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# **Market-Based Coordination for Domestic Demand Response in Low-Carbon Electricity Grids**

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Institute for Adaptive and Neural Computation

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Efforts towards a low carbon economy are challenging the electricity industry. On the supply-side, centralised carbon-intensive power plants are set to gradually decrease their contribution to the generation mix, whilst distributed renewable generation is to successively increase its share. On the demand-side, electricity use is expected to increase in the future due to the electrification of heating and transport. Moreover, the demand-side is to become more active allowing end-users to invest in generation and storage technologies, such as solar panels and home batteries. As a result, some network reinforcements might be needed and instrumentation at the users' end is to be required, such as home energy systems and controllers. The electricity grid must balance supply and demand at all times in order to maintain technical constraints of frequency, voltage and current, and this will become more challenging as a result of this transition. Failure to meet these constraints compromises the service and could damage the power grid assets and end-users' appliances. Balancing generation, although responsive, is carbon-intensive and associated with inefficient asset utilisation as these generators are mostly used during peak hours and sit idle the rest of the time. Furthermore, energy storage is a potential solution to assist the balancing problem in the presence of non-dispatchable low-carbon generators; however, it is substantially expensive to store energy in large amounts. Therefore, demand response (DR) has been envisioned as a complementary solution to increase the system's resilience to weather-dependent, stochastic, and intermittent generation along with variable and temperature-correlated electric load. In the domestic setting, operational flexibility of some appliances, such as heaters and electric cars, can be coordinated amongst several households so as to help balance supply and demand, and reduce the need of balancing generators.

Against this background, the electricity supply system requires new organisational paradigms that integrate DR effectively. Although some dynamic pricing schemes have been proposed to guide DR, such as time of use (ToU) and real-time pricing (RTP), it is still unclear how to control oscillatory massive responses (e.g., large fleet of electric cars simultaneously responding to a favourable price). Hence, this thesis studies an alternative approach in which end-users proactively submit DR offers that express their preferences to their respective retailer in exchange for a discount. This study develops a computational model of domestic electricity use, and simulates appliances with operational flexibility in order to evaluate the effects and benefits of DR for both retailers and end-users. Furthermore, coordination mechanisms are proposed to determine the allocation of DR offers and guide a collective response. The theoretical properties of these mechanisms are studied and evaluated in simulations based on data from a survey of UK household electricity use. In addition, forecasting methods are assessed on the end-users' side in order to make better DR offers and avoid penalties. The results show that, under reasonable assumptions, the proposed coordination mechanisms achieve significant savings for both end-users and retailers, as they reduce the required amount of expensive balancing generation.

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# Abstract

Efforts towards a low carbon economy are challenging the electricity industry. On the supply-side, centralised carbon-intensive power plants are set to gradually decrease their contribution to the generation mix, whilst distributed renewable generation is to successively increase its share. On the demand-side, electricity use is expected to increase in the future due to the electrification of heating and transport. Moreover, the demand-side is to become more active allowing end-users to invest in generation and storage technologies, such as solar photovoltaics (PV) and home batteries. As a result, some network reinforcements might be needed and instrumentation at the users' end is to be required, such as controllers and home energy management systems (HEMS). The electricity grid must balance supply and demand at all times in order to maintain technical constraints of frequency, voltage, and current; and this will become more challenging as a result of this transition. Failure to meet these constraints compromises the service and could damage the power grid assets and end-users' appliances. Balancing generation, although responsive, is carbon-intensive and associated with inefficient asset utilisation, as these generators are mostly used during peak hours and sit idle the rest of the time. Furthermore, energy storage is a potential solution to assist the balancing problem in the presence of non-dispatchable low-carbon generators; however, it is substantially expensive to store energy in large amounts. Therefore, demand response (DR) has been envisioned as a complementary solution to increase the system's resilience to weather-dependent, stochastic, and intermittent generation along with variable and temperature-correlated electric load. In the domestic setting, operational flexibility of some appliances, such as heaters and electric cars, can be coordinated amongst several households so as to help balance supply and demand, and reduce the need of balancing generators.

Against this background, the electricity supply system requires new organisational paradigms that integrate DR effectively. Although some dynamic pricing schemes have been proposed to guide DR, such as time of use (ToU) and real-time pricing (RTP), it is still unclear how to control oscillatory massive responses (e.g., large fleet of electric cars simultaneously responding to a favourable price). Hence, this thesis proposes an alternative approach in which households proactively submit DR offers that express their preferences to their respective retailer in exchange for a discount. This research develops a computational model of domestic electricity use, and simulates appliances with operational flexibility in order to evaluate the effects and benefits of DR for both

retailers and households. It provides a representation for this flexibility so that it can be integrated into specific DR offers. Retailers and households are modelled as computational agents. Furthermore, two market-based mechanisms are proposed to determine the allocation of DR offers. More specifically, a one-sided Vickrey-Clarke-Groves (VCG)-based mechanism and penalty schemes were designed for electricity retailers to coordinate their customers' DR efforts so as to ameliorate the imbalance of their trading schedules. Similarly, a two-sided McAfee-based mechanism was designed to integrate DR offers into a multi-retailer setting in order to reduce zonal imbalances. A suitable method was developed to construct DR block offers that could be traded amongst retailers. Both mechanisms are dominant-strategy incentive-compatible and trade off a small amount of economic efficiency in order to maintain individual rationality, truthful reporting, weak budget balance and tractable computation. Moreover, privacy preserving is achieved by including computational agents from the independent system operator (ISO) as intermediaries between each retailer and its domestic customers, and amongst retailers. The theoretical properties of these mechanisms were proved using worst-case analysis, and their economic effects were evaluated in simulations based on data from a survey of UK household electricity use. In addition, forecasting methods were assessed on the end-users' side in order to make better DR offers and avoid penalties. The results show that, under reasonable assumptions, the proposed coordination mechanisms achieve significant savings for both end-users and retailers, as they reduce the required amount of expensive balancing generation.

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# Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.



*(Sergio Iván Elizondo-González)*

*15th September 2017*

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# Chapter 1

## Introduction

This thesis examines two direct market-based coordination mechanisms for domestic demand response (DR). The first mechanism is set up between electricity retailers<sup>1</sup> and households as a means to reduce each retailer's trading imbalances. The second mechanism induces a higher level coordination amongst multiple retailers within a zone. The first mechanism assumes that each retailer uses DR for itself, whereas the second one focuses on the zonal imbalance and allows DR exchange amongst competing retailers. Electricity retailers and households are computationally modelled as self-interested rational agents residing in controllers (e.g., *smart meters*, home energy managements systems) and following the end-user's designated policies. Individual and holistic perspectives are considered in a multiagent setting to evaluate which mechanisms are most effective in achieving efficiencies.

The following sections describe the motivation for research into low-carbon electricity systems, the definition of the problem under consideration, the scientific contributions, and the thesis outline.

### 1.1 Research Motivation

Energy use is essential to support quality of life. In fact, they are both directly correlated (Pasten and Santamarina, 2012). Since the industrial revolution, substantial progress has been made to improve the standard of living, which has come at the expense of increasing energy needs. This thirst for energy has led a quest for fossil fuels, such as coal and gas, that are commonly scarce, hard to find and expensive to extract. Not only

---

<sup>1</sup>Electricity retailers are also referred to as load-serving entities (LSE), facilities, electric companies, or electricity suppliers.

fossil fuels extraction has brought political and economic instability in some countries, but also their use produces high greenhouse gases (GHG) emissions that are likely to be one of the main causes of climate change (MacKay, 2009). Public concern is increasingly pressing for alternative sources of energy, specially those which can help to meet carbon targets. In addition, the global demand for energy is projected to increase due to reasons such as population growth, modernisation and industrialisation of developing countries, and a wider range of technology uptake (U.S. Energy Information Administration, 2012).

A predominant alternative to improve energy security, yet meet carbon targets, is the inclusion of a considerably increasing share of renewable sources (e.g., wind, sunlight) into the electricity generation mix (UK HM Government, 2009; Appelrath et al., 2012). Electricity is directly related to economic growth (U.S. Department of Energy, 2003) and its decarbonisation can pave the way for reducing GHG emissions without sacrificing too much comfort. Moreover, shifting from internal combustion engine vehicles (ICEV) to electric vehicles (EV) that are recharged with decarbonised electricity is seen as a pathway to considerably reducing GHG emissions as well as oil reliance (European Commission, 2009). MacKay (2009) concludes that switching to EVs is a good decision, even when using electricity that is not generated from low-carbon sources, since they are at least as good as the most efficient ICEV. Also, EVs offer potential to accommodate renewable energy, as their batteries could provide flexibility to be recharged during off-peak periods or when there is an excess of renewable energy. They could even provide electricity to the grid under specific circumstances, i.e., vehicle-to-grid (V2G) (European Commission, 2009). In addition, using efficient heat pumps instead of conventional heaters could add up to reducing emissions. Although EVs and heat pumps are convenient for carbon targets, they put significant strain on the power sector infrastructure, as they considerably increase electricity demand (Department of Energy & Climate Change, 2009). This exacerbates the problem of supplying electricity generated from low-carbon sources.

The decarbonisation of the power sector raises several challenges. First, decarbonisation of electricity could be achieved by using carbon capture and storage (CCS) technologies and/or replacing carbon-intensive supply with renewable generation (Department of Energy & Climate Change, 2009). On the one hand, CCS and respective logistics could become costly, and thus increase the electricity price. Although they allow for controllable supply (i.e., dispatchable power plants), they depend on not so abundant fossil fuels. On the other hand, renewable generation has a small operational

cost, as they mostly require no fuels (or if they do, these are not so expensive biofuels). Despite of the fact that renewable sources are abundant, they are stochastic and intermittent, as the main sources are weather dependent, such as wind and sunlight.

Second, electricity storage is limited and it carries significant investments to accommodate large capacities, such as pumped hydroelectric energy storage (PHES), (Kirschen and Strbac, 2004). Due to the fact that the future of the electricity supply system is unclear, no single stakeholder wants to invest in expensive storage projects that might not return on their costs (Claessen and La Poutré, 2014; U.S. Department of Energy, 2003).

Third, the nature of renewables calls for a paradigm shift from few centralised massive power plants to decentralised and distributed energy resources (DER) (Ramchurn et al., 2012). This implies replacing a stable dispatchable supply-side by many micro- and small-scale generators that mostly depend on weather conditions, resulting in a less controllable supply (e.g., solar photovoltaics, wind turbines). Due to the nature of this shift, some gains are obtained by bringing generation closer to demand, as less energy is lost as dissipated heat in transmission cables, and some distributed generators (DG) take advantage of the waste heat (Lasseter and Paigi, 2004), e.g., combined heat and power plants (CHP). Notwithstanding, this paradigm shift requires big efforts on decentralised coordination with many autonomous entities (i.e., agents) with different technologies and own interests.

Fourth, the electrification of transport, heating and cooling can cause severe load peaks if their demand is not managed properly, thus, causing infrastructure overload and potential damage (Department of Energy & Climate Change, 2009).

Regardless of the generation sources, a key constraint of the electricity supply system is that supply and demand must be in continuous balance, otherwise blackouts and infrastructure damages are likely to happen (Department of Energy & Climate Change, 2009; Ramchurn et al., 2012). The expected new dynamics for future electricity supply systems make this key constraint hard to be satisfied, and thus to reconsider the traditional approach of ‘supply follows demand’ so that demand also becomes adaptive to supply conditions, i.e., demand-side management (DSM), (Schweppe, Tabors, et al., 1980; Schweppe, Daryanian, et al., 1989; Ramchurn et al., 2012). This change along with consumers that can also generate electricity (i.e., *prosumers*<sup>2</sup>) require new organisational paradigms to account for these new dynamics and roles (Claessen and

---

<sup>2</sup>Portmanteau term from the words producer and consumer, that is commonly used in low-carbon electricity systems to refer to end-users with generation capacity.

La Poutré, 2014).

Since the modernisation of the electricity supply system cannot be done by industry or government alone, significant efforts have been made to develop a common vision amongst all stakeholders to foster long-term investments (U.S. Department of Energy, 2003; European Commission, 2006). This vision has been included under the concept of a ‘Smart Grid’, which comprises a reengineering of the current electricity grid to support bidirectional flows of electricity and information, sensing and automation in order to improve the efficiency, reliability, sustainability and affordability of electric power delivery (U.S. Department of Energy, 2003; European Commission, 2006). Within this vision, information and communication technology (ICT) plays a major role integrating the value chain, connecting all the participants and automating the decision making (Claessen and La Poutré, 2014).

DSM has been advocated for accommodating to the stochasticity and intermittency from low-carbon sources of electricity generation. Within this context, domestic DR is the ability of end-users to adapt a fraction of their electricity use, i.e., by anticipating or deferring the use of some appliances, so as to better match the variable supply. For instance, if there is an unplanned surplus of renewable electricity, it would be expected to become less expensive, so those with the ability to respond and use it would benefit, provided that there are incentives to do so. Similarly, if electricity is scarce, it would be expected to be more expensive, so its use could be deferred. Analogously, the supply-side can also be incentivised or disincentivised in agreement with the laws of supply and demand.

The problem of coordinating DR can be cast as a task allocation problem amongst self-interested profit-maximising agents through carefully designed auctions. An auction is any protocol that allows agents to indicate their preferences over one or more resources, it determines the resulting allocation of these resources according to the agents’ preferences, and it settles the payments (Shoham and Leyton-Brown, 2008, Ch11). This framework for resource allocation has been studied in several fields, such as, microeconomics, electronic market design, operational research (OR), power systems economics, and artificial intelligence (AI) through algorithmic mechanism design and multiagent systems (MAS). It is a reasonable assumption to expect the DR allocation process to be automated by autonomous software agents acting on behalf the end-users, residing in their home energy management systems (HEMS), and operating through controllers (Ramchurn et al., 2012; Claessen and La Poutré, 2014). Therefore, the research problem has been computationally modelled and studied as a MAS, using

tools from mechanism design and agent-based modelling and simulation (ABM/S).

Multiagent systems (MAS) have increasingly been used to model complex systems such as smart grids, simulate their emergent behaviour, and solve coordination problems amongst their actors (e.g., Vytelingum et al. (2011), Ramchurn et al. (2011a), Kok (2013), Pipattanasomporn et al. (2009), Oyarzabal et al. (2005), and Dimeas and Hatziargyriou (2010)). ABM/S can be used to computationally model and simulate new business roles, market mechanisms, communication and coordination protocols, find out the overall impact of policies and regulations as a result of assessing their effect in a realistic simulation.

## 1.2 Problem Statement

Traditionally, in countries with liberalised electricity markets, electricity is financially traded in the wholesale market several time periods before the actual physical delivery. At the retail level, end-users sign a contract with a retailer that trades in the wholesale market and offers electricity serving at usually one or two fixed rates, whose billing is done at the end of a specified period, i.e., monthly, quarterly. In order to make profit, retailers need to estimate their customers' demand as accurately as possible so as to trade proper amounts in the wholesale market. Failure to do so will generally involve either an opportunity cost or expensive procurement due to balancing generation, thus reducing their margin. Moreover, wholesale electricity prices are variable and they are computed through an optimisation procedure that matches generation offering curves and load bidding curves along with network-related technical constraints. This procedure results in usually different zonal prices per time period within a day, usually 24 hours or 48 half-hours. This means that the price of electricity is variable and it is basically governed by the microeconomic laws of supply and demand, plus technical constraints to guarantee a reliable cost-effective service.

### 1.2.1 Supply and Demand Balance

A hard constraint in the electricity supply system is that supply and demand must be in continuous balance all the time. This means that frequency and voltage must be kept within range. Failure to maintain this balance could lead to infrastructure damage, blackouts, brownouts or general lost of load that could be translated into lack of comfort and economic losses, amongst other things. The conventional approach has generation

assets ready to cover for load variability, i.e., ‘supply follows demand’. With stable supply (i.e., dispatchable generators) and somehow predictable consumption (e.g., temperature correlated electricity use, day of the week), the supply and demand problem boils down to managing load peaks. The highest aggregated domestic peak load, under conventional circumstances, commonly takes place in the evening. Expensive load-following generators are reserved to be used during the few hours of the peak, and they are often under-utilised.

In monopoly-based electricity systems the balance of supply and demand is performed in accordance to an internal schedule. On the other hand, in unbundled electricity systems with liberalised electricity markets, this task is carried out by clearing several sequential markets, where participants compete to get their bids (or asks) accepted. Dynamics for future low-carbon electricity systems are expected to challenge the conventional approach of ‘supply follows demand’ and make it impractical to satisfy the supply and demand balance. Besides, storage is a limitation. Therefore, new approaches in which demand becomes adaptive (or at least manageable) are required. Thus, consumers and prosumers need to be guided to keep peak problems within a controllable extent.

### **1.2.2 Domestic End-Users Desiderata**

For end-users it is a top priority to have access to an inexpensive and very reliable electricity service, regardless whether it comes from a retailer or their own generating technologies. This includes having the freedom to use electricity at their will. In addition, if they had invested in generating technologies, renewable or not, they would like to be paid if they exported electricity to the grid. Although this idea is appealing, it is not easy to organise thousands or potentially millions of small contributors to the electricity supply, specially if they might not provide a reliable power output, as in the case of renewable technologies.

The electricity wholesale market provides access to usually better prices that, for instance, could result in a cheaper service if retailing intermediaries are to be avoided. For an industrial customer it could be beneficial to directly buy their electricity from the wholesale, provided that it invests some effort in determining a beneficial procurement strategy. However, this might not be as convenient for domestic customers, as they would be exposed to the high volatility of market prices. Moreover, not meeting the traded positions in the wholesale market could result in expensive penalties due to the

balancing constraint. Furthermore, a considerable upfront investment would be needed to determine a profitable procurement strategy under uncertainty and to acquire technologies (e.g., batteries, domestic dispatchable generators) so as to hedge balancing prices or penalties. As a result, domestic customers could end up paying a more expensive service than if they are served by a specialised party. Therefore, electricity retailers are convenient for end-users, so that the value they add in the organised trade of electricity is fixing one or two hopefully competitive prices, so end-users are not exposed to the wholesale market risks.

Several pricing schemes have been studied in the literature for the purpose of adapting to supply conditions. Starting from cheaper night tariffs that end-user might take advantage of, to more dynamic settings in which renewables are part of the generation mix. Particularly, these prices are aimed to incentivise or deter electricity use according to the state of the sources of supply and, sometimes, paired with network constraints. On the one hand, fixed prices do not incentivise end-users to modify their use patterns, and thus redistribute peaks resulting from common human behaviour and weather conditions, mainly temperature. On the other hand, dynamic prices such as real-time pricing (RTP) could cause undesired aggregate effects, such as having an *avalanche* of end-users reacting to a rise (or fall) of price, thus inducing a large demand fluctuation. For instance, there could be a large number of electric vehicles (EV) waiting for the right price to be charged at, then as soon as they sense a price that is considered inexpensive, most of them will start recharging, driving the supply scarce and thus an increase in price to discourage consumption. Basically, the latter scenario converts a behavioural peak problem to an economically induced peak problem that is only shifted to a different time of the day, unless some randomisation is induced too (Ramchurn et al., 2011a). One of the fundamental problems of this Walrasian-style pricing scheme is that the economic feedback loop is not instantaneous and such delay can cause the undesired peak effects (Vickrey, 1971; Tesfatsion, 2006).

One benefit of liberalised electricity markets, that include their retail echelon, is that end-users can select the retailer that gives them the most competitive tariffs, specially if these are kept fixed for some months or years. Furthermore, if some supply-demand loop needs to be in place between the retailer and end-users, the latter would not like to be expected to monitor the loop themselves in order to respond to a certain signal. That is, end-users would like to maximise their comfort from electricity use, thus they require a controller device that could be delegated the job of monitoring the loop, such as an HEMS that has access to the (smart) meter and is able to schedule some devices



that can respond to the loop signals. Some examples of these scheduling tasks are EV recharging, home battery (HB) recharging and discharging, heating and cooling, washing and drying, etc. It is also desirable for end-users to preserve some of their privacy while anonymising their profile under the aggregate use of devices. End-users can also be concerned for their privacy, since they (or their HEMS) could respond to signals or direct incentives from their retailer, they would not like other entities (e.g., retailer, broker, aggregator, market operator) to know that the end-user has an EV, HB, or how often they are recharged or needed. In this case, it would be impractical for the retailer to schedule and price according to specific technical requirements of multiple devices and preferences from many end-users. Also, end-users would not like to give much information to the retailer that could be used against them in order to extract more revenue.

### 1.2.3 Retailers Desiderata

In general, electricity retailers are interested in making profit. This comes from the difference of serving end-users and trading in the wholesale market, through bilateral contracts and trading in the pool market if there is one. In a liberalised retail electricity market, if a retailer is unable to offer competitive prices, its customers might decide to switch to a different supplier. Moreover, if a retailer misses its aggregate demand forecast, it could face serious imbalance charges, or contract for differences (CFD) from bilateral trading, narrowing its profit or even making it to incur in losses. Future dynamics, due to a wide adoption of DER, will compromise the ability of retailers to forecast their demand accurately, thus becoming exposed to higher market risks.

Against this background, retailers need to find alternatives to manage these risks, and yet keep their tariffs competitive so as to have a large group of subscribed customers, that translate into higher returns. It is an advantage to retailers to be flexible and responsive enough to accommodate for electricity surplus or deficit. First, if a proper mechanism were in place, retailers could use DR from their customers to account for differences in their already traded position, i.e., their schedule. Second, this mechanism could help to accommodate differences at a zonal level. For instance, the distribution system operator (DSO) could be aware of unexpected surplus and offer it to retailers within a zone, e.g., from a near wind farm or solar PV farms that were not forecast accurately by other wholesale participants. The opposite can happen too; there could be an unexpected deficit and reducing the load could be compensated, i.e.,

economically rewarded. Therefore, retailers that are able to exploit these opportunities by incentivising some change by their customers use-patterns will become more apt to maximising profit and keep competitive prices. Moreover, the retailer would like to exploit the benefits of DR and be economically rewarded, perhaps by the independent system operator (ISO) or the corresponding DSO, as it helps to reduce the balancing gap.

A societal benefit if such mechanism were in place would be to reduce the amount for expensive balancing generation, thus reducing the overall cost of the supply system, as fewer peaking power plants would have to be reserved to respond to balancing supply and demand. The power output from balancing generators is generally very expensive, because these assets are only used a few hours a day and remain idle the rest of the time, thus the high price in order to be profitable investments. In this sense, DR could lower the overall cost per kWh, and reduce the carbon footprint while helping accommodate renewable energy.

### 1.3 Research Contributions

The contributions of this thesis are relevant to smart energy systems and electronic market design that, in a wider context, fit into the fields of operational research, computational science, multiagent systems, microeconomics, and power system economics. The scientific contributions are the following:

1. Design of a computationally tractable VCG-based DSIC mechanism with verification for domestic DR coordination. This mechanism extends the state-of-the-art in the following aspects.
  - (a) It provides a computational model of operational flexibility that is general and simple enough to capture domestic appliance use. This model allows end-users to schedule *flexible* tasks (i.e., use of appliances) and express their associated comfort costs for time-shifting with one of three different linear functions: increasing, decreasing, and constant per time step.
  - (b) The ask (bid) format is minimally designed to express the operational flexibility integrated with the electric meter readings so that the actual achievements can be verified for allocated DR offers. The ask structure comprises several parameters, however, they are abstracted to a single-dimensional domain. Due to this reduction, an additional allocation rule needs to be

imposed so that end-users do not exploit the mechanism through deceitful offers.

- (c) The state-of-the-art toolset of algorithmic mechanism design is used in order to make this auction-based protocol implementable in the dominant strategy incentive compatible (DSIC) solution concept, with allocations and payments computation solved in polynomial time.
  - (d) Three penalty schemes and one inspection procedure are proposed in order to incentivise end-users to report their preferences truthfully. That is, the VCG-based mechanism is *strategy-proof* about the costs, but not about the end-users' offered capacities. Therefore, these penalties are used to restore the DSIC implementation, and their properties are evaluated and benchmarked against another suitable penalty scheme adapted from the literature.
  - (e) This mechanism along with four penalty schemes (three proposed and one from the literature) are evaluated through simulations based on data from a survey of UK domestic electricity use, and market imbalance settlement prices. Under reasonable assumptions, it shows to be beneficial for both retailers and end-users, although not so for balancing generators, when compared to the business-as-usual case. At first, savings seem to be low, however, as balancing generation becomes more expensive, the savings become considerable. Similarly, these savings are expected to be more significant with an increasing electricity use due to foreseen EV deployment (and other appliances such as heat pumps). However, these savings will plateau as both the number and capacity of demand responders increases.
2. Design of a multi-unit McAfee-based DSIC mechanism with verification for zonal domestic DR coordination in a multi-retailer setting. This mechanism contributes to the state-of-the-art in the following.
- (a) It adapts the well-known single-unit McAfee's double auction (DA) to a multi-unit setting compatible to the model in this thesis, and it preserves the DSIC property as in the original McAfee's mechanism.
  - (b) It extends the single-sided VCG-based mechanism from the point 1 above to a double-sided mechanism that allows multi-retailer DR coordination, within a geographical zone.

- (c) A methodology is developed to create stepwise offers from both retailers' expected deviations and DR offers. These integrated offers allow for a more efficient use of DR before the imbalance settlement (or any other conventional balancing market). That is, instead of each retailer procuring DR to cover its own deviation with its pool of customers, the mechanism allows them to trade (or *balance*) both their expected energy imbalances and blocks of DR offers. The result of this mechanism produces greater efficiencies since, in general, fewer DR offers are triggered; whilst retailers grant fewer discounts, end-users' comfort is impacted less.
  - (d) Similar to the single-sided mechanism above, allocations and payments from this double-sided mechanism can be computed in polynomial time. This is not surprising for double auctions, however, the proposed mechanism is DSIC, which is generally difficult to achieve in multi-unit double auctions.
  - (e) The proposed mechanism is simulated and compared against the above mechanism under the same circumstances so as to evaluate the same dimensions.
3. Empirical study and benchmark of several automated forecast methods to predict a household's inflexible net-load. The aim of this study is to support the argument that it is reasonable for end-user agents to make DR offers based on their prediction, at least for one time period ahead. The used household profiles are based on data from a survey of UK domestic electricity use, in which loads from potentially flexible domestic tasks (e.g., heating, washing, drying, etc.) were removed so as to obtain inflexible electricity use (or net-load when generation is considered). The forecast methods include: naive methods, time-series based approaches, artificial neural networks (ANN), naive combinations of predictions based on central tendency measures, and one exponentially weighted average forecaster (EWAF) that combines the first three types of predictors. Results show that it is possible to forecast the household's inflexible net-load with a relatively low root-mean-square error (i.e., below 200 Wh), which consecutively helps to improve the accuracy of DR offers.

## 1.4 Thesis Outline

This thesis is organised into seven chapters. Chapter 2 provides background information on liberalised wholesale electricity markets. It describes the organisation of electricity markets and time framework for decision making on electricity trading. It also provides the relevant background on multiagent systems and mechanism design, and it surveys the relevant literature.

Chapter 3 develops a computational model to study the coordination problem between electricity retailers and end-users with operational flexibility. It presents the design of a polynomial time VCG-based truthful mechanism with verification to ameliorate the balancing problem. Moreover, three penalty schemes are designed and discussed, with a fourth one adapted from the literature, in order to restore the DSIC property under the problem settings. Furthermore, an inspection procedure is introduced to review end-user agents skill to predict their intended net-load.

Chapter 4 proposes a double-sided market-based mechanism for multi-retailer settings, where the focus is on balancing supply and demand within a geographical zone. It develops a methodology for stepwise offers that integrate energy-based trade differences and DR offers, and provides a suitable extension of the well-known McAfee's mechanism to facilitate the exchange of joint retailer and end-user offers, in a multi-offer, multi-unit setting so as to reduce zonal imbalances.

Chapter 5 examines and evaluates by simulation the proposed mechanisms from Chapters 3 and 4, under reasonable assumptions, based on data from a survey of UK domestic electricity use.

Chapter 6 presents several automated forecasting methods used to estimate the inflexible net-load on the end-users' side, in order to improve DR offers and thus reduce penalties.

Chapter 7 summarises the results from this thesis and draws conclusions. It also discusses broader implications of the followed approach. In addition, some ideas for future work are outlined.

# Chapter 2

## Background

This chapter provides the necessary background information and discusses the relevant work that justifies the reasoning in the following chapters. First, a basic organisation of the electrical power supply in the UK is presented, and the main challenges of the electricity sector for a low-carbon economy are outlined. Second, the organisation of liberalised wholesale electricity markets is described along with its time frames and participating agents. Third, a brief background on Multiagent Systems (MAS) and its intersection with Mechanism Design (MD) are provided, which includes the main auction protocols used in this thesis for coordinating demand response (DR) efforts. Finally, the related work is discussed and the scientific gap that this work contributes to is formally introduced.

### 2.1 Electric Power Supply

#### 2.1.1 Current Electricity Grid

The current electric power supply, often known as *the grid*, comprises the infrastructure used to generate and deliver electric power for its end-use. The electricity grid has been one of the greatest engineering achievements of the 20th century (U.S. Department of Energy, 2003). It is a *just-in-time* (JIT) production system and supply chain where electricity is generated, delivered, and consumed instantaneously (The Institution of Engineering and Technology (IET), 2013). Historically, in the UK, the US and other industrialised nations, the electric power supply started as localised independent systems that covered limited zones of urban areas, and were managed by a local authority (The Institution of Engineering and Technology (IET), 2013). These independent systems across

one country had generating assets close to the point of delivery. In the UK, for instance, these systems were connected together in the late 1930s by a larger and wider network at national level, known as the transmission system or national grid (The Institution of Engineering and Technology (IET), 2013). Other countries followed different processes towards developing their electricity supply. Regarding the UK, massive power stations were built far away from demand centres and electricity was efficiently transported large distances through the transmission system. This basically allowed for further grid developments, better economies of scale, increased efficiency, and improved security of supply. As a result, the independent systems gradually lost their generation capacity and became the current distribution systems (The Institution of Engineering and Technology (IET), 2013). Later, the grid was nationalised, it became vertically integrated, and so a national monopoly (Electricity Acts 1947 and 1957) (Simmonds, 2002). Further on, with the argument of increasing efficiency, the electric power system evolved into a competition-based grid that became open to private companies so they could take part in electricity generation and retail supply (Electricity Act 1989) (Simmonds, 2002). This process resulted in the unbundling of the grid, the emergence of (liberalised) electricity markets, and the creation of regulatory agencies to ensure proper operation (Utilities Act 2000) (Simmonds, 2002)<sup>3</sup>.

An electrical grid is broadly divided into generating stations, transmission system, and distribution systems. Its design and energy mix vary from country to country. Figure 2.1 shows the basic components of the electric power supply in the UK (excluding renewables) (U.S.-Canada Power System Outage Task Force, 2004; Lincoln, 2011). Most generating stations in the UK are based on fossil fuels, such as coal and natural gas, which accounts for 60% of the total capacity, the rest is from nuclear, renewables and other fuels (MacLeay et al., 2015). Generation and transmission usually take place in a three-phase alternating current (AC) power system. Each coil or winding of a generator is connected to a phase. Phases are conductors that carry high voltage sinusoidal electrical waveforms, offset to provide three complementary currents separated from each other by  $120^\circ$  and oscillating at 50Hz approximately (Lincoln, 2011) (or 60Hz in other countries). The output from a generator, commonly from 11kV to 25kV, is stepped-up to 275kV or 400kV (or 132kV in Scotland) so it can be transmitted over long distances through the transmission network (Lincoln, 2011). Certainly, all these values vary by country. Transmission networks, also known as high-voltage

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<sup>3</sup>Electricity reforms and regulations in the UK have been more convoluted than described in this thesis. More information can be found in (Simmonds, 2002; UK Government, 2016).

(HV) networks, usually have a meshed topology, because it is more resilient to failures and maintenance, since a line can be taken down and the power flow will be redirected over the available lines (Lincoln, 2011). The distribution system starts at the substation where transformers steps the voltage down to 33kV, 11kV or 6.6kV for industrial consumers, and to pole-mounted transformers that step the voltage further down to 400V and 230V for commercial and domestic loads (Lincoln, 2011). Distribution networks, also known as low-voltage (LV) networks, generally have topologies that are less resilient than that of the transmission network; their topology may be a ring circuit (as in some urban areas) or a radial circuit (as in rural areas or less engaged zones) (Lincoln, 2011). Distribution networks end at the customers' meters, where the electric system at the end-users' premises starts and appliances can directly use electricity.

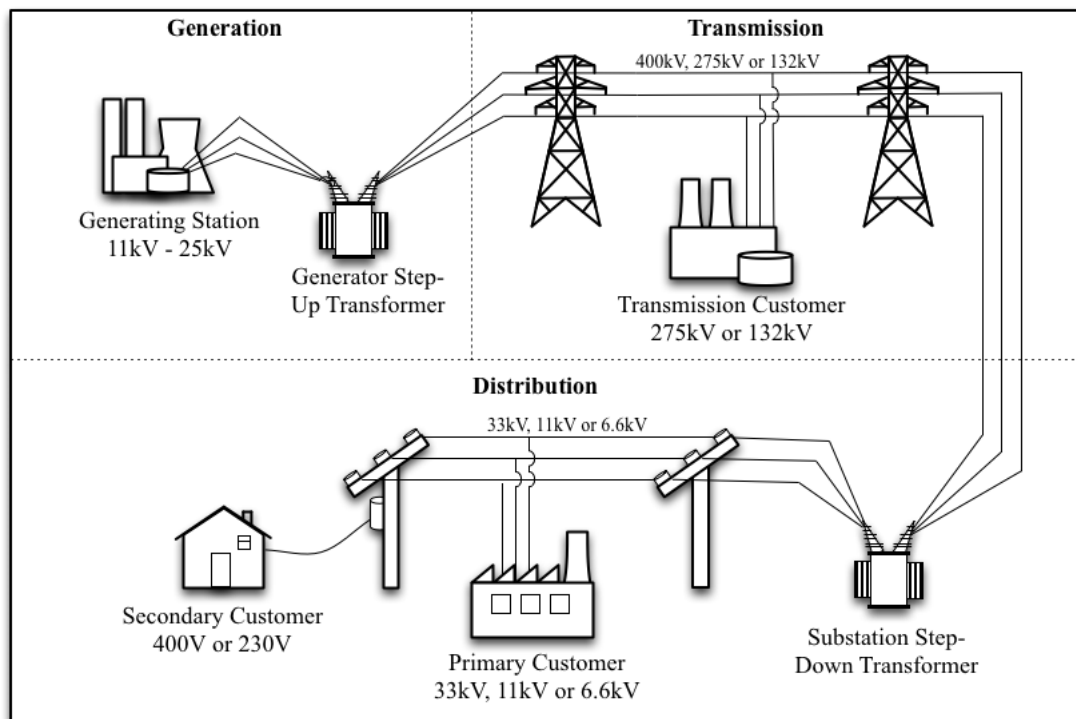


Figure 2.1: Basic structure of an electricity grid.

Although the current grid has served well up to now, the recent efforts towards a low-carbon economy have been pressing for non-trivial changes. This is because the electric power industry has the most potential for reducing greenhouse gas (GHG) emissions, such as carbon dioxide ( $CO_2$ ), methane ( $CH_4$ ) and nitrous oxide ( $N_2O$ ) (MacKay, 2009). These gases result from the combustion of fossil fuels, such as coal, oil, and natural gas, to produce electricity. That is, if electricity can be produced from zero- or



low-carbon sources, it will significantly reduce its contribution to climate change due to GHG. Furthermore, transportation, heating and cooling will soon be powered by electricity, thus reducing the shares of GHG emissions from other sectors, provided that the electricity comes from low-carbon sources. In addition, electricity can be produced from more abundant sources than fossil fuels, thus improving the security of supply; fossil fuels are generally scarce, hard to find, expensive to extract, pollutant, and often inside politically difficult regions (Ramchurn et al., 2012).

### 2.1.2 Near-Future Electricity Grid: the *Smart Grid* Vision

The current grid is aging and unable to cope with the requirements of a low-carbon agenda. The Smart Grid vision rises from the need to guide a collective capital investment amongst the many stakeholders to renew the grid (at least at a national level) and achieve energy security. Stakeholders of the electric power sector include users, generators, electric network companies, electricity retailers, ICT and technology providers, power exchanges, governmental agencies, environmental agencies, researchers, amongst others (U.S. Department of Energy, 2003; European Commission, 2006). Along with this vision, a regulatory framework is notably very important, as it determines the roles and responsibilities of the many stakeholders over the available resources, such as land use, water impact, data collection and privacy policies, etc. Overall, it is a challenging activity to balance the interests of many different parties, but at least this vision sets a common ground for further research, innovation, and development.

Figure 2.2 shows a basic structure of a smart grid that builds on the current electric power grid. Although there is no single agreement on how the future electrical grid should be, common features include (U.S. Department of Energy, 2003; European Commission, 2006; The Institution of Engineering and Technology (IET), 2013; Ramchurn et al., 2012):

- Infrastructure that supports bidirectional flows of electricity, information, and money.
- Emphasis on minimising environmental impact, minimising cost and losses, maximising infrastructure utilisation, and maintaining a service level that is comparable to that of the current grid.
- Integration of DG, including those from intermittent renewable sources.
- Adaptive demand-side to supply conditions.

- Integration of storage technologies at different scales.
- Some attributes include: market-oriented, sustainable, economic, efficient, reliable, resilient, scalable (*plug-and-play* capabilities), compatible with newer appliances, with open architecture and common standards, safe and privacy compliant.
- Smart or with some degree of distributed intelligence to manage a massive amount of heterogeneous DER from many different parties with different (usually selfish) interests.

