0.002708843	4220
COTT	WBUR	0.001321	3330
COUA	BIHI	0.01705	252
COVE	HAMH	0.007351	1150
COVE	RATS	0.026384	1000
COWL	CULJ	0.00113	2770
COWL	DIDC	0.002001	2770
COWL	ECLA	0.006314	2770
COWL	LEIB	0.009095	2770
COWL	MITY	0.018493	1180
COWL	WALH	0.016366	1180
COWT	PYLE	0.009291	935

COYL	COYT	0.01037	113
COYL	COYW	3.10E-04	1910
COYL	MAHI	0.02762	690
COYL	MAYT	0.02179	114
COYT	KILS	0.03994	132
COYT	MAYB	0.04072	132
COYW	KILS	0.002805	1910
CRAI	FOGG	0.005285	264
CRAI	KINT	0.01985	290
CRAI	REDM	0.00765	314
CRAI	WOHI	0.0011	260
CREB	GART	0.002791249	5840
CREB	SAEN	0.007587	1750
CREB	SAES	0.007813	1750
CREB	THTO	0.002586486	5840
CROO	NEIL	0.01341	458
CRUA	DALL	0.0018	566
CRYR	FALL	0.00249	1250
CRYR	TORN	0.00194	1250
CULJ	DIDC	8.52E-04	2780
CULL	DEAN	0.0212	111
CUPA	LEVT	0.014895	286
CURR	GORG	0.00463	222
CURR	GRMO	0.01731	1090
CURR	KAIM	0.00373	1090
CURR	KINC	0.02269	1090
CURR	LING	0.01285	264
CURR	SIGH	4.20E-04	610

CURR	SMEA	0.00732	1090
DAIN	CARR	4.96E-04	2170
DAIN	DEES	0.005787249	6200
DAIN	MACC	0.006516	2400
DALL	INVR	0.00925	570
DALL	WIYH	0.03247	570
DALM	SANX	0.001435	448
DEES	GWYN	0.002628	5560
DEES	TREU	0.001401	4610
DENS	TEAL	0.019	183
DEVM	ERSK	0.03937	132
DEVM	INKI	0.00269	1350
DEVM	SPAV	0.00846	214
DEVM	WIYH	0.00524	1000
DEVO	STIR	0.02131	221
DEVO	WFIE	0.07155	162
DEWP	WHHO	2.82E-04	552
DINO	PENT	6.42E-04	3360
DOUN	GORW	0.03166	535
DOUN	THSO	0.018	264
DRAK	HAMH	0.005857	2010
DRAK	OLDB	0.009795	1000
DRAK	RATS	0.006532	2010
DRAK	RUGE	0.004173	2010
DRAK	WILE	0.00337	2010
DRAX	EGGB	1.00E-03	4870
DRAX	FENW	0.002338	2770
DRAX	THOM	0.003992	2980

DRAX	THTO	0.0019635	5550
DRUM	WIYH	5.09E-04	1910
DUBE	MYBS	0.0486	126
DUDH	GLAG	4.50E-04	240
DUDH	MILC	0.00221	262
DUGR	EDIN	0.01997	83
DUMF	TONG	0.1071	132
DUNB	INWI	0.00985	220
DUNE	GALA	0.05514	152
DUNE	SMEA	0.04207	152
DUNF	INKE	0.00863	264
DUNF	MOSM	0.01204	430
DUNG	NINF	0.0037845	6140
DUNG	SELL	0.00253725	3700
DUNO	WHTB	0.02025	198
DYCE	KINT	0.01325	290
EALI	LALE	0.001956	1050
EALI	WISD	0.001391	750
EASO	WYMO	0.0030675	5560
EAST	GLLE	0.0039	132
ECCL	GALA	0.03494842	264
ECCL	STWB	6.05E-04	5540
ECCL	TORN	0.003265	2500
ECLA	LEIB	0.002745	3820
ECLA	PAFB	0.004457235	4020
EERH	LOAN	0.01637	1500
EERH	NEAR	0.00632	950
EGGB	FERR	0.002063	2780