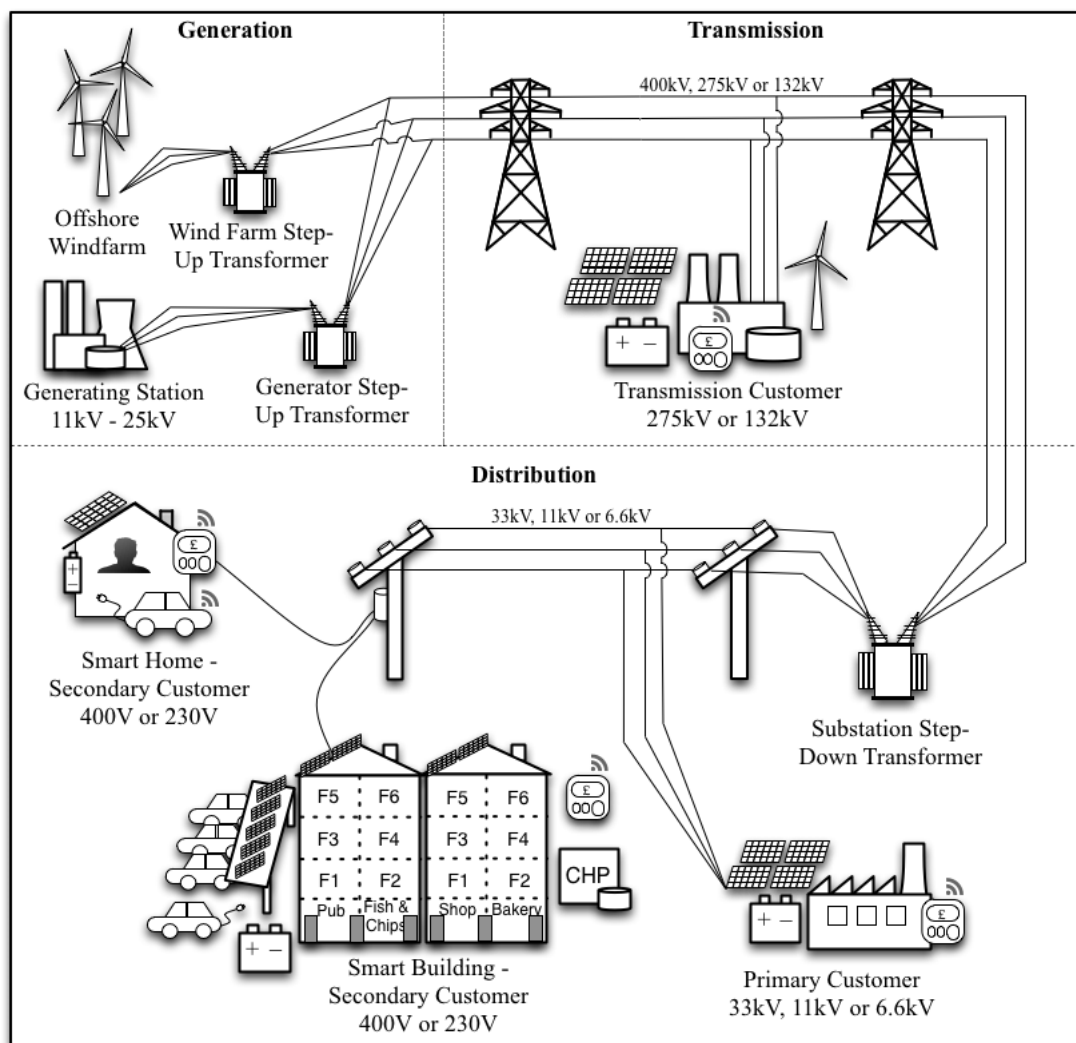


Figure 2.2: Basic structure of a future electricity grid (usually referred as a smart grid).

### 2.1.2.1 Technical Challenges

For the grid to ensure stable operation, it needs to maintain frequency, voltage and current within their limits (The Institution of Engineering and Technology (IET), 2013). Frequency is controlled globally on a second by second basis at which generation and load (i.e., supply and demand) are required to be matched. The frequency will drop if the load surpasses the overall generation, and it will rise if the opposite happens (The Institution of Engineering and Technology (IET), 2013). Failure to keep frequency at their nominal value (approximately 50Hz or 60Hz, varying by country) can cause damage to synchronous machines and other appliances, as well as loss of service, i.e., a potential *brown-out*, or even a blackout (Ramchurn et al., 2012). Voltage is controlled locally at different parts of the grid. Over- or under- voltage cannot only damage end-use appliances, but also compromise some of the grid components, such as transmission wires and transformers, that are essential to maintain the quality of supply (The Institution of Engineering and Technology (IET), 2013). Current is also controlled locally, usually by means of spare capacity (The Institution of Engineering and Technology (IET), 2013). Every device in the grid has an upper limit for current that, if exceeded, it would result in failures and potential outages (also, safe mechanisms might get triggered to prevent damages) (The Institution of Engineering and Technology (IET), 2013). Frequency, voltage, and current are regularly monitored in all or several areas of the transmission system; however, monitoring in the distribution system is less common, since the network is designed to meet voltage limits, and current problems are prevented with protective devices (The Institution of Engineering and Technology (IET), 2013).

The future electricity grid will need far more instrumentation, more resilient network configurations, and a larger set of ancillary services in order to keep the grid within stable operation and accommodate the required changes in an economical way. Some challenges and potential effects include (U.S. Department of Energy, 2003; European Commission, 2006; The Institution of Engineering and Technology (IET), 2013; Ramchurn et al., 2012):

- Replacing of fossil-fired generation with zero or low-carbon generation technologies that are non-dispatchable. Renewable generation usually suffers from intermittency and stochasticity, therefore, prediction errors can become quite problematic. Also, electricity from renewable sources must be prioritised; that means renewable technologies must become cheaper than conventional generation, so

that they are selected first in the merit order (their operational cost is regarded as close to zero as they require no fuels). Nonetheless, the amount of load-following capacity might become larger and presumably more expensive. In addition, nuclear generation has potential to provide the base load, but these plants cannot vary their output as fast as coal- or gas-fired units.

- The power flows in the transmission network can become less predictable due to non-dispatchable generation, and there could cause indirect congestion. In addition, connecting to the distribution network and controlling a massive number of small distributed generators, of several capacities, degrees of controllability/dispatchability, different costs and technical requirements (such as ramp- up/down, pickup/drop rates) can make the distribution system unstable. Potentially millions of users that can produce their own electricity and include loads from heat pumps and EVs can aggravate the peak problems (e.g. EV charging at 7kW for several hours compared to a kettle using 3kW for a couple of minutes (The Institution of Engineering and Technology (IET), 2013), or rapid EV charging at a higher power rate). The low-voltage network would need reinforcement, and perhaps a more resilient design that might support dynamic reconfigurations, due to a wide variety of plug-and-play devices that would be expected to operate.
- The demand-side is expected to be more dynamic. Different dynamics from DR, energy storage, and electricity export to the grid over different schemes, including home-to-grid (H2G), vehicle-to-grid (V2G), and vehicle-to-home (V2H). These dynamics can easily result in less predictable load patterns, and more variable (potentially larger and more frequent) spikes and drops. Also, aggregate net-load patterns could be characterised by prolonged weather-driven mismatches, e.g., during winter, when heat loads increase and solar panels generate less than during summer (The Institution of Engineering and Technology (IET), 2013).
- End-users will require more automation, so that they are able participate more actively responding to supply and demand conditions in the grid (or at least within the distribution system they are connected to). This requires technological investments that need to be economically justified. Amongst these technologies are smart meters, controllers, solar PV, inverters, ICT to enable communications, etc. It is not clear how the end-users' resources will be managed to achieve a common benefit.

### 2.1.2.2 Opportunities for Artificial Intelligence (AI)

Some of the challenges of future electricity grids that AI can help solve (Ramchurn et al., 2012):

- Design of algorithms that can predict energy consumption patterns based on historical data, and learn to adapt their profile against a specific pricing scheme (e.g., RTP, TOU, etc.).
- Development of simulation and predictive tools to assess the consequences of policies or mechanisms with intelligent agents (i.e., end-users represented by a software agent residing in the smart meter).
- Design of decentralised control mechanisms that coordinate DER, including mobile loads such as EVs.
- Design of agent-based models for virtual power plant (VPP) actors so as to capture the complexity of forming and managing them.
- Design of search algorithms and negotiation mechanisms for individual agents to decide which VPP, or cluster of end-users, to form and for how long, as well as how to assess their performance and how to divide the payoff.
- Development of autonomous trading agents that would learn to predict net-load profiles from *prosumers* (i.e., end-users that also generate electricity) and trade in electricity market(s) so as to maximise the expected profit.
- Development of interaction mechanisms between humans and the software agent in the smart meter, so that the former can instruct the latter on preferences and constraints.
- Design of computationally efficient algorithms for network state estimation and automation of strategies for active network management.

### 2.1.2.3 Benefits and Criticisms

One of the benefits of the future electricity grid is that it will improve the energy security while reducing environmental concerns. This implies a more diversified mix of energy sources that are in general more available, as well as the efficient use of technological means to provide at least the same service level and quality of supply as the current

grid. However, the collective investment to renew the grid is massive; although more abundant sources suggest that operational electricity costs will be reduced, the initial investment makes it expensive.

In addition, concerns about smart meters include not only privacy, but also the vulnerability of some end-users that could easily be disconnected from the electric utility if they fail to pay on time. Some privacy and freedom is given away in exchange of a more sustainable electricity supply. Furthermore, cybersecurity is essential, as cyber attacks could jeopardise the stability of the grid and its components, as well as the end-users' appliances.

According to European Commission (2006), in the grid of tomorrow, the users will specify the quality of service. However, end-users would basically be given no option but to trade off the cost of supply vs. their needs and preferences. Also, smart grids are usually advertised as enabling the customer to actively take part in the electric power supply, however, some protection for end-users will be needed. First, why would an end-user actively participate in the smart grid? Either the cost of electricity would have to be expensive under some conditions and cheaper in others so the rational end-users have incentives to guide their consumption, or selling electricity is justifiably profitable (at least under some conditions). Taking a stance on liberalised electricity markets, at least theoretically, consumers benefit from competition in the supply-side; however, it is not clear what would it mean to have competition from the demand-side at retail level, where end-users would compete to be served, as this might not result in abundantly cheap electricity. In my personal opinion, it is clearly not desirable for consumers to compete for this service, although one could argue that end-users would find innovative ways of using electricity more economically. In this vein, the consuming end might require protection through policy so they get a fair service, for instance by using cap prices that are not too tight for retailers to compete over (Littlechild, 2000), without leaving (domestic) end-users vulnerable to market forces.

## **2.2 Electricity Markets**

The privatisation of the previous national monopoly-based electricity supply system in some countries has restructured the electric power sector and brought about the emergence of electricity markets. Chile pioneered the liberalisation of their electricity sector in 1982 (Conejo et al., 2010, Ch1). The UK followed as the first industrialised country and created the pool market in England and Wales in the early 1990s (Conejo et al.,

2010, Ch1). In the late 1990s, electricity markets started to operate in other countries, such as, New Zealand (1996), Australia (1998), and the East Coast of the USA (e.g., PJM in 1997, ISO New England in 1999 and New York ISO in 1999) (Conejo et al., 2010, Ch1). Similarly, other regions followed the liberalisation of their electricity sector, while in others it still remains as a national monopoly.

In a traditional regulated electricity sector, a company has a monopoly for supplying electricity to end-users within a geographical area (Kirschen and Strbac, 2004, Ch1). Following a liberalisation, the electricity supply system passed from being vertically integrated to become unbundled, open to private companies to participate in the the electricity delivery chain (Kirschen and Strbac, 2004; Simmonds, 2002). As a result, generation-related activities and network-related activities have been separated, so that competition could be introduced at some of the echelons of the electricity delivery chain (Kirschen and Strbac, 2004, Ch1). The electricity delivery chain is generally divided into generation, transmission, distribution, supply, and demand (customers), and private companies may take part in one or more of these echelons.

In this thesis, electricity markets provide the time framework and rationale for the agents modelled in further chapters. The following sections provide a brief description of market participants, a general organisation of the marketplace, and a brief description of the UK's electricity market including some of its most common DR services that are currently available.

### 2.2.1 Market Participants

Electricity market agents participate buying and/or selling electricity depending on their interests. Their objectives, constraints and dynamics differ from each other. Also, they can be subject to different regulatory frameworks or benefit from various tax incentives (such as the case of renewables in some countries). Amongst these participants, the most common ones are<sup>4</sup>:

- **Generating companies (*gencos*):** they produce and sell electricity. These companies own a power plant or a portfolio of different technologies for electric power generation, such as conventional steam stations, nuclear stations, combined cycle gas turbines (CCGT), etc. (Simmonds, 2002). They may also sell services like regulation, voltage control, and reserve capacity (Kirschen and Strbac,

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<sup>4</sup>Brokers, marketers, and aggregators could also be present in electricity markets, however they usually represent one or some of the described participants, optimising their own portfolio and being paid a fee.

2004, Ch1). Moreover, they may be non-dispatchable (e.g., wind or solar farms), and their selling strategy and services they provide will depend on their ability to deliver them (Conejo et al., 2010, Ch1).

- **Transmission companies (*transcos*):** they transfer electricity from generators to distribution systems. They own transmission assets such as overhead lines, underground cables, transformers, and reactive compensation devices (Kirschen and Strbac, 2004; Simmonds, 2002). They are regulated and operate according to instructions of the independent system operator (ISO) (Kirschen and Strbac, 2004, Ch1). These companies may be subsidiaries of gencos (Kirschen and Strbac, 2004, Ch1); however, in a liberalised setting, they are heavily regulated to guarantee equal access to gencos, because transcos constitute natural monopolies (Simmonds, 2002).
- **Distribution companies (*discos*):** they own and operate low-voltage distribution networks (Kirschen and Strbac, 2004, Ch1). Similar to transcos in conventional settings, discos also constitute natural monopolies for selling electricity to all end-users connected to their network (Kirschen and Strbac, 2004; Simmonds, 2002). However, under a liberalised setting, the operation, maintenance and development of the network is decoupled from the sale of electricity, so that competition can be introduced in the retail market (Kirschen and Strbac, 2004, Ch1); therefore, regulation must guarantee equal access to all electricity retailers under this scheme (Simmonds, 2002).
- **Retailers:** these entities provide electricity to consumers that not participate in electricity markets, such as commercial and domestic users (Conejo et al., 2010, Ch1). Retailers rarely own production assets and their main interest is to maximise profit through trading (Conejo et al., 2010, Ch1). They do so by signing contracts and procuring electricity at the least cost possible and selling it to consumers at some, usually capped, retail price (Conejo et al., 2010, Ch1). If the retail price is not competitive enough, consumers might decide to switch to a more competent retailer, subject to contract constraints, thus impacting the potential profit making from the former retailer. In addition, to keep competitive prices, retailers try to minimise risk/penalties due to schedule deviations.
- **Small consumers:** they are connected to a local distribution network (i.e., they lease a connection from their local distribution company), and they are served by



their chosen retailer (Kirschen and Strbac, 2004, Ch1). These consumers do not participate in the wholesale market; their participation is limited to choosing a retailer, according to their preferences (e.g., customer service, contracts), if they have this option (Kirschen and Strbac, 2004, Ch1).

- **Large consumers:** these are usually industrial end-users that may procure electricity from the wholesale market. These participants want to minimise the procurement cost while maximising their electricity use benefit (e.g., maintaining a reasonable comfort level, or avoiding inconvenient changes to their production plan) (Conejo et al., 2010, Ch1). Apart from participating in pool markets, these consumers can sign bilateral contracts (with producers and retailers), forward contracts and options (Conejo et al., 2010, Ch1). If available, they can also participate in reserve markets providing DR services (Kirschen and Strbac, 2004; Conejo et al., 2010), such as load-shedding services during the peak load.
- **Independent system operator (ISO):** this is usually a non-for-profit entity that is in charge of the technical management of transmission and distribution systems so as to maintain the security of the power system (Conejo et al., 2010, Ch1). It owns assets for monitoring and controlling the electricity grid (Kirschen and Strbac, 2004, Ch1). In liberalised electricity markets, it oversees the operation so that market participants are not favoured or penalised unfairly (Kirschen and Strbac, 2004, Ch1). Furthermore, the ISO usually operates a market of last resort to procure services for meeting technical constraints, such as maintaining frequency and voltage (Conejo et al., 2010, Ch1).
- **Market operator (MO):** it is responsible for the economic management of the wholesale market place (Conejo et al., 2010, Ch1). It typically matches bids and offers from electricity buyers and sellers, ahead of the time of delivery, and takes care of the settlement amongst the parties (Kirschen and Strbac, 2004, Ch1). Typically, MOs are independent for-profit companies (e.g., APX, North Pool Spot) (Kirschen and Strbac, 2004, Ch1).
- **Regulator:** it is usually a government-based institution that oversees and ensures a competitive and adequate functioning of these markets (Conejo et al., 2010, Ch1). It determines the policies of market operation, sets the prices of regulated monopolies, and investigates suspected cases of market abuse (Kirschen and Strbac, 2004, Ch1).

Electricity markets provide the rules and means of coordination, so these participants can come together to trade electricity. Apart from electric power, other commodities such as reserve, regulation or load following capability, and balancing energy can also be traded, but electric energy is the main product (Conejo et al., 2010). The market's competitive framework has been intended to increase operational efficiency, while guaranteeing acceptable quality at reasonable cost to end-users (Conejo et al., 2010). Moreover, this framework provides better incentives for capital formation, research and innovation (Conejo et al., 2010). However, in practice, markets are exposed to design flaws and exploiting practices, such as tacit collusion<sup>5</sup> and cartel-like<sup>6</sup> agreements. Therefore, regulating authorities must consider a careful market organisation so that these cases are limited and detectable.

### 2.2.2 Market Organisation

Electricity trading in most European countries and the USA are organised into bilateral contracts, futures market and pool markets. Brief general descriptions are presented below; these descriptions depend on the market rules defined by the regulatory framework in each specific country (Conejo et al., 2010, Ch1). Most of these markets work as double-sided markets/auctions or exchanges where sellers (e.g., conventional gencos, non-dispatchable gencos) submit selling offers (also known as asks) and buyers (e.g., consumers, retailers) submit purchasing bids. The MO, or in some cases the ISO, clears the market with an optimisation procedure, and the result is the accepted energy quantities (generation and load schedules) and their respective trading prices in that particular market.

Offers and bids are matched in a merit order basis, i.e., the cheapest first for offers and the most expensive first for bids. Figure 2.3 shows the basic structure of offer and bid curves that are submitted to the MO. An offering curve, for a specific time period, is formed by pairs of energy blocks and minimum prices at which the trader will sell, usually reflecting the seller's cost structure, arranged in non-decreasing order. On the other hand, a bidding curve, for a determined time period, consists of pairs of energy blocks and maximum prices at which the trader is willing to buy, usually reflecting the bidder preferences, arranged in non-increasing order. The offer curves and bid curves are submitted for each time period of the market horizon.

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<sup>5</sup>In tacit collusion, companies agree or just follow the premise of not cutting price(s) and not using excessive advertising (as it is costly too).

<sup>6</sup>In a cartel, competing firms agree to control prices and/or block new competitors in the market.

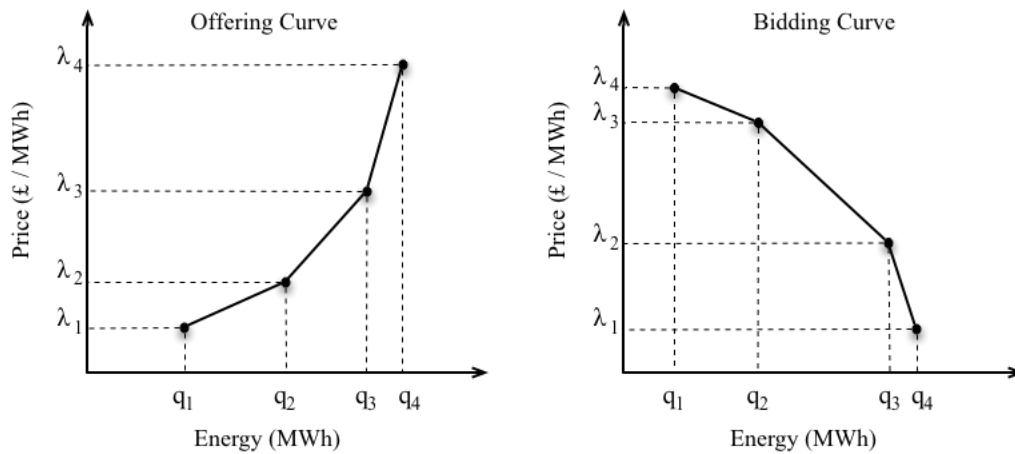


Figure 2.3: Offering and bidding curves.

Electricity markets can have different pricing rules. If discriminatory pricing is used, accepted offers and bids are sold and purchased at different prices, these could be their listed prices, or prices that account for congestion and losses in the transmission lines, i.e., locational marginal prices (LMP). If non-discriminatory pricing is used, then the MO clears the market at a single price, that is, a uniform clearing price is collected or paid for the matched offers and bids. Sequentially arranged markets in time contribute to approximating and fixing schedules, in order to reduce anxiety to big fluctuations or scarcity of supply, as well as to be able to anticipate certain conditions (from the market outcomes) so that the ISO can take actions promptly.

Electricity trading in a liberalised setting commonly falls in one of the following categories (Conejo et al., 2010):

- **Bilateral contracts:** these are free arrangements between two parties, usually between supplier and consumer, and take place outside the marketplace (e.g., a contract between a generator and a supplier/retailer, a contract between a retailer and a household customer). These can also be over-the-counter (OTC) contracts, that are usually mediated by a broker.
- **Futures market:** the products traded in this market comprise medium- and long-term horizons, such as months, quarters and years (weeks are also possible). The products (also known as derivatives) are standardised and the prices are known beforehand. For instance, contracts or options to buy or sell electricity during time periods that share specific patterns, such as off-peak or peak (or, valley, shoulder, peak; at weekdays or weekends, etc.). Generally, this market is cleared

by the MO that in some countries it could be a for-profit organisation, e.g., APX. This market is used as a tool to hedge against uncertainty in pool prices, which usually exhibit high volatility.

- *Forward contracts*: these are signed agreements that state a determined amount of electricity delivery (or use) at a future time period, at a fixed price per kWh (or MWh). Contractual agreements are added to the trading schedule of market participants.
- *Options*: these are financial products that corresponds to an agreement of having the choice of delivering or consuming a specified amount of energy in a future time period. Signing involves a payment known as premium, regardless whether the option is used or not.
- **Pool market**: it is usually referred as *the pool*. The pool is a market for short-term trade, and it is comprised of sequentially arranged markets, whose horizons vary from one day to a half an hour, or even closer to the point of delivery (to near real-time delivery). Generally, these markets are cleared by the MO as opposed to reserve and regulation markets, where the ISO needs to intervene. Depending on the specific market rules, the clearing of the pool may take into account the transmission network constraints and compute LMP.
  - *Day-ahead market*: it covers the bulk of energy within a day. This market is cleared once a day, several hours before the actual day/time of delivery, for all time periods during the trading day. Market agents submit non-decreasing offer curves and non-increasing bid curves for each of the time periods during the day. These curves represent their trading preferences under competition, and reflect the minimum or maximum prices at which they will trade. The result of this market is the accepted quantities and prices per time period.
  - *Adjustment market(s)*: it is sometimes referred as intra-day market(s). Depending on the market design, there could be more than one adjustment market. They are similar to the day-ahead market, but they are cleared closer to the time of delivery and can cover shorter horizons than a day. Basically, it is used to tailor positions previously traded in the day-ahead. Non-dispatchable producers tend to rely more on these markets because the

forecasts are more accurate as they get closer to the time of delivery/production (as compared to conventional producers).

- *Balancing market(s)*: it is sometimes referred as spot market. This market is used for last minute adjustments to cover for deviations from previously traded positions in the day-ahead and adjustment markets, generally caused by forecast errors, and sometimes transmission constraints. This market is cleared once per time period, i.e., hourly or half-hourly (in some cases it could even be cleared several times per time period). The result of this market is usually a settlement of two ex-post imbalance prices (depending on the market design, it could be one or two prices; the latter is regarded as a better approach to avoid arbitrage, and these prices also depend on whether the system is in deficit or excess).
- **Other markets**: these are to ensure secure system operation and energy delivery, i.e., avoid lost of load (LL) due to current supply scarcity or transmission congestion (sometimes the reserve is used to relieve congestion). Generally, these markets are cleared by the ISO (which is usually a non-for-profit organisation).
  - *Reserve market*: it clears once a day and consists of stand-by power (spinning and not) to cover for failures (e.g., a damaged generator, transmission lines that are being taken down for maintenance), large load fluctuations, and intermittent renewable generation from non-dispatchable sources. Usually, energy and reserve are co-optimised within the same clearing optimisation problem (jointly or immediately after the day-ahead market clearing process). This market is seen as a capacity market (capacity commitment) that guarantees enough back-up generation. As a general practice in most power markets, the reserve is at least of the size of the capacity of the largest generation unit plus some fraction of the peak load, although other factors are considered like transmission lines, general availability, anticipated prediction errors, how fast they can respond, etc. Generally, this capacity is offered by dispatchable producers, however, there could be available DR instruments that large (industrial) consumers can offer such as agreeing to reduce consumption by a pre-specified band/amount at command of the ISO.
  - *Regulation market*: it clears once a day on an hourly or half-hourly basis and it assigns production units that can provide up and down real-time load-

following capability to power bands. This market enforces a continuous balance between generation and load. Similar to the reserve, this market is a capacity market and clears several hours prior to power delivery. It allocates load following bands (or ranges) amongst production units with capability and rational interest in load following services. The ISO determines the amount for regulation and runs an auction with an increasing price rule to procure the determined level (of course this procedure may vary). The bands specify the amount of power up and down (for load-following) for a specified time period at the command of the ISO.

- *Other services*: these might cover reactive power management and voltage control, system restoration after a blackout, and other technical aspects.

### 2.2.3 UK Electricity Market and its DR Programmes

Liberalised electricity markets in the UK started with the creation of the England and Wales Electricity Pool in March 1990. This was a centralised one-sided pool market whose main characteristic would be to decrease prices to consumers by introducing competition in the supply-side. However, there were concerns about the market power that generators had, their ability to manipulate prices, the lack of involvement from the demand-side (retailers, suppliers that would buy from generators, and large consumers), and the pricing mechanism was considered not very transparent (Tovey, 2005; Onaiwu, 2009). Because of these concerns, the New Electricity Trading Arrangements (NETA) reform was introduced in March 2001. This reform replaced the pool with bilateral trade that gave freedom to generators and suppliers/retailers to negotiate between themselves, in a decentralised fashion, relying on self-dispatching (Tovey, 2005). In April 2005, under The Energy Act 2004, Scotland was included in a new reform, the British Electricity Transmission and Trading Arrangements (BETTA). Within BETTA, traders can negotiate and trade contracts at will, to be fulfilled in a future period of time, and are negotiated from any time up to the *Gate Closure* (one hour and a half before delivery), when no more trading is allowed for the specific time period (Onaiwu, 2009). After the gate closures, traders reveal their contracted position to the ISO, so that it can procure for balancing and ancillary services, in order to balance supply and demand (Elexon, 2014; Onaiwu, 2009). Deviations from contracted positions result in the obligation to cover the differences at the imbalance prices for the specific time period, determined by the ISO. If a party under-generates or over-consumes compared to its contracted

volume, it is required to buy the deficit at the System Buy Price (SBP). Similarly, if a party over-generates or under-consumes compared to its contracted volume, it is required to sell the excess at the System Sell Price (SSP) (Elexon, 2014). These prices reflect the cost of balancing actions undertaken by the ISO, which essentially consist of hierarchically triggering previously procured balancing services that are provided by certified companies.

### 2.2.3.1 UK Balancing Services

The UK National Grid, as the ISO, offers several DR programmes so that companies can participate as providers of ancillary services and generate some profit while helping the ISO to meet technical constraints (UK National Grid, 2017). There are two main categories of response services: primary, and secondary. *Primary response* must be fully available within 10 seconds of an event, and continuously deliver for 20 seconds more (Kirschen and Strbac, 2004). *Secondary response* must be fully available within 30 seconds and be sustained for further 30 minutes (Kirschen and Strbac, 2004). The UK National Grid determines the response time, volumes, and other conditions of service. Some of the available programmes in the UK are the following (UK National Grid, 2017; Proffitt, 2016):

- **Frequency response:** system frequency is a measure of the balance between generation and load. Frequency rises when there is more generation than load in the system, and it falls when load is higher than generation. The UK National Grid is bound to maintain frequency within plus and minus one percent of 50 Hz. Therefore, it must ensure that there are enough resources, such as generation and demand responsive services, to satisfy the load under frequency constraints. Usually, frequency response is either static or dynamic. *Static frequency response* is triggered at specified frequency values (or bands) with the aim of keeping it within set limits in case of a fault or unexpected events. *Dynamic frequency response* deals with frequency under normal operation and it is continuously provided as an automated service. Some of the available frequency response services include:
  - *Firm Frequency Response (FFR):* providers of FFR must deliver a minimum of 10 MW to the grid within 30 seconds of a frequency event. These providers go through a certification process and tender in to supply this service for one or multiple months. Companies that cannot deliver 10 MW of

volume can provide frequency response through *FFR Bridging*, a similar programme to build up the required volume over a set time frame (e.g., one or two years).

- *Frequency Control by Demand Management (FCDM)*: providers of FCDM reduce their net-load by a minimum of 3 MW, so that frequency increases. They must be able to respond within two seconds and sustain the load reduction for a minimum of 30 minutes. This programme is generally suitable for customers who use large amounts of electricity. To participate in this programme, they must have a suitable operational meter and frequency relay device to automatically interrupt some of their electricity load when frequency falls from a pre-set value.
- *Enhanced Frequency Response*: providers of this service must respond in less than a second and sustain the full amount of agreed power for at least nine seconds. Moreover, this programme is a dynamic service, in which providers must be ready to continually vary their response (generation or load). This programme is in development, and the National Grid might adjust the service requirements as it sees fit.
- **Reserve Services**: these are sources of additional generation or load reduction that the National Grid can use in case of unforeseen events, such as a power plant tripping out, or an unexpected sudden load increase.
  - *Short Term Operating Reserve (STOR)*: this service requires providers to deliver a minimum of 3 MW generation or steady net-load reduction. In general, depending on the service contract requirements, providers must respond in less than 20 minutes and continuously deliver the contracted power for a minimum of two hours. Also, the National Grid requires these providers to be able to deliver a minimum number of times per week, currently three times.
  - *Fast Reserve*: providers of this service must respond very rapidly to deliver a large amount of MW within a small time frame, that is usually to cope with huge surges in demand, such as during TV pick-ups when a large number of people turn on their kettles during a TV advert break. The active power delivery must start within two minutes of dispatch instruction, provide a rate higher than 25 MW/minute so that it can reach 50 MW within four



minutes, and it must be sustained for a minimum of 15 minutes. Examples of technologies that can provide this rapid response are pump storage and combined cycle gas turbines.

- *Demand Turn Up*: this balancing service is used to increase the load when there is more generation, for instance overnight or when there is an unexpected excess of renewables. Providers are expected to respond within ten minutes of a signal, and sometimes the service can be requested for the day-ahead. It is therefore a way to incentivise businesses to use more electricity when demand is low. These providers are currently paid an availability fee, and something between £60-£75 per MWh, which reduces their running costs.
- *Demand Side Balancing Reserve (DSBR)*: this programme is only available during the winter period, and consists on reducing electricity use (or using on-site generation) between 4pm and 8pm during weekdays in exchange for a payment. Any business that is subject to half-hourly metering and has a stable, high demand can participate. The response time needs to be at least two hours, and payments can be quite substantial (currently up to £16,000 per MW of demand reduction from 2016/17).
- **Capacity Market**: this market allows the National Grid to ensure that there will be sufficient capacity of electricity supply to meet future demand. The National Grid runs two auctions to procure long-term capacity: (1) T-4 auction, that is the main auction and runs every year for contractual obligations to deliver capacity in four year's time; and (2) T-1 auction, that is a top-up of the T-4 auction and allows businesses that would not take longer contractual obligations than one year to participate, and it also runs annually.
- **Others**: DR to reduce transmission network use of system (TNUoS) and distribution use of system (DUoS) costs.
  - *Triad management*: the UK National Grid charges transmission costs to half-hourly metered consumers using three half-hours, or triads, with the highest system demand. Each of these consumers pay transmission costs that are directly proportional to the electricity they used during this triads. These half-hours (triads) must be separated by at least ten days; they usually happen between November and February, and typically between 4pm and

7pm. Therefore, if consumers are able to identify the triads (generally by assistance from their electricity retailer) and take action to reduce their load through DR, then they can reduce their annual transmission costs. Non half-hourly metered consumers are charged on the same triads, but using a consumption estimate.

- *Distribution time bands management*: DUoS are in essence similar to TNUoS, that is, they contribute to the operation, maintenance and development of the network. However, DUoS are computed differently. Discos post distribution charges for three time bands, which are significantly different from each other. The time band corresponding to the peak load is much more expensive than the off-peak band. Therefore, using DR actions to shift the load to off-peak times helps the electricity retailer, and potentially the consumer if its contract reflects direct savings over distribution costs.

## 2.3 Multiagent Systems and Mechanism Design

Multiagent systems methods and algorithms have recently received substantial attention as suitable approaches to deal with the challenges of the Smart Grid vision.

### 2.3.1 Intelligent Agents

According to the Oxford English Dictionary, the word agent comes from the Latin *agere*, which means *doing*, and refers to ‘someone or something that produces an effect’. In a general sense, an agent is regarded as someone or something that acts on behalf of another someone or something within a specific environment. In Computer Science and Artificial Intelligence (AI), agents are expected to not only do something, but also do it with some degree of intelligence in order to achieve a desired outcome. AI mostly deals with agents that are rational<sup>7</sup>, that is, they do the *right* thing within the environment they act upon (Russell and Norvig, 2010). Russell and Norvig (2010, p.37) provide the following definition for rational agent: “For each possible percept sequence a rational agent should select an action that is expected to maximise its performance measure, given the evidence provided by the percept sequence and whatever built-in knowledge

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<sup>7</sup>There have been studies in AI that model non-rational agents using human-like mentalistic notions, such as knowledge, belief, intention and obligation (Shoham, 1993), and emotions (J. Bates, 1994). There are good reasons for such studies, however they are not relevant to this thesis.

the agent has". In an AI sense, rational agents can become *intelligent* by incorporating learning<sup>8</sup> capabilities to update their built-in knowledge or model, and reasoning over it, so as to better meet its design objectives. Figure 2.4 shows a basic representation of an intelligent agent interacting with its environment.

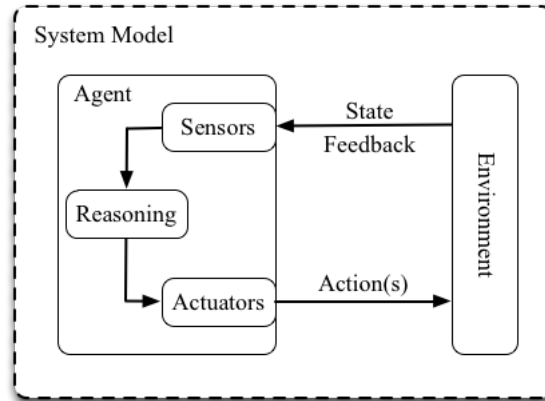


Figure 2.4: A basic notion of an agent.

Wooldridge and Jennings (1995) describe weak and stronger notions of agency, as well as they provide some attributes of intelligent agents, the most relevant for this thesis are:

- **autonomy**: agents operate without explicit guidance (from humans or other agents), and have control over their actions and internal state;
- **social ability**: agents interact with other agents or humans (using a common language, passing messages);
- **reactivity**: agents perceive their environment and respond promptly to its changes;
- **pro-activeness**: agents take the initiative and pursue their design goals;
- **rationality**: agents act to maximise their expected performance measure toward their design goals.

A *Multiagent System* (MAS) is one that consists of interacting intelligent agents. The agents usually interact through a telecommunications network exchanging messages.

<sup>8</sup>Sometimes learning is either not central to the system design or undesirable as it can lead to agents changing their behaviour during runtime (see, for instance (Wooldridge, 2009)). Although in this thesis learning is not central, it is highly desirable to derive more profitable outcomes.

Agent interactions usually include some sort of cooperation, coordination, competition and negotiation in order to achieve individual objectives (Wooldridge, 2009). There are two fundamental problems when designing multiagent systems: (1) the agent design and, (2) the society design. The first one concerns with individual objectives, the modelling of an agent's internal state, learning and adaptation to changes in the environment. The second one deals with defining protocols or rules of interaction, as well as achieving desired outcomes in the agent society (in some cases they are not explicit, in others they are studied as a result of agent interactions).

Furthermore, other researchers classify agents into different types or at least they distinguish some properties concerning their internal state, such as reflex agents, model-based agents, utility-based agents, learning agents (Russell and Norvig, 2010). In this particular case, the agents are model-based utility-based<sup>9</sup> agents, and learning is not essential, but highly desirable. MAS incorporates theory from other fields, such as economics, game theory, operational research, control theory, complex adaptive systems, computer science, distributed AI, machine learning, and others.

### 2.3.2 Task Environment

Russell and Norvig (2010) describe the task environment as the 'problem' to which rational agents are the 'solution', and describe the following properties that are useful for the environment specification:

- **Fully observable vs. partially observable**<sup>10</sup>: if an agent can perceive the complete state of the environment at each period of time, then is fully observable, and partially observable otherwise (or unobservable in some cases).
- **Single agent vs. multiagent**: the environment is single-agent when there is one agent interacting only with its environment. Depending on the modelling abstraction, the environment can encompass other agents not being modelled independently and aggregated into the environment dynamics. When an agent needs to interact with other agents to achieve its goals, then is a multiagent environment. This interaction can be directly or indirectly through commonly understood protocols and communications. Furthermore, the environment can be cooperative or competitive.

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<sup>9</sup>In this case, utility is an economic term that is used as a measure of performance and describes how 'happy' the rational agent is after an outcome is realised.

<sup>10</sup>Previously referred as accessible vs. inaccessible in (Russell and Norvig, 1995).

- **Deterministic** vs. **stochastic**: the environment is deterministic if its next stage is completely determined, and stochastic otherwise. The stochastic nature is associated with uncertainty and implies that the possible outcomes are quantified by their respective probabilities.
- **Episodic** vs. **sequential**: if an agent's decisions are independent, then the environment is episodic. On the other hand, if an agent's current decisions could affect future decisions, then the environment is classified as sequential. In sequential environments, the agents need to think ahead. There could also be episodes or rounds of sequential decision making, in such case what is relevant is the focus of the problem.
- **Static** vs. **dynamic**: the environment is static if it does not change while an agent is reasoning, and dynamic otherwise.
- **Discrete** vs. **continuous**: this distinction applies to how the environment states are being modelled, how the time is treated and how the agent's percepts and actions are characterised. Discrete refers to finite sets of states, time periods, percepts, and actions; continuous refers to an infinite number of any values, perhaps within a range, that the states, time periods, percepts and actions can take.
- **Known** vs. **unknown**: if the environment is known, the outcomes or their respective probabilities are given for all actions. On the contrary, if the environment is unknown, the agent has to figure out how the environment works to make good decisions.

From these properties, the environment for the computational model and market-based mechanisms that this thesis deals with are the following. The environment is: *partially observable*, as agents (retailers and end-users) cannot perceive what other agents are doing; *multiagent*, since there are several agents interacting simultaneously through auction-based protocols; *stochastic*, because DR offers are based on forecasts and might not be fully delivered by the end-users; *episodic*, due to simplicity reasons and better forecast accuracy for a single step ahead, future work will consider a sequential setting, for the purpose of this thesis the agents are myopic; *static*, because each retailer serves a fixed population of end-users and the proposed mechanisms do not change with time, only the parameters can be tuned, but this is not done online; *discrete*, since time is modelled discretely, so that the auctions are run periodically at every time period; and *known*, as the interaction rules are common knowledge amongst the agents.

### 2.3.3 Mechanism Design

Mechanism design is a subfield of economics that is interested in implementing a societal outcome amongst multiple strategic self-interested agents that have private preferences on this outcome. It relies on the rationality assumption and mathematical models from game theory so that a mechanism that implements a desired outcome can be engineered in strategic settings. Classic examples of these mechanisms are political elections and auction markets. Mechanism design plays a major role in several disciplines and it is widely used in economics (e.g., electronic market design), operational research and computer science. For instance, several market-based coordination mechanisms have been proposed in the literature to solve resource and/or task allocation problems. Some examples include: airport takeoff and landing allocations (Rassenti et al., 1982), Federal Communications Commission (FCC) for spectrum allocation (McMillan, 1994), supply chain formation (Babaioff and Walsh, 2005), multi-robot coordination (Dias et al., 2006), wholesale power exchanges (O’Neill et al., 2007), grid computing services (Moßmann et al., 2010), electric vehicle charging (Gerding, Robu, et al., 2011; Robu, Stein, et al., 2011; Stein et al., 2012; Gerding, Stein, et al., 2013), coordination for a smart electricity grid (Kok, 2013), emission trading schemes (European Commission, 2016), and others.

The following subsections go through most of the concepts that are relevant to this thesis, from a computer science perspective. A more thorough introduction to the subject, including computational aspects, can be found in (Nisan, Roughgarden, et al., 2007, Ch9), (Shoham and Leyton-Brown, 2008, Ch10&11), and (Parkes, 2001, Ch2&3).

#### 2.3.3.1 Basic Concepts

The following concepts assume that money is used to express a degree of willingness or preference over outcomes, and it can be transferred amongst the participating agents in a mechanism.

- **Type:** the type of an agent corresponds to its preferences over the different outcomes of the mechanism. The type of agent  $i$  is given by a valuation function  $v_i: O \mapsto \mathbb{R}$ , where  $O$  is the space of outcomes and  $v_i(o)$  determines how preferable is outcome  $o$  to agent  $i$ .
- **Strategy:** a strategy is a policy that maps every state of the world to an action.

For instance, in ascending auctions, an agent's strategy refers to how much the agent bids with regard its private valuation of the good(s) being auctioned, by how much it will increase its bid at every round, etc.

- **Utility:** it is the benefit that an agent gets from the outcome of the mechanism, given its preferences and strategies. Let  $p$  be a payment that agent  $i$  receives from the mechanism, its utility then is  $u_i := v_i(o) + p$ . Payment  $p$  could be negative to denote a cost, or the payment the agent makes to the mechanism.
- **Quasilinear preferences:** this concept refers to utility functions that allow the separation between valuation (type) and payment, and are both linearly dependent.
- **Revelation principle:** this fundamental principle in mechanism design states that if an arbitrary mechanism implements a social choice function, then there exists a truthful mechanism (i.e., one in which agents are directly asked to reveal their private preferences truthfully) that implements the same social choice function. Furthermore, the expected payments, from and to the agents, are identical in the truthful mechanism to those of the arbitrary mechanism in equilibrium. This principle applies to dominant-strategy incentive-compatible (DSIC) and Bayesian-Nash incentive-compatible (BNIC) implementations.

### 2.3.3.2 Main Properties of Mechanisms

- **Incentive compatibility (IC):** this means that every agent is better off reporting their type honestly to the mechanism.
  - DSIC: in this IC implementation, every agent is weakly better off (i.e., never worse) by reporting truthfully, regardless of the strategies of the other agents. Mechanisms with this property are also called truthful or *strategy-proof*.
  - BNIC: in this solution concept, every agent is weakly better off by reporting their preferences honestly, provided that there is a Bayesian Nash equilibrium in which all agents reveal their true preferences. This is a weaker notion of IC than DSIC.
- **Individual rationality (IR):** this property is also known as voluntary participation and it holds when every agent is not worse off by participating in the mechanism.

ism. That is, agents weakly prefer to participate in the mechanism. IR is further described by the following three degrees:

- *Ex-post* IR: this is the strongest notion of IR and it requires that agents' utility is never worse by participating in the mechanism.
  - *Ex-interim* IR: given prior beliefs of the preferences of the others, the expected utility of an agent is weakly better when it participates in the mechanism.
  - *Ex-ante* IR: in this case, the agents do not know their preferences and have no prior knowledge about the preferences of the others. Then, the expected utility of the agents, averaged over all possible preferences, is at least their expected utility when they decided not to participate.
- **Budget balance (BB)**: this property requires that the amount of payments collected from the agents by the mechanism equals the amount of payments made to the agents by the mechanism. There are two notions of BB:
    - Strong BB: it requires that the mechanism never makes neither profit nor loss.
    - Weak BB: this notion of BB requires that the mechanism never runs a deficit, but it is allowed to make profit.
  - **Allocative efficiency (AE)**: the chosen societal outcome maximises the sum of reported valuations from the participating agents in the mechanism. It is traditionally seen as an outcome that puts the goods into the hands of those who value them the most.

### 2.3.3.3 Vickrey's Auction and VCG Mechanism

The well-known Vickrey's seal-bid second-price auction is a very simple and remarkable idea that is strategy-proof and economically efficient (Vickrey, 1961). It puts a single item into the hands of the agent who values it the most, but the winning agent pays the reported valuation by the runner-up. That is, winning agent  $i$  pays price  $p := \max_{j \neq i} v_j$ . Moreover, rational manipulation cannot yield a higher utility for the agents.

The Vickrey (1961)-Clarke (1971)-Groves (1973) mechanism is a generalisation of Vickrey's second-price auction, in which there are multiple items and multiple units



that are to be allocated amongst several participants.

Under quasilinear preferences, the outcome of a mechanism is determined by an allocation rule and a payment rule. The allocation function  $f: V_1 \times \dots \times V_n \mapsto O$ , where  $V_i$  is all valuations available to agent  $i$  and  $O$  is the space of outcomes. The payment function  $p_i: V_1 \times \dots \times V_n \mapsto \mathbb{R}$ , for each agent  $i$ . The VCG allocation function, given a vector of valuation functions  $v$ , is computed such that:

$$f(v) := \arg \max_{o \in O} \sum_{i \in N} v_i(o) \quad (2.1)$$

The VCG payment function is given by:

$$p_i(v) := h_i(v_{N \setminus i}) - \sum_{j \neq i} v_j(f(v)) \quad (2.2)$$

If  $h_i: V_{N \setminus i} \mapsto \mathbb{R}$  is set to an arbitrary function of the reported valuations of the other agents apart from  $i$ , then the mechanism is of the family of Groves mechanisms, which are DSIC and AE under quasilinear preferences. Furthermore, the mechanism is a standard VCG mechanism if  $h_i$  is set to Clarke's pivot rule, which is the maximum social welfare of the others had agent  $i$  been absent, and it is computed as follows.

$$h_i(v_{N \setminus i}) := \max_o \sum_{j \neq i} v_j(f(v_{N \setminus i})) \quad (2.3)$$

The standard VCG mechanism, under quasilinear preferences, can achieve DSIC, AE, ex-post IR, and weak BB. In order to achieve ex-post IR, two additional properties are required: choice-set monotonicity and no negative externalities. The first one requires that removing any agent results in never more available choices or outcomes  $O$ . The second one means that every agent  $i$  has a non-negative utility for any outcome where  $i$  was not selected. Finally, to achieve weak BB, the environment must exhibit no single-agent effect, where if agent  $i$ 's valuation is selected by the allocation function, preventing agent  $i$  from participating yields an outcome  $o$  that makes the other agents better off. Shoham and Leyton-Brown (2008, Ch10) provide a thorough treatment of these VCG properties.

### 2.3.3.4 McAfee's Mechanism

In his seminal paper, McAfee (1992) designed a single-unit double auction (DA) that yields DSIC for both buyers and sellers. The DA works as follows.

- Buyers are ranked by non-increasing reported values  $b_1 \geq b_2 \geq \dots$ , while sellers are ranked by non-decreasing reported costs  $s_1 \leq s_2 \leq \dots$ .
- The last efficient trade  $k$  is determined by  $b_k \geq s_k$  and  $b_{k+1} < s_{k+1}$ .
- The potential clearing price  $p_0$  is set to  $\frac{1}{2}(b_{k+1} + s_{k+1})$ .
- Case 1: if  $p_0 \in [s_k, b_k]$ , buyers and sellers from  $1, \dots, k$  trade at price  $p_0$ .
- Case 2: otherwise, i.e.,  $p_0 \notin [s_k, b_k]$ , buyers and sellers from  $1, \dots, k-1$  trade, buyers pay  $b_k$  and sellers receive  $s_k$ , and the auctioneer makes  $(k-1)(b_k - s_k)$  profit.

This mechanism is weakly DSIC, IR, weakly BB (as in the second case the auctioneer makes profit), and not AE (as in the second case it gives up the last feasible trade). The lost in efficiency is small since it happens some of the time and it only gives up the least significant trade in order to achieve a DSIC implementation. The lost in efficiency is bounded by  $1/n$ , where  $n := \min\{|M|, |N|\}$ ,  $M$  is the set of sellers, and  $N$  is the set of buyers. McAfee's mechanism has been adapted to the multi-retailer DR setting in Chapter 4, and further details can be found in (McAfee, 1992).

## 2.4 Related Work

### 2.4.1 Early Work

Price-based DR for the electricity supply system has been proposed in the literature for almost half a century. Vickrey (1971) advocated for free market principles and argued that responsive pricing for perishable commodities is the closest approach to a free market in a context of fixed prices and economies of scale. He gave examples of perishable commodities, such as electricity, water, air and road travel, where a price feedback helps to balance supply and demand. He claimed that, although it would be a radical departure from fixed prices, a price responding to fluctuations in supply and demand would improve efficiency on asset utilisation and would lower costs. However, he also warned about the timing of the information feedback regarding the price signal,

which it may take longer time than ideal (e.g., electricity bills in the 1970s), so that each side could adapt to each other.

Moreover, Schweppe (1978) envisioned the notion of a smarter electrical grid, in which customers (residential, commercial, industrial) have means for electric power generation, storage, and are more actively responding to fluctuations in the electricity supply system. He anticipated the use of sensors and actuators at homes (today's concept of smart homes (U.S. Department of Energy, 2003)) to be able to respond to supply signals, thus evolving the conventional approach of 'supply follows demand' to one where 'demand follows supply'. Like Vickrey (1971), he suggested that the use of spot prices would help to signal the supply and demand states. Moreover, he foresaw the use of a microcomputer at home to process the information regarding energy use patterns, and update mathematical models so that it could be determined when is the best time to use (electrical) energy; this is one of the expected features of smart meters (U.S. Department of Energy, 2003; U.S. Department of Energy, 2009; U.S. Department of Energy, 2012). Decisions would be made on the family's own energy use model, the spot price of electricity, and the predicted weather, resulting in this microcomputer showing how much electricity is costing (Schweppe, 1978). Under certain conditions, the utility would command the microcomputer to drop the load, depending on the family's contract that would state how much of the load can be interrupted (Schweppe, 1978). In line with this idea, he distinguished between (economical) soft load control under a normal state, and (physical) hard load control under emergency conditions, for both of which more sophisticated control systems and stochastic mathematical models would be needed (Schweppe, 1978).

Furthermore, Schweppe, Tabors, et al. (1980) developed a control model for supply and demand based on the biological concept of homeostasis and microeconomic principles for the distributed automation and control of dispersed storage, generation and load. Their model included a microcomputer-based scheduler of interruptible loads (i.e., those not considered for immediate need), the use of spot prices of electricity at discrete intervals (5 to 15 mins.), and a market interface to customer (MIC) that not only would record power usage, but also would register its cost so that it could provide the total cost of electricity use (early concept of a 'smart meter').

Afterwards, some research focused on optimal methods for the spot pricing of electricity including dimensions of space and time, and control-based algorithms for responding to spot prices in the domestic setting (e.g., (Bohn et al., 1984), (Schweppe, Daryanian, et al., 1989)). In addition, the initial prototypes and tests of 'smart homes'

with ‘smart meters’ and ‘smart appliances’ that responded to dynamic prices by Rosenfeld et al. (1986) offered insights on the potential of these ideas. Moreover, there were also substantial research on pricing schemes so that they could help to redistribute the demand more evenly throughout the day (e.g., experiments about implementations of time-of-use pricing (TOU) and consumers’ economic elasticities (Caves and Christensen, 1980; Caves, Christensen, and Herriges, 1984; Sexton et al., 1987), demand-layered prices according to the end-user’s load duration curve and its service level for load increments (H.-p. Chao et al., 1986)).

Alternatively, some forms of direct market-based mechanisms were proposed in this area, like the bartering approach by Williams and Schweppe (1986) to limit the power demand peak amongst loosely related but independent buildings, such as those of a college campus. Their mechanism involves no money and allows the exchange of time-based rights to consume in a way that eliminates the gaming (i.e., misreporting preferences) in some of the cases. The buildings are assumed to have rights to consume power that not necessarily fit their profile, so that they have incentives to exchange them. They are also assumed to have diverse use profiles (e.g., classrooms, dormitories, dining halls, etc.) and perfect knowledge of their future energy demand so that some loads can be planned, such as those of heating and cooling. The objective to avoid peak demand coincidence is imposed, and this mechanism coordinates the available resources (i.e., rights to consume) according to time availability.

This thesis builds on auction-based protocols for decentralised scheduling of DR efforts, similar to the bartering approach proposed by Williams and Schweppe (1986) but allowing use of money to express preferences, in which households (i.e., end-user agents) proactively submit DR offers to a centre in exchange for a discount. Auction-based protocols have been extensively studied for the liberalisation of the wholesale market and its organisation (e.g., (Rozek, 1989; Stoft and Kahn, 1990; McCabe et al., 1991; Post et al., 1995)), including more recent approaches of agent-based methods to simulate several market organisations under transmission network constraints (e.g., AMES (Li and Tesfatsion, 2009), EMCAS (Veselka et al., 2002), MASCEM (Praça et al., 2003)).

### **2.4.2 More Recent Work**

Currently, there is a considerably large gap regarding effective auction-based protocols for integrating DR efforts into retail electricity markets, in the context of a low-carbon

economy. There is no general agreement on retailer electricity markets and the integration of more active end-users into the supply and demand balance. Researchers who believe in free market principles have suggested that electricity retailers add no particular value regarding price competition, and that end customers should have access to the wholesale market without the need of this type of intermediaries (a notable example is (Joskow, 2000)). This is precisely what Vickrey (1971) implied by proposing a Walrasian equilibrium approach to the balancing problem, where regional aggregators (not exactly retailers) could submit the aggregate demand to a Walrasian auctioneer, who computes the clearing price and broadcast it back, and customers respond accordingly to this signal. However, other researchers have acknowledged that the electricity supply system has physical constraints (i.e., maintaining the frequency, voltage, and current) that are required for stability, thus it cannot be left dependent on pure market forces (although it would make the work of tariff makers easier) (McCabe et al., 1991). H.-P. Chao and Wilson (1987) point out that the spot pricing of electricity has not been successful in retail markets, despite being the predominant approach in wholesale markets and the technological advances in metering, communication, and control. They identify the following reasons: customers want to know what the monthly electricity bill will look like; monitoring spot prices and responding to those impose costs for customers; and failures of generation equipment can make spot prices vary quickly and greatly. Moreover, Littlechild (2000) argues that retail competition is important for price formation and that the approach on spot prices neglects the role of contract markets. Furthermore, Tesfatsion (2006) emphasises that the Walrasian equilibrium shows that efficient allocations can be supported through decentralised market prices, but it is not meant to address how real-world procurement processes take place. In this regard, this thesis offers a view on domestic DR flexibility that have not been explored, which includes its characterisation and the design of two DSIC mechanisms for its allocation, that are alternative to the Walrasian *tâtonnement* approach.

Over the last decade, there have been considerable efforts to define a low-carbon electricity grid that takes into account the interests of several stakeholders (U.S. Department of Energy, 2003; U.S. Department of Energy, 2009; U.S. Department of Energy, 2012; European Commission, 2006; European Commission, 2009). These have reinvigorated the research on smart homes and their active participation in the balancing problem through DR, under this low-carbon setting. For instance, the Olympic Peninsula Project that performed a field demonstration of automated price-responding appliances, such as space and water heaters, at different comfort levels in 112 respond-

ing homes (Hammerstrom et al., 2007). Moreover, research tools have been proposed to facilitate the modelling and simulation of smart homes along with different network considerations and market organisations (e.g., GridLAB-D (Chassin et al., 2014), Market Garden (Liefers et al., 2014), Mosaik (Schütte et al., 2012), Power TAC (Ketter et al., 2013)). For instance, the Power Trading Agent Competition (Power TAC) (Ketter et al., 2013) provides a platform where researchers can design and test competing broker agents that balance a portfolio of customers with different profiles and distributed energy resources (DER), trade in the wholesale market, and determine retail tariffs.

Methods for balancing supply and demand in low-carbon electricity grids are varied for the retail marketplace, and generally they include some degree of DR given some preferences. These methods are usually device-specific, such as thermostats, home batteries, and EV, and use some degree of mathematical optimisation. Other approaches are dependent on different levels of abstraction, organisation, and interaction, for instance microgrids, VPP, clusters of consumers, etc. The following survey is modest considering the recent amount of research in this area, although there are some overlaps regarding methods, this thesis develops an alternative characterisation of flexibility that is useful for generic domestic DR under reasonable realistic assumptions.

Kok (2013) proposes a market-based coordination mechanism under smart grid settings, coined PowerMatcher, where DER devices trade electricity in tree-shaped distribution markets. This model assumes price-taking agents with negligible ability to manipulate the mechanism, thus it does not consider game-theoretic implications. Supply and demand are aggregated up in the tree-like structure, until it reaches a Walrasian auctioneer that determines the resulting price by a *tâtonnement* procedure. The resulting price is reported back to the DER devices. The exploitation of DR flexibility is indirect and determined by the willingness to buy or sell electric energy with a single bid (ask) per DER device stating the truth marginal benefit (cost), and amount of energy. It includes demand and supply functions for an extension on locational marginal prices (LMP). As previously discussed, the work in this thesis is different from the Walrasian equilibrium approach, that the PowerMatcher is based on, and it does include game theoretic considerations. Nonetheless, this thesis is focused on the domestic setting, whereas the PowerMatcher's scope is more general regarding DER devices with multiple levels of abstraction.

Dimeas and Hatziargyriou (2004) focus on the application of MAS technologies for controlling the operations within a microgrid so as to locally balance supply and demand. Dimeas and Hatziargyriou (2005) provide the characterisation of their model

and an auction-based negotiation protocol for power exchanges. They adapt the problem so that it can be expressed as a symmetrical assignment problem, using equally sized blocks for generation and load. This negotiation protocol is rather akin to bilateral trade than to market institutions, since each negotiation cycle exchanges up to eight messages between each pair of seller and buyer. Moreover, Dimeas and Hatziargyriou (2007b) extend the abstraction model to group microgrids with other generation and load units in to VPP. Furthermore, Dimeas and Hatziargyriou (2007a) and Dimeas and Hatziargyriou (2010) extend the setting by adapting a reinforcement learning algorithm (Q-learning), which is used by each of the agents to model the environment transitions and find optimal policies. On a similar line of research, Oyarzabal et al. (2005) provide a microgrid architecture with a Contract Net Protocol (CNP) (Smith, 1980) for distributed management operations. Their work, however, is focused on the communication feasibility and architecture scalability rather than on game theoretic considerations.

Ramchurn et al. (2011a) propose an agent-based control mechanism for decentralised DSM that is based on the emergent behaviour resulting from end-user agents responding to RTP tariffs. They provide mathematical models for deferrable and shiftable appliances, as well as a model for heating. They note that RTP should not be used alone, as it might cause undesirable peaks. Therefore, they adopt the Widrow-Hoff learning mechanism, with randomised learning rates, to gradually adapt the agents response, so that responding peaks can be avoided. This approach of adapting the agents' response is very important and can also be achieved by a hysteresis procedure so that appliances gradually switch on or off, similar to the one used by Rosenfeld et al. (1986). Similarly, Ramchurn et al. (2011b) design a homeostatic mechanism that uses a price signal based on a measure of carbon intensity in a retailer's portfolio (i.e., generation mix). End-user agents use this signal to optimise their storage by using mathematical programmes. In a similar vein, Voice et al. (2011) design a decentralised control mechanism in which an electricity retailer adaptively uses a price signal that end-users receive in order to optimise their micro-storage. Vytelingum et al. (2010) and Vytelingum et al. (2011) use the same principle of designing a price signal to which end-user agents respond in order to optimise the charging and discharging cycle of their home batteries. They compute and analyse the competitive equilibria of a population of agents and predict their best response. These methods use price-based control signals to guide DR, whereas the work in this thesis designs DR offers (asks) that end-user agents can submit, with the aim to receive a discount, to a procurement auction to ameliorate their retailer's expected imbalance.

Auction protocols that are based on mechanism design, similar to the methods used in this thesis, have been used for the scheduling of EV recharging. For instance, Gerding, Robu, et al. (2011) have framed this scheduling as a multi-dimensional online mechanism design coordination problem, in which agents report their valuation of electricity, arrival and departure times. They use a greedy allocation that in some cases leave power unallocated in order to achieve monotonicity, and thus truthfulness, in a model-free setting. Moreover, Robu, Stein, et al. (2011) extend the previous mechanism to allow multi-unit demands per time period in order to accommodate heterogeneous EV loads and flexible charging speeds. They also provide worst-case bounds on allocative efficiency, and empirically evaluate the proposed mechanism using data from a UK real-world trial of EVs. Furthermore, Stein et al. (2012) extend previous mechanisms by adding a notion of pre-commitment, in which the online mechanism reserves resources, but it retains some degree of flexibility over when and how the actual recharging is allocated. They modify the Consensus online optimisation algorithm in order to achieve monotone allocations and further adjustments to prevent unallocated agents from influencing future pre-commitment allocations. They achieve a DSIC mechanism and achieve a bound of 93% with respect to an offline optimal. Improving on a similar line of research, Gerding, Stein, et al. (2013) propose a two-sided market, in which EV charging stations report their availability and EV agents report their reservations for charging (i.e., preferences). They design a payment scheme that results in a DSIC mechanism for the buyer side (EV agents). Moreover, they prove an impossibility result for the sellers' payments, in which no payment can incentivise honest reports for sellers when a greedy allocation rule is used. The work in this thesis differs from the previous mechanisms mainly in the following aspects. First, the characterisation of bids and asks has been designed so that it does not reveal much information about end-users, resulting in a single-dimensional characterisation. Second, the number of interacting agents is static, and the setting does not consider online allocation (scheduling), although that could be considered for future work. Third, allocations and payment rules are different due to the specifics of the model, but the monotonic greedy allocation is common to achieve DSIC. Fourth, their mechanisms do not consider uncertainty on the ability of agents to fully supply their offers, whereas here this is dealt with by designing suitable penalty schemes. Finally, DR flexibility is not explicitly considered in their model, but it is indirectly present in the reported preferences.

Another work that shares some degree of similarity with this thesis includes (Dash et al., 2007) where a suitable penalty scheme is proposed so that suppliers are incentiv-



ised to report their capacity as certain as possible. Their penalty scheme is adapted in Subsection 3.3.5.4 for the purpose of comparison. However, the cost structure and used mechanisms are different. Dash et al. (2007) use a cost structure that include fixed and variable costs, the setting assumes a small number of suppliers and the adapted VCG mechanism results are computationally feasible due to the limited number of offers. The mechanisms in this thesis cannot use the VCG mechanism due to the large number of participating agents, therefore it resorts to VCG-based mechanisms, in which the allocation function is solved approximately (as the exact solution is NP-hard). Nonetheless, in both cases, the mechanisms include verification and penalties that are designed to restore the DSIC property.

Furthermore, Ströhle et al. (2014) design an online mechanism for allocating uncertain non-interruptible demand that could be scheduled in the presence of uncertain supply. They extend the expectation and consensus algorithms from the online scheduling domain in order to apply them to online mechanism design. They deal with uncertainty in the supply and demand sides through scenarios that are weighted online according to their likelihood and available data, and a predictive model is later solved offline. This predictive approach could be considered for future work in this thesis. Their characterisation of jobs is multi-dimensional and similarly expressed as the EV charging problem (i.e., valuation, consumption rate, number of time periods, arrival/start, departure/deadline). Different from their approach, this thesis abstracts bids and asks regarding DR flexibility into a single dimension so that it can be tractably computed. Also, several jobs can be included into a single offer and interruption is possible but modelled into separate DR offers. Finally, their mechanism and the one in this thesis uses critical value payments.

Other recent similar approaches include (Jain et al., 2014) that uses multi-armed bandits to crowdsource DR. The objective is similar, however, the model, methods, and focus are different. In their work, end-users are modelled as being part of a cluster. The retailer asks the clusters to report their unit cost for reducing the load, and the former proposes offers to the cluster exploring their response and calibrating the acceptance rate. Although interesting, it does not deal with the responsive capacity of end-users, but it takes into account the likelihood to which end-users accept these kind of offers from the retailer. Moreover, there are no penalties for non-responsive end-users. Zhou et al. (2015) adopt a similar line of reasoning as the mechanism described in Chapter 3. They also use a knapsack auction in a single-dimensional domain with Myerson's critical value payments, where micro-storage agents offer a set of pairs com-

prised by energy quantity and its marginal cost. Their knapsack auction uses the XOR-bidding language so that only one offer is allocated per agent. However, the micro-storage agents are modelled as micro-suppliers of energy selling it to the grid, rather than demand responders offering flexibility. They assume deterministic outcomes, and neither verification nor penalties are considered as opposed to the mechanism described in Chapter 3. Furthermore, (Ma et al., 2016) also cast the DR setting as procurement auction, but they focus on reliability, where they aim to select the minimal set of agents that collectively meet a given probability threshold for responding. They provide two DSIC mechanisms, one of which is direct and the other indirect. Also, they offer a fixed reward for responding and a variable penalty for those who does not respond. Agents are expected to respond decreasing electricity use if they are selected; if they fail to respond, they receive a discriminatory penalty resulting from their mechanism. However, in their model, it is not clear how much load needs to be reduced to account as a response, and the outcome of receiving a penalty is discrete (i.e., either agents receive a penalty or not), as opposed to this thesis where penalties are inversely proportional to the achievement on the net-load target (i.e., increase or decrease load) set by the agents. Moreover, Chapter 4 provides a chained mechanism for a multi-retailer DR exchange, that has not been proposed in the literature for this problem.

Other work that deals with DR from a different perspective than auction-based protocols include stochastic mathematical programmes and joint optimisation of profiles (e.g., (Morales et al., 2014; Anderson et al., 2011; Halvgaard et al., 2012; Livengood, 2011; Vasirani and Ossowski, 2012)); and coalition-based approaches in cooperatives or VPP, in which game-theoretic considerations are taken into account, particularly to divide the payoff (e.g., (Chalkiadakis et al., 2011; Robu, Kota, et al., 2012; Kota et al., 2012; Akasiadis and Chalkiadakis, 2013; Mihailescu, Vasirani, et al., 2011; Mihailescu, Klusch, et al., 2013)). These interesting approaches are not discussed further because they are not directly related with the mechanisms presented in this thesis, as well as for brevity reasons.

## 2.5 Summary

This chapter has provided the necessary background information on the organisation of the electricity supply system and its potential for a low-carbon economy. The main challenges for this industry under low-carbon constraints were discussed along with the potential of AI to help to solve some of those challenges. The structure of whole-

sale electricity markets was described, including its main participants, time frame, and currently available balancing services/DR in the UK. Moreover, a brief background on MAS and MD was introduced because they comprise a suitable toolset for implementing desirable systemic goals, such as coordinating DR so as to balance supply and demand, amongst strategic self-interested agents. The related work briefs from historical aspects to the application of economic principles and development of diverse methods for integrating a more adaptive demand-side in order to improve the efficiency of the electricity supply system. The scientific gap was introduced and established on direct-revelation DSIC mechanisms between responsive end-users and their retailer, and amongst retailers, for the purpose of coordinating DR efforts. As opposed to the current trend in the literature, the focusing gap considers explicit DR offers that characterise a notion of operational flexibility that, rather than expressing the willingness to buy or sell energy, it expresses the willingness to shift some net-load.

## Chapter 3

# A Single-Sided VCG-Based Coordination Mechanism for Domestic Demand Response

In this chapter, a novel market-based coordination mechanism is proposed to enable electricity retailers to leverage demand response (DR) efforts from their domestic customers. The research question that is addressed in this chapter is how electricity retailers should incentivise their domestic customers to adjust their end-use patterns for better supply and demand matching. An Algorithmic Mechanism Design (AMD) approach is taken in order to deal with multiple autonomous agents that are self-interested, and economic incentives are used to guide their efforts. The proposed mechanism aims to balance the interests of both parties, retailers and end-users, so as to avoid either of the parties being exploited. Participation of end-users is voluntary; the higher the participation, the larger the collective capacity to accommodate imbalances from electricity supply and demand, and thus reduce the need for expensive balancing generation.

The organisation of this chapter is as follows. First, an introductory reasoning about the proposed mechanism is provided. Second, the setting of the mechanism is described along with the general assumptions that are being made. In addition, the computational models of the agents who represent end-users and retailers are specified, as well as their common understanding of *flexibility* is defined. Third, the specification of the single-sided VCG-based mechanism is provided, including the offer format, allocation procedure, payment agreement, four penalty schemes, and inspection procedure. Fourth, the theoretical properties of this mechanism are proved. Finally, a summary and a list of symbols are provided. The empirical evaluation is reserved for Chapter 5 because

the experimental set-up for simulations is reused to comparatively show all the mechanisms proposed in this thesis, along with some variations.

### 3.1 Introduction

The proposed market-based coordination mechanism in this chapter is a single-sided VCG-based mechanism. Vickrey (1961), Clarke (1971), and Groves (1973) (VCG) mechanisms are one of the positive results in game theory and economics which implement a social choice function that maximises welfare (or minimise the social cost) in a non-dictatorial setting, in which agents have quasi-linear preferences (Arrow, 1951; Gibbard, 1973; Satterthwaite, 1975; Nisan, Roughgarden, et al., 2007). VCG mechanisms use a social choice function whose exact computation is intractable, but it is typically feasible if the number of agents is small. Therefore, Nisan and Ronen (1999) proposed VCG mechanisms in which the social choice function is replaced with one that is computable in polynomial time, and payments are computed as in the VCG mechanism. They termed this family of mechanisms as *VCG-based* mechanisms. Furthermore, Nisan and Ronen (1999) showed that, although VCG-based mechanisms are computable in polynomial time, they lose the dominant-strategy incentive-compatibility (DSIC) property, because the VCG payments are computed over a suboptimal allocation and agents could manipulate the outcome by misreporting their preferences. However, the computational model for this setting, that is defined in Section 3.2, abstracts the problem into a single-dimensional domain for which is known that computationally efficient DSIC mechanisms exist (Roughgarden, 2016, Ch4).

More specifically, the proposed VCG-based mechanism corresponds to a (*direct revelation*) multi-unit single-item *reverse* Vickrey auction with sealed offers, transferable utility, reservation prices, and *post-production* verification. That is, each retailer procures operational flexibility as a homogeneous commodity from their customers and pays them in a common currency. Furthermore, as it will be showed in the following sections, retailers can only accept complete offers from their customers. This integrality constraint makes this mechanism a *knapsack* auction (e.g., Engelbrecht-Wiggans (1977), Aggarwal and Hartline (2006)), because the allocation of complete offers resembles the canonical 0/1-Knapsack Problem (KP) (Dantzig, 1957). This well known problem is NP-hard, but it accepts a fully polynomial-time approximation scheme (FPTAS), assuming  $P \neq NP$ , (Vazirani, 2001, Ch8). However, standard approximation techniques generally not result in monotone allocations (Roughgarden, 2016,

Ch4), which are required to maintain the mechanism DSIC (Myerson, 1981, Lemma 3). Under these considerations, Briest et al. (2005) provide a general method to transform a pseudo polynomial-time algorithm to a monotone FPTAS, that is applicable to knapsack auctions. Moreover, VCG payments cannot generally be used even with monotone approximately efficient truthful mechanisms (Nisan and Ronen, 2007, Lemma 2.1), instead Myerson's payment formula, which is commonly known as *critical value* payments, is used in order to maintain the DSIC property (Roughgarden, 2016, Ch4). This critical value corresponds to the minimum bid (maximum ask) that the bidder could have reported and still have won the same allocation. In single-dimensional auctions, the critical value replicates the payments of Vickrey's second-price auction (Roughgarden, 2016, Ch3). Since the Vickrey auction is itself a VCG mechanism (Nisan and Ronen, 2007), therefore, the proposed auction becomes a VCG-based mechanism for DR coordination that is approximately Pareto efficient, DSIC, its allocation is computable in time polynomial in  $n$  and  $\frac{1}{\epsilon}$ , and the computation of payments (discounts and penalties) is also tractable.

## 3.2 Computational Model

This section defines the general setting of the mechanism, which includes the main assumptions and computational models for end-users and retailers' agents.

### 3.2.1 General Assumptions

It has been assumed that the information and communication technology (ICT), necessary to exploit the benefits of smart meters and controllers for DSM, is already in place. Also, it has been taken for granted that there is an effective regulatory framework that supports a business model in which retailers are engaged in more active interactions with their customers in aid of a smarter grid challenges. At the time of writing this thesis, there is an ongoing debate on the scope of smart meters, as of what it is meant by smart, concerns of whether is possible of willingly disconnect vulnerable end-users from the service (for instance, due to having an outstanding balance), who will see and store the collected data, amongst other worries (e.g., (House of Commons, 2016; Hoenkamp et al., 2011)). This thesis does not particularly focus on any of those issues, even though the assumed intervention of the ISO/DSO auctioneer may allow for privacy of end-users' data (provided that details are not shared with retailers). Furthermore, the

model assumes that end-users are subscribed to only one retailer and that communication between the retailer and the meters is possible (perhaps through direct connection or via the ISO/DSO that interfaces between them). Moreover, in this model, end-users cannot trade neither in the wholesale market nor amongst themselves. If an end-user is displeased with its retailer's tariffs or overall service, it might decide to switch to another more convenient retailer available within its geographical area. Switching retailers might include fees for finishing contracts early, however neither the switching nor these fees are modelled in this study due to clarity of exposition, but the models could be easily extended to include this situation. Finally, it has been assumed that meters are reliable, that they provide the meter reading whenever the retailer asks for it (or as allowed by regulation), and that they have not been hacked by malicious end-users that in such a case the law would be enforced by a proper regulatory institution. Figure 3.1 provides an idea of the interactions amongst a retailer and its subscribed end-users, as well as examples of the technologies involved.

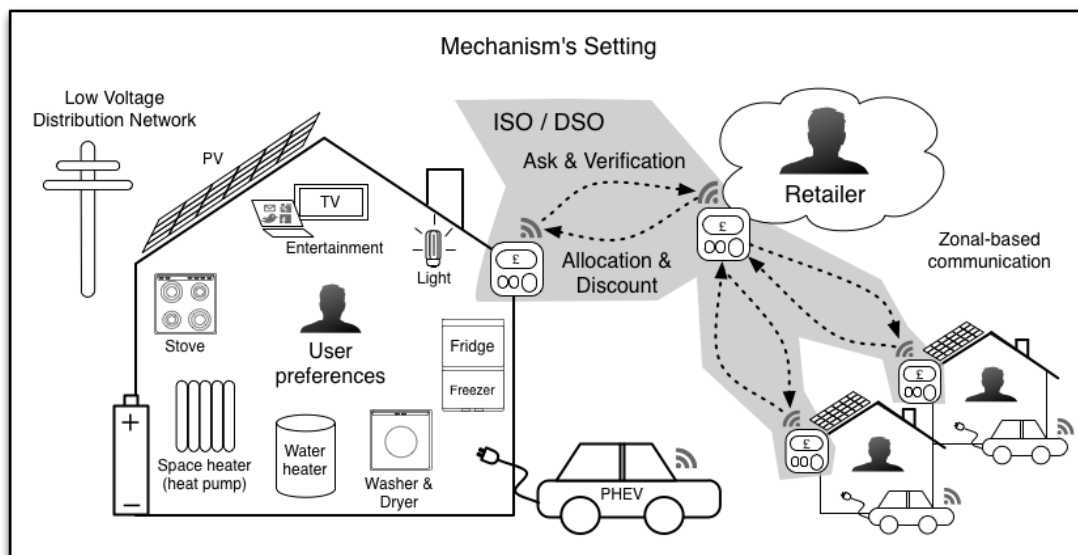


Figure 3.1: Setting of the VCG-based mechanism.

### 3.2.2 DR Operations

DR has been abstracted into two main operations for the domestic setting: *net-load peak-shaving* and *net-load valley-filling*. Before defining these operations, it is convenient to define the net-load in order to address DR within this context.

**Definition 3.1.** Net-load is the difference between electricity use and electricity generation within one time period at one specific abstraction level (e.g., household, distribution system, traded schedule, group of domestic customers that are subscribed to one retailer within a geographic zone). Net-load daily profile, measured in kWh (or higher orders), is a set of net-load values corresponding to each of the time periods within a single day (larger time frames could be considered too, i.e., weekly, monthly, seasonal, yearly profiles).

**Definition 3.2.** Net-load peak-shaving is a DR effect intended to reduce the net load and it is accomplished by turning off some load appliances or turning on generation devices, including discharging batteries, if possible. The appliances that are turned off are expected to be turned on later at non-peak time periods. Similarly, generation devices can be turned off, and batteries can be recharged, at non-peak times.

**Definition 3.3.** Net-load valley-filling is a DR effect opposite to net-load peak-shaving that is intended to increase the net load. This is performed by turning on some load appliances, including recharging batteries, or turning off generation devices, if possible. The appliances basically fulfil a task in advance, which means that such tasks will not be needed during peak time, resulting in a more even daily profile.

These two DR operations are important to the problem of balancing supply and demand, because they can be coordinately grouped to ameliorate imbalances, so as to reduce expensive balancing generation and help accommodate low-carbon renewable generation, especially from non-dispatchable sources that although free, their output is usually stochastic and intermittent.