EGGB	MONF	9.02E-04	4090
EGGB	ROCH	0.016214	1000
EGGB	STSB	0.008363	2780
EGGB	THOM	0.004911	2220
EKIL	STHA	0.001095	2100
EKIS	NEIL	0.01192	1090
EKIS	STHA	0.0026	955
EKIS	WLEE	0.00101	457
EKIS	WLEX	0.00346	340
ELDE	JOHN	0.002799991	458
ELDE	NEIL	0.00408	458
ELGI	KEIT	0.03215	252
ELGI	NAIR	0.0411	252
ELLA	FERR	0.018245	1320
ELLA	KIRK	0.015765	760
ELLA	STAL	0.016624	955
ELST	MILH	0.001978746	1050
ELST	SJOW	0.00176	1770
ELST	SUND	0.003479739	2590
ELST	WARL	0.012359192	1520
ELST	WATS	0.001185623	1520
ELVA	GRNA	0.01225	2010
ELVA	HAKB	0.01277	2010
ELVA	STHA	0.0092	2010
ENDE	PAFB	0.0040255	4020
ENDE	RATS	0.002933498	5560
ERRO	FAUG	0.0984	264
ERRO	KIIN	0.0858	132

ERRO	TUMB	0.0011	252
ESST	KIER	0.0019	100
ESST	PART	0.00641	203
ESST	WIYH	0.00187	128
EXET	TAUN	0.003792999	4020
FASN	FAUG	0.02895	266
FAUG	GLDO	0.0047	127
FAUG	LAGG	0.0023	203
FAUG	LOCL	0.0099	252
FAWL	LOVE	0.004115	3820
FAWL	MANN	0.010014	2780
FAWL	MAWO	0.003062	2300
FECK	HAMH	0.008621	2010
FECK	IRON	0.013148	2010
FECK	MITY	0.015677	1970
FECK	WALH	0.013527	1970
FENW	KEAD	0.002161	3070
FENW	THOM	0.001653	2980
FERR	MONF	7.70E-04	2340
FERR	SKLG	0.004885723	1730
FFES	TRAW	0.001538999	1030
FIDD	FOGG	0.06157	112
FIDF	FROD	0.001683	2640
FIDF	RAIN	0.001339	2640
FIFE	WFIE	0.00249	260
FINL	KIIN	0.005	132
FLEE	LOVE	0.004088	4420
FOUR	HARK	0.023608	855

FOUR	STEW	0.011751	855
FOYE	KNOC	0.005145	1050
FRAS	LUMB	0.0117	252
FROD	ROCK	2.38E-04	1100
FWIL	KILO	0.05	132
FWIL	LOCL	0.04055	252
GALA	HAWI	0.02684	132
GARB	GARE	0.005799569	252
GARB	HELE	0.0352	126
GARB	STLE	0.0633	126
GARE	WHTL	0.002	200
GARE	WIYH	0.039714994	218
GART	KILL	0.006467	3160
GLEN	LAGG	0.012	111
GLLE	KEOO	0.01655	132
GLLE	NETS	0.033814988	250
GLLE	TONG	0.07678	132
GLLU	NETS	0.024521803	98
GLNI	MOSM	0.001395867	260
GLNI	REDH	0.02259	157
GLNI	WFIE	0.008	264
GLRB	GLRO	0.0053	49
GLRO	WFIE	0.00496	950
GORG	TELR	0.001355	160
GORW	STRB	0.00561	535
GOVA	HAGR	0.001210472	138
GRAI	KEMS	7.56E-04	5280
GRAI	KINO	0.002028	3100