### 3.2.3 End-User Agent

The end-user and the computational agent that works on its behalf are used almost identically in this thesis, although the main focus is on the latter. End-user agent  $i \in N$  has access to read the electricity meter at its end-user's premises. Let  $m_{it}$  denote the meter reading that agent  $i$  gathers at time period  $t \in T$ , where  $T$  is a set of consecutive discrete time periods (e.g., hourly or half-hourly), whose horizon can easily be considered infinite. Let  $q_{it} \in \mathbb{R}$  denote the electric energy used by end-user  $i$  at time period  $t$ , which corresponds to the change in meter readings between  $t$  and  $t - 1$ , i.e.,  $q_{it} := m_{it} - m_{i(t-1)}$ . Specifically,  $q_{it}$  represents the net-load at end-users' premises, where  $q_{it} < 0$  means export of electricity to the grid,  $q_{it} > 0$  indicates import of electricity, and  $q_{it} = 0$  corresponds to zero net-energy exchange.



End-users are given two fixed tariffs by their retailer, which are the retail sell and buy prices. These tariffs are assumed to be the same for all end-users subscribed to the same retailer<sup>11</sup>. More formally, these tariffs are denoted by  $\lambda^{RS} \in \mathbb{R}_{>0}$  and  $\lambda^{RB} \in \mathbb{R}_{>0}$ , which are the retail sell price and retail buy price per kWh, respectively,  $\forall i \in N, \forall t \in T$ . Particularly, when  $q_{it} < 0$ , agent  $i$  is paid  $\lambda^{RB} q_{it}$  at time period  $t$ ; similarly, when  $q_{it} > 0$ , agent  $i$  is charged  $\lambda^{RS} q_{it}$  at time period  $t$ . Also, as expected by retailing dynamics, it is assumed that  $\lambda^{RS} > \lambda^{RB}$ . These fixed prices provide no incentives for end-users to modify their use patterns, except for the case of prioritising the use of their own generated electricity, since the retail buy price is strictly lower than the retail sell price.

Provided that end-users are willing to adapt their use patterns and offer this *flexibility* in order to accommodate for supply fluctuations, they need to quantify their responsive capacity and its offering price at time period  $t$ . This quantification relies on an in-house scheduler in which end-users set certain domestic tasks to run and finish within a time frame as a hard constraint. The model for the scheduler is formalised after the definition of flexibility, that is as follows.

**Definition 3.4.** (Flexibility) Domestic demand-side operational flexibility, or just flexibility in this thesis, is the ability of an end-user (agent) to either implement peak-shaving or valley-filling operations at a single time period  $t$ , so as to drive its net-load up or down at will. Either operation, or DR direction, is assumed to have a negligible cost for the end-users (i.e., people, not their agent), as the scheduled tasks will finish within the specified time frame. That is, this flexibility corresponds to a non-meaningful degradation in quality of service for the end-user, due to anticipating or deferring electricity use. Henceforth, the linear cost functions presented in this chapter (i.e., Figure 3.3) should be seen as valuation schemes for DR offers according to end-users' preferences, as opposed to bearing hard costs. By means of this definition of flexibility, end-users have a utility of zero (i.e., no economic cost) for DR offers that are not selected by the mechanism.

Figure 3.2 shows examples of appliances that could be expected to be scheduled according to end-users' preferences, in order to exchange some flexibility for a discount. It also provides examples of appliances that would not be expected to be scheduled, such as those for cooking and entertainment.

In order to quantify the end-user's DR capacity and its offering price, a scheduler is used to manage a set of domestic tasks that involve turning on or off electrical appli-

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<sup>11</sup>This model could easily be extended to include different pricing groups per retailer, but it would not affect the properties of this market-based mechanism.

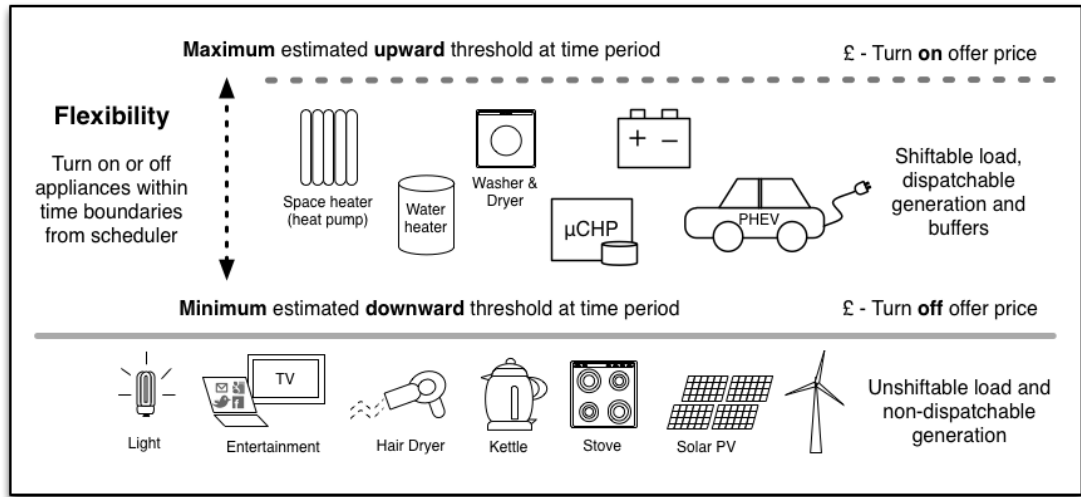


Figure 3.2: Examples of end-users' schedulable appliances for DR.

ances during a time window. It has been assumed that this scheduler is part of a home energy management system (HEMS), and that appliances have controllers which allow for domestic tasks planning, such as clothes washing and drying, and EV recharging. Table 3.1 shows an example of a basic schedule and the data it uses to keep track of domestic tasks.

Task $k$	$q_k$ (kWh)	$r_k$	$d_k$	$s_k$	$c_k$	$z_k$	Flags
Recharge EV	3.5	6	12	0.15	0.05	+1	Interruptible
Heat bedrooms	2.5	2	6	0.10	0.02	-1	Interruptible
Wash clothes	1.5	3	14	0.01	0.01	0	Non-interruptible
Wash dishes	1.0	2	2	0.00	0.00	0	Must-run
Discharge HB	-2.5	4	9	0.10	0.02	0	Interruptible

Table 3.1: Example of a basic schedule for domestic tasks.

For each task  $k \in K$ , where  $K$  is a set of single-appliance<sup>12</sup> tasks in the schedule,  $q_k \in \mathbb{R}$  is the amount of kWh that task  $k$  requires per time period  $t$ . This amount could be estimated using the technical specifications or simply from its past use (e.g., washing machine programmes, which consume different amount of electricity depending on the water temperature, water volume, centripetal force to centrifugate the water from the clothes, etc.). Moreover, the number of time periods that task  $k$  requires is denoted by

<sup>12</sup>In general, some domestic tasks may involve more than a single appliance, and this can be dealt with by a more sophisticated scheduler. However, such complexity is unnecessary for the exposition of the mechanism, which only needs the summed up amounts of flexibility up and down.

$r_k \in \mathbb{N}$  (e.g., 3 hours, 6 half-hours), and its deadline is expressed by  $d_k \in \mathbb{N}$ , which is the maximum number of time periods (e.g., 6 hours, 12 half-hours) that task  $k$  may take to finish. This deadline is interpreted as a limit that cannot be exceeded, but certainly tasks can finish before their deadline.

Moreover, a very simple strategy<sup>13</sup> to map end-users' preferences to DR offering prices is used as follows. The cumulative offering cost of deferring or anticipating task  $k$  is defined by  $s_k \in \mathbb{R}_{>0}$  from the schedule. The cost per time step is denoted by  $c_k \in \mathbb{R}_{>0}$ , and cost type  $z_k \in \{-1, 0, 1\}$  determines if the cumulative cost  $s_k$  increases with time ( $z_k = 1$ ), decreases ( $z_k = -1$ ), or remains the same ( $z_k = 0$ ). For simplicity, cost types ( $z_k$ ) are modelled as linear functions, although more complex functions are possible. Figure 3.3 illustrates examples of cost functions associated to some tasks and their interpretation. When  $z_k = 1$ , the end-user prefers that task  $k$  is performed at the beginning of the scheduling horizon (e.g., EV charging), and thus its carrying offering cost will be higher as it gets near the end. Similarly, when  $z_k = -1$ , the end-user prefers task  $k$  to be finished by the deadline (e.g., space and water heating) rather than at the beginning, thus its carrying offering cost will be lower as it gets closer to the end. When  $z_k = 0$ , the end-user is indifferent as long as task  $k$  is performed within the time frame (e.g., washing clothes). Both  $s_k$  and  $c_k$  are restricted to be strictly greater than zero, for instance a small constant  $\epsilon$ , as otherwise the mechanism clearing price could yield zero discounts under the presence of heavy competition.

At every time step  $t$ , the vectors  $r_k$ ,  $d_k$ , and  $s_k$  are updated as follows.

$$r_k := \begin{cases} r_k - 1: & \text{if } k \text{ ran at } t - 1 \\ r_k: & \text{otherwise} \end{cases} \quad \forall k \in K \quad (3.1)$$

$$d_k := d_k - 1 \quad \forall k \in K \quad (3.2)$$

$$s_k := s_k + c_k z_k \quad \forall k \in K \quad (3.3)$$

For the purpose of DR, the schedule is queried to extract both flexible and inflexible operational amounts and their offering costs. For instance, in Table 3.1 the maximum net-load that could be achieved is 8.5 kWh at a comfort cost of 26 pence and the minimum would be  $-1.5$  kWh at a compensation of 10 pence during time period  $t$ . Since

<sup>13</sup>More sophisticated strategies can be used to map end-users' preferences to DR offering prices; however, this is out of the scope of this thesis.

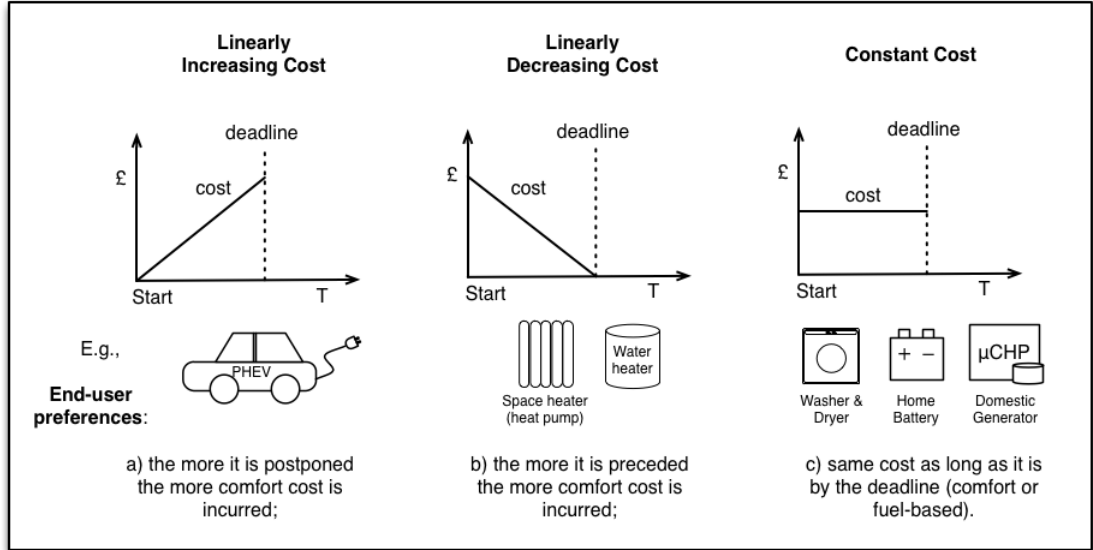


Figure 3.3: Cost types to model end-users' preferences in order to price flexibility offers.

the task *wash dishes* has no flexibility, it must run either way. This offering cost is basically what the agent is asking for as a minimum compensation (or discount), provided that its offer is allocated and it fulfils the agreed net-load target.

More formally, flexibility and costs are determined as follows. Let  $D_t$  be a subset of  $K$ , which contains tasks that have peak-shaving flexibility, or downward capacity, i.e.,  $D_t \subseteq \{K \mid q_k < 0, d_k > r_k\}$ . Similarly, let  $U_t$  be a subset of  $K$ , that contains tasks with valley-filling flexibility, or upward capacity, i.e.,  $U_t \subseteq \{K \mid q_k > 0, d_k > r_k\}$ . Subsets  $D_t$  and  $U_t$  are disjoint<sup>14</sup>, i.e.,  $D_t \cap U_t = \emptyset$ . Let  $q_t^d \in \mathbb{R}_{\leq 0}$  denote the amount for peak-shaving in kWh, i.e.,  $q_t^d := \sum_{k \in D_t} q_k$ . Correspondingly, let  $q_t^u \in \mathbb{R}_{\geq 0}$  be the amount for valley-filling in kWh, i.e.,  $q_t^u := \sum_{k \in U_t} q_k$ . Let the offering prices be expressed by  $\lambda_t^d \in \mathbb{R}_{> 0}$  and  $\lambda_t^u \in \mathbb{R}_{> 0}$ , where  $\lambda_t^d := \sum_{k \in D_t} s_k$  and  $\lambda_t^u := \sum_{k \in U_t} s_k$ . The inflexible amounts from the schedule can be computed analogously, however, since this model only takes into account the net-load, the inflexible amounts for generation and load are summarised into a single figure. That is, all tasks from the schedule that no longer have flexibility are set to run, including tasks that generate power and tasks that use it. Hence, let  $C_t$  be a subset of  $K$  which has the tasks with no flexibility, i.e.,  $C_t \subseteq \{K \mid d_k \leq r_k\}$ . Let  $q_t^c \in \mathbb{R}$  be the net-load amount of kWh from tasks that must run according to schedule, i.e.,  $q_t^c := \sum_{k \in C_t} q_k$ . At this point, due to Definition 3.4 (Flexibility), the added up cost of these inflexible tasks is disregarded, since their flexibility is no longer offered

<sup>14</sup>Charging and discharging of batteries (e.g., home, EV) are regarded as different tasks.

to the retailer. That is, end-users no longer ask for a discount regarding the effect of these tasks in their net-load. Furthermore, let a forecast function  $h: \mathbb{N}|\mathbb{R}^H \mapsto \mathbb{R}$ , where  $h(t|H)$  estimates the end-user's (inflexible) net-load at period  $t$  excluding scheduled tasks, given a finite rolling history  $H$ . Finally, the end-user agent can determine the minimum and maximum meter readings that it could achieve, as in Equations 3.4 - 3.6, in which  $m_{(t-1)}$  is the actual meter reading at  $t - 1$ . Intermediate values at different costs, as opposed to minimum and maximum meter readings, could also be possible; however, since the capacity of a single domestic end-user is in general very low, compared to its retailer's trading schedule, the extra complexity in this case would not add any substantial value in the face of thousands or millions of end-user agents submitting offers.

$$m_t^y := m_{(t-1)} + h(t|H) + q_t^c \quad (3.4)$$

$$m_t^d := m_t^y + q_t^d \quad (3.5)$$

$$m_t^u := m_t^y + q_t^u \quad (3.6)$$

Furthermore, flags can be added to this schedule to specify a variety of constraints; for instance if a task is non-interruptible, whenever it runs, it will no longer have flexibility within its scheduling time frame, so it will have to run, i.e.,  $d_k \leq r_k$ . It can be safely assumed, without loss of generality, that appliances run for the whole time period they are selected to run, and that they use or generate their respective per-time-period amount specified in the schedule, i.e.,  $q_k$ ; it would be trivial to extend this schedule to cover, perhaps by means of an additional flag, the fraction in kWh for the last time period so as to estimate the flexibility more accurately. Similarly, more complex schedules can be designed, with more constraints and task validations (e.g., cannot discharge an empty battery, etc.), but the one presented in this chapter results convenient to capture most of the attributes for domestic tasks that are relevant to DR.

Finally, the electricity bill of end-user agent  $i$  is computed using Equation 3.7, where subset  $\tau \subseteq T$  contains all time periods being billed. Parameters  $\lambda^{RS} \in \mathbb{R}_{>0}$  and  $\lambda^{RB} \in \mathbb{R}_{>0}$  are the previously defined retail tariffs from the retailer's perspective, i.e., end-users buy electricity at retail sell price  $\lambda^{RS}$ , and end-users sell their excess at retail buy price  $\lambda^{RB}$ . Let  $b_{it} \in \{0, 1\}$  denote whether end-user agent  $i$  imported (bought) or exported (sold) electricity at time period  $t$ . The value of  $b_{it}$  is assigned according to  $q_{it}$ , which is the change in meter readings between  $t$  and  $t - 1$ , i.e.,  $q_{it} := m_{it} - m_{i(t-1)}$ .

Therefore,  $b_{it} := 1$  if  $q_{it} > 0$ , and  $b_{it} := 0$  otherwise. The last term  $\gamma_{it} \in \mathbb{R}$  is the discount computed by the mechanism, whose procedure is described in Section 3.3.

$$c_{i\tau} := \sum_{t \in \tau} \lambda^{RS} q_{it} b_{it} + \lambda^{RB} q_{it} (1 - b_{it}) - \gamma_{it} \quad (3.7)$$

### 3.2.4 Retailer's ISO-Controlled Zonal Auctioneer Agent

In a similar fashion that a reliable electricity meter is used to bill end-users, there needs to be a reliable centre (i.e., an auctioneer) that implements the rules of an agreed mechanism. Therefore, an *independent* auctioneer is proposed in order to prevent retailers from exploiting end-users by extracting more profit from DR rather than using it to balance their trading schedules (e.g., by untruthfully reporting clearing prices). The auctioneer agent is assumed to be controlled by a non-profit independent system operator (ISO). Depending on the structure of the electricity supply system, the controlling entity could also be the distribution system operator (DSO); essentially, the auctioneer must not be owned by any retailer and its procedures must be certified and regulated.

The computational model for retailer agents is much simpler than that of end-user agents. The retailer agent and the auctioneer agent, which are separate entities, are used almost identically under the assumption that, although the auctioneer represents the retailer, the auctioneer agent is controlled by the ISO/DNO. Hence, at every  $t \in T$ , the retailer provides the auctioneer agent with its forecasts of imbalance prices, the expected amount to procure from DR, and the DR direction (i.e., peak-shaving or valley-filling). More formally, let  $\tilde{\lambda}_t^S \in \mathbb{R}_{>0}$  be a forecast of the system sell price (or balancing sell price), and  $\tilde{\lambda}_t^B \in \mathbb{R}_{>0}$  be a forecast of the system buy price (or balancing buy price) at time period  $t$ . Let  $\tilde{Q}_t \in \mathbb{R}_{\geq 0}$  denote a forecast of the quantity to procure for DR, and  $y_t \in \{0, 1\}$  be the DR direction, where  $y_t = 0$  means that peak-shaving will be procured, and valley-filling otherwise.

Furthermore, the auctioneer agent collects offers from end-user agents, implements the mechanism described in the next section, which involves an allocation procedure, a payment agreement and a chosen penalty scheme, that are assumed to be all agreed beforehand, i.e., the protocol is common knowledge amongst the agents representing retailers and end-users.

Let  $M$  be the set of electricity retailers. Utility  $u_{jt} \in \mathbb{R}$  for retailer  $j \in M$  at time period  $t \in T$  is modelled as a linear combination of retail trading, balancing market

position, and DR discounts. Formally, let  $\lambda_j^{RS} \in \mathbb{R}_{>0}$  and  $\lambda_j^{RB} \in \mathbb{R}_{>0}$  be the previously defined retail tariffs offered by retailer  $j$ . Similarly,  $q_{jt}^{RS} \in \mathbb{R}_{\geq 0}$  and  $q_{jt}^{RB} \in \mathbb{R}_{\geq 0}$  are the amount of kWh sold to and bought from end-users; these quantities are easily computed by Equations 3.8 and 3.9, as well as the respective retail trading in Equation 3.10.

$$q_{jt}^{RS} := \sum_{i \in \{N_j | q_{it} > 0\}} q_{it} \quad (3.8)$$

$$q_{jt}^{RB} := \sum_{i \in \{N_j | q_{it} < 0\}} q_{it} \quad (3.9)$$

$$\rho_{jt} := \lambda_j^{RS} q_{jt}^{RS} + \lambda_j^{RB} q_{jt}^{RB} \quad (3.10)$$

The balancing market position is determined ex-post. If retailer  $j$  is in deficit, it pays the shortfall  $Q_{jt} \in \mathbb{R}$  at the per-unit system buy price (SBP)  $\lambda_t^B \in \mathbb{R}_{\geq 0}$  to the balancing market. Likewise, if retailer  $j$  is in surplus, it receives a payment equivalent to the excess  $Q_{jt}$  at the per-unit system sell price (SSP)  $\lambda_t^S \in \mathbb{R}_{\geq 0}$  from the balancing market. Let  $\eta_{jt} \in \mathbb{R}$  be the exchange with the balancing market computed by the cases in Equation 3.11.

$$\eta_{jt} := \begin{cases} \lambda_t^B Q_{jt} & Q_{jt} < 0 \\ \lambda_t^S Q_{jt} & Q_{jt} \geq 0 \end{cases} \quad (3.11)$$

DR discounts are determined by the mechanism defined in Section 3.3. Let  $\gamma_{it} \in \mathbb{R}$  be the actual DR discount paid by the mechanism to end-user agent  $i$  with regard time period  $t$ . Then, let  $S_t \subseteq N$  denote the end-user agents that were selected by the mechanism to perform DR operations, and thus, will be rewarded with a proportional discount subject to verification. For convenience, let  $\gamma_{jt} := \sum_{i \in S_t} \gamma_{it}$ . Finally, Equation 3.12 computes retailer  $j$ 's utility  $u_j$ , where subset  $\tau \subseteq T$  contains all time periods being considered for this computation (e.g., time periods within a week, month, quarter, etc.).

$$u_{j\tau} := \sum_{t \in \tau} \rho_{jt} + \eta_{jt} - \gamma_{jt} \quad (3.12)$$

### 3.3 Mechanism Specification

In general, a single household does not have sufficient capacity to correct a non-trivial difference between its retailer's traded schedule and the actual net-load from the collective served by this retailer. It is, however, a large number of end-users that can significantly drive up or down the collective net-load, provided that they have the incentives to do so. End-users' offers are subject to the market-based forces of the proposed mechanism. That is, end-users' asks might not be allocated if their price is not competitive enough or if the DR quantity to be procured has already been covered. This mechanism boils down to a repeated auction, where at every time period a fraction of the population is competing to allocate their flexibility in exchange for compensation. There is no penalty for end-users who decide not to participate or whose ask has not been allocated, since they end up paying fixed tariffs. Each auction instance is treated as independent from each other, there are a massive number of bidders, and each auction is worth very little (i.e., a few pence). In general, end-users should win several auctions to accrue noticeable savings with regard to their electricity bill.

The scope of this protocol is restricted to take place within one contiguous geographical zone, and its relational cardinality corresponds to one retailer to many flexibility providers. The retailer might communicate with demand responders more frequently than with non-responsive customers; although the protocol is quite flexible to query each customer at every time period, this is discouraged as the communication burden would be heavier. For simplicity, it has been assumed that the reading frequency is aligned to the retailer's participation in the wholesale market, specially at the balancing stage, for which DR is more useful. Moreover, for clarity of exposition, only one zone has been modelled, even though retailers are expected to serve the electric load in several zones within a region or country. If the retailer needed to balance its overall traded position, it would have to decide the amount of DR to be procured per zone, so as to cover the whole imbalance with these DR amounts.

#### 3.3.1 Modelling Approach and Additional Assumptions

The mechanism is modelled using the tools of Algorithmic Mechanism Design (AMD) from within Computer Science (CS), as opposed to Classical Game Theory from Economics. While the former does not make assumptions on probabilistic distributions about the agents' valuations (Nisan, Roughgarden, et al., 2007, Ch9), the latter relies on these distributional assumptions and usually considers them to be public knowledge



amongst the participating agents. The predominant modelling framework in Economics is Bayesian Games, due to the work of Harsanyi (1967), and it usually models Bayes-Nash Incentive Compatible (BNIC) implementations. However, the perspective from CS mainly focusses on DSIC implementations, which are generally simpler and more robust, and the followed approach involves a worst-case analysis over unknown information (Nisan, Roughgarden, et al., 2007, Ch9). Since the CS approach has been taken in this thesis, two additional assumptions are needed to model this auction: *independent private values* (IPV) and *strict incomplete information* (SII) (Nisan, Roughgarden, et al., 2007, Ch9). IPV means that the utility of end-user agents only depends on its own private information (i.e., schedule and forecasts about inflexible net-load), and ignores the other agents' information (Nisan, Roughgarden, et al., 2007, Ch9). According to Nisan, Roughgarden, et al. (2007, Ch9), SII is not completely standard and refers to not having probabilistic information in the model, which translates to using worst case analysis over unknown information to evaluate DSIC implementations.

Another important assumption is that this mechanism is *normalised*. That is, agents have a utility of zero when their asks are not allocated by the mechanism (Nisan, Roughgarden, et al., 2007, Ch9). This assumption is aligned to the definition of flexibility above (i.e., Definition 3.4). Even though the characterisation of flexibility in this thesis uses multiple parameters, the balancing problem is cast into a single-dimensional auction between a retailer and its customers (by means of their respective agents). That is, flexibility offers comprise two dimensions, one for net-load peak-shaving, and the other one for net-load valley-filling; nonetheless, the retailer chooses a single dimension for DR procurement.

### 3.3.2 Ask Format

The retailer collects meter readings and asks from flexibility providers at the beginning of every time period  $t \in T$ . Let a meter reading be formalised as a tuple  $\langle m_{t-1} [ , m_t^y, (m_t^d, \lambda_t^d), (m_t^u, \lambda_t^u) ]? \rangle \mapsto \langle \mathbb{Z} [ , \mathbb{Z}, (\mathbb{Z}, \mathbb{R}_{>0}), (\mathbb{Z}, \mathbb{R}_{>0}) ]? \rangle$ . The first element  $m_{t-1}$  is the actual meter reading at the end of  $t - 1$  or, what is the same, it is what the meter displays at the beginning of time  $t$ . The second element  $[ , m_t^y, (m_t^d, \lambda_t^d), (m_t^u, \lambda_t^u) ]?$  is optional, that is, the whole expression within square brackets can be present either zero or once as denoted by the wildcard character '?' from regular expressions. This second term is comprised of three elements: (1)  $m_t^y$  is the meter reading that results from how much net-load the end-user agent estimates the

household will use if no DR operations are performed; (2) the pair  $(m_t^d, \lambda_t^d)$  is an offer to drive the meter down to or beyond the threshold  $m_t^d$  at the price of  $\lambda_t^d$ , at a single time period  $t$ ; and (3) the pair  $(m_t^u, \lambda_t^u)$  is an offer to drive the meter up to or beyond the threshold  $m_t^u$  at the price of  $\lambda_t^u$ , at time period  $t$ . If the second term  $[\cdot]$  is present, it must include all its arguments and satisfy  $m_t^d \leq m_t^y \leq m_t^u$  in order to be valid. Henceforth, the term  $[\cdot]$  is referred as an ask. Figure 3.4 shows a graphic interpretation of the ask components. Zonal indices are omitted because this exposition is limited to one zone, however it could be extended to cover more than one.

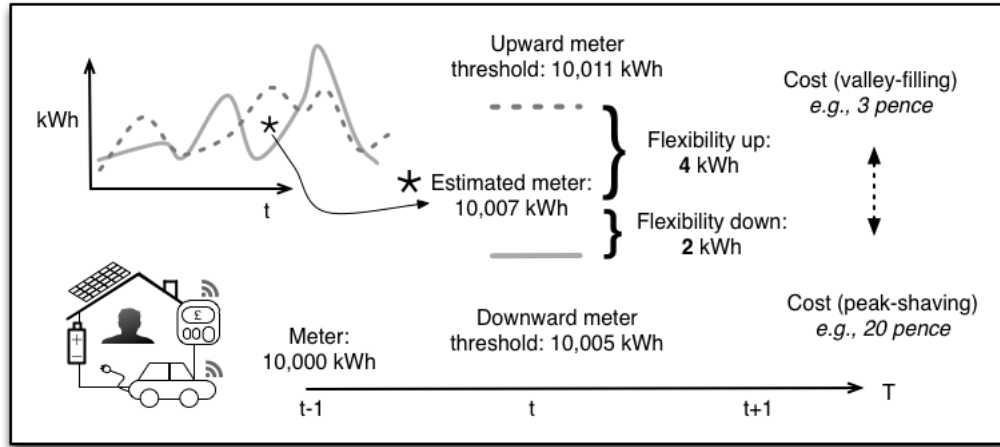


Figure 3.4: Ask components.

If the auctioneer selects an ask, it will choose either of the two threshold pairs, but it cannot choose both. Therefore, the interpretation is similar to the XOR operator  $\oplus$  in bidding languages (Nisan, 2006), however the level of abstraction used in this mechanism considers the ask  $[m_t^y, (m_t^d, \lambda_t^d), (m_t^u, \lambda_t^u)]$  to be atomic. That is, if an XOR ask were to be used, it would be  $[m_t^y, \langle [(m_t^d, \lambda_t^d), (m_t^u, \lambda_t^u)]_1 \oplus \dots \oplus [(m_t^d, \lambda_t^d), (m_t^u, \lambda_t^u)]_n \rangle]$  and such level of complexity is unnecessary. That would require the flexibility provider to cluster *flexible* tasks into different combinations of upward and downward offering pairs that, in the orders of kWh and pence-based compensations, might result in unneeded communication complexity. This could be used by industrial customers, where they could specify several levels of response at different costs. However, according to this model, the whole set of actions for a domestic flexibility provider, such as whether to recharge EV and turn on heating, or not to do so, must be summarised into a single atomic ask. For example, a reading like  $\langle 10000, [10007, (10005, 20), (10011, 3)] \rangle$  can be interpreted as the current meter displays 10000, the flexibility provider agent estimates that, after considering *unshiftable* net-load (i.e., the estimated meter without DR at

10007), the minimum meter it could achieve is 10005 at the cost of 20 pence, perhaps as comfort cost of not turning some devices on; likewise, the agent estimates that if it turned on some scheduled appliances, adding them up, the meter would be at least 10011 and it would cost 3 pence, perhaps for some small comfort impact for running them in advance, or just for the sake of giving away some information, for which the agent would like to be compensated.

One of the main reasons to join the meter reading with the ask is the ability to verify the actual change with respect the actual electricity use. This is assuming that the meters are secure devices that have not been hacked. Without the actual metering reading it would be easier for an agent to cheat, claiming some sort of DR that cannot be verified. It is in the interest of both parties, retailer and customer, to be able to verify their services, being the meter the primary tool to do so. Otherwise, a domestic customer could promise to decrease its load the next time period overstating its predicted load and simulating a non-truthful decrease, for which it would be compensated with a discount. Similarly, a retailer could assert that it trusted a customer to reduce its load (or adjust its electricity use to an arbitrary measure) and falsely claim that it did not detect any favourable change, so as to exploit the customer by penalising its supposedly false DR. Therefore, the meter is used to make the mechanism more transparent and avoid unfavourable disagreements.

Furthermore, including both downward and upward meter thresholds in an ask, without knowing which one is going to be chosen, limits the ability of end-users to manipulate the mechanism by making over- or understatement about their net-load, so as to gain discounts for false DR. For instance, suppose the customer knows that its electricity use for the next time period is going to be 6 kWh and that the retailer is following a valley-filling strategy, so it would be advantageous for the customer to understate its use, e.g., 1 kWh, and offer that it could increase its use in exchange for compensation, and yet being freely rewarded without performing any DR. The analogous case would also be possible. The customer could promise to decrease its load from an actually inflated amount, and yet be rewarded for no DR action at all. In this vein, end-user agents must also report their intended electricity use without DR, so that offers can be measured more accurately if they are selected.

The ask format in this section uses the meter readings for backward compatibility reasons. Nonetheless, the meter reading format, including the ask term, can be expressed more concisely using kWh quantities rather than the meter readings. That is, the reading format could be expressed as  $\langle q_{t-1} [ , q_t^y, (q_t^d, \lambda_t^{dk}), (q_t^u, \lambda_t^{uk}) ] \rangle \mapsto$

$\langle \mathbb{R} [ , \mathbb{R}, (\mathbb{R}_{\geq 0}, \mathbb{R}_{> 0}), (\mathbb{R}_{\geq 0}, \mathbb{R}_{> 0}) ] \rangle$ , where each  $q$  corresponds to the respective change in meters readings and  $\lambda$ s are costs per kWh, i.e.,  $\langle m_{t-1} - m_{t-2} [ , m_t^y - m_{t-1}, (m_t^y - m_t^d, \frac{\lambda_t^d}{m_t^y - m_t^d}), (m_t^u - m_t^y, \frac{\lambda_t^u}{m_t^u - m_t^y}) ] \rangle$ . For instance, the meter reading and ask from Fig. 3.4, assuming  $m_{t-2} = 9999$ , could be expressed as  $\langle 1 [ , 7, (2, 10), (4, 0.75) ] \rangle$  (cf.  $\langle 10000, [10007, (10005, 20), (10011, 3)] \rangle$ ). Both formats are equivalent for the purpose of this thesis, although the latter is more efficient for communication and computation, as the mechanism performs fewer mathematical operations.

Lastly, the ask format is expressive enough to separate the costs of peak-shaving responses from those of valley-filling. Domestic comfort costs might be different from deferring appliance use than from using them in advance. Conversely, comfort and fuel cost of other appliances might be the same during a specified time window. Therefore, the ask format allows for aggregating the costs of the actions aligned for peak-shaving in one field, and those aligned for valley-filling in another one, as opposed of using a combined measure of both DR directions (e.g., mean, overall sum).

### 3.3.3 Allocation Procedure

The auctioneer agent is given the amount of DR to be procured, presumably by the retailer's sales and operations planning system that might use a predictive model to determine this quantity. Similarly, the auctioneer is also given the reservation prices for procuring DR; these prices might be a function of the forecast of the imbalance settlement. Let  $\tilde{Q}_t \in \mathbb{R}$  be the DR quantity to be procured, and let  $\tilde{\lambda}_t^{S*} \in \mathbb{R}_{\geq 0}$  and  $\tilde{\lambda}_t^{B*} \in \mathbb{R}_{\geq 0}$  be the respective reservation prices for selling and buying kWh from DR at time period  $t \in T$ . Similarly, let  $y_t \in \{0, 1\}$  be a boolean parameter that denotes the procurement direction depending on  $\tilde{Q}_t$ , where  $y_t := 0$  indicates net-load peak-shaving and  $y_t := 1$  corresponds to net-load valley-filling. That is, the auctioneer agent interprets that if it is given a  $\tilde{Q}_t \in \mathbb{R}_{> 0}$ , the retailer's schedule is in surplus, and thus the DR procurement direction is set for net-load valley-filling (i.e.,  $y_t := 1$ ); if  $\tilde{Q}_t \in \mathbb{R}_{< 0}$ , the retailer's schedule is in shortage and net-load peak-shaving will be procured (i.e.,  $y_t := 0$ ). When  $\tilde{Q}_t = 0$ , the auctioneer interprets that no DR is to be procured. Furthermore, the size of DR offers is constrained within an range  $[\underline{w} \in \mathbb{R}_{> 0}, \bar{w} \in \mathbb{R}_{> 0}]$  which is defined by the retailer, and it is common knowledge amongst the auctioneer and DR providers. These parameters enable the retailer to specify the minimum and maximum DR amounts to be considered by the mechanism.

Subsequently, the auctioneer agent, on behalf of the retailer, queries the end-users

to collect meter readings and asks. Let  $A_t \subseteq N$  be the set of agents that submitted an ask at time period  $t$ . For convenience, the ask format is expressed in kWh quantities rather than in meter readings, as it is described in the previous section. Therefore, let  $\hat{\theta}_{it}$  be the reported *type* of end-user  $i \in A_t$ , where  $\hat{\theta}_{it} := \left\langle q_{i(t-1)} \left[ \hat{q}_{it}^y, \left( \hat{q}_{it}^d, \hat{\lambda}_{it}^{dk} \right), \left( \hat{q}_{it}^u, \hat{\lambda}_{it}^{uk} \right) \right] \right\rangle$ . The hat-notation is used to denote agent's reported types, however, for simplicity of notation and because this mechanism is DSIC, it is standard to assume that agents report their values truthfully, i.e.,  $\hat{\theta}_{it} \equiv \theta_{it}$ ,  $\forall i \in A_t$ , since it is their best response. Let  $A_t^* \subseteq A_t$  be the set of valid DR offers at time period  $t$ , which are the offers whose offering prices do not exceed reservation prices and meet the offer size constraint, i.e.,  $A_t^* := \left\{ i \in A_t \mid \lambda_{it}^{dk} \leq \tilde{\lambda}_t^{B*}, \lambda_{it}^{uk} \leq \tilde{\lambda}_t^{S*}, q_{it}^u y_t + q_{it}^d (1 - y_t) \in [\underline{w}, \bar{w}] \right\}$ . The constraints on reservation prices are simultaneously enforced and independent from the chosen DR direction  $y_t$ . This is done in order to limit gains from misreporting and its reasoning is provided later in this section. Then, the auctioneer computes the minimum DR amount that can be feasibly procured, so that this quantity becomes a valid constraint for a minimisation objective. Let  $\tilde{Q}_t^* \in \mathbb{R}_{\geq 0}$  be computed as the minimum between the DR amount to be procured and the sum of all valid offers received at time period  $t$ , i.e.,  $\tilde{Q}_t^* := \min \left\{ |\tilde{Q}_t|, \sum_{i \in A_t^*} q_{it}^u y_t + q_{it}^d (1 - y_t) \right\}$ . Henceforth, the allocation rule over the valid offers,  $A_t^*$ , solves a cost minimisation problem for procuring at least  $\tilde{Q}_t^*$  in DR offers, and its formulation is as follows.

$$\mathbf{x}_t^* := \arg \min_{x_{it}} \sum_{i \in A_t^*} \left[ \lambda_{it}^{uk} y_t + \lambda_{it}^{dk} (1 - y_t) \right] x_{it} \quad (3.13)$$

subject to:

$$\sum_{i \in A_t^*} \left[ q_{it}^u y_t + q_{it}^d (1 - y_t) \right] x_{it} \geq \tilde{Q}_t^* \quad (3.14)$$

$$0 \leq x_{it} \leq 1 \quad (3.15)$$

This minimisation problem is equivalent to a continuous knapsack problem (CKP)<sup>15</sup> (Dantzig, 1957). Although, knapsack problems are traditionally framed as maximisation problems, translating them into minimisation problems is trivial. It is convenient to provide some definitions to explain the allocation reasoning.

<sup>15</sup>The continuous knapsack problem is also known as the fractional knapsack problem (FKP).

**Definition 3.5.** (Dantzig’s 0/1-KP Greedy Approximation) Dantzig (1957) proposed a simple greedy approximation (GA) based on sorting the items in decreasing order by value per unit of weight, i.e.,  $v_i/w_i$ , and greedily selecting items from the beginning of the sorted list and placing them into the knapsack until there is no space. The cost minimisation version of this GA is achieved by changing the sort to increasing order by cost per unit of weight, i.e.,  $c_i/w_i$ , and greedily select the items under the knapsack constraint(s). For instance, 8 kWh procured at 20 pence has a cost of 2.5 pence per kWh, i.e.,  $0.20/8 = 0.025$ . Similarly, 10 kWh procured at 20 pence is cheaper than the previous 8 kWh at 20 pence, i.e.,  $0.20/10 = 0.020$ , that is 2 pence per kWh.

Dantzig’s 0/1-KP GA yields an optimal solution for the CKP, however, for the integral case it can give solutions that are far from optimal. Depending on the problem, this GA could give optimal or reasonable solutions; as Dantzig (1957) suggested, rounding the solution for the CKP might be practically accepted in cases where the model is imperfect about the knapsack capacity or where the size of the items is small relative to the size of the knapsack. This is precisely the case for this knapsack auction. First, the DR quantity to procure comes from a forecast, thus it is imperfect. Second, the flexibility size of domestic end-users is small (e.g., single-digit kWh flexibility offers per time period) compared to a much larger imbalance quantity at a retailer’s trading schedule (e.g., three-digit kWh per time period), due to how electricity is traded in advance of its use. Should this solution rounding becomes too inefficient for accepting whole DR offers (integral knapsack problem), it is possible to tailor the GA to produce less inefficient solutions, such as 2-PTAS<sup>16</sup> solutions that are monotone (e.g., (Mu’alem and Nisan, 2008), (Roth, 2015)). Monotone allocations, along with Myerson’s critical payments, are required to achieve DSIC (Myerson, 1981). Alternatively, the state-of-the-art for knapsack auctions can be used, which is an FPTAS algorithm that yields monotone allocations proposed by Briest et al. (2005). However, given the described setting in this chapter, Dantzig’s 0/1-KP GA is sufficient.

The solution to the allocation problem consists of all DR offers where the resulting decision vector  $x_t^*$  from mathematical programme 3.13-3.15 assigned a value greater than zero, i.e.,  $\{i \in A_t^* \mid x_{it} > 0\}$ . Using Dantzig’s 0/1-KP GA, it can only be up to one fractional item (DR offer) (Dantzig, 1957), which in this case it is rounded. The end-user agents that submitted an ask that did not result allocated are notified by the auctioneer.

<sup>16</sup>The factor of 2, which is an upper bound, even becomes much more smaller if the item sizes are small relative to the knapsack capacity.

Constraint 3.14 limits the amount of flexibility that is being procured. Parameter  $\tilde{Q}_t$  is determined by the retailer and it could be set to the expected deviation with regard the amount that has been traded in the wholesale market (i.e., pool markets and/or bilateral contracts). Since retailers trade (or generally buy) electricity in the wholesale market several time periods in advance, and their forecasts tend to be more accurate as they get closer to the time of delivery, the value of  $\tilde{Q}_t$  can be determined at  $t - 1$  by the retailer. Moreover, it could be the case that, at  $t - 1$ , the DSO knows about an unexpected surplus (or deficit) for time period  $t$  and offers it to retailers at a better price. Then, some retailers could take these last time-period offers, update their schedules and DR procurement  $\tilde{Q}_t$ .

Constraint 3.15 is a linear relaxation to reduce the allocation problem from an intractable mixed integer linear programme (MILP) to a tractable linear programme (LP), which can be solved efficiently. However, the retailer is committed to allocate the last fraction as an integral offer. The main reasons for this, as discussed above, are the imperfect nature of the model, and relative small sizes and values of offers with respect the amount being procured. Therefore, accepting a whole offer instead of a fraction from a domestic end-user is negligible for the retailer. In addition, tractability is a practical requirement so that the auction can be cleared and end-users advised of this result in a few seconds, so they have enough time to run the respective tasks from their schedules within time period  $t$ . Furthermore, Dantzig's 0/1-KP GA can be implemented without the need of a mathematical programming solver, and it is practical for processing a large number of asks (as required for this mechanism); it has polynomial time complexity of  $O(n \log n)$  due to the sort, where  $n$  is the number of valid asks. The allocative efficiency is not affected by the linear relaxation when the collective amount of DR is smaller than the amount that is being procured. However, when valid DR offers amount for a larger quantity than the one being procured, the last allocated offer will very likely be rounded up and it is bounded by  $\bar{w}$ . In average, it could be expected that the mechanism allocates  $\frac{\bar{w}}{2}$  more than needed per time period due to rounding up. This additional amount could be subtracted from  $\tilde{Q}_t$  so that the rounding up approaches the procured quantity in expectation.

Reservation prices  $\tilde{\lambda}_t^{S*}$  and  $\tilde{\lambda}_t^{B*}$  could be a function of the forecast of imbalance settlement prices (i.e., system sell price (SSP) and system buy price (SBP), respectively), but the retailer is free to choose a different policy to determine them<sup>17</sup>. For

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<sup>17</sup>For the purpose of this thesis, it has been assumed that the auction's objective is to minimise the social cost of balancing supply and demand, and not to maximise revenue. These prices are interpreted

instance, in Chapter 5, these prices are set to the minimum marginal gain of procuring DR with regard to the forecast balancing price, including the impact on retail sales (i.e.,  $\tilde{\lambda}_t^{S*} := \lambda^{RS} - \tilde{\lambda}_t^S$  and  $\tilde{\lambda}_t^{B*} := \tilde{\lambda}_t^B - \lambda^{RS}$ , expressed in terms of the retail sell price, as it has been assumed that  $\lambda^{RS} > \lambda^{RB}$  and a setting in which  $\tilde{\lambda}_t^B > \lambda^{RS}$  most of the time). Moreover, it is important to simultaneously impose both constraints on reservation prices in the allocation problem, as otherwise end-user agents could get a benefit from lying. Consider the case in which an end-user agent always submit an ask with a misrepresented part, such as an ask of the form  $\langle q_{t-1} [ , q_t^y, (q_t^{dl}, \lambda_t^{dkl}), (q_t^{ul}, \epsilon) ] \rangle$ , where  $q_t^y$  is fake and deliberately low;  $q_t^{dl}$  is a fake small amount that is offered at a very expensive cost of  $\lambda_t^{dkl}$ , so as to avoid being chosen when the auctioneer is procuring for peak-shaving;  $q_t^{ul}$  is the net-load forecast amount  $q_t^y$ , which is offered at the very small cost  $\epsilon$ . Therefore, when valley-filling is selected, the ask is very likely to be allocated since its cost  $\epsilon$  is very low, and the retailer would give a discount to the end-user for the fake merit of providing flexibility of  $q_t^{ul}$  kWh, when it is just regular electricity use. In addition, the end-user faces no risks of being penalised for cheating when the retailer chooses peak-shaving, as  $\lambda_t^{dkl}$  is deliberately expensive, and thus unlikely to be allocated. An analogous case can be constructed to avoid valley-filling and be rewarded for fake peak-shaving. Thus, asks that do not satisfy these constraints are simply rejected. It cannot be assumed that either DR strategy is equally likely, and end-users could lie and win a discount in expectation, therefore Section 3.3.5 proposes suitable penalty schemes to counteract these dynamics and make the mechanism *strategy-proof*.

Lastly, it rests to show that Dantzig's 0/1-KP GA yields monotone allocations.

**Definition 3.6.** (Monotone Allocation Rule) An allocation function  $X$  for a single-dimensional environment is *monotone* if  $\forall i \in A_t$ , the ask of agent  $i$ , i.e.,  $a_i$ , and the asks by the others except  $i$ , i.e.,  $a_{\setminus i}$ , the allocation  $X_i(a_i, a_{\setminus i})$  to  $i$  is nondecreasing in its ask (Roughgarden, 2016, Ch3). That is, for an allocated ask  $a_i$ , while having all other asks  $a_{\setminus i}$  fixed, if agent  $i$  makes its cost smaller (i.e., a better offer), it can only continue to win.

**Proposition 3.7.** *Dantzig's 0/1-Knapsack Problem Greedy Approximation yields monotone allocations.*

*Proof.* The cost minimisation version of the integral knapsack problem using Dantzig's greedy approximation requires that the items are sorted by cost-per-weight ratio in ascending order, and then proceeds to put as many items as possible inside the knapsack,

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as if they were asks from the balancing market, and the retailer cannot carry any inventory, thus it has to allocate its whole imbalance per time period.



one by one until it gets full. Formally, let  $K$  be the set of items that could be placed inside the knapsack. Let the size of the knapsack be denoted by  $W \in \mathbb{R}_{\geq 0}$ . Each item  $k$  has cost  $c_k$  and weight  $w_k$ . Let  $S := \emptyset$  be the initial solution to the knapsack problem. First, the procedure sorts all items,  $\forall k \in K$ , by  $c_k/w_k$  in ascending order and places them into a sorted list  $A \subseteq K$ . Second, while there is enough space in the knapsack, i.e.,  $\sum_{k' \in S} w_{k'} \leq W$ , the top item, which has the lowest cost-per-weight ratio, is removed from the sorted list  $A$  and placed into the knapsack, i.e.,  $S := S \cup \{x \in A \mid x = A_0\}$  and  $A := A \setminus A_0$ . For each  $k \in S$ , lowering cost  $c_k$  while having the same weight  $w_k$  and fixing the cost and weight of items other than  $k$ , i.e.,  $\forall k' \in K \setminus k$ , will make each  $k$  part of the solution if the procedure had to be performed again. The proof follows from sorting by cost-per-weight ratio,  $c_k/w_k$ , in ascending order, since having a weakly lower cost for  $k$ , i.e.,  $c'_k \leq c_k$ , can only make item  $k$  to weakly move its position up in the sorted list  $A \subseteq K$ , due to  $\frac{c'_k}{w_k} \leq \frac{c_k}{w_k}$ , and thus item  $k$  continues to be part of the solution set  $S$ . This proof is analogous for the utility maximisation problem.  $\square$

**Corollary 3.8.** *The mathematical programme 3.13-3.15 solved by Dantzig's 0/1-KP GA yields monotone allocations.*

*Proof.* First, the auctioneer is given the DR direction, either  $y_t = 0$  for peak-shaving or  $y_t = 1$  for valley-filling; this boolean parameter  $y_t$  cancels the term that corresponds to the opposite DR direction in the mathematical formulation 3.13-3.15. This reduces the multidimensional type (i.e.,  $\langle q_{t-1} [ , q_t^y, (q_t^d, \lambda_t^{dk}), (q_t^u, \lambda_t^{uk}) ] \rangle$ ) into a single dimension, from where Definition 3.6 is used for this proof. Second, the mathematical formulation uses the conveniently simplified ask format (cf. Subsection 3.3.2), where reported costs  $\lambda_{it}^{dk}$  and  $\lambda_{it}^{uk}$  are the cost to DR quantity ratios, i.e.,  $\lambda_{it}^{dk} = \frac{\lambda_{it}^d}{q_{it}^d}$  and  $\lambda_{it}^{uk} = \frac{\lambda_{it}^u}{q_{it}^u}$ , for end-user agent  $i \in A_t^*$  at time period  $t \in T$ . Third, substituting  $\lambda_{it}^{dk}$  and  $\lambda_{it}^{uk}$  into the mathematical programme, along with parameter  $y_t$ , yields a knapsack problem of the same category as the one used in Proposition 3.7. For instance, for  $y_t = 0$ , the mathematical formulation 3.13-3.15 becomes  $\mathbf{x}_t^* := \arg \min_{x_{it}} \sum_{i \in A_t^*} \frac{\lambda_{it}^d}{q_{it}^d} x_{it} \mid \sum_{i \in A_t^*} q_{it}^d x_{it} \geq \tilde{Q}_t^*, 0 \leq x_{it} \leq 1$ , that is essentially the cost minimisation version of the KP with the difference that the proposed mechanism rounds up the fractional offer, whereas the IKP discards the fractional item as it does not fit in the knapsack. The formulation is analogous for  $y_t = 1$ . Finally, through Proposition 3.7, the mathematical programme 3.13-3.15 solved by Dantzig's 0/1-KP GA yields monotone allocations.  $\square$

### 3.3.4 Payment Agreement Procedure

Due to the physics of how electricity is generated and used, as well as the nature of this repeated reverse auction for domestic flexibility procurement as an ancillary service, the payments from time period  $t$  need to be computed at  $t + 1$ , when the actual achievements can be measured by checking the meters. Therefore, when  $t := t + 1$ , the auctioneer queries the meters and verifies the achievements according to agreed prices and quantities for those end-users who had an ask allocated at  $t - 1$ . Depending on the privacy policy, the auctioneer may allow the retailer to read and store the meter states for future forecasts. When asks are allocated, the corresponding discounts are computed such that if an end-user fulfil its offer, it is credited the full agreed discount. Discounts are computed using Myerson's critical payments (Myerson, 1981), that incidentally replicates the pricing rule from the multi-unit single-item Vickrey auction (Roughgarden, 2016, Ch3).

The payment agreement procedure adapts the allocation problem described above, Equations 3.13-3.15, to determine the discounts. The procedure is as follows.

1. Asks that do not satisfy reservation prices and offer size constraints are rejected. Let  $A_t$  be the set of submitted DR offers at time period  $t$ . Let  $A_t^* \subseteq A_t$  be a subset that contains the valid DR offers at time period  $t$ , where  $A_t^* := \left\{ i \in A_t \mid \lambda_{it}^{dk} \leq \tilde{\lambda}_t^{B*}, \lambda_{it}^{uk} \leq \tilde{\lambda}_t^{S*}, q_{it}^u y_t + q_{it}^d (1 - y_t) \in [\underline{w}, \bar{w}] \right\}$ , as described in Subsection 3.3.3. Therefore, DR offers in  $A_t \setminus A_t^*$  are rejected.
2. Dantzig's 0/1-KP GA is used to determine the selected asks  $S_t \subseteq A_t^*$ , while keeping track of the biggest ask quantity  $q_t^{\max}$  that is selected. The subset  $S_t$  is essentially the allocation vector  $x_t^*$  resulting from 3.13 subject to constraints 3.14-3.15.
3. Dantzig's 0/1-KP GA is used to determine the set of runner-up asks  $L_t \subseteq A_t^* \setminus S_t$  that amount up to  $q_t^{\max}$ . If there are not enough runner-up asks, the corresponding reservation price is used to cover the remaining amount up to  $q_t^{\max}$ , as if this were an ask by an extra participant. That is, let  $q_t^L \in \mathbb{R}_{\geq 0}$  be the runner-up DR capacity, i.e.,  $q_t^L := \sum_{\ell \in L_t} q_{\ell t}^u y_t + q_{\ell t}^d (1 - y_t)$ ; if  $q_t^L < q_t^{\max}$  then  $L_t := L_t \cup \left\langle 0 \left[ , 0, \left( q_t^{\max} - q_t^L, \tilde{\lambda}_t^{B*} \right), \left( q_t^{\max} - q_t^L, \tilde{\lambda}_t^{S*} \right) \right] \right\rangle$ .
4. Discounts are computed by finding the critical values  $\forall \theta_i \mid i \in S_t$  with regard to runner-up asks  $L_t$ . Mathematical formulation 3.16 below shows this computa-

tion.

$$z_{it}^* := \arg \min_{z_{it}} \sum_{\ell \in L_t} \left[ \lambda_{\ell t}^{uk} y_t + \lambda_{\ell t}^{dk} (1 - y_t) \right] z_{it} \quad \forall i \in S_t \quad (3.16)$$

subject to:

$$\sum_{\ell \in L_t} \left[ q_{\ell t}^u y_t + q_{\ell t}^d (1 - y_t) \right] z_{it} \geq q_{it}^u y_t + q_{it}^d (1 - y_t) \quad (3.17)$$

$$0 \leq z_{it} \leq 1 \quad (3.18)$$

Let  $p_{it} \in \mathbb{R}_{>0}$  be the discount given to end-user agent  $i \in S_t$  at time period  $t$ , which corresponds to the cost of procuring agent  $i$ 's DR offer from the set of runner-up offers, i.e.,  $p_{it} := \sum_{\ell \in \{z_{it}^* | z_{it} > 0\}} \left[ \lambda_{\ell t}^{uk} q_{\ell t}^u y_t + \lambda_{\ell t}^{dk} q_{\ell t}^d (1 - y_t) \right] \quad \forall i \in S_t$ .

5. The results of the allocation with the respective agreed discounts are communicated to end-users,  $\forall i \in A_t$ . End-users  $i \in S_t$  are informed of discount  $p_{it}$  resulting from formulation 3.16-3.18, and DR direction  $y_t$ . End-users  $i \notin S_t$  obtain a discount  $p_{it} := 0$ .

Linear programme 3.16, subject to constraints 3.17 and 3.18, solves the critical value payment, which is the maximum ask (minimum bid) that agent  $i$  could have reported and still have won the allocation. In other words, agent  $i$  receives a discount  $p_{it}$  that is weakly greater than its reported (truthful) cost. Through Myerson's Lemma (and incidentally, Vickrey's auction), the described payments incentivise honest reporting, that is, agents are weakly better off reporting their type truthfully than they would be otherwise. This claim is proved in Proposition 3.9. Moreover, the computation of these discounts is tractable, more precisely is  $O(n)$ , where  $n$  is  $\|S_t\|$ , provided that the list has already been sorted in the allocation procedure.

The following toy example in Table 3.2 illustrates this pricing scheme. The electricity retailer estimates that the collective net-load will exceed its trading position by seven kWh. Therefore, peak-shaving will be procured for time period  $t$ , i.e.,  $y_t := 0$  and  $\tilde{Q}_t := 7$  kWh. The retailer submit the parameters  $y_t$ ,  $\tilde{Q}$ , and reservation prices  $\tilde{\lambda}_t^{B*}$  and  $\tilde{\lambda}_t^{S*}$  whose values are not relevant in this example. Then, the auctioneer agent queries the subscribed end-user agents for DR offers, and it discards the offers that not satisfy reservation prices and offer size constraints. That is, after Step 1,  $A_t^*$  contains only valid offers. Step 2 sorts asks by  $\lambda_{it}^{dk}$  in ascending order; from Table 3.2, the solution set is  $S_t := \{1, 2, 3\}$  and  $q_t^{\max} := 4$  (i.e.,  $q_t^{\max} := q_{\{2\}t}^d$ ). Step 3 procures  $q_t^{\max}$  from the

next offers in the sorted list that are not in the solution, i.e.,  $A_t^* \setminus S_t$ , put them into set  $L_t := \{4, 5\}$  (where  $\sum_{\ell \in L_t} q_{\ell t}^d = 5$  and greater than  $q_t^{\max} = 4$ ), and discard the following offers. Step 4 computes the discounts for all agents whose offer is part of the solution, i.e.,  $p_{it}$ ,  $\forall i \in S_t$ . Discount of agent  $i = 1$  is equals to the value of offers from  $L_t = \{4, 5\}$  needed to procure agent  $i$ 's DR quantity  $q_{\{1\}t}^d$  (i.e., 1 kWh), where offers cannot be taken fractionally; thus,  $p_{\{1\}t} := \lambda_{\{4\}t}^{dk} q_{\{4\}t}^d$ , which is the same as  $\lambda_{\{4\}t}^d$ , i.e., 16 pence; similarly,  $p_{\{2\}t} := \lambda_{\{4\}t}^{dk} q_{\{4\}t}^d + \lambda_{\{5\}t}^{dk} q_{\{5\}t}^d$ , i.e., 43 pence; and  $p_{\{3\}t} := \lambda_{\{4\}t}^{dk} q_{\{4\}t}^d$ , i.e., 16 pence. Step 5 communicates the discounts agreed to all agents in  $A_t$ ; agents whose offer is in the solution set  $S_t$  receive a potential discount of  $p_{it}$  subject to delivering the offered DR quantity in the chosen direction; all other agents  $i \notin S_t$  receive zero discount.

$i$	$q_{it}^d$	$\lambda_{it}^d$	$\lambda_{it}^{dk}$	$p_{it}$
1	1	2	2	16
2	4	20	5	43
3	2	12	6	16
4	2	16	8	0
5	3	27	9	0

Table 3.2: Toy example of critical payments computation.

The computation of the payment agreement or potential discount is done assuming that end-user agents have the capacity to comply with their offers. In general, domestic prosumers might make mistakes when estimating their values. Also, it could be the case they intentionally decide to lie about their quantities, provided that they believe it would increase their utility. Therefore, several penalty schemes are proposed in the next section in order to counteract misreporting and incentivise accurate predictions, specially because there is uncertainty about the agents' ability to fulfil their DR offers.

### 3.3.5 Penalty Schemes

When  $t := t + 1$ , meters are read and the achievements from those who had an ask allocated are verified. The following penalty schemes are designed with the aim of: (1) counteracting misreports, (2) encouraging end-user agents to make reasonable estimations about their offers, and (3) incentivising end-user agents to not forsake their allocated offers when they are not able to meet the target. The onus is on end-user

agents to learn their values and cope with the inherent changes in the household environment. On the one hand, allocated asks with under-reported meter thresholds are not compensated for their extra quantity provided, and thus they face an opportunity cost if they not estimate the offer accurately. On the other hand, asks with over-reported meter thresholds must be penalised for not fully supplying their agreed quantity, but they should be incentivised to try to reduce this gap. The penalty schemes presented below are mainly designed to deal with over-reporting; the first three are designed for this situation, the fourth one is adapted from Dash et al. (2007) for the purpose of comparison. In addition, an inspection procedure is proposed so that end-users' forecasts of electricity use without DR are reviewed.

### 3.3.5.1 Middle Point Agreement Penalty Scheme

This penalty scheme is proposed as a naive baseline that meets the three design objectives previously mentioned. This *middle point* penalty consists on accrediting a linear discount directly proportional to the quantity supplied, and charging a linear amount directly proportional to the missing quantity. For instance, if the auctioneer agrees to pay 60 pence to agent  $i$  for reducing 6 kWh, but the agent is only able to reduce 4 kWh, then the agent receives 40 pence for the achieved reduction of 4 kWh, but it has to pay 20 pence for the missing 2 kWh, resulting in a net discount of 20 pence (i.e.,  $\frac{2}{3}60 - \frac{1}{3}60 = 20$ ). The net discount neutralises right in the middle of the agreed DR amount, where discount and penalty are the same (e.g.,  $\frac{1}{2}60 - \frac{1}{2}60 = 0$ ). In addition, this penalty scheme is bounded by design in the range of  $[-p_{it}, p_{it}]$ . That is, the maximum amount an end-user agent can be charged for not delivering the DR offer is  $p_{it}$  (i.e., the previously agreed payment); similarly, the maximum discount an end-user agent can receive is the agreed payment of  $p_{it}$ . The lower bound is set in order to protect end-users against very bad estimates, and the upper bound is put in place to incentivise accurate DR offers. Figure 3.5 shows a graphical intuition of the regions of this penalty scheme according to different scenarios.

The computation of the middle point penalty is as follows. Let  $S_{t-1} \subseteq A_{t-1}^*$  be the end-user agents who had their ask allocated at  $t - 1$ . Let  $\beta_{i(t-1)} \in \mathbb{R}$  be the achievement ratio of agent  $i$ 's offer after verification. This ratio depends on the DR direction that was procured in the previous time period, thus Equation 3.19 include the boolean parameter  $y_{t-1}$ , where  $y_{t-1} = 0$  denotes peak-shaving and  $y_{t-1} = 1$  denotes valley-filling.

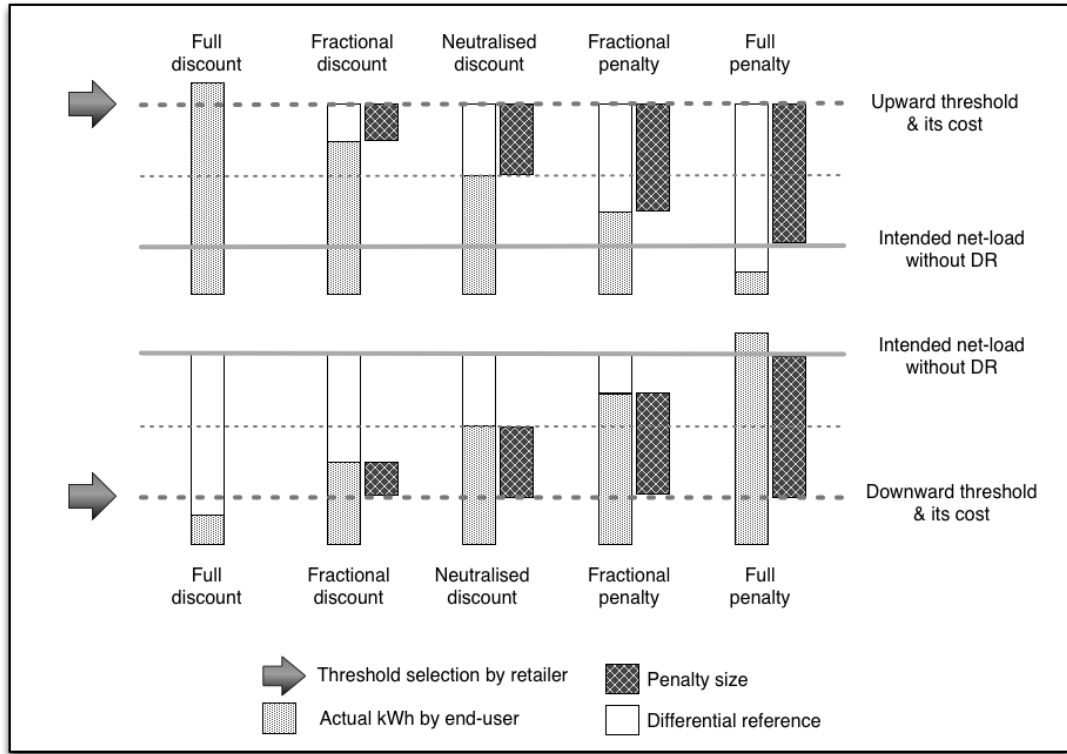


Figure 3.5: Graphical intuition of the middle point penalty scheme.

$$\beta_{i(t-1)} := \frac{q_{it} - q_{i(t-1)}^y}{q_{i(t-1)}^u} y_{t-1} + \frac{q_{i(t-1)}^y - q_{it}}{q_{i(t-1)}^d} (1 - y_{t-1}) \quad \forall i \in \mathcal{S}_{t-1} \quad (3.19)$$

For this penalty scheme, the achievement ratio  $\beta_{i(t-1)}$  is partitioned into three sections in order to determine the discount or penalty. When ratio  $\beta_{i(t-1)} \in \mathbb{R}_{\geq 1}$ , it means that agent  $i$  supplied or exceeded the offered quantity, thus it receives the agreed discount; when ratio  $\beta_{i(t-1)} \in \{x \in \mathbb{R} \mid 0 < x < 1\}$ , it means that agent  $i$  partially fulfilled its offer and it receives partial discount and partial penalty; and when  $\beta_{i(t-1)} \in \mathbb{R}_{\leq 0}$ , it means that the agent failed to deliver its offer, thus it pays the full penalty. For instance, in the previous example where the auctioneer agreed to pay 60 pence to agent  $i$  for reducing 6 kWh, but the agent is only able to reduce 4 kWh, the value of  $\beta_{i(t-1)}$  is  $\frac{2}{3}$ . That is, as peak-shaving was procured (i.e.,  $y_{t-1} = 0$ ) the first term is cancelled; hypothetically, assume that agent  $i$ 's net-load prediction for time period  $t$ , that was made at  $t - 1$ , was 7 kWh (i.e.,  $q_{i(t-1)}^y = 7$ ), and that the actual net-load for time period  $t$  is 3 kWh (i.e.,  $q_{it} = 3$ ). Then,  $\beta_{i(t-1)} := \frac{7-3}{6} (1 - 0)$ , which is previous  $\beta_{i(t-1)} := \frac{2}{3}$ . The case for valley-filling is analogous.

Finally, the resulting discount, or penalty, is computed according to the three described achievement sections.

$$\gamma_{i(t-1)} := \begin{cases} p_{i(t-1)} : & \beta_{i(t-1)} \geq 1 \\ p_{i(t-1)}\beta_{i(t-1)} - p_{i(t-1)}(1 - \beta_{i(t-1)}) : & 0 > \beta_{i(t-1)} > 1 \\ -p_{i(t-1)} : & \beta_{i(t-1)} \leq 0 \end{cases} \quad (3.20)$$

This middle point penalty scheme might seem a bit arbitrary, but there are real-world DR programmes that offer similar regions of reward. For instance, one that is of particular interest is the demand bidding programme (DBP) by Southern California Edison (SCE), in which participant customers bid load reduction over the Internet for hours between noon and 8 p.m., Monday to Fridays (excluding holidays) (Patterson et al., 2014). SCE offers credits of 50 cents per reduced kWh to large customers provided that the actual reduction is between 50% and 200% of their bid amount (Patterson et al., 2014). Although there are no penalties in SCE's DBP, their programme share some similarities with the middle point penalty scheme. Table 3.3 shows a comparison over several attributes. Given the setting described in this thesis, the middle point penalty scheme provides a reasonable baseline, and is comparable to a DR programme that has been implemented by a company.

<b>Attribute</b>	<b>SCE's DBP</b>	<b>Middle Point PS</b>
Customer types	Industrial, business.	Domestic (residential).
DR direction	Peak-shaving.	Peak-shaving and valley-filling.
DR time periods	12:00h - 20:00h (8 time periods of one hour each), from Monday to Friday (excluding holidays).	All days, 48 half-hourly time periods each day.
Intended load	10-day average of the same hour in similar days (excluding holidays and days with DR events).	Reported by end-user agent.
Verification	Interval meter readings.	Interval meter readings.
Clearing price	Posted price, 50 cents per reduced kWh, uniform price for participants.	Critical payments, discriminatory pricing. Linear discount granted w.r.t. achieved DR; linear penalty charged w.r.t. non-achieved DR. Bounded price agreement.
Discount awarding range	Inside 50% and 200% of bid amount.	Greater than 50% delivery of DR offer.
Penalty range	None.	Lower than 50% delivery of DR offer.

Table 3.3: Southern California Edison's demand bidding programme.



### 3.3.5.2 Minimum Proportion Agreement with Slope-Based Penalty

This penalty scheme is similar to the middle point, however the penalty threshold is not in the middle. The penalty threshold is given as a parameter  $\delta \in [0.5, 1)$  that is a percentage of the quantity offered  $\forall i \in S_{t-1}$ . For instance, a penalty threshold of 0.8 means that the discount for the proportional achievement regarding the offer will be neutralised at 80% of the quantity offered. That is, the size of the discount will decrease in the range  $[p_{i(t-1)}, 0]$  in a slope-based fashion according to linear proportions within  $(1, \delta]$  (e.g.,  $(1, 0.8]$ ) of the offered quantity. If the achieved quantity falls below  $\delta$ , then the potential discount becomes a penalty, which (negatively) increases in the range  $(0, -p_{i(t-1)}]$  according to the slope of the linear proportion within  $(\delta, 0]$  (e.g.,  $(0.8, 0]$ ) of the offered quantity. Figure 3.6 shows a graphical intuition of the regions of this penalty scheme.

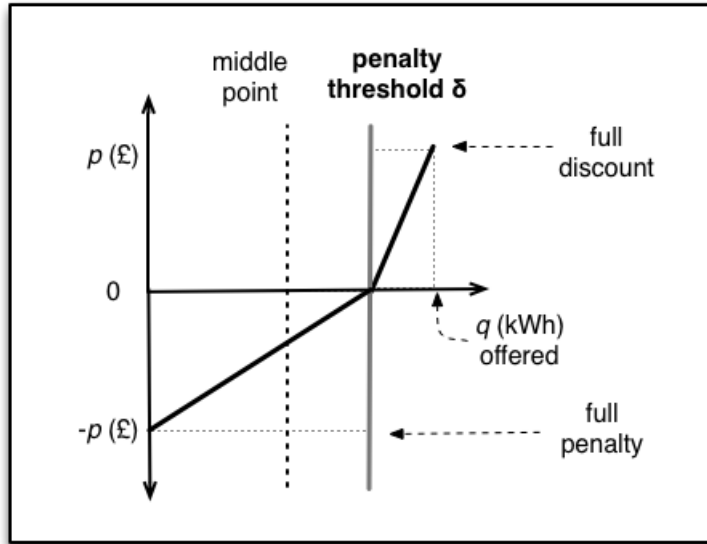


Figure 3.6: Graphical intuition of the slope-based penalty scheme.

The computation of this penalty scheme is as follows. Let  $S_{t-1} \subseteq A_{t-1}^*$  be the end-user agents who had an ask allocated at  $t - 1$ . Let  $\beta_{i(t-1)} \in \mathbb{R}$  be the achievement ratio of agent  $i$ 's offer after verification, which is computed by Equation 3.19. For this penalty scheme, the achievement ratio  $\beta_{i(t-1)}$  is partitioned into four sections in order to determine the amount of discount or penalty  $\forall i \in S_{t-1}$ . Using the achievement ratio  $\beta_{i(t-1)}$  computed by Equation 3.19, the resulting discount (or penalty) from these four sections are computed as follows.

$$\gamma_{i(t-1)} := \begin{cases} p_{i(t-1)} : & \beta_{i(t-1)} \geq 1 \\ \frac{p_{i(t-1)}\beta_{i(t-1)}}{1-\delta} : & \delta \leq \beta_{i(t-1)} < 1 \\ -\frac{p_{i(t-1)}\beta_{i(t-1)}}{\delta} : & 0 \leq \beta_{i(t-1)} < \delta \\ -p_{i(t-1)} : & \beta_{i(t-1)} < 0 \end{cases} \quad (3.21)$$

In the first case, when ratio  $\beta_{i(t-1)} \in \mathbb{R}_{\geq 1}$ , agent  $i$  supplied or exceeded the offered quantity, thus it receives the agreed discount  $p_{i(t-1)}$ .

In the second case, where  $\beta_{i(t-1)} \in \{x \in \mathbb{R} \mid \delta \leq x < 1\}$ , the agent receives a proportional discount that decreases linearly as it approaches to  $\delta$ , where it becomes zero. The computation of this case, i.e.,  $\frac{p_{i(t-1)}\beta_{i(t-1)}}{1-\delta}$ , comes from the resulting slope multiplied by the achieved quantity. That is, the discount slope is  $\frac{p_{i(t-1)}-0}{q_{i(t-1)}-\delta q_{i(t-1)}}$ , i.e.,  $\frac{p_{i(t-1)}}{q_{i(t-1)}-\delta q_{i(t-1)}}$ , where  $q_{i(t-1)} \in \mathbb{R}_{>0}$  is the quantity that agent  $i$  must supply to get full discount, i.e.,  $q_{i(t-1)} := q_{i(t-1)}^u y_{t-1} + q_{i(t-1)}^d (1 - y_{t-1})$ . Let the actual DR quantity supplied be represented by  $q_{i(t-1)}^a \in \mathbb{R}_{>0}$ , which is computed as  $q_{i(t-1)}^a := (q_{it} - q_{i(t-1)}^y) y_{t-1} + (q_{i(t-1)}^y - q_{it}) (1 - y_{t-1})$ . Therefore, in this case, the discount is determined by  $q_{i(t-1)}^a \frac{p_{i(t-1)}}{q_{i(t-1)}-\delta q_{i(t-1)}}$ . By algebraic manipulation, the discount can be expressed as  $\frac{q_{i(t-1)}^a p_{i(t-1)}}{q_{i(t-1)}(1-\delta)}$ , and since  $\beta_{i(t-1)} := \frac{q_{i(t-1)}^a}{q_{i(t-1)}}$ , thus the expression in the second section becomes  $\frac{p_{i(t-1)}\beta_{i(t-1)}}{1-\delta}$ .

The third case is the penalty computation for the case where the achievement ratio falls below the minimum threshold  $\delta$ , i.e.,  $\beta_{i(t-1)} \in \{x \in \mathbb{R} \mid 0 \leq x < \delta\}$ . Following the same reasoning, the penalty is computed as actual quantity supplied multiplied by the penalty slope. That is,  $q_{i(t-1)}^a \frac{0 - (-p_{i(t-1)})}{\delta q_{i(t-1)} - 0}$ , that can be rewritten as  $\frac{q_{i(t-1)}^a p_{i(t-1)}}{\delta q_{i(t-1)}}$ , and since  $\beta_{i(t-1)} := \frac{q_{i(t-1)}^a}{q_{i(t-1)}}$ , the computation can be simplified to charging a penalty of  $\frac{p_{i(t-1)}\beta_{i(t-1)}}{\delta}$  (thus the minus sign in the Equation 3.21).

The fourth case charges full penalty (i.e., the previously agreed discount) because the agent fails to deliver any amount in the chosen DR direction.

Finally, this penalty scheme becomes equivalent to the middle-point from the previous section when  $\delta = 0.5$ .

### 3.3.5.3 Minimum Proportion Agreement with EWMA-Based Penalty

Similar to the previous penalty schemes, if the achieved ratio  $\beta_{i(t-1)} \in \mathbb{R}_{\geq 1}$ , a full discount is awarded. Likewise, if the achieved ratio  $\beta_{i(t-1)} \in \mathbb{R}_{<0}$ , a full penalty is charged. However, the case in which  $\beta_{i(t-1)} \in \{x \in \mathbb{R} \mid 0 \leq x < 1\}$  is dealt differently. This scheme consists on having a *fitness* attribute for end-user agents, that is a parametric measure of how well each agent has complied with its offers in the past. This fitness indicator is computed using an exponentially weighted moving average (EWMA).

Let  $\phi_i \in (0, 1]$  denote the fitness  $\forall i \in N$ , and  $\phi_i := 1, \forall i \in N \mid t = 0$ . That is, all end-users have their fitness initialised to 1 before the beginning of the simulation horizon. Let  $\alpha$  be a parameter, which the retailer is allowed to tweak, that determines whether more importance is placed on more recent achievements by end-user agents or on their overall historical performance, so as to update their fitness. Figure 3.7 offers a graphical intuition about the influence of parameter  $\alpha$  over the fitness attribute. For instance, when  $\alpha < 0.5$ , more importance is placed on earlier performance, when  $\alpha = 0.5$  the trade-off is indifferent, and when  $\alpha > 0.5$  more weight is placed on recent performance.