GRAI	TILB	0.004832	2000
GREN	STAY	0.020259	2510
GREN	SUND	0.003964724	4020
GRIW	KEAD	0.00873	3070
GRIW	SHBA	0.002284	2860
GRMO	KINC	0.00591	1050
GRNA	HAKB	4.00E-04	2010
GRNA	HAWI	0.12417	132
GRNA	JUNV	0.01136	132
GRSA	LACK	2.33E-04	2230
GRSB	LACK	1.49E-04	2260
GRUB	MOSS	0.0032	252
GWYN	BODE	4.52E-05	2710
GWYN	PENT	0.004786	5560
HACK	TOTT	0.0012585	1910
HACK	WHAM	4.52E-04	3540
HAMH	NECH	0.0019215	2360
HAMH	OCKH	0.014112	820
HAMH	WILE	0.01582	2010
HARK	HAKB	0.0010055	3980
HARK	HUTT	0.0081345	2780
HARK	JUNV	2.729	111
HARK	STEW	0.03549	775
HARM	HAWP	0.007317	1090
HATL	HARM	0.00602	1090
HATL	SALH	0.003364	1380
HATL	TODP	0.007606	1090
HATL	WBOL	0.020909	1090

HAWI	JUNV	0.11252	132
HAWP	NORT	0.003619282	1910
HAWP	OFFE	0.004027	1090
HEDD	STEW	6.01E-04	4720
HEDD	STWB	0.0075445	6770
HELE	WIYH	0.0565	109
HEYS	HAMB	0.002227226	6660
HEYS	QUER	8.25E-04	7150
HIGM	RATS	0.012957	2150
HIGM	THUR	0.019585	625
HIGM	WBUR	0.002958	2210
HINP	BRWA	0.003870994	480
HINP	MELK	0.0085995	3920
HINP	TAUN	0.00265125	4420
HUER	HUNF	8.00E-05	292
HUER	INKI	0.005607249	2640
HUER	JUNA	0.00365	175
HUER	KILS	0.01051	1390
HUER	NEIL	0.0059	1350
HUMR	GART	0.007015	3160
HUMR	KILL	5.43E-04	2770
HUNF	KILW	0.02926	146
HUNF	SACO	0.0211	146
HURS	LITT	0.001393	1730
HURS	NEWX	0.002461193	1780
HUTT	QUER	0.003435	3400
IMPP	MELK	0.014129	1420
INDQ	LAND	0.0049605	2780

INGA	LOCL	0.0058	126
INKI	STHA	0.01613	1390
INNE	KNOC	0.001899947	342
INNE	NAIR	0.0329975	252
INRU	PEHE	0.001919057	558
INRU	PEHG	0.00205	252
INRU	SFER	0.00546808	585
INVB	INVR	5.00E-05	2000
INVE	ANSU	0.02615	99
INVE	FERO	0.03571	99
INVE	KILC	0.0355	99
INVE	PORA	0.0832	99
INVE	SLOY	0.0525	126
INVR	SLOY	0.01356	1000
INVR	WIYH	0.02322	570
INWI	TORN	3.05E-04	220
IROA	MELK	0.008706907	1160
IROA	OLDS	0.572906937	1820
IROA	WHSO	0.007326243	1330
IRON	LEGA	0.011938	2000
IRON	PENN	0.002605553	2000
IRON	RUGE	0.011701	1390
IRON	SHRE	0.00291	2400
IVER	LALE	0.007143	595
IVER	NHYD	0.0017445	840
IVER	WATS	0.003001746	1550
IVER	WWEY	0.01059	960
JORD	NORL	7.19E-04	420