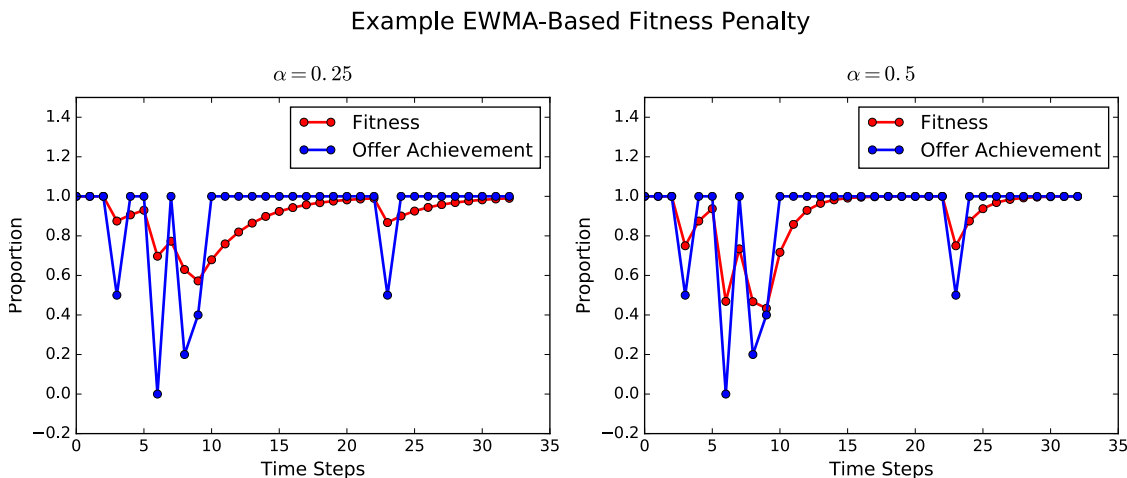


Figure 3.7: Effect of parameter  $\alpha$  on the EWMA-based fitness attribute w.r.t. offer achievement.

A bounded fraction  $f_{i(t-1)} \in [0, 1]$  corresponds to end-user agent  $i$ 's DR achievement ratio at  $t - 1$ , which is easily determined as follows.

$$f_{i(t-1)} := \begin{cases} 1: & \beta_{i(t-1)} \geq 1 \\ \beta_{i(t-1)}: & 0 > \beta_{i(t-1)} > 1 \\ 0: & \beta_{i(t-1)} \leq 0 \end{cases} \quad (3.22)$$

At every  $t \in T$ , the EWMA-based fitness  $\phi_i$  is updated for all the agents that had an allocated offer at  $t - 1$ , which are in the solution set  $S_{t-1}$ .

$$\phi_i := \alpha f_{i(t-1)} + (1 - \alpha) \phi_i \quad \forall i \in S_{t-1} \quad (3.23)$$

The retailer can set a fitness threshold  $\delta \in (0, 1)$ , that the auctioneer can use to reject valid offers  $A_t^*$  from agents whose  $\phi_i < \delta$ .

Furthermore, fitness  $\phi_i$  is gradually regenerated by sending valid offers, even if they are not allocated by the mechanism, i.e.,  $\forall i \in A_t^*$ , for which the agent's fitness is updated using the EWMA formula from Equation 3.23 with a  $f_{i(t-1)} := 1$  over set  $A_t^*$ . This emulates a tit-for- $n$ -tats scheme, forgiving underachieving agents and allowing them back to participate after some rounds, hopefully after they have improved the accuracy of their offers. Finally, this penalty scheme is indirect; it does not charge money, but it translates into opportunity losses for household agents if they do not commit to their offers.

#### 3.3.5.4 Penalty Scheme from Dash et al. (2007)

Dash et al. (2007) propose a penalty scheme for a VCG mechanism with verification where suppliers have limited capacities that they are uncertain about. Their penalty scheme involves computing the VCG payment twice, one with the offered quantity and another one with the actual quantity while having all other offers fixed. Although the problem is different in structure, their penalty scheme can easily be adapted to the mechanism proposed here. Basically, the allocation problem is determined by the reported quantities, but the VCG payments are computed with the actual quantity from each agent keeping the other reported quantities fixed, plus a penalty  $\delta$  to those who over-reported. If an agent has overstated its capacity, its VCG payment after verification along with penalty  $\delta$  will become strictly smaller than if it had not over-reported. This must be computed using the original allocation set  $S_{(t-1)}$  with the verified offer

from agent  $i$ . In their case, Dash et al. (2007), the agents would not exceed their reports and the VCG mechanism was feasible because a small number of agents was assumed, thus the allocation and payments were solved optimally. For the mechanism presented in this chapter, VCG payments coincide with critical payments and this penalty scheme can be applied directly.

$$\gamma_{i(t-1)} := p\left(q_{i(t-1)}^a \mid S_{t-1}, L_{t-1}\right) - \delta_{(t-1)} v_{i(t-1)} \quad (3.24)$$

Equation 3.24 integrates both the critical payment and penalty. The term  $p\left(q_{i(t-1)}^a \mid S_{t-1}, L_{t-1}\right)$  computes the critical payment with the verified achieved quantity  $q_{i(t-1)}^a$  over the original allocation set  $S_{t-1}$  and the runner-up asks that help determine the critical value payment. Parameter  $\delta_{(t-1)}$  is a penalty that is set according to how critical is to meet the supply and demand balance at  $t-1$ , as well as to punish agents for deviating from their reports. In the setting described in this thesis,  $\delta_t$  can be set to the corresponding balancing system price (or a factor of it). Lastly, boolean variable  $v_{i(t-1)}$  indicates if agent  $i$  misreported at  $t-1$ , i.e.,  $v_{i(t-1)} := 1$  if  $q_{i(t-1)} > q_{i(t-1)}^a$ , and  $v_{i(t-1)} := 0$  otherwise.

### 3.3.5.5 Random Inspection Penalty Scheme

There is a possibility that end-user agents could learn the distribution of their retailer's balancing shortage and surplus, only from interacting with the mechanism. For instance, if an end-user agent knows that it is very likely that the retailer will choose peak-shaving on weekdays from 17:00h to 21:00h, given past interactions with the auctioneer, then it could make their intended net-load  $q_{it}^y$  appear higher, so that it could pretend to reduce it and claim a larger offer if it gets allocated. Therefore, a random inspection scheme is proposed to counteract this form of cheating.

The scheme works as follows. After collecting asks but before the allocation, the auctioneer samples asks uniformly from the valid offers set  $A_t^*$  with probability  $\xi$  without replacement, and moves each sampled ask to set  $I_t$ , in order to check their intended net-load prediction  $q_{it}^y$ . The offers in set  $I_t$  are prevented from allocation (i.e.,  $A_t^* := A_t^* \setminus I_t$ ), but agents are notified so they can follow their intended net-load. Let  $g: \langle \mathbb{R}, \mathbb{R} \rangle \mapsto \mathbb{R}$  be a forecast error function, where  $g\left(q_{i(t-1)}^y, q_{it}\right)$  estimates the prediction error between the reported intended net-load and its realisation. Let  $\lambda^J \in \mathbb{R}_{\geq 0}$  be a

fixed penalty for end-user agents providing bad predictions. Furthermore, let  $\delta \in \mathbb{R}_{\geq 0}$  be the error tolerance for predictions. Then, this penalty is computed as follows.

$$\gamma_{i(t-1)} := \begin{cases} -\frac{\lambda^I}{\xi} & : g(q_{i(t-1)}^y, q_{it}) > \delta \\ 0 & : \text{otherwise} \end{cases} \quad (3.25)$$

When threshold  $\delta$  is exceeded, the auctioneer charges the agent a fixed penalty times the inverse of the inspection probability  $\xi$ . For example, suppose  $\delta := 1$  kWh,  $\xi := 20\%$ , agent  $i$ 's prediction error is  $g(q_{i(t-1)}^y, q_{it}) := 1.2$  kWh, and fixed penalty  $\lambda^I := 6$  pence. Then, the resulting penalty  $\gamma_{i(t-1)} := -\frac{6}{0.20}$ , i.e., the agent is charged 30 pence due to its bad prediction error. Nonetheless, when the EWMA-based penalty is used with the idea of not explicitly charging monetary penalties to end-users, if agent  $i$  is inspected and surpasses the threshold error, then its fitness attribute will be set to zero, i.e.,  $\phi_i := 0$ . Hence, end-user agents are better off not lying, as well as they have incentives to improve their forecast methods.

### 3.3.6 Theoretical Properties

**Proposition 3.9.** *The proposed single-sided VCG-based mechanism, with any one of the penalty schemes proposed as verification combined with the inspection scheme, is DSIC.*

*A mechanism is DSIC, also known as truthful or strategy-proof, if it is a (weakly) dominant strategy for agents to reveal their types (i.e., preferences) honestly, regardless of what other agents report. In the DR setting, this means that end-user agents reveal their flexibility offers truthfully.*

*Proof. Part 1:* take the end-users' offer format  $\langle q_{t-1} [ , q_t^y, (q_t^d, \lambda_t^{dk}), (q_t^u, \lambda_t^{uk}) ] \rangle$ , which is a multi-dimensional type. However, as the mechanism relies on the auctioneer procuring only one DR direction depending on the retailer's expected imbalance, this type is reduced to a single-dimensional domain. Suppose the retailer's trading position is in shortage, thus the auctioneer will procure net-load peak-shaving to cover this deficit. For this case, end-users' type becomes  $\langle q_{t-1} [ , q_t^y, (q_t^d, \lambda_t^{dk}) ] \rangle$  (i.e.,  $(q_t^u, \lambda_t^{uk})$  are ignored for net-load peak-shaving). The meter reading  $q_{t-1}$  is only included for verification purposes and cannot influence the allocation. Argument  $q_t^y$  is dealt with in Part 2 of this proof; in this part it can be assumed that this argument cannot influence

the allocation. Therefore, the auctioneer will only consider the pair  $(q_t^d, \lambda_t^{dk})$ , that is itself a single-dimensional type.

Solving the allocation optimally for the presented setting involves solving an integral knapsack problem, which is NP-complete (assuming  $P \neq NP$ ) and intractable for a moderate number of DR offers. The integrality constraint in DR offers comes from the chosen computational model, justified in Section 3.2, that considers the allocation of domestic DR offers as discrete (since most of the current domestic appliances cannot be controlled to draw different levels of power than they are intended to for the task they will perform). Therefore, an approximate solution for the allocation problem is necessary for this model, so that the result of the allocation is determined in a small amount of time. However, payments that incentivise truth-telling as those of VCG cannot generally be used in auctions with approximate allocation functions, with the aim of achieving a DSIC implementation (Nisan and Ronen, 2007, Lemma 2.1). The only proven solution for this case is the use of Myerson's critical payments, that guarantee DSIC in this setting (Roughgarden, 2016, Theorem 3.7).

Myerson (1981, Lemma 3) states that, for single-parameter domains (i.e., agents with single-dimensional types), an allocation function is implementable (i.e., there is a payment rule that makes direct-revelation mechanisms DSIC) if and only if:

a) the allocation rule is monotone (cf. Definition 3.6);

b) the payment rule is the critical value (i.e., the minimum bid or maximum offer they could have reported and still have won the allocation) for the agents in the allocation solution set, and zero for all the others.

Dantzig's 0/1-KP GA procedure that is used to solve the allocation problem yields monotone allocations, as it has been proved in Proposition 3.7. Furthermore, the payment procedure in Subsection 3.3.4 uses Myerson's critical payments. Incidentally, the critical payment rule for single-parameter domains replicates Vickrey's second-price auction payment rule (Roughgarden, 2016, Ch3), which is itself a VCG mechanism, and thus renders a DSIC mechanism.

**Part 2:** assume, continuing with Part 1, that an agent over-reports  $q_t^d$  and is allocated; then, when its meter is verified the agent will receive a penalty for not delivering completely, as it was overstated. Similarly, assume that the agent under-reports  $q_t^d$ ; since the cost-to-unit ratio  $\lambda_t^{dk}$  is computed as  $\frac{\lambda_t^d}{q_t^d}$  (where the numerator is the total offering cost of the net-load peak-shaving tasks from the house scheduler), reducing  $q_t^d$  will make this cost ratio higher, and the offer could result in not being allocated. Although an allocated under-reported quantity will not face a penalty of the ones de-

scribed Subsection 3.3.5, extra DR achievements are not rewarded, so the agent faces an opportunity cost. Therefore, under-reporting  $q_t^d$  is not profitable.

However, if the agent over-reports its prediction  $q_t^y$ , it will make  $q_t^d$  looks larger. Similarly, if the agent under-reports its prediction  $q_t^y$ , it will make  $q_t^d$  looks smaller. Suppose the agent learns the distribution of the DR direction of its retailer's expected imbalance, which is very likely, as there are only two DR directions; then, it can exploit the mechanism by reporting  $q_t^y$  untruthfully, i.e., overstating when it predicts net-load peak-shaving and understating otherwise so as to pretend that the offered DR is larger. Therefore, to avoid this kind of manipulation, the simple inspection scheme described in Subsection 3.3.5.5 is used, where a fixed fine multiplied by the inverse of the inspection probability is charged, so that the agent cannot consistently win in expectation through misreporting. Therefore, agents are weakly better off reporting their type truthfully,  $\hat{\theta}_{it} = \theta_{it}$ , i.e.,  $\langle q_{t-1} [ \hat{q}_t^y, (\hat{q}_t^d, \hat{\lambda}_t^{dk}), (\hat{q}_t^u, \hat{\lambda}_t^{uk}) ] \rangle = \langle q_{t-1} [ q_t^y, (q_t^d, \lambda_t^{dk}), (q_t^u, \lambda_t^{uk}) ] \rangle$ .

Both parts of the proof are analogous for the case of net-load valley-filling.  $\square$

**Proposition 3.10.** *The proposed mechanism combined with the EWMA-based penalty and EWMA-based inspection scheme is ex-post individually-rational (IR).*

*A mechanism is IR, or exhibits voluntary participation, if agents do not lose from participating. Moreover, if the agents never derive a negative utility, it is said to be ex-post IR.*

*Proof.* First, the mechanism is normalised (cf. Section 3.3.1), and it implies that agents receive zero utility from not participating or from non-allocated offers. This follows from the definition of end-users' operational flexibility (cf. Definition 3.4). That is, flexibility is extracted from scheduled domestic tasks (load and generation) that are set to run within a time frame; human end-users are assumed indifferent as long as these tasks finish by their deadlines, and this is enforced as a hard constraint in the proposed model. The agent that represents human end-users uses linear (cost) functions as strategies for valuating offers in line with end-users preferences. Therefore, human end-users and their agent carry no real costs for anticipation or postponement of scheduled tasks.

Second, by definition of a (reverse) VCG-based mechanism, end-user agents are never paid less than their reported offer. However, there is uncertainty as DR offers rely on predictions, and the onus is on end-user agents to deal with it. The uncertainty in the proposed model mainly comes from the intended net-load to be used,  $q_t^y$ , whose computation includes a forecast of the inflexible net-load excluding the schedule, and



the tasks from the schedule that no longer have flexibility with regard to their deadline. Reported DR quantities,  $q_t^d$  or  $q_t^u$ , depend on the intended net-load  $q_t^y$ , and are verified with the actual meter reading  $q_{t-1}$ .

Third, suppose the auctioneer procures net-load peak-shaving, and end-user agent  $i$  under-reports  $q_{it}^d$  and its offer gets allocated. In the following time period,  $q_{it}^d$  is compared against  $q_{it-1}$ , but since the agent under-reported, it actually delivered more than its reported DR, and it gets paid the agreed discount. For this case, had agent  $i$  over-reported  $q_{it}^d$ , it would have failed to fully deliver it and would have been penalised with the EWMA-based scheme. The actual delivered fraction  $f_{it}$  is computed using Equation 3.22 and yields a value such that  $f_{it} \in [0, 1]$ . Then the historical parameter  $\phi_i$  is weighted using Equation 3.23 in order to trade off past and current performance and use it as an indicator of how well agent  $i$  sticks to its offers. If  $\phi_i$  is less than a minimum proportion threshold  $\delta$ , then agent  $i$  is prevented from the allocation until it reaches  $\phi_i \geq \delta$ , which is gradually regenerated when agent  $i$  submits valid offers (cf. Subsection 3.3.5.3). Therefore, agent  $i$  cannot derive a negative utility, although it faces opportunity costs when is prevented from participating due to bad performance, that serves as an incentive to report more accurately. The case for procuring net-load valley-filling is analogous.

Fourth, independently from which DR direction is being procured, the EWMA-based inspection scheme reviews, with some probability  $\xi$ , how accurate is agent  $i$ 's prediction for the intended use,  $q_{it}^y$ , when it is not selected for DR. If prediction error  $g(q_{i(t-1)}^y, q_{it}^y)$  is higher than  $\delta$ , then agent  $i$  is penalised with  $\phi_i := 0$ , which prevents it from having offers allocated until it reaches  $\phi_i \geq \delta$ . This translates to an opportunity cost that, along with the normalisation property, makes it impossible for end-user agents to derive a negative utility from participating in this configuration of mechanism.

Finally, since this is a VCG-based mechanism, the strongest notion of IR, i.e., *ex-post*, requires the environment to exhibit *choice-set monotonicity* and *no negative externalities* (Shoham and Leyton-Brown, 2008, Ch10). Choice-set monotonicity means that when an agent is removed, the set of possible choices, that the mechanism can select from, weakly decreases (Shoham and Leyton-Brown, 2008, Ch10). This follows from the fact that preventing an agent from participating never increases the list of valid asks that the auctioneer can choose from, i.e.,  $\{A_t^* \setminus i\} \subseteq A_t^* \forall i$ . The environment exhibits no negative externalities, if every agent  $i$  has a non-negative utility for any allocation in which it does not participate (Shoham and Leyton-Brown, 2008, Ch10), i.e.,  $\forall i \forall x \in X(A_t^* \setminus i), u_i(x) \geq 0$ . This follows from the IPV and normalisation assumptions

discussed in Subsection 3.3.1. IPV implies that agent  $i$ 's utility only depends on its own information and ignores everything about the others. The normalisation assumption implies that agent  $i$ 's utility is zero from not participating or not having an allocated offer. That is, agent  $i$  cannot derive a negative utility from offers that are allocated to the others or that are not allocated to itself. Therefore, as the environment exhibits choice-set monotonicity and no negative externalities, and the mechanism does not make agents derive negative utilities, this single-sided VCG-based mechanism with EWMA-based penalty and EWMA-based inspection schemes is ex-post IR.  $\square$

*Remark 3.11.* It is important to note that using any of the other proposed penalty schemes (i.e., middle point, slope-based, and the one based on Dash et al. (2007)) and the non-EWMA version of the inspection scheme may result in end-user agents deriving negative utilities. Nonetheless, end-user agents should be able to derive a non-negative utility in expectation (i.e., ex-ante IR), for instance by forecasting reasonably well (cf. Chapter 6) and managing risks accordingly (e.g., under-reporting involves no monetary losses for end-users). The proof for ex-ante IR of these mechanism configurations, and a detailed study of the calibration of parameters such as thresholds (e.g., delivered offer, prediction error), probability of inspection, and amount of penalties have been left for future research.

**Proposition 3.12.** *The mechanism is (strongly) budget-balanced.*

*A mechanism is (strongly) budget-balanced if the auctioneer never makes either a profit or a loss. That is, the amount from the payments collected by the centre is equal to the amount from payments made by it, at every time period.*

*Proof.* Since the mechanism is single-sided, it is trivial to see that it is budget-balanced; the auctioneer distributes the same amount of money it collects after verification, at every time period. For VCG mechanisms, or in this case the VCG-based mechanism, an additional property is required to satisfy budget-balancedness, the environment must exhibit *no single-agent effect* (Shoham and Leyton-Brown, 2008, Ch10). The mechanism environment exhibits this property when the welfare of agents other than  $i$  is weakly increased by removing  $i$  (Shoham and Leyton-Brown, 2008, Ch10). That is, assuming truthful reports, there exists a feasible allocation without  $i$  that results in other agents apart from  $i$  increasing their utility. As a single-sided auction, removing an agent only reduces the amount of competition for the other agents, and they are weakly better off (Shoham and Leyton-Brown, 2008, Ch10). Since the environment of the mechanism exhibits no single-agent effect and the auctioneer exactly distributes the same amount

from the payments it collects, at every time period, the proposed one-sided VCG-based mechanism, with any of the penalty schemes, is (strongly) budget-balanced.  $\square$

**Proposition 3.13.** *The mechanism is robust to uncertainties about the DR capacity of agents.*

*As defined by Dash et al. (2007), a mechanism is robust to uncertainties regarding the ability of participants to fulfil their offers, if it provides incentives for participants to reduce the gap between their offer and their actual achievement.*

*Proof.* All proposed penalty schemes in this chapter offer a proportional element regarding the achievement; the bigger the difference from the committed offer, the bigger the penalty (i.e., lesser utility). That is, if an end-user agent knows that it will fail to completely supply its allocated DR offer, it is in the best of its interests (at least in a myopic sense) to try to make the gap as small as possible, as otherwise the penalty will be higher and thus its utility lower. Therefore, the proposed mechanism, with any of the penalty schemes designed for this setting, is robust to uncertainties regarding end-users' DR capacity.  $\square$

**Proposition 3.14.** *The mechanism is computationally efficient.*

*A mechanism is computationally efficient if both its allocation and payment procedures, including penalties, are tractable, i.e., computable in polynomial time.*

*Proof.* As described in Subsection 3.3.3, Dantzig 0/1-KP GA is  $O(n \log n)$  due to the sorting, where  $n = \|A_t^*\|$  (i.e., all collected valid asks). Moreover, the payment agreement procedure, described in Subsection 3.3.4, uses the already sorted list from the allocation procedure and takes  $O(n)$  to determine the discounts, where  $n = \|S_t\|$  (i.e., the size of the solution set). Similarly, the integration of any of the penalty schemes from this chapter also takes  $O(n)$ , where  $n = \|S_t\|$ . Therefore, the mechanism is computable in time polynomial  $O(n \log n)$ , where  $n = \|A_t^*\|$  and  $A_t^*$  is the set of valid asks collected at time period  $t$ .  $\square$

**Proposition 3.15.** *The mechanism allows for privacy-preserving.*

*In the described setting, a mechanism is privacy-preserving if the data regarding asks cannot be disaggregated up to the tasks that are being scheduled at the agents' premises.*

*Proof.* The ask format, as described in Subsection 3.3.2, provides summarised amounts of intended net-load  $q_t^y$ , offered quantity for peak-shaving  $q_t^d$ , and offered quantity for

valley-filling  $q_t^u$ . These quantities enclose a variety of operations that can be done in the domestic setting. Domestic tasks and constraints from the schedule are private to end-users and their agent. DR offers tell nothing about single operations at home; response capacity is summed over all scheduled tasks that satisfy their technical and time constraints. Moreover, sending offers to the auctioneer does not imply any information of whether the household is empty or not, since automation by a HEMS is assumed at the end-users' end. Disaggregating what is enclosed in the offering quantities is not trivial, and even harder if those individual quantities (at the household level) are protected by the ISO controlled auctioneer through regulation. The only information at the household level that the auctioneer is expected to provide the retailer with is the actual net-load meter readings, which are needed for billing purposes. Under this model, retailers are allowed to see aggregate quantities of DR offers, and price indicators (e.g., average DR prices, clearing price, etc) per time period, without exposing individual agents, so that retailers can use these to make better predictions, tailor their wholesale trading strategy accordingly (i.e., using DR recourse), and evaluate retail service contracts. Therefore, using an independent auctioneer, whose protocol and information exchange is certified by the ISO/DSO, limits the ability of retailers to exploit private information, and thus manipulate the mechanism and clearing prices (i.e., discounts). Considering the ask format and the independent auctioneer under the described computational model, the proposed mechanism preserves privacy.  $\square$

### 3.3.6.1 Additional Remarks

This mechanism is not economically efficient, i.e., Pareto efficient. Due to *Myerson-Satterthwaite impossibility theorem*, it is known that no mechanism can simultaneously be Pareto efficient, (weakly) budget-balanced, and (ex-interim) individually rational, not even restricting the space of preferences to quasi-linear utility functions with Bayes-Nash incentive-compatible (BNIC) implementation (which is a weaker solution concept than DSIC) (Myerson and Satterthwaite, 1983). Economic efficiency has been foregone in order to allow a computationally tractable DSIC implementation that is IR and BB. Moreover, mechanisms that use reservation prices are generally not economically efficient, as the goods do not necessarily end in the hands of those who value them the most (or the least cost in minimisation problems). In addition, some economic efficiency is also sacrificed due to the allocation constraint of only selecting asks that are selectable from both sides of the DR offer, in order to limit dishonest reports. Further economic efficiency is sacrificed due to the inspection procedure, as perfectly

valid offers are set aside to test their prediction of intended net-load; nonetheless, this is necessary to achieve a DSIC implementation in the described setting, as otherwise agents could exploit the mechanism. Providing a bound for the efficiency loss in this mechanism is still an open research question and has been left for future work.

The communication complexity is linear in the number of demand responders per time period, i.e.,  $O(n)$ , where  $n = \|N\|$ . Also, data types in meter readings and asks can efficiently be represented using integers, which reduces the message size as compared to float-point numbers.

The household's net-load pick-up and drop-down power rate constraints are disregarded for simplicity; however, the model could be extended so that the HEMS adapts the domestic task scheduling in order to comply with these power rate constraints.

### 3.4 Summary

This chapter provided a computationally tractable single-sided VCG-based mechanism with verification for domestic DR coordination, that is DSIC. The chapter also introduced the design of a simple computational model for operational flexibility, which is general enough to capture most of the domestic task scheduling regarding electrical appliances. The model enables end-user agents with heterogeneous technologies to reason about their own operational flexibility so as to encode it into specific and verifiable offers that the electricity retailer, by means of the mechanism, could take in exchange for a discount. Several parameters regarding this domestic flexibility are carefully abstracted into a compact representation in order to reduce the communication burden yet maintain reasonable expressiveness. The mechanism induces coordination over a pool of autonomous demand responders so that DR operations, such as peak-shaving and valley-filling, can be implemented more effectively. The state-of-the-art toolset from Algorithmic Mechanism Design (AMD) is used to conceive a market-based mechanism with highly desired properties, such as DSIC, IR, BB, computational tractability, robustness to uncertainty about end-users' skill to fully deliver offers, and privacy-preserving of end-users' data in order to avoid further revenue extraction by their profit-maximising retailer. In addition, three penalty schemes were designed for this domain, and another one adapted from the literature, not only to counteract misreporting, but also to provide incentives to autonomous end-users so they strive to fulfil their offers. Moreover, an inspection procedure was designed and included in the mechanism, in order to review end-user agents' predictions of their intended net-load excluding DR. The

proposed penalty schemes capture some desirable properties for the domestic DR setting described in this thesis; however, this is not an exhaustive study of penalty schemes for this setting, and further composition of procedures are left for future research. Finally, the proposed mechanism benefits retailers and end-users, because retailers get to reduce their imbalance costs and end-users get discounts; however, (expensive, carbon-intensive) balancing generators reduce their market share.

### 3.5 List of Symbols

<b>Symbol</b>	<b>Description</b>
$A$	Sorted list of items by cost-to-weight ratio for a knapsack problem.
$a_i$	Ask or offer submitted by agent $i$ , in Definition 3.6 (Monotone Allocation Rule).
$A_t$	Subset of agents (i.e., $A_t \subseteq N$ ) that submitted an offer at time period $t$ .
$A_t^*$	Subset of valid DR offers, after satisfying reservation prices and bounded range for offers, at time period $t$ .
$\alpha$	Weighting parameter of the EWMA-based penalty to trade off past and present performance.
$\beta_{i(t-1)}$	Achievement ratio of agent $i$ 's offer after verification.
$c_i$	Cost-per-unit of weight used in Definition 3.5 (Dantzig's 0/1-KP GA).
$c_{i\tau}$	Electricity bill for the period $\tau \subseteq T$ .
$c_k$	Cost or offering price of task $k$ per time period.
$C_t$	Subset with the tasks that no longer have flexibility in the household schedule.
$\gamma_{it}$	Discount or penalty computed by the mechanism for agent $i$ at time period $t$ .
$\gamma_{jt}$	Ex-post amount of economic exchange of retailer $j$ with allocated demand responders.
$d_k$	Maximum time periods (or deadline) for task $k$ .
$D_t$	Subset with the tasks that have peak-shaving flexibility in the household schedule.
$\delta$	Depending on the context, this parameter might refer to a minimum achievement ratio of DR offers (or net-load prediction) after verification, so that agents avoid penalties (cf. middle point penalty scheme, slope-based penalty scheme, inspection scheme). It may also refer to the fixed penalty used in the penalty scheme based in Dash et al. (2007).

$f_{it}$	Achievement ratio of agent $i$ 's DR offer after verification, truncated between zero and one.
$g(\cdot)$	Forecast error function used to review agents' skill to predict their intended net-load use.
$h(t H)$	Forecast function for end-user's inflexible net-load at period $t$ , excluding scheduled tasks, given a finite rolling history $H$ .
$H$	Time periods for rolling history.
$\eta_{jt}$	Ex-post economic exchange of retailer $j$ with the balancing market at time period $t$ .
$\theta_{it}$	True private type of agent $i$ at time period $t$ .
$\hat{\theta}_{it}$	Reported type of agent $i$ at time period $t$ .
$i$	Index variable for end-user agents (demand responders).
$I_t$	Inspection set of sampled DR offers to be reviewed with regard to intended net-load without DR.
$j$	Index variable for retailers.
$k$	Index variable for scheduled tasks. It is also used to index items in a knapsack problem (cf. Proof 3.7).
$K$	Set of single-appliance tasks in the schedule. It is also used as the set of items in a knapsack problem (cf. Proof 3.7).
$L_t$	Runner-up or losing offers at time period $t$ .
$\lambda_t^B$	Ex-post system buy price at time period $t$ .
$\tilde{\lambda}_t^B$	Forecast of the system buy price at time period $t$ .
$\tilde{\lambda}_t^{B*}$	Retailer's reservation price for buying its deficit from DR at time period $t$ .
$\lambda_t^d$	Offering price for peak-shaving in pence/kWh at time period $t$ (by agent $i$ ).
$\lambda_t^{dk}$	Price-to-quantity ratio of the amount of kWh offered for net-load peak-shaving at at time period $t$ (by agent $i$ ).
$\lambda_t^I$	Fixed penalty for bad predictions in the intended net-load in DR offers.
$\lambda_j^{RB}$	Fixed retail buy price (tariff) offered by retailer $j$ (also denoted as $\lambda^{RB}$ in this chapter, as it deals with a single retailer).
$\lambda_j^{RS}$	Fixed retail sell price (tariff) offered by retailer $j$ (also denoted as $\lambda^{RS}$ in this chapter, as it deals with a single retailer).
$\lambda_t^S$	Ex-post system sell price at time period $t$ .
$\tilde{\lambda}_t^S$	Forecast of the system sell price at time period $t$ .
$\tilde{\lambda}_t^{S*}$	Retailer's reservation price for selling its contracted surplus to end-users through DR, as opposed to selling it back to the balancing market (imbalance settlement).
$\lambda_t^u$	Offering price for valley-filling in pence/kWh.

$\lambda_t^{uk}$	Price-to-quantity ratio of the amount of kWh offered for net-load valley-filling at time period $t$ (agent $i$ ).
$M$	Set of electricity retailers (assumed singleton in this chapter).
$m_{it}$	Meter reading of agent $i$ at time period $t$ .
$m_t^d$	Estimated meter reading if peak-shaving would be implemented at time period $t$ (of agent $i$ ).
$m_t^u$	Estimated meter reading if valley-filling would be implemented at time period $t$ (of agent $i$ ).
$m_t^y$	Meter reading prediction for time period $t$ (of agent $i$ ).
$N$	Set of all end-user agents (demand responders).
$v_{i(t-1)}$	Boolean variable that indicates if agent $i$ misreported at $t - 1$ .
$\xi$	Probability of inspection of intended net-load use.
$p_{it}$	Resulting payment to agent $i$ at time period $t$ , subject to full delivery.
$q_{it}$	Electric energy (kWh) used by end-user $i$ at time period $t$ .
$Q_{jt}$	Actual (ex-post) imbalance quantity of retailer $j$ at time period $t$ .
$q_k$	kWh that task $k$ uses per time period.
$q_{t-1}$	kWh used at time period $t - 1$ (by agent $i$ ).
$\tilde{Q}_t$	DR quantity to be procured at time period $t$ , which comes from retailer's prediction.
$\tilde{Q}_t^*$	Feasible DR quantity to be procured at time period $t$ .
$q_{i(t-1)}^a$	Actual amount of DR kWh provided by agent $i$ at time period $t - 1$ .
$q_t^c$	Net-load amount of kWh from tasks that must run according to schedule (in the household of agent $i$ ).
$q_t^d$	Offered amount of kWh for net-load peak-shaving at time period $t$ (agent $i$ ).
$q_t^L$	Runner-up DR capacity at time period $t$ , that is used for computing critical payments.
$q_t^{\max}$	Largest amount from selected DR offers, that is used for computing critical payments.
$q_{jt}^{RB}$	Amount of kWh that retailer $j$ bought from end-users at time period $t$ .
$q_{jt}^{RS}$	Amount of kWh that retailer $j$ sold to end-users at time period $t$ .
$q_t^u$	Offered amount of kWh for net-load valley-filling at time period $t$ (agent $i$ ).
$q_{it}^y$	Intended net-load use of agent $i$ at time period $t$ (which is a forecast).
$r_k$	Remaining time periods to complete task $k$ in the household schedule.
$\rho_{jt}$	Amount of money from retail trading of retailer $j$ at time period $t$ .
$S$	Solution set (items selected to place inside the knapsack).
$s_k$	Summed cost or offering price of task $k$ at the current time period (from the household schedule).



$S_t$	Subset of end-user agents that were selected by the mechanism at time period $t$ to perform DR operations.
$t$	Index variable for time periods.
$T$	Set of consecutive discrete time periods (e.g., hourly or half-hourly).
$\tau$	Subset of $T$ that contains all time periods being billed.
$u_{jt}$	Utility of retailer $j$ at time period $t$ .
$U_t$	Subset of $K$ , that contains tasks with valley-filling flexibility at time period $t$ (from the household schedule).
$\phi_i$	Fitness attribute of agent $i$ , which is a measure of its past performance on delivering DR offers.
$v_i$	Value, in value-per-unit of weight in Definition 3.5 (Dantzig's 0/1-KP GA).
$W$	Size of the knapsack, in Proof 3.7.
$\underline{w}$	Minimum amount of kWh for DR offers to be considered by the mechanism.
$\bar{w}$	Maximum amount of kWh for DR offers to be considered by the mechanism.
$w_i$	Weight, in value-per-unit of weight in Definition 3.5 (Dantzig's 0/1-KP GA).
$w_k$	Weight of item $k$ in a knapsack problem.
$X$	Allocation function in Definition 3.6 (Monotone Allocation Rule).
$\mathbf{x}_t^*$	Resulting vector from solving the allocation problem, which contains all the agents who had their offer allocated.
$y_t$	Boolean parameter used to denote the DR direction to procure at time period $t$ ; where $y_t = 0$ indicates net-load peak-shaving and $y_t = 1$ corresponds to net-load valley-filling.
$z_{it}^*$	Resulting allocation of runner-up asks to compute payment of agent $i$ at time period $t$ .
$z_k$	Linear cost function used to compute offering price of task $k$ from the household schedule.

## **Chapter 4**

# **A Double-Sided McAfee-Based Coordination Mechanism for Multi-Retailer Domestic DR**

This chapter extends the single-sided mechanism proposed in the previous chapter in order to include multi-retailer dynamics. This extension encompasses scenarios in which retailers cover their imbalances not only with DR from their own customers, but also with that from customers of other retailers. The main question addressed in this chapter is how the ISO/DSO should integrate domestic DR into the zonal-based supply and demand balancing (SDB) problem regardless of which retailer serves the demand responders. Integration of DR to SDB has broad implications for retailers, as end-users from one retailer may respond to the imbalance of another retailer while causing a negative externality to the former. Negative externalities in this context account for unintended deviations by retailers as a result of DR for the zonal SDB. A double-sided market-based mechanism has been designed to guide domestic DR efforts within a zone, where multiple retailers operate, so as to avoid these negative externalities. Moreover, this mechanism chains the single-sided auction proposed in Chapter 3, between a single retailer and multiple end-users, with a double-sided auction for coordination at the multi-retailer echelon. This integrated mechanism is dominant-strategy incentive-compatible (DSIC) for both retailers and DR end-users.

The chapter is organised as follows. First, the balancing problem and its context are introduced. Second, the computational model and the setting of the mechanism are defined. Third, the specification of the proposed double-sided mechanism is provided, which includes a methodology for stepwise offering with DR integration,

feasible trade determination, clearing prices computation, and redistribution of compensations. Fourth, the theoretical properties of this mechanism are proved. Finally, a summary and a list of symbols are provided. The empirical evaluation is reserved for Chapter 5 because the experimental set-up for simulations is reused to comparatively show all the mechanisms proposed in this thesis, along with some variations.

## 4.1 Introduction

Chapter 3 presented a mechanism that helps a single retailer to manage DR efforts from its customers in order to minimise the imbalance with regard to the already traded schedule in the wholesale market. However, the problem of SDB goes beyond the interaction between one retailer and its subscribed demand responders. That is, the ISO<sup>18</sup> has to balance supply and demand regardless of the ability of retailers to keep to their schedules, with or without DR. Moreover, retailers could offer DR to other retailers. Nonetheless, it is clearly undesirable to penalise retailers that deviate from their traded schedules because their end-users responded to help the zonal balancing, and even unfairer when the imbalance has been caused by competitors. Furthermore, there may be imbalances across retailers that can be cancelled out without the need for DR procurement, in which case the trade of imbalances could be more economical for retailers, i.e., they provide less discounts to responders. Therefore, under this setting, some sort of cooperation is highly desirable.

In Operational Research (OR), or more precisely in Supply Chain Management (SCM), this type of problems are ameliorated by introducing horizontal integration or a scheme of *coopetition* (i.e., cooperation amongst competitors). That is, competitors from the same echelon (e.g., car dealers) form explicit cooperation alliances in which they agree the terms on transferring inventory when one falls in stock-out. These terms, where one party owns the sale and another party owns the stock, determine who pays for logistic costs and how the profit is shared between the parties. These strategic interactions are not trivial and are usually modelled through *cooperative newsvendor games* (Montrucchio et al., 2012), that include solution concepts from Cooperative Game Theory (CGT), particularly the *core* to split the payoff.

However, within the electric power systems (and economics) community this type

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<sup>18</sup>Depending on how the electricity supply system is organised, this entity could be the Independent System Operator (ISO), the Distribution System Operator, or an independent party from retailers that is responsible for balancing generation and load.

of problem is usually modelled through non-cooperative games (i.e., competition) by use of sophisticated auctions, such as adjustment and balancing markets (Stoft, 2002; Morales et al., 2014). The work in this chapter proposes a mechanism amongst competing retailers, which indirectly induces cooperation about DR through market-based coordination. That is, although retailers compete, it is in their interest to not only trade their imbalances, but also offer DR to the other retailers within the zone. In general, it would be more expensive for retailers to isolatedly trigger their DR pool to cover their own imbalance, than to financially trade their differences (i.e., buy deficit and sell surplus) amongst themselves and only trigger DR to correct the zonal imbalance. Of course, these procedures would have to be performed prior to the physical balancing market (i.e., imbalance settlement). For example, suppose that there are two retailers *A* and *B*. Retailer *A* expects a surplus of 1 MWh, while retailer *B* expects a deficit of 0.5 MWh, during the same time period. If they separately procured DR, the discounts would correspond to 1.5 MWh of DR flexibility, whereas if they traded first between themselves, the discounts would correspond to 0.5 MWh of DR flexibility, although excluding other effects on retail sales due to DR.

The work in this chapter provides a methodology and a mechanism for integrating DR offers into stepwise energy blocks that retailers can trade amongst themselves. The stepwise offers are formed by the ISO-controlled auctioneers, and the mechanism is run by an ISO-controlled market operator (MO) with the objective to minimise the supply and demand imbalance within its zone.

## 4.2 Computational Model

The computational models for end-user agents and retailer's auctioneer agents are the same as those of Chapter 3, and so are the general assumptions, such as the use of smart meters, a suitable regulatory framework that enables DR, and more dynamic interactions between end-users and retailers. However, the setting for this mechanism includes two levels of interaction instead of one. The first echelon is between end-users and their retailer's auctioneer. The second one is between retailers' auctioneers and the zonal market operator (MO). Figure 4.1 shows this two-level interaction protocol in this mechanism. The shaded area is controlled by the ISO to prevent retailers and end-users from dishonest exploitation.

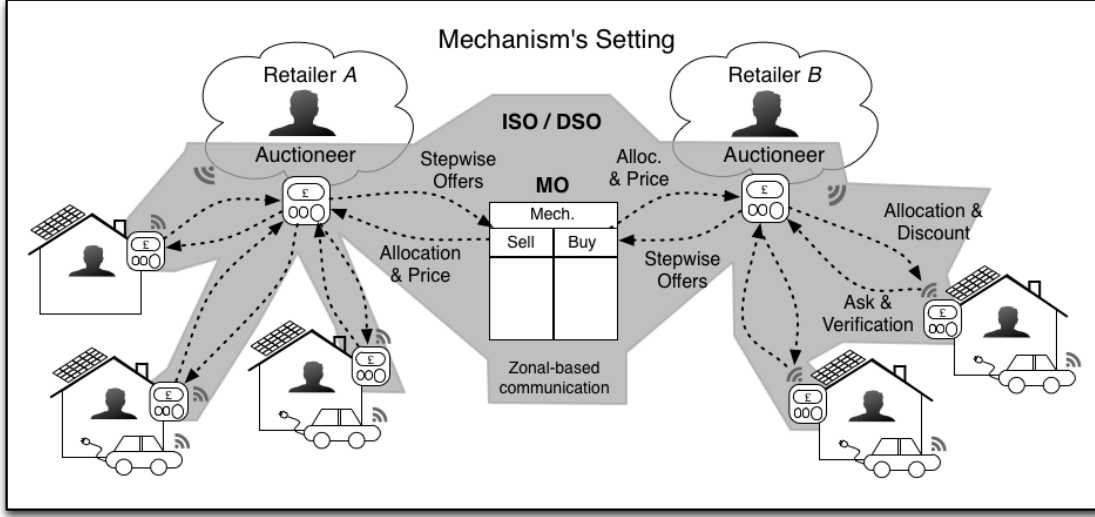


Figure 4.1: Setting of the proposed double-sided mechanism.

As previously defined in Section 3.2, end-user agents  $i \in N_j$  submit at most one ask  $\theta_{it}$  per time period  $t \in T$  to their retailer's ISO-controlled auctioneer agent, henceforth (retailer's) auctioneer  $j \in M$ . The ask format is the same as the one described in Subsection 3.3.2, which is embedded in the meter reading and formalised as a tuple  $\langle m_{t-1} [ , m_t^y, (m_t^d, \lambda_t^d), (m_t^u, \lambda_t^u) ]? \rangle \mapsto \langle \mathbb{Z} [ , \mathbb{Z}, (\mathbb{Z}, \mathbb{R}_{>0}), (\mathbb{Z}, \mathbb{R}_{>0}) ]? \rangle$ . For convenience of computation, the simplified ask format is preferred and will be used in this chapter. That is, the reading format is expressed as  $\langle q_{t-1} [ , q_t^y, (q_t^d, \lambda_t^{dk}), (q_t^u, \lambda_t^{uk}) ] \rangle \mapsto \langle \mathbb{R} [ , \mathbb{R}, (\mathbb{R}_{\geq 0}, \mathbb{R}_{>0}), (\mathbb{R}_{\geq 0}, \mathbb{R}_{>0}) ] \rangle$ , where each  $q$  corresponds to the respective change in meter readings and  $\lambda$ s are the costs per kWh, i.e.,  $\langle m_{t-1} - m_{t-2} [ , m_t^y - m_{t-1}, (m_t^y - m_t^d, \frac{\lambda_t^d}{m_t^y - m_t^d}), (m_t^u - m_t^y, \frac{\lambda_t^u}{m_t^u - m_t^y}) ] \rangle$ , as previously described in Subsection 3.3.2. In addition, every time period  $t$ , auctioneer  $j$  receives from its retailer's information system a tuple  $\langle \tilde{\lambda}_t^{S*}, \tilde{\lambda}_t^{B*}, \tilde{Q}_t \rangle \mapsto \langle \mathbb{R}_{>0}, \mathbb{R}_{>0}, \mathbb{R} \rangle$ , where  $\tilde{\lambda}_t^{S*}$  and  $\tilde{\lambda}_t^{B*}$  are the reservation prices per unit of energy, i.e., minimum price to sell and maximum price to buy, (e.g., £/kWh, £/MWh), and  $\tilde{Q}_t$  is the expected deviation from the retailer's trading schedule in energy units (e.g., kWh, MWh). Reservation prices are assumed to be a function of the forecast of the system's sell and buy prices, but the retailer is free to choose a different policy<sup>19</sup>. When  $\tilde{Q}_t < 0$  the retailer expects a deficit

<sup>19</sup>For instance, in Chapter 5, these prices are set to the marginal gain of procuring DR w.r.t. the forecast of balancing prices, including the impact on retail sales. That is,  $\tilde{\lambda}_t^{S*} := \lambda^{RS} - \tilde{\lambda}_t^S$  and  $\tilde{\lambda}_t^{B*} := \tilde{\lambda}_t^B - \lambda^{RS}$ , expressed in terms of the retail sell price  $\lambda^{RS}$ , because it has been assumed that  $\lambda^{RS} > \lambda^{RB}$  and a setting in which  $\tilde{\lambda}_t^B > \lambda^{RS}$  most of the time (i.e., buying electricity from the physical balancing market is more expensive than retail selling prices, otherwise retailers would not lose by procuring last minute electricity).

with regard to its schedule, when  $\tilde{Q}_t > 0$  it expects a surplus, and  $\tilde{Q}_t = 0$  means that it expects no imbalance. Furthermore, the auctioneer uses the collected DR asks  $A_t$  and tuple  $\langle \tilde{\lambda}_t^{S*}, \tilde{\lambda}_t^{B*}, \tilde{Q}_t \rangle$  to construct the stepwise offers that are sent to the zonal market operator (MO) for SDB.

Electrical energy and DR are seamlessly treated as one single homogenous commodity, i.e., electricity. Retailers are modelled as *virtual* generators with respect their traded schedules. In other words, when retailer  $j$  procures peak-shaving DR from its customers, it is actually increasing its collective net output; similarly, when it procures valley-filling DR, it decreases its net output. Without loss of generality, it has been assumed that retailers own neither DG nor shiftable loads, thus the increase or decrease in their energy output with respect to their schedules is performed only by the effects of domestic DR from their own customers<sup>20</sup>.

### 4.3 Multi-Retailer DA Mechanism for Domestic DR

A double auction (DA) is a process of matching buyers and sellers that come to trade amongst themselves in a two-sided marketplace. An auctioneer collects purchasing bids and selling asks, determines feasible trade, and the price(s) that clear the market. This auctioneer will be referred as a (zonal) market operator (MO) to avoid confusion with retailers' auctioneers from Chapter 3. In this particular problem of SDB with multi-retailer DR, retailers simultaneously submit bids and asks, although later they become either a buyer or a seller for a particular time period  $t$ . That is, electricity retailers can offer to either increase or decrease their expected (virtual) output with respect to their trading schedule by allocating DR services amongst their customers.

In this section, a methodology is proposed for integrating domestic DR into stepwise-offering energy blocks. Moreover, the allocation problem is first formalised as a linear programme (LP) and its uniform clearing price is determined by the dual variable of the balancing constraint. Furthermore, a multi-unit McAfee-based DSIC DA is specified for the same problem, including an allocation procedure, clearing price(s) computation, and discount distribution to end-users according to their DR achievements. Also, this mechanism is modelled using the tools of Algorithmic Mechanism Design (AMD) from Computer Science (CS), as in Chapter 3.

<sup>20</sup>For the case in which retailers do own strategic DG or shiftable loads, it is possible to model them as if they were owned by an abstract (dummy) customer.

### 4.3.1 Stepwise Offering Methodology

There could be hundreds of thousands of domestic DR offers, whose size is generally small (i.e., a few kWh), within a geographical zone during a single time period. It seems more convenient to aggregate these DR offers into blocks of more meaningful numbers, so that retailers can offer them to the zonal MO. This aggregation into blocks reduces the communication burden towards a single point (i.e., at the MO's), and it allows faster computation for a DA at the centre. Therefore, each retailer's auctioneer performs the following steps in order to aggregate DR offers into arbitrary-sized<sup>21</sup> blocks,  $\forall t \in T$ .

1. Auctioneer  $j \in M$  collects its retailer's values  $\langle \tilde{\lambda}_{jt}^{S^*}, \tilde{\lambda}_{jt}^{B^*}, \tilde{Q}_{jt} \rangle$ , and DR offers  $A_{jt}$  from the retailer's customers  $i \in N_j$ .
2. Let  $S_{jt} := \emptyset$  and  $B_{jt} := \emptyset$  be two empty sets for sell and buy offering DR blocks, respectively. Also, let block  $x \in \{S_{jt} \cup B_{jt} \mid S_{jt} \cap B_{jt} = \emptyset\}$  be denoted by a pair  $\langle w_x, \lambda_x \rangle$ , where  $w_x$  is the sum of flexibility provided by the end-users' asks that fit into block  $x$ , and  $\lambda_x$  is the unit price at which block  $x$  cleared. Moreover, let  $w^*$  be a fixed parameter to denote the minimum cut size in kWh of DR blocks. This parameter must be set by the MO, because the block size has a direct impact in the clearing price of each block (as prices are set by Vickrey-based second prices). Then,  $S_{jt}$  and  $B_{jt}$  are populated by auctioneer  $j$  as follows.
  - (a) Set  $S_{jt}$  corresponds to net-load peak-shaving blocks formed by the following procedure:
    - i. DR offers whose peak-shaving quantity  $q_{it}^d$  does not satisfy a pre-agreed range  $[\underline{w}, \bar{w}]$  are rejected, as discussed in Chapter 3. That is, the subset of valid asks  $A_{jt}^* := \{\theta_{it} \in A_{jt} \mid q_{it}^d \in [\underline{w}, \bar{w}]\}$ ; retailer  $j$ 's reservation prices are not considered in this step, because the blocks will be offered to other retailers too.
    - ii. Asks in  $A_{jt}^*$  are sorted by increasing cost-per-unit of kWh for peak-shaving, i.e.,  $\lambda_{it}^{dk}$ .
    - iii. The sorted list is cut into segments with peak-shaving capacity of at least  $w^*$ , and each of these list segments will be used to define a block  $k \in S_{jt}$ . That is, asks are greedily selected from the sorted list and appended to a new list  $L_k^S$ , of current block  $k$ , which is used to keep

<sup>21</sup>The minimum size of these offers are determined by the MO, and only the last DR block of each retailer is allowed to be fractional.

track of which DR offers correspond to each block. This procedure is repeated until it achieves the end of the sorted list of asks.

- iv. Each block  $k$  is defined as  $k := \left\langle \sum_{x \in L_k^S} q_x^d, \tilde{\lambda}_{jt}^{S^*} + \lambda_{(k+1)[0]}^{dk} \right\rangle$ , where  $\lambda_{(k+1)[0]}^{dk}$  is the cost-to-quantity ratio of the first ask that did not fit into  $L_k^S$ , which belongs to block  $L_{k+1}^S$ . Price  $\lambda_{(k+1)[0]}^{dk}$  is therefore a (single-bid  $k+1$ ) Vickrey-based price.
- v. Each block  $k$  is added to the set of sell DR offers, i.e.,  $S_{jt} := S_{jt} \cup k$ . The last block may be allowed to be fractional, for which the last ask of the sorted list would set its price, and thus this last ask would be excluded from the mechanism. In other words, this procedure cuts the sorted list of asks into net-load peak-shaving blocks of ideally  $w^*$  kWh (MWh), whose cost-to-quantity ratio is that of the first losing ask from each block.

(b) Set  $B_{jt}$  corresponds to net-load valley-filling blocks formed by a procedure analogous to that of  $S_{jt}$ :

- i. DR offers whose valley-filling quantity  $q_{it}^u$  does not satisfy a pre-agreed range  $[\underline{w}, \bar{w}]$  are rejected, as discussed in Chapter 3. That is, the subset of valid asks  $A_{jt}^* := \{\theta_{it} \in A_{jt} \mid q_{it}^u \in [\underline{w}, \bar{w}]\}$ ; retailer  $j$ 's reservation prices are not considered in this step, because the blocks will be offered to other retailers too.
- ii. Asks in  $A_{jt}^*$  are sorted by increasing cost-per-unit of kWh for valley-filling, i.e.,  $\lambda_{it}^{uk}$ .
- iii. The sorted list is cut into segments with valley-filling capacity of at least  $w^*$ , and each of these list segments will be used to define a block  $\ell \in B_{jt}$ . That is, asks are greedily selected from the sorted list and appended to a new list  $L_\ell^B$ , of current block  $\ell$ , which is used to keep track of which DR offers correspond to each block. This procedure is repeated until it achieves the end of the sorted list of asks.
- iv. Each block  $\ell$  is defined as  $\ell := \left\langle \sum_{x \in L_\ell^B} q_x^u, \tilde{\lambda}_{jt}^{B^*} - \lambda_{(\ell+1)[0]}^{uk} \right\rangle$ , where  $\lambda_{(\ell+1)[0]}^{uk}$  is the (single-bid  $k+1$ ) Vickrey-based price.
- v. Each block  $\ell$  is added to the set of buy DR offers only if  $\tilde{\lambda}_{jt}^{B^*} - \lambda_{(\ell+1)[0]}^{uk} > 0$ , i.e.,  $B_{jt} := B_{jt} \cup \ell$ . Negative prices are not allowed. The last block may be allowed to be fractional, for which the last ask of the sorted list would set its price, and thus this last ask would be excluded



from the mechanism. In other words, this procedure cuts the sorted list of asks into net-load valley-filling blocks of ideally  $w^*$  kWh (MWh), whose cost-to-quantity ratio is that of the first losing ask from each block.

This procedure assumes that end-user agents can only submit a single ask per time period, and that the chained mechanism only deals with a single time period at a time. Since there are no temporal interdependencies amongst these asks within the mechanism, this stepwise offering procedure does not have the problem of *demand reduction* that is common to multi-unit auctions. The problem of demand reduction allows different valuations per unit, where bidders have an incentive to differentially shade their bids so as to influence the  $(k+1)$  clearing price (Ausubel et al., 2014). Therefore, this procedure for pricing DR block offers incentivise end-users to report truthfully. Moreover, the mechanism includes verification on quantities (by reading end-users' meters). Hence, the mechanism for constructing block offers is DSIC. Figure 4.2 shows an exemplary representation of these stepwise offers that integrate DR costs and retailer  $j$ 's valuation for buying and selling electricity at time period  $t$ , i.e.,  $\tilde{\lambda}_{jt}^{B*}$  and  $\tilde{\lambda}_{jt}^{S*}$ , including the expected imbalance  $\tilde{Q}_{jt}$ .

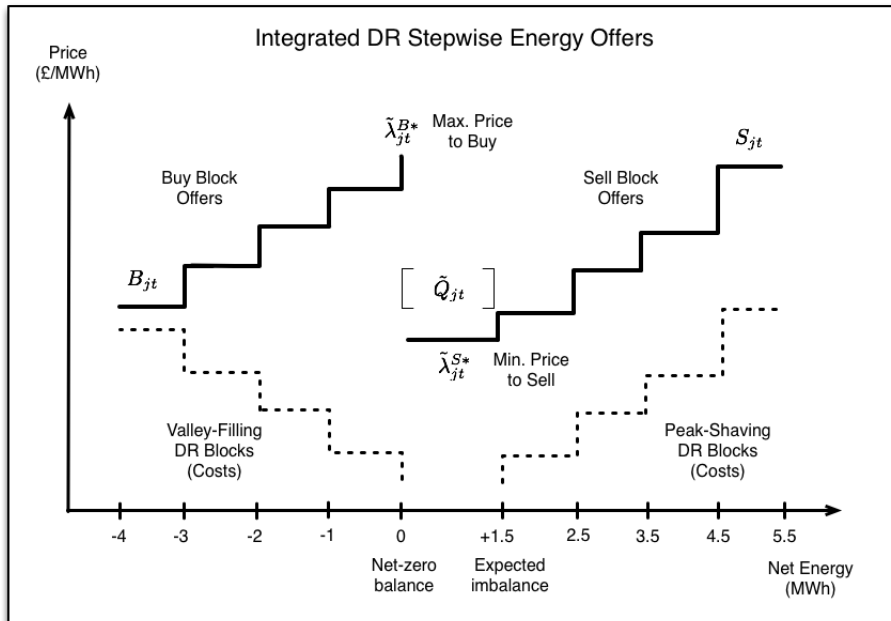


Figure 4.2: Stepwise energy offers with DR integration.

The lists  $L_k^S \forall k \in S_{jt}$  and  $L_\ell^B \forall \ell \in B_{jt}$  are used to trigger and keep track of individual DR asks according to the allocated blocks by the DA. Trading of fractional

blocks is allowed, but the domestic DR asks must be integral, because of the modelling assumptions discussed in Chapter 3. Then, the retailer's auctioneer  $j$ , notifies end-users  $i \in N_j$  whether they had their ask allocated, according to the blocks allocated by the DA mechanism and using lists  $L_k^S$  and  $L_\ell^B$  to identify the allocated DR offers. Furthermore, end-users' achievements can be verified and a penalty scheme imposed to punish misreporting, as described in Subsection 3.3.5.

Finally, the parameter  $w^*$ , regarding the minimum cut to construct blocks from a sorted list of valid asks  $A_{jt}^*$ , must be set by the MO as otherwise the retailer could reduce these blocks up to single asks that will result in a Generalised Second Price (GSP)-style pricing, in which the discounts could be much smaller for end-users, and the communication and computation burden could be heavier for the MO. Conversely, if  $w^*$  is very big, it could be the case that it is only possible to construct a single fractional block with an expensive unit price (as it is determined by the last ask in the merit order) that might not be possible to allocate it in the zonal DA.

### 4.3.2 DR Allocation Problem

An average discrete-time periodic double auction (DA), such as a call market or clearing house, receives selling asks and purchasing bids, then sorts the asks by per-unit cost in ascending order and sorts the bids by per-unit value in descending order, after that, it determines the feasible trade (i.e., matches bids to asks without exceeding reservation prices), settles the trading prices, and clears the market. Without loss of generality, it has been assumed that only electricity retailers (through their ISO proxy auctioneers) participate in this DA. They may trade their differences from their schedule and DR in order to reduce the zonal imbalance. As a result of this allocation, retailers' trading schedules are updated.

At the beginning of time period  $t$ , the MO receives  $\langle \tilde{\lambda}_{jt}^{S*}, \tilde{\lambda}_{jt}^{B*}, \tilde{Q}_{jt}, S_{jt}, B_{jt} \rangle$ ,  $\forall j \in M$ , and computes the zonal imbalance as  $\sum_{j \in M} \tilde{Q}_{jt}$ . If  $\sum_{j \in M} \tilde{Q}_{jt} = 0$ , which is rarely the case, the DA ends without allocation. If  $\sum_{j \in M} \tilde{Q}_{jt} > 0$ , there is surplus in the zone, and the MO will look for purchasing blocks. Conversely, if  $\sum_{j \in M} \tilde{Q}_{jt} < 0$ , the zone is in deficit and the MO will focus on selling blocks so as to correct the imbalance. The expected imbalance  $\tilde{Q}_{jt}$  is also treated as an offer with its respective reservation price. However, the imbalance offer  $\tilde{Q}_{jt}$  is treated separately from the blocks in  $S_{jt}$  and  $B_{jt}$  in order to facilitate its distinction.

Reservation prices  $\tilde{\lambda}_{jt}^{S*}$  and  $\tilde{\lambda}_{jt}^{B*}$  provide retailers with the ability to express how

willingly they are to balance their schedule with other retailers and with DR offers, as compared to paying for the imbalance settlement in the actual physical market. This balancing auction is a zonal-based financial market that mainly helps to guide the local DR efforts. The physical market is not optional and the imbalance settlements are the result of the required ex-post correction; these settlements are assumed to be expensive (which include penalties and opportunity costs to retailers due to balancing generation).

For the sake of computational tractability, it is assumed that the MO computes the (zonal) imbalance and only searches in the direction to correct it, as shown in Figure 4.3. It is unlikely that a better solution can be found by searching on the direction that makes the imbalance worse. For instance, if the zone is in deficit, it is unlikely that a better minimum would be found by making retailers that are already in deficit to keep going into more deficit by increasing the load of their customers, since this would also generate more cost due to DR. Besides, searching in both directions makes this problem NP-hard<sup>22</sup>, and the benefit is potentially null due to the structure of this DR problem. Another important reason is the format used to express DR flexibility (i.e., end-user asks), in which at most one direction is to be allocated, either increase or decrease electricity use. As a result of this format, end-users' asks might be present in (collective) offers in both sides, i.e., in  $S_{jt}$  and  $B_{jt}$ , and thus, it would violate the allocation rule for end-users' asks if it happened to be allocated in both DR directions (i.e., peak-shaving and valley-filling).

In the following subsection, an LP formulation is provided because it makes it mathematically convenient to think about the allocation problem and price clearing computation. However, this LP formulation does not yield a DSIC mechanism, and thus a McAfee-based mechanism that is DSIC is proposed afterwards.

#### 4.3.2.1 LP-Based Mechanism

Morales et al. (2014, Ch4) provide several examples of simple mathematical formulations for balancing auctions with dispatchable and non-dispatchable generators and (non-domestic) proactive demand, including stepwise offers and network constraints. Building on these mathematical formulations by Morales et al. (2014, Ch4), the allocation problem, which is similar to an economic dispatch, for SDB with multiple retailers and domestic DR, including reservation prices, is formalised as follows.

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<sup>22</sup>Contribution of blocks to the minimisation objective would need to be evaluated combinatorially as in a Mixed-Integer Linear Programme (MILP). Furthermore, if marginal pricing is used, it would not be as easy as computing the dual variable from the balancing constraint, which is possible for Linear Programmes (LP), but for MILPs duals it is still an open question.

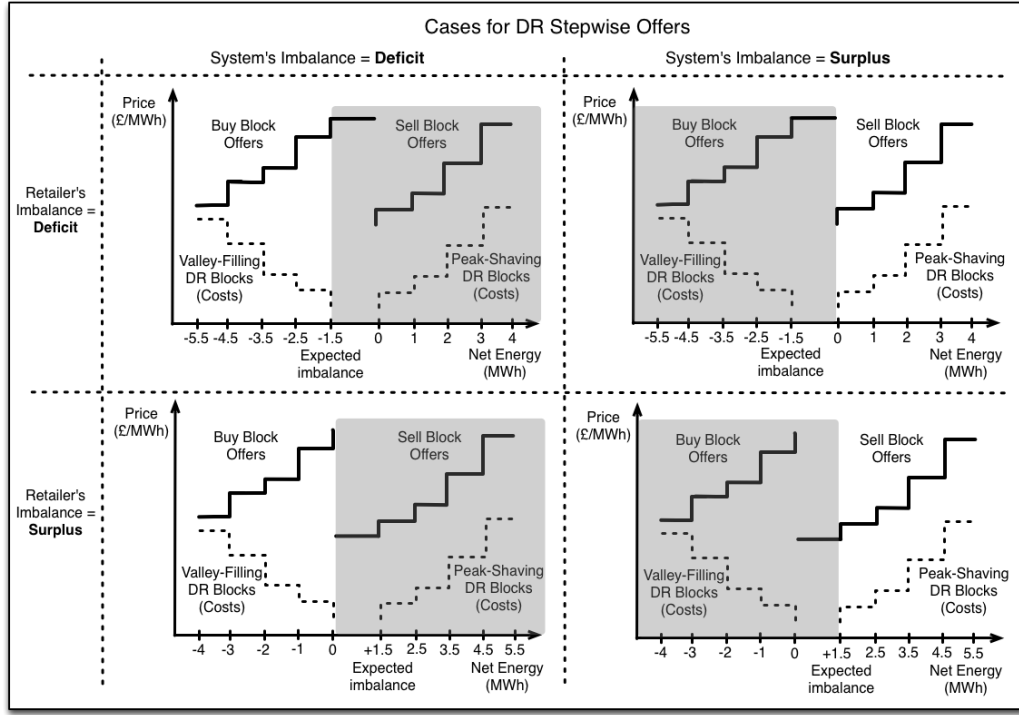


Figure 4.3: Allocation cases for stepwise DR offers w.r.t. zonal imbalance. The shaded area shows the direction to correct the imbalance.

When the zonal system is in deficit, i.e.,  $\sum_{j \in M} \tilde{Q}_{jt} < 0$ , the MO searches for sell offers, that may include DR costs, in order to correct the deficit. Let  $B_t$  be the DA's buy-side, where  $B_t := \left\{ \left\langle |\tilde{Q}_{jt}|, \tilde{\lambda}_{jt}^{B*}, j \right\rangle \mid \tilde{Q}_{jt} < 0, \forall j \in M \right\}$ , which is the purchasing bids of retailers in deficit with their respective maximum buying per-unit prices. Let  $S_t$  be the DA's sell-side, where  $S_t := \left\{ \left\langle \tilde{Q}_{jt}, \tilde{\lambda}_{jt}^{S*}, j \right\rangle \mid \tilde{Q}_{jt} > 0, \forall j \in M \right\} \cup \left\{ \left\langle Q_k^S, \lambda_k^S, j \right\rangle \mid k \in S_{jt}, \forall j \in M \right\}$ , which not only includes the imbalance sell offers, but also contains the integrated DR energy offers for sale, both with their respective minimum per-unit prices.

Moreover, let  $\tilde{\lambda}_t^{B*}$  be the minimum per-unit price from the set  $B_t$  so as to denote the reservation price of the buy-side. Then, the MO needs to compute the maximum amount of feasible trade possible between the DA's sides,  $S_t$  and  $B_t$ . The maximum feasible trade  $Q_t^F$  is formulated as an LP below. In addition, in order to make the LP formulation more readable, let  $\langle Q_k^S, \lambda_k^S, j_k^S \rangle, \forall k \in S_t$  be the quantity, unit price, retailer of sell offer, and let  $\langle Q_\ell^B, \lambda_\ell^B, j_\ell^B \rangle, \forall \ell \in B_t$  denote the quantity, unit price, and retailer of buy bid.

$$Q_t^F := \underset{Q_k^F}{\text{Maximise}} \sum_{k \in S_t} Q_k^F \quad (4.1)$$

subject to:

$$\sum_{k \in S_t} Q_k^F \leq \sum_{\ell \in B_t} Q_\ell^B \quad (4.2)$$

$$0 \leq Q_k^F \leq Q_k^S, \quad \forall k \in S_t \quad (4.3)$$

$$0 \leq \lambda_k^S \leq \tilde{\lambda}_t^{B*}, \quad \forall k \in S_t \quad (4.4)$$

The mathematical programme 4.1-4.4 maximises the amount that can be gathered from the sell-side,  $\sum_{k \in S_t} Q_k^F$ , so as to fulfil the total amount on the (imbalance) buy-side,  $\sum_{\ell \in B_t} Q_\ell^B$ , within block amount and reservation price constraints.

After the feasible trade  $Q_t^F$  has been computed, the allocation  $Q_k^A$ ,  $\forall k \in S_t$  and uniform clearing price  $\lambda^P$  can be computed as follows.

$$\underset{Q_k^A}{\text{Minimise}} \sum_{k \in S_t} \lambda_k^S Q_k^A \quad (4.5)$$

subject to:

$$\sum_{k \in S_t} Q_k^A = Q_t^F : \lambda^P \quad (4.6)$$

$$0 \leq Q_k^A \leq Q_k^S, \quad \forall k \in S_t \quad (4.7)$$

$$0 \leq \lambda_k^S \leq \tilde{\lambda}_t^{B*}, \quad \forall k \in S_t \quad (4.8)$$

The LP 4.5-4.8 finds the least expensive allocation of sell offers that is equal to the feasible trade amount. The clearing price  $\lambda^P$  is the dual variable from the balancing constraint 4.6 and is equal to the price of the last allocated offer. Moreover, for convenience, these two LPs 4.1-4.4 and 4.5-4.8 can be joined into a single one by using an auxiliary variable (in this case  $Q_k^F$ ) as shown next.

$$\text{Minimise}_{Q_k^A, Q_k^F} \sum_{k \in S_t} \lambda_k^S (Q_k^A - Q_k^F) \quad (4.9)$$

subject to:

$$\sum_{k \in S_t} Q_k^A - Q_k^F = 0: \quad \lambda^P \quad (4.10)$$

$$\sum_{k \in S_t} Q_k^F \leq \sum_{\ell \in B_t} Q_\ell^B \quad (4.11)$$

$$0 \leq Q_k^A \leq Q_k^S, \quad \forall k \in S_t \quad (4.12)$$

$$0 \leq Q_k^F \leq Q_k^S, \quad \forall k \in S_t \quad (4.13)$$

$$0 < \lambda_k^S \leq \tilde{\lambda}_t^{B*}, \quad \forall k \in S_t \quad (4.14)$$

The allocation vector  $Q_k^A$  is the amount allocated per offer from the sell-side,  $\forall k \in S_t$ . The auxiliary vector  $Q_k^F$  corresponds to the feasible amounts that can be allocated from  $S_t$  up to demand constraint 4.11, and bounded by the block sizes as in constraint 4.13. Constraint 4.10 limits the allocation to be equal to the maximum feasible trade (as by the minimisation of the auxiliary vector  $-Q_k^F$ ), and the dual variable  $\lambda^P$  of this constraint is the cost of the marginal block from  $S_t$ , i.e., the last sell-block that is part of the feasible trade while aiming to fulfil demand  $\sum_{\ell \in B_t} Q_\ell^B$ . Constraints 4.12-4.13 bound the allocated and auxiliary block sizes. Finally, constraint 4.14 limits the unit price from sell blocks to be at most the maximum buying unit price (which is actually the minimum unit price from set  $B_t$ ).

The LP above solves the allocation to the sell-side and uniform clearing price. The allocation to the buy-side is trivially determined by taking the amount  $\sum_{k \in S_t} Q_k^A$  and greedily allocate it to a sorted list of set  $B_t$  by non-increasing order until this amount is depleted. Then, the MO communicates the individual allocation results to each retailer,  $\forall j \in \{j_k^S, \forall k \in S_t\} \cup \{j_\ell^B, \forall \ell \in B_t\}$ .

Analogously, when the zonal system is in surplus, i.e.,  $\sum_{j \in M} \tilde{Q}_{jt} > 0$ , the MO searches only for buy offers, that may include DR costs. In such a case, the buy-side and sell-side are defined as follows. Set  $S_t := \left\{ \langle \tilde{Q}_{jt}, \tilde{\lambda}_{jt}^{S*}, j \rangle \mid \tilde{Q}_{jt} > 0, \forall j \in M \right\}$ , and set  $B_t := \left\{ \langle |\tilde{Q}_{jt}|, \tilde{\lambda}_{jt}^{B*}, j \rangle \mid \tilde{Q}_{jt} < 0, \forall j \in M \right\} \cup \left\{ \langle Q_\ell^B, \lambda_\ell^B, j \rangle \mid \ell \in B_{jt}, \forall j \in M \right\}$ . Let  $\tilde{\lambda}_t^{S*}$  be the maximum per-unit price from the set  $S_t$  so as to denote the reservation price

of the sell-side. The analogous LP formulation is as follows.

$$\text{Minimise } \sum_{\substack{Q_\ell^A, Q_\ell^F \\ \ell \in B_t}} \lambda_\ell^B (Q_\ell^A - Q_\ell^F) \quad (4.15)$$

subject to:

$$\sum_{\ell \in B_t} Q_\ell^A - Q_\ell^F = 0: \quad \lambda^P \quad (4.16)$$

$$\sum_{\ell \in B_t} Q_\ell^F \leq \sum_{k \in S_t} Q_k^S \quad (4.17)$$

$$0 \leq Q_\ell^A \leq Q_\ell^B, \quad \forall \ell \in B_t \quad (4.18)$$

$$0 \leq Q_\ell^F \leq Q_\ell^B, \quad \forall \ell \in B_t \quad (4.19)$$

$$\lambda_\ell^B \geq \tilde{\lambda}_t^{S*} > 0, \quad \forall \ell \in B_t \quad (4.20)$$

The explanation of LP 4.15-4.20 is analogous to previous LP 4.9-4.14.

LP-based allocations can be solved efficiently by using algorithms such the simplex method (Dantzig, 1963, Ch5), the ellipsoid method (Khachiyan, 1980), and interior-point methods, such as Karmarkar's algorithm (Karmarkar, 1984). Provided that the search is on one side of the market, this problem can also be efficiently solved by a greedy algorithm that sorts the offers (DR blocks) by per-unit value (or cost) and allocate them sequentially until the imbalance is corrected as much as possible (similar to the single-sided mechanism proposed in Chapter 3). The allocation implies downward communication to advise retailers, and these propagate the message to their responding end-users. It is also important to note that these mathematical programmes are formulated under the retailers' point of view, and it is opposite to the view of end-users. For instance, when an end-user offer is allocated to increase the net-load, it means that the retailer will be exporting less energy w.r.t its trading schedule.

This LP-based mechanism, although convenient, is not DSIC. Since the clearing price is set by the marginal offer, retailers have an incentive to lie about their real prices if they consider it might help them to influence the marginal offer and get more profit. This also applies to mechanisms that trade the Walrasian quantity (which is the one determined by the feasible trade above), in the competitive equilibrium, at the uniform

price determined by the interval  $\lambda^P := [\max\{\lambda_k^S, \lambda_{\ell+1}^B\}, \min\{\lambda_{k+1}^S, \lambda_\ell^B\}]$  (Loertscher and Mezzetti, 2014; Zimmerman, 2010). This level of manipulation could reduce the mechanism's economic efficiency and its predicted stable equilibria. In order to restore the DSIC property, the winning offers must not set the clearing price, such as in Vickrey's second price auction. An alternative approach that uses the pricing rule of McAfee's mechanism is described next.

#### 4.3.2.2 McAfee-Based Mechanism

Designing a DSIC DA is a challenging task (Dütting et al., 2014). Preston McAfee designed an influential single-unit DA that is DSIC for both buyers and sellers, and sometimes has to give up the least profitable trade in order to maintain truthful reporting as a weakly dominant strategy (McAfee, 1992). Due to the *Myerson-Satterthwaite's impossibility theorem* (Myerson and Satterthwaite, 1983), it is known that a mechanism cannot simultaneously be strategy-proof, individually rational (IR), budget balanced (BB), and Pareto efficient, so the designer has to trade off these properties in line with the mechanism's objectives. Therefore, McAfee's approach gives away a small amount of economic efficiency  $1/n$ , where  $n := \min\{|M|, |N|\}$ ,  $M$  is the set of sellers, and  $N$  is the set of buyers) in order to have a mechanism that is DSIC, IR, and requires no subsidies (i.e., BB).

There is no currently agreed extension of McAfee's single-unit DA to a multi-unit setting that allows multiple offers per participant. The main problem expressed by McAfee (1992) in the multi-unit (multi-offer) setting is that agents have an incentive to shade their bids so as to try to influence the clearing price, which causes the problem of demand reduction (Ausubel et al., 2014). That is, a bidder has the incentive to include an extra offer with a small quantity (e.g., one unit) and a small price with the possibility of lowering the price for the regular quantity demanded. The case for the seller is analogous. Nonetheless, Loertscher and Mezzetti (2014)<sup>23</sup> have been working on a DSIC multi-unit auction which is an extension of McAfee's DA, but their procedure reduces to a regular McAfee's DA in this particular problem for DR. More precisely, they use McAfee's pricing rules to determine reservation prices for each side of the market, and then run VCG mechanisms (forward and reverse, with reservation prices) on each side. Their procedure finds the last feasible trading price first with McAfee's approach, then the trading quantity is determined, and finally VCG mechanisms are performed over

<sup>23</sup>This reference corresponds to a working paper retrieved from:  
<http://www.simonloertscher.net/data/downloads/12120/LM-DoubAuc270616.pdf>.



that trading quantity, which is the minimum of both sides. While the VCG mechanism on the short side of the market is equivalent to charging the reservation price of that side (as in the original McAfee's mechanism), the VCG mechanism on the long side reduces to a multi-unit Vickrey auction, since there is one homogeneous commodity. In the DA presented here, this multi-unit Vickrey auction on the long side is equivalent to locating the Walrasian quantity first, and then performing McAfee's pricing rules. This happens because the procedure for constructing stepwise offers, described in Subsection 4.3.1, does not allow for bid shading, and thus, the approach of Loertscher and Mezzetti (2014) is equivalent to a regular McAfee's mechanism in this setting.