JUNA	KILW	0.02629	146
JUNA	SACO	0.01813	151
KAIM	SMEA	0.0036	1090
KAIM	WHHO	7.20E-04	552
KAIM	WISH	0.02196	950
KEAD	GART	4.95E-04	6360
KEAD	KEAP	4.59E-05	6000
KEAD	KILL	0.007345	3060
KEAD	WBUR	0.00246498	6110
KEAR	PADI	0.007296	2170
KEAR	WHGA	0.003096231	1665
KEIT	GLFA	0.09623	126
KEIT	KINT	0.0244	1090
KEIT	MACD	0.088	111
KEMS	CANT	0.005411	3100
KEMS	LOFI	0.003663896	3860
KEOO	MAYT	0.07702	114
KIBY	LISD	0.001197372	1520
KIBY	RAIN	0.001889	2800
KIBY	WASF	0.002242245	3040
KIER	WIYH	0.00647	100
KIIN	INVR	0.0392	264
KIIN	LOCH	0.0058	111
KIIN	SFIL	0.052	132
KILB	WIYH	0.001019387	278
KILC	NANT	0.0103	99
KILC	TAYN	0.0178	99
KILL	SHBA	0.003134	2860

KILS	KILT	7.80E-04	560
KILS	MEAD	0.02711	162
KILS	STHA	0.00678	1390
KILW	MEAD	0.015195	292
KINB	KINC	0.00215	86
KINC	LOAN	9.35E-04	1240
KINO	NFLE	0.004216	3100
KINO	TILB	0.002893	2000
KINT	FOGG	0.03742	112
KINT	KINB	0.0731	955
KINT	PEHE	0.012781939	2180
KINT	PERS	0.0123	1090
KINT	TEAL	0.017568123	2865
KIRK	SKLG	0.002402	760
KITW	OCKH	0.005743	770
KITW	OLDB	0.003318	665
KNOC	DAAS	0.02375	525
LACK	NORT	0.00445	1590
LACK	THTO	0.0082685	4840
LACK	TODP	0.002415	1090
LAGG	MILW	0.0133	111
LAIR	SHIN	0.0252	111
LAKE	LITT	5.63E-04	3880
LAKE	TILB	0.001186727	3880
LALE	WWEY	0.003434	750
LAMB	LOAN	0.02073	820
LAMB	PORD	8.15E-04	600
LAMB	WIYH	0.00369	1900

LAND	LAGA	0.00213098	2780
LEGA	SHRE	0.009028	2000
LEGA	TREU	0.001158	5720
LEIB	SUND	0.001154249	7640
LEVE	LEVT	0.002454745	286
LEVT	REDH	0.01995	143
LEVT	WFIE	0.04157	143
LITT	LOFI	8.16E-04	2780
LOAN	MOSM	0.01078	760
LOAN	WFIE	0.012	760
LOCL	QUOI	0.0454	111
LOFI	ROWD	0.0026735	3180
LONO	CANT	0.030599	180
LOVE	NURS	0.003172	5550
LUIC	ORRI	0.035125	264
LUMB	SFER	0.0073	252
LUMB	STRI	0.0092	266
LUNA	TEAL	0.01955	366
MACC	STAL	0.006244	1710
MAGA	PYLE	0.002592	1105
MANN	NURS	0.006631	2780
MAWO	NURS	0.001281	2420
MAYB	MAYT	0.02896	132
MELK	MITY	0.002792998	4220
MELK	SEAB	0.009451	2550
MILC	TEAL	0.0074	366
MONF	PADI	0.016286	2520
MONF	POPP	0.008300242	1010

MOSH	MOSM	2.99E-04	264
MOSM	WFIE	0.00123	955
MOSS	LUIC	0.0032	252
MOTA	SHIN	0.0386	252
MYBS	SHIN	0.2184	126
MYBS	THSO	0.01875	252
NEAR	WISH	0.00323	570
NEEP	PITS	0.001378	420
NEEP	SHEC	0.001494	420
NEEP	STSB	0.002627	750
NEIL	PAIS	0.007345	536
NEIL	WIYH	0.01028	955
NEWX	WIMB	0.0015435	1645
NFLE	WTHU	7.47E-04	4000
NORL	PITS	0.002752	420
NORL	SHEC	0.001119	420
NORM	SIZE	0.020412	1590
NORM	WALP	0.006792498	5870
NORT	OSBA	0.007965	4020
NORT	SALH	0.00526	1370
NORT	SPEN	0.002033	5100
OCKH	WIEN	9.99E-04	1195
OFFE	WBOL	0.003474	1090
ORMO	HEYS	0.002153	165
ORRI	BEAU	0.02431	264
OSBA	THTO	0.00146	4790
PADI	PEWO	0.007049	2170
PART	WIYH	0.00969	203

PEHE	PERS	0.0208	1090
PELH	RYEH	0.002019831	5560
PELH	SUND	0.00752	3180
PELH	WYMO	0.004469	2770
PEMB	SWAN	0.014709	2770
PEMB	WALH	0.038196	1110
PENT	TRAW	0.009563	2810
PENT	WYLF	0.0030645	5560
PERS	WIOW	0.00105	240
PEWO	HAMB	0.001955495	3490
PEWO	WASF	0.004807246	3040
PITS	TEMP	0.001713	420
PITS	WIBA	5.81E-04	440
POOB	SHRU	5.15E-04	540
POOB	SMEA	0.0017	720
PORA	ANSU	0.05705	99
PORD	WGEO	2.61E-04	610
QUER	PEWO	0.003070984	6200
RANN	TUMB	0.02755	252
RASS	WALH	0.012927	1110
RATS	STAY	0.008685	2150
RATS	WILE	0.002165963	3320
RAVE	WISH	5.00E-06	476
RAYL	TILB	0.004077	2010
REBR	TOTT	0.00104358	2420
REDH	WFIE	0.02162	157
ROCH	STAL	0.013183	1320
ROCH	WHGA	0.002465749	1745

RYEH	WALX	4.69E-04	5560
SAEN	SAES	1.80E-04	1520
SEAB	WHSO	0.005858	1420
SFER	SFEG	0.00245	252
SFER	SFEM	0.002785	264
SING	KINO	0.003076	2890
SING	NFLE	0.00114	2890
SIZE	LEIS	0.030599	180
SJOW	TOTT	0.001808217	1740
SJOW	WISD	8.14E-04	1500
SLOY	GARB	0.008262481	528
SLOY	INVR	0.02614	132
SMEA	STHA	0.01446	1390
SMEA	TORN	0.00998	1250
SPEN	STEW	0.003688495	4990
SPLN	WALP	0.005117	3190
SSHI	TYNE	0.002985	995
SSHI	WBOL	0.001848	1090
STAL	STSB	0.00556	1400
STAL	THOM	0.012982	1040
STHA	WISH	0.00504	1050
STIR	WFIE	0.09286	162
STLE	WIYH	0.03056	109
SUND	WYMO	0.00302	3050
SWAN	PEMB	0.007334117	5560
TARL	FOGG	0.0399	264
TAYN	FERO	0.01759	99
TEAL	BIHI	0.005995	458

TEAL	GLRB	0.0167	955
TEAL	KINB	0.0371	955
TEAL	WFIB	0.0167	955
TEMP	WIBA	9.23E-04	420
THOM	WMEL	0.005400743	1530
THUR	WMEL	0.007099	955
TILB	WARL	0.002747135	2360
TRAW	TREU	0.006433	3420
TREM	USKM	0.007162	625
TYNE	WBOL	0.004835	995
USKM	WHSO	6.63E-04	3485
WAAW	HEYS	0.024667	204
WAAW	STAH	0.025965263	183
WFIB	WFIE	0.0093	22.3
WHTB	WHTL	0.00195	44.6
WIMB	WISD	0.004733	740
WIOW	WOHI	9.67E-04	522
WYLF	PERH	0.014488	660

Table 3: UK transmission grid database

UK transmission grid base values

Base apparent power (MVA)	*Base voltage (kV)*	*Soft penalty weight*
100	10	0.005

Table 4: UK transmission grid base values