Huang et al. (2002) propose a multi-unit DSIC DA based on the trading reduction rule, where the last trade is foregone because it is used to set the price for each side of the market. They considered as winners all the asks strictly lesser than the clearing price on the sell-side and all the bids strictly greater than the clearing price on the buy-side. Then, to determine the allocation, they redistribute the quantity in the long side (either a surplus or a deficit) equally amongst all of its winners. This is incompatible with the DR allocation setting described here, because this trade surplus (or deficit) redistribution will violate the allocation of DR asks in the echelon between a retailer and its end-users, unless the retailer's auctioneer monotonically reallocate the DR quantities again. That is, this redistribution of the excess (deficit) could allocate a share to more than one fractional integrated DR offer blocks by the same retailer, resulting in end-users asks not being chosen monotonically.

This mechanism amongst retailers is inherently linked to the mechanism between each retailer and its end-users. Babaioff and Nisan (2004) have designed protocols for sequences of market-based mechanisms along a single supply chain. Their approach works in settings with vertical integration, as opposed to the horizontal integration setting amongst retailers, that is being considered in this chapter. Nonetheless, their approach is relevant because they linearly chain several DAs that are DSIC, although in this case a version of the single-sided mechanism from Chapter 3 is chained to a DA. Furthermore, McAfee's mechanism resulted incompatible for their problem, but they proposed a variant of it that implements a trade reduction mechanism with some probability  $p \in [0, 1]$  and the VCG mechanism with probability  $1 - p$ . Moreover, Babaioff and Walsh (2005) extended this model into more general classes of supply chain topologies, not only linear, where bundles are considered. Another line of research is that of spatially distributed markets (SDM), where there is a cost associated with moving goods between locations (Babaioff, Nisan, and Pavlov, 2009), including virtual analogs

for financial markets. This idea is more applicable to horizontal integration, however, their work extends on computational solutions over the probabilistic approach from (Babaioff and Nisan, 2004; Babaioff and Walsh, 2005), which is not considered here because of the BB property is *ex ante*, i.e., in expectation, and a stronger notion of BB is desirable for an independent MO.

Furthermore, the proposed DR mechanism relies on the *revelation principle* (Nisan, Roughgarden, et al., 2007, Ch9) for its direct implementation, and it is divided into three stages that follow the same searching assumptions as the LP-based mechanism. First, the MO estimates the zonal imbalance and prepares the blocks into their respective side of the market. Second, the allocation of trade is performed so as to ameliorate the balance. And third, clearing prices are computed and retailers advised of the results. It has been assumed that retailers' trading schedules are updated as a result of this mechanism, and that retailers' auctioneers will communicate end-users agents, so that they implement their allocated DR offers.

1. **Zonal imbalance estimation.** This step is the same as in the LP-based mechanism in Subsection 4.3.2.1, with the exception that blocks of the side of the imbalance are not discarded. These blocks are kept only to set the price on that side of the market. In brief, when the zonal system is in deficit, i.e.,  $\sum_{j \in M} \tilde{Q}_{jt} < 0$ , the MO searches for sell offers. The buy-side is populated with  $B_t := \left\{ \left\langle |\tilde{Q}_{jt}|, \tilde{\lambda}_{jt}^{B*}, j \right\rangle \mid \tilde{Q}_{jt} < 0, \forall j \in M \right\}$ . The integrated DR energy blocks on the buy-side are kept in an auxiliary set  $D_t := \left\{ \left\langle Q_\ell^B, \lambda_\ell^B, j \right\rangle \mid \ell \in B_{jt}, \forall j \in M \right\}$ , for price-setting purposes. And, the sell-side is formed by both imbalances and DR energy blocks as  $S_t := \left\{ \left\langle \tilde{Q}_{jt}, \tilde{\lambda}_{jt}^{S*}, j \right\rangle \mid \tilde{Q}_{jt} > 0, \forall j \in M \right\} \cup \left\{ \left\langle Q_k^S, \lambda_k^S, j \right\rangle \mid k \in S_{jt}, \forall j \in M \right\}$ . This process is analogous when the zonal system is in surplus, i.e.,  $\sum_{j \in M} \tilde{Q}_{jt} > 0$ , in which the MO separates the sell-side imbalances and DR blocks into sets  $S_t$  and  $D_t$ , and tries to match the former with the joint set  $B_t$  of imbalances and DR blocks. The auxiliary set in this case is used to set the price of the sell-side. Finally, if there is no imbalance, i.e.,  $\sum_{j \in M} \tilde{Q}_{jt} = 0$ , which is unlikely, the DA ends without any trade.

2. **Allocation procedure.**

- (a) The MO sorts  $S_t$  by per-unit cost in non-decreasing order, and sorts  $B_t$  by per-unit value in non-increasing order. Ties are broken randomly.
- (b) The MO searches for the last feasible trade not only by prices, but also by quantities. In other words, it locates the block  $k$  from the sell-side and the

block  $\ell$  from the buy-side that are marginal with regard to the allocation.

The MO solves  $\langle k, \ell \rangle := \{ \arg \min_{k, \ell} \sum_{k \in S_t} Q_k^S - \sum_{\ell \in B_t} Q_\ell^B \geq 0, \lambda_k^S \leq \lambda_\ell^B \}$ .

3. **Clearing price computation.** McAfee's pricing rule (McAfee, 1992), adjusted to this setting, is used to determine the clearing price(s) and corresponding allocation.

- (a) Let  $\lambda_k^S$  and  $\lambda_\ell^B$  be the prices of sell offer  $k$  and buy offer  $\ell$ , respectively. Moreover, let  $\lambda_{k+1}^S$  and  $\lambda_{\ell+1}^B$  be the prices of the first offers that are not allocated. These offers may be non-existent, in which case they are determined with the following rules.
- i. If the zonal system is in deficit and offer  $k+1$  does not exist, then  $k := k-1$ . Thus, the older  $k$  becomes the  $k+1$ .
  - ii. If the zonal system is in deficit and offer  $\ell+1$  does not exist, then first offer that would be selected from the auxiliary set  $D_t$ , whose price is less than  $\lambda_\ell^B$ , is inspected, i.e.,  $\ell' := \{ \arg \max_{\ell'} \lambda_{\ell'}^B \forall \ell' \in D_t, \lambda_{\ell'}^B \leq \lambda_\ell^B \}$ . Then, if  $\ell'$  exists, the offer  $\ell+1 := \ell'$ , otherwise  $\ell := \ell-1$  and  $\ell+1$  becomes the older  $\ell$ .
  - iii. If the zonal system is in surplus and offer  $k+1$  not exists, it is then taken from the auxiliary set  $D_t$ . Thus,  $k' := \{ \arg \min_{k'} \lambda_{k'}^S \forall k' \in D_t, \lambda_{k'}^S \geq \lambda_k^S \}$ , analogous to the previous step, although looking for the offer with the smallest price greater than  $\lambda_k^S$ . Then, if  $k'$  exists,  $k+1 := k'$ , otherwise  $k := k-1$  and  $k+1$  becomes the older  $k$ .
  - iv. If the zonal system is in surplus and offer  $\ell+1$  does not exist, then  $\ell := \ell-1$ . Thus,  $\ell+1$  becomes the older  $\ell$ .
- (b) As in (McAfee, 1992), let  $\lambda^P := \frac{\lambda_{k+1}^S + \lambda_{\ell+1}^B}{2}$ , and compute the clearing price as in the following two cases.
- i. If  $\lambda^P \in [\lambda_k^S, \lambda_\ell^B]$ , then the  $\min \{ \sum_{s:=1}^k Q_s^S, \sum_{b:=1}^\ell Q_b^B \}$  is allocated greedily at the uniform unit price of  $\lambda^P$  (cf. Figure 4.4).
  - ii. If  $\lambda^P \notin [\lambda_k^S, \lambda_\ell^B]$ , then the  $\min \{ \sum_{s:=1}^{k-1} Q_s^S, \sum_{b:=1}^{\ell-1} Q_b^B \}$  is allocated greedily; allocated offers from the sell-side are paid  $\lambda_k^S$  and allocated offers from the buy-side pay  $\lambda_\ell^B$  per traded unit. In this case, the last feasible trade is *reduced* or forbidden from trade as it set the prices for selling and buying offers (cf. Figure 4.5).

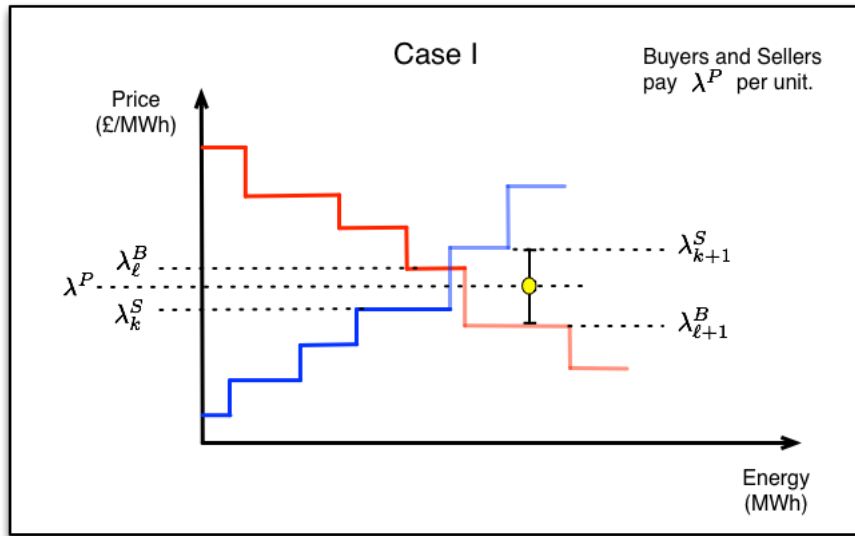


Figure 4.4: Case I of McAfee's pricing rule.

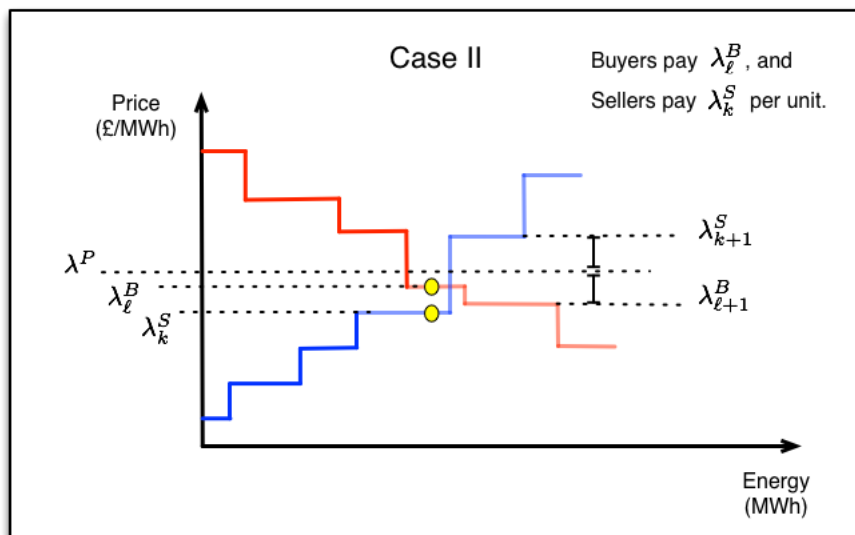


Figure 4.5: Case II of McAfee's pricing rule.

### 4.3.3 Theoretical Properties

The proposed mechanism inherits the properties from Chapter 3, regarding retailers and their end-users. Moreover, the methodology developed for constructing integrated DR energy stepwise offers incentivises end-users to report their preferences truthfully, as discussed in Subsection 4.3.1. Therefore, the following properties are only proved for the multi-retailer McAfee-based DA.

**Proposition 4.1.** *This mechanism is dominant strategy incentive compatible (DSIC).*

*A mechanism is incentive compatible or strategy-proof in a dominant strategy implementation if agents are (weakly) better off by revealing their truth types (preferences).*

*Proof.* In order to prove that retailers cannot gain any profit by misreporting their types in a one-shot seal-bid auction, it is sufficient to show that they cannot manipulate the clearing price (Vickrey, 1961). Following McAfee's pricing rule, if an offer sets the price, it is prevented from trading (McAfee, 1992). For instance, if clearing price  $\lambda^P := \frac{\lambda_{k+1}^S + \lambda_{\ell+1}^B}{2}$  is feasible for agents' offers  $k$  and  $\ell$ , i.e.  $\lambda^P \in [\lambda_k^S, \lambda_\ell^B]$ , then agents from offers  $k$  and  $\ell$  did not set the price. The only way agents from offers  $k$  and  $\ell$  can manipulate the price is when  $\lambda^P \notin [\lambda_k^S, \lambda_\ell^B]$ , in which case they are removed from the trade. Therefore, if an agent, that does not have an offer allocated for trade, reported  $\hat{\lambda}_t^B > \lambda_t^B$  so as to have its offer allocated for trade, it would lose because it ends up paying more than it values the good. The case of the selling offer is analogous, i.e.,  $\hat{\lambda}_t^S < \lambda_t^S$ . Moreover, if an agent reports a price  $\hat{\lambda}_t^B \mid \lambda_t^P := \hat{\lambda}_t^B$ , that sets the clearing price (for the others) at least from its side of the market, then it does not trade; such deviation cannot be profitable for that agent. Furthermore, if an agent has its offer allocated and reports  $\hat{\lambda}_t^B > \lambda_t^B$ , it does change the clearing price, so it does not have an incentive to report more than it values the good. The reasoning is analogous for buyers and sellers. Therefore, agents have no incentives to misreport their unit costs and unit valuations. However, McAfee (1992) points out that his mechanism works only for the single-unit case, because in multi-unit cases participants could try to game the mechanism by misreporting one of their offers, i.e., price-quantity pairs so as to hit the clearing price. For instance a buyer may include an additional bid of only one item at a lower price, with the aim of trying to hit the clearing price down and reduce its whole procurement cost. Similarly, a seller could add an ask of one item at a higher price and drive the clearing price up. The proposed mechanism does not suffer from this problem because retailers cannot manipulate their stepwise offering blocks. These blocks are created by the ISO-controlled auctioneer, who follows the methodology described in Subsection 4.3.1, in

which retailers are not allowed to set the price of DR blocks. These prices are computed separately through a  $k+1$  Vickrey-based price from end-users' DR offers, where the price-setting offer is excluded from the block; and later the stepwise offers are offset by the retailer's reservation prices, so that DR offers are placed below real energy imbalance offers in the DA. Moreover, the quantities expressed by retailers, as well as the integrated DR offers, are verifiable and liable for trade if they result allocated, in which case the trading schedules are updated, before the physical balancing market operates. Hence, it is a weakly dominant strategy to report the quantities, their valuations and costs truthfully.  $\square$

**Proposition 4.2.** *This mechanism is ex-post individually rational for retailers.*

*A mechanism is ex-post individually rational if agents never lose by participating in the mechanism with regard to the values they report.*

*Proof.* This follows immediately from the fact that in this DA retailers never pay more than their buying offers and are never paid less than their selling offers. From McAfee's pricing rule there are two cases. In the first case, the clearing price is in between the prices from the marginal trade, i.e.,  $\lambda^P \in [\lambda_k^S, \lambda_\ell^B]$ , thus  $\lambda^P \not\prec \lambda_k^S$  and  $\lambda^P \not\prec \lambda_\ell^B$ . In the second case, where the last feasible trade sets the prices but it is not allowed to trade, the unit prices in the sell-side are ranked in non-increasing order, i.e.,  $\lambda_1^S \leq \dots \leq \lambda_{k-1}^S \leq \lambda_k^S$ , with ties randomly broken, thus the clearing price for the sell-side set by  $\lambda_k^S$  is weakly greater than  $\lambda_{k-1}^S$  and than all other allocated sell offers, i.e.,  $\lambda_k^S \not\prec \lambda_{k'}^S, \forall k' \in [1, \dots, k-1]$ . Similarly, the offers in the buy-side are ranked in non-increasing order, i.e.,  $\lambda_1^B \geq \dots \geq \lambda_{\ell-1}^B \geq \lambda_\ell^B$ , thus the clearing price  $\lambda_\ell^B$  is weakly smaller than  $\lambda_{\ell-1}^B$ , i.e.,  $\lambda_\ell^B \not\prec \lambda_{\ell'}^B, \forall \ell' \in [1, \dots, \ell-1]$ .  $\square$

**Proposition 4.3.** *This mechanism is weakly budget-balanced.*

*A mechanism is said to be strongly budget-balanced if the amount of payments collected from buy offers (or buyers) is equals to the payments made to sell offers (or sellers). A mechanism is weakly budget-balanced if this amount of payments collected and made is never negative.*

*Proof.* It follows immediately from McAfee's pricing rule. The first case yields a strongly balanced budget since the clearing unit price  $\lambda^P$  is uniform. Hence, the amount traded is  $Q^\tau := \min \{ \sum_{s=1}^k Q_s^S, \sum_{b=1}^\ell Q_b^B \}$ , and the MO charges  $\lambda^P Q^\tau$  to buyers and distributes the same  $\lambda^P Q^\tau$  to sellers. The second case, yields a weakly balanced budget since, by definition, the last feasible trade between marginal offers  $k$  and  $\ell$ , have prices

$\lambda_\ell^B > \lambda_k^S$  (they are not equal, as otherwise it would be the first case). The amount traded in both sides is  $Q^\tau := \min \left\{ \sum_{s=1}^{k-1} Q_s^S, \sum_{b=1}^{\ell-1} Q_b^B \right\}$ , thus, the MO charges  $\lambda_\ell^B Q^\tau$  to buyers and pays  $\lambda_k^S Q^\tau$  to sellers, and ends up with a non-negative profit.  $\square$

**Proposition 4.4.** *The allocation and payments settlement are computationally efficient.*

*A mechanism is computationally efficient if both its allocation and payment determination can be solved in polynomial time, i.e., computationally tractable.*

*Proof.* It is easy to see that this mechanism can be cleared, both the allocation and payment computation, using greedy algorithms. Determining the system imbalance takes linear time in the number of retailers, since they send at most one offer for their expected imbalance. Populating the sell-side and buy-side with their respective offers take linear time in the number of offers; however, they are subsequently sorted, which takes  $O(n \log n)$  on each side, where  $n$  is the number of offers in its respective side. Determining the marginal blocks  $k$  and  $\ell$  can also be done in linear time, traversing both sides while cumulatively computing quantities, and comparing quantity and price feasibilities. Moreover, determining blocks  $k+1$  and  $\ell+1$  may involve finding the minimum or maximum unit price from the auxiliary set  $D_t$ , whose unit price is also lower or higher than blocks  $k$ 's or  $\ell$ 's unit price, respectively. This can also be done in linear time. Finally, finding the clearing price takes few mathematical operations. Hence, the time complexity is  $O(n \log n)$ , where  $n$  is the number of offers submitted to the DA.  $\square$

#### 4.3.4 Additional Remarks

Economical efficiency has been sacrificed in order to maintain this mechanism DSIC, IR and BB. This trade-off is necessary to maintain the other properties, as it is commonly known due to the *Myerson-Satterthwaite impossibility theorem*, previously discussed in Chapter 3 and in Subsection 4.3.2.2. However, the efficiency is still high, since only the least profitable trade is foregone some of the time (only in the second case of McAfee's pricing rule).

Moreover, the communication complexity is  $O(m \log n)$ , where  $m$  is the number of retailers and  $n$  is the number of end-users providing DR offers. Also, messages can be encoded efficiently using data types with low cost of representation, such as integers, to represent energy units and pence/cents.

Regarding the management of offers, the ontology between agents to understand types (i.e., preferences) correctly is taken for granted. Also, it has been assumed that

the retailers' auctioneer has proper data structures that map end-users to DR stepwise offering blocks so that the allocation determined by the MO can be propagated down to the level of end-users. The retailer (by means of its auctioneer) assesses its end-users' DR achievements at the end of the time period (or beginning of the next one), according to a previously agreed penalty scheme for all its end-users to determine their discount, as discussed in Chapter 3.

This mechanism couples DR with a financial balancing market, which in overall involves a chain of two market-based mechanisms: (1) a single-sided auction between a retailer and its customers, and (2) a double-sided auction amongst retailers.

## 4.4 Summary

This chapter provides a multi-unit McAfee-based DA for zonal supply and demand balancing with multi-retailer dynamics. This mechanism, amongst retailers, chains the one-sided mechanism proposed in Chapter 3 with the aim of aligning domestic DR efforts to the zonal balancing needs. Moreover, a methodology is developed for expressing domestic DR offers into stepwise offering blocks that retailers can exchange amongst themselves, through the proposed mechanism. Although not DSIC, an LP formalisation of the allocation problem is provided for the case of a uniform-price DA with the designed stepwise offers. Furthermore, the DSIC McAfee-based mechanism is specified and its theoretical properties proved. Finally, the overall approach aligns end-users and retailers' interest with those of the ISO for balancing supply and demand, and yields a chained mechanism that is DSIC, IR, BB and computationally tractable.

## 4.5 List of Symbols

<b>Symbol</b>	<b>Description</b>
$A_{jt}$	Subset DR offers submitted to retailer's auctioneer $j$ at time period $t$ .
$A_{jt}^*$	Subset of valid DR offers that auctioneer $j$ will use to construct DR blocks at time period $t$ .
$B_{jt}$	Buy blocks; they integrate retailer $j$ 's deficit joined with net-load valley-filing DR blocks at time period $t$ .
$B_t$	Double auction's buy-side at time period $t$ .
$D_t$	Auxiliary set that is used to keep the block in the side of the imbalance that, although it is not allocated, it is used to set the clearing prices (McAfee's pricing rule).



$\theta_{it}$	DR offer of agent $i$ at time period $t$ .
$i$	Index variable for end-user agents.
$j$	Index variable for retailers (or the auctioneer that represents them).
$j_\ell^B$	Retailer index of buying block $\ell$ (net-load valley-filling).
$j_k^S$	Retailer index of selling block $k$ (net-load peak-shaving).
$k$	Index variable for selling blocks.
$\ell$	Index variable for buying blocks.
$L_k^B$	List that links DR offers $\theta_{it}$ to block $\ell \in B_{jt}$ .
$L_k^S$	List that links DR offers $\theta_{it}$ to block $k \in S_{jt}$ .
$\lambda_x$	Unit clearing price (price-to-quantity ratio) of block $x$ .
$\lambda_\ell^B$	Price of buying block $\ell$ (net-load valley-filling).
$\lambda_{it}^d$	Offering price for peak-shaving in pence/kWh at time period $t$ (by agent $i$ ).
$\lambda_t^{dk}$	Price-to-quantity ratio of the amount of kWh offered for net-load peak-shaving at time period $t$ (by agent $i$ ).
$\lambda_{(k+1)[0]}^{dk}$	Price-to-quantity ratio of the first ask that did not fit into $L_k^S$ ; (single-bid $k+1$ ) Vickrey-based price.
$\lambda_k^S$	Price of selling block $k$ (net-load peak-shaving).
$\lambda_{it}^u$	Offering price for valley-filling in pence/kWh at time period $t$ (by agent $i$ ).
$\lambda_t^{uk}$	Price-to-quantity ratio of the amount of kWh offered for net-load valley-filling at time period $t$ (agent $i$ ).
$\lambda_{(\ell+1)[0]}^{uk}$	Price-to-quantity ratio of the first ask that did not fit into $L_\ell^B$ ; (single-bid $k+1$ ) Vickrey-based price.
$\lambda^P$	Uniform clearing price (at time period $t$ ).
$\tilde{\lambda}_t^{B*}$	Retailer's reservation price for buying its contracted deficit from DR, as opposed to buying it from the balancing market (imbalance settlement).
$\tilde{\lambda}_t^{S*}$	Retailer's reservation price for selling its contracted surplus to end-users through DR, as opposed to selling it back to the balancing market (imbalance settlement).
$M$	Set of retailers.
$m_{t-1}$	Meter reading at time period $t-1$ (of agent $i$ ).
$m_t^d$	Estimated meter reading if peak-shaving would be implemented at time period $t$ (of agent $i$ ).
$m_t^u$	Estimated meter reading if valley-filling would be implemented at time period $t$ (of agent $i$ ).
$m_t^y$	Meter reading prediction for time period $t$ (of agent $i$ ).
$N_j$	Set of all end-users subscribed to retailer $j$ .
$q_{t-1}$	kWh used at time period $t-1$ (by agent $i$ ).

$q_t^d$	Offered amount of kWh for net-load peak-shaving at time period $t$ (agent $i$ ).
$q_t^u$	Offered amount of kWh for net-load valley-filling at time period $t$ (agent $i$ ).
$q_t^y$	Intended net-load use of agent $i$ at time period $t$ (which is a forecast).
$Q_k^A$	Least expensive allocation of the feasible trade.
$Q_\ell^B$	Amount of buying block $\ell$ (net-load valley-filling).
$Q_t^F$	Amount of feasible trade at time period $t$ .
$Q_k^S$	Amount of selling block $k$ (net-load peak-shaving).
$Q^T$	Traded amount (at time period $t$ ).
$\tilde{Q}_t$	DR quantity to be procured, which comes from retailer $j$ 's prediction
$S_{jt}$	Sell blocks; they integrate retailer's surplus joined with net-load peak-shaving DR blocks.
$S_t$	Double auction's sell-side.
$t$	Index variable for time periods.
$T$	Set of consecutive discrete time periods (e.g., hourly or half-hourly).
$\underline{w}$	Minimum amount of kWh for DR offers to be considered by the mechanism.
$\bar{w}$	Maximum amount of kWh for DR offers to be considered by the mechanism.
$w_x$	Amount of kWh (or MW) of block $x$ .
$w^*$	Fixed parameter to denote the minimum cut size in kWh of DR blocks.
$x$	Temporary index variable for lists $L_k^S$ and $L_\ell^B$ .



# Chapter 5

## Empirical Evaluation of Proposed Mechanisms

This chapter evaluates the mechanisms described in Chapters 3 and 4 through simulations that use realistic data from the UK. The theoretical properties of these mechanisms, from an Algorithmic Mechanism Design (AMD) perspective, were proved within their respective chapter. Nonetheless, the economic effects of these mechanisms for end-users, retailers, and the zonal-based Independent System Operator (ISO) have been reserved for the present chapter. The assessed effects are: the amount in the electricity bill for end-users, the revenue and imbalance settlement for retailers, and the absolute net imbalance volume (NIV) for the ISO. Moreover, these effects are in line with the end-users and retailers' desiderata introduced in Chapter 1, and ultimately with the objective of balancing supply and demand, or at least reducing the imbalance by means of domestic demand response (DR), which is of interest to the ISO.

### 5.1 Experiment Design

The mechanisms proposed in Chapters 3 and 4 are implemented in a rather controlled setting in order to test how well they perform regarding the economic outcomes for end-users, retailers, and the ISO. The experiments consider only one geographical zone, which is controlled by the ISO. The ISO not only is responsible for balancing electricity demand with physical supply, but also runs the zonal market-based mechanism through its market operator (MO) agent. Three retailers have been modelled within this zone, and it has been assumed that they only operate in this zone. Each retailer serves a fixed population of households, and they are all assumed to be demand responders. All

retailers offer the same retail prices to all their subscribed households.

Each household has an electricity-use profile, which is separable into inflexible net-load and operational flexibility. That is, the inflexible net-load is the amount of electricity that end-users will not change, and the operational flexibility corresponds to schedulable loads. The capacity of operational flexibility is simulated for each household, but it is controlled amongst mechanisms, so that the economic effects can be compared against the same amount of electricity use for the whole simulation horizon. Therefore, the resulting distributions of electricity bills from different mechanisms, for the same retailer, correspond to each household using its same amount of kWh for each mechanism. Different degrees of flexibility were simulated by controlling the quantity of schedulable appliances per household, the electricity they consume, and frequency of use. These degrees are fixed, but retailers have a different proportion of them within the population they serve. This notion is akin to having households with different responding capacities due to their technological equipment.

For convenience, the modelled retailers procure DR greedily. That is, the amount of DR procurement is myopically decided for the current time period without assessing the impact on future time periods<sup>24</sup>. It has been assumed that retailer can perfectly forecast their NIV and the imbalance prices for the current time period. Although these assumptions are unrealistic, they facilitate the analysis regarding the effects of the mechanisms, thus isolating these effects from other factors, such as retailers' forecast ability. However, end-user agents are simulated with two forecast methods, naive and perfect, so that the effect of penalty schemes can be included in the assessment. Similar to the controlled household profiles, each retailer's NIV profile is fixed across mechanisms and varies per simulation, while time-varying imbalance prices are fixed for all simulations.

Time was modelled as a series of half-hourly time periods. The simulation horizon was arbitrarily selected, consisting of the months of January and July. In the UK, January and July are often the coldest and warmest months of the year, and electricity use widely varies in between these months due to (electrical) heating demand. Moreover, when solar PVs are considered, the net-load differs more evidently between these months. Each mechanism was simulated ten times for each retailer, for all time periods within each month, and for each end-user agents' forecast ability, i.e., naive and perfect. This results in each mechanism being simulated  $31 \text{ days} \times 48 \text{ time peri-}$

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<sup>24</sup>Further experimentation could be done to add look-ahead capabilities and different forecasting methods for retailers in order to see how the effects change. However, for simplicity, the experiments in this chapter do not consider this possibility.

ods  $\times$  10 runs = 14,880 times, and its cumulative effects are assessed per month, per retailer, and per distribution of end-users, so that these mechanisms can be compared against each other, and especially contrasted to business-as-usual (BAU).

Before describing the independent and dependent variables regarding the experiments, the next subsection describes how the end-users' inflexible net-load profiles were generated based on a dataset from a survey of domestic electricity use in the UK. The characterisation of the three retailers, however, is made implicit in Subsection 5.1.2 within the collective of controlled variables.

### 5.1.1 End-Users' Inflexible Net-Load Profiles

End-users' net-load profiles in this study are formed by an inflexible net-load profile and operational flexibility; the latter modelled by schedulable domestic tasks that use a single appliance. The inflexible profiles are based on the Household Electricity Survey (HES) in England, UK. This project was funded by the Department of Environment, Food and Rural Affairs (DEFRA), the Department of Energy and Climate Change (DECC), and the Energy Saving Trust. Detailed information about this survey is found in (Zimmermann et al., 2012). The survey monitored the electricity use in 251 owner-occupier households in England, over the period May 2010 to July 2011. Zimmermann et al. (2012) emphasise that the demographic profile is as representative as possible of the owner-occupier population in England, and not the population of England as a whole. The HES project involved recruiting households, surveying the appliances, installing monitoring devices, collecting and processing these data. From the sample of 251 households, 26 were monitored for a whole year, and the rest for a single month over a span of one year. The readings, which include electric energy, inside and outside temperatures, were taken every two or ten minutes depending on the configuration of the monitoring equipment. The dataset is disaggregated per appliance, provides a time stamp, measurement interval and, in most of the cases, there are values for inside and outside temperatures. Processing of these dataset regarding insights on household electricity use and potential for demand-side management (DSM) can be found in (Zimmermann et al., 2012; Terry and Palmer, 2013; Palmer et al., 2013).

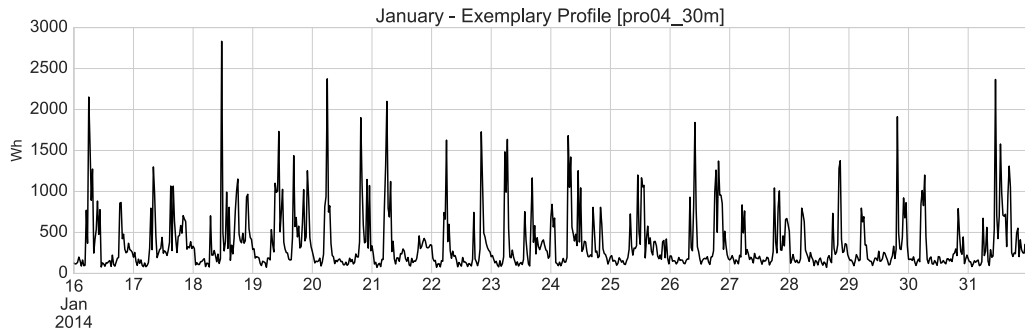
For the current experiments, only the readings from the 26 households that were monitored for a whole year were considered. This is because the experiment considers two separate months, January and July, and the data cannot be easily extrapolated, as the generated profiles in each month would be sourced from different households.

Moreover, one of these profiles was discarded due to a wide range of missing data. Nonetheless, several inconsistencies in the data were found and further research led to a report by Cambridge Architectural Research (CAR) where these inconsistencies are described and dealt with (Terry and Palmer, 2013). The remaining 25 profiles were corrected based on this report, especially the off the scale readings. Some profiles had small gaps with corrupted or missing data; the gaps of electric energy readings were generated using time series based interpolation, and the missing outside temperature readings were replaced by the outside temperature mean of the other households containing these data.

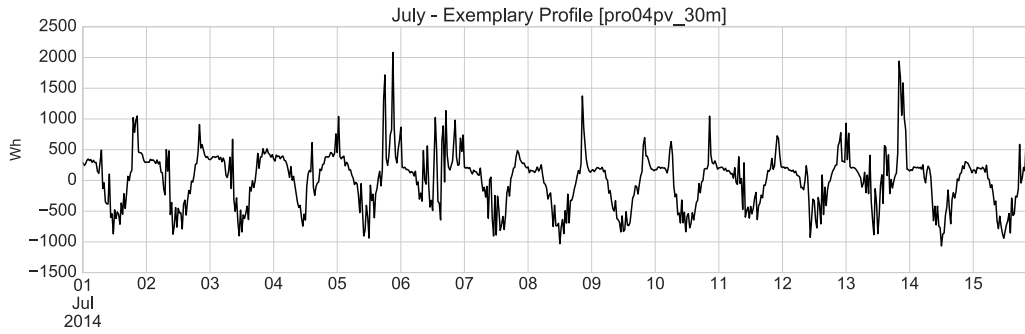
Moreover, appliances that could provide operational flexibility (e.g., space and water heaters, washing and drying machines) were removed from within these profiles, so that schedulable appliances could be modelled separately. These resulting profiles correspond to the 25 inflexible net-load profiles without electricity generation, from which the experiments generate the household profiles. Operational flexibility of appliances is modelled using Poisson processes over a finite set of schedulable tasks, that is described in Subsection 5.1.2.

Since the sample of households from the HES project excluded those with domestic renewable energy sources, the resulting 25 inflexible net-load profiles were paired with a fixed configuration of solar PV, so as to generate additional 25 profiles. The solar PV output was modelled with PVLIB-Python (Holmgren et al., 2015). The PV installation consisted of an arbitrary  $4kW_p$  configuration, which uses an approximate area of  $26m^2$  covered with panels, whose efficiency was set to 13%. The PVLIB-Python package estimated the clear-sky solar irradiance to the longitude, latitude and elevation of London. In addition, the effects of cloud shadows were modelled by a random factor  $\zeta \in [0, 1]$ , sampled from a Beta distribution  $\zeta \sim \mathcal{B}(6.5, 3.5)$ , to compute the final PV output under cloud cover dynamics. As a result of this procedure, there were 50 main inflexible net-load profiles, which were comprised of 25 households without generation facilities, and 25 with the described PV installation.

Figure 5.1 provides two exemplary inflexible profiles over an arbitrary time window for each month in this study. For instance, Figure 5.1a shows a profile with no solar PV over a cold month, whereas Figure 5.1b shows the same inflexible profile but paired with the previous solar PV installation over a warm month.



(a) Second half January.



(b) First half July.

Figure 5.1: Two exemplary inflexible net-load profiles.

Finally, the experiments uniformly sample households from these profiles, but they are arbitrarily perturbed in order to add variation, i.e., similar profiles as the original, but not exactly the same one. The perturbation used is a draw from a normal distribution centred in each value with an arbitrary standard deviation of 40% of the original value, i.e.,  $y'_t \sim \mathcal{N}(y_t, 0.4y_t)$ .

For reproducibility purposes, a set of seeds has been used to generate pseudo-random numbers in order to produce the same inflexible profile for each simulated household across all mechanisms for each simulation.

### 5.1.2 Independent Variables

- Number of geographical zones: 1
- Number of retailers: 3 (indexed by 1:3).
- Number of households that each retailer serves: 1000, 1350, and 850, respectively.



- Retail prices: all retailers provide the same prices, 15 pence per kWh for selling and 8 pence per kWh for buying.
- Inflexible net-load profiles for households: 50 different main profiles, which are uniformly sampled and include random variation as described in Subsection 5.1.1.
- Degrees of operational flexibility, which include a finite number of load-using devices and a frequency parameter for tasks arriving to the schedule, that use one of these devices. Table 5.1 shows the parameters used for these degrees. The operational flexibility is modelled as a Poisson process to simulate the arrival of tasks to the household schedule (considering half-hourly time steps). Operational flexibility of electrical generation devices was excluded from these experiments. This is because the retailer sells at a higher price than it buys, therefore, rational end-users are better off using their dispatchable generators if their operation is cheaper than their retailer's selling price. Moreover, solar PVs are modelled in the inflexible profile, assuming no storage.

Degree	# Flex. Load Devices	$\lambda$ (Poisson process)	# Tasks
1	5	0.05	$\sim 2.4$ per day
2	5	0.10	$\sim 4.6$ per day
3	10	0.10	$\sim 4.6$ per day
4	10	0.15	$\sim 7.5$ per day

Table 5.1: Different degrees of DR flexibility.

- Each load-using device with operational flexibility is characterised by its  $Wh$  usage, number of required time periods, number of flexibility time periods, cost and cost type, as described in Subsection 3.2.3.  $Wh$  usage per time period is drawn from a uniform distribution,  $\sim \mathcal{U}(500, 1500)$ . The number of required time periods is sampled from a discrete uniform distribution,  $\sim \mathcal{U}\{1, 8\}$ . Similarly, the flexible time periods is  $\sim \mathcal{U}\{1, 8\}$ . Thus, the minimum required time periods is the number of required time periods, and the maximum is the required time periods plus the flexible time periods. The cost is a small random number  $0.1x$ , where  $x \sim \mathcal{U}(0, 1)$ . Finally, the cost type, or pricing strategy for DR asks, is  $\sim \mathcal{U}\{1, 3\}$ , i.e., increasing, decreasing, or constant.

- The following restriction on flexible task arrivals from the Poisson process is enforced. When a task arrives to the schedule, it links to a single schedulable device, and this device cannot be scheduled by another task until the former exhausts its maximum schedulable time steps (both required time periods and flexibility time periods). This was imposed to ensure that the flexibility simulation always picks the same appliances for each mechanism, otherwise BAU may sample different devices as the other mechanisms, because it does not hold devices for a scheduling time span. This was controlled in order to compare the dependent variables more fairly.
- Proportion of degrees of flexibility for each retailer's serving population are sampled according to the probabilities in Table 5.2.

Retailer	Pr(deg1)	Pr(deg2)	Pr(deg3)	Pr(deg4)
1	0.3	0.2	0.3	0.2
2	0.1	0.3	0.4	0.2
3	0.1	0.2	0.3	0.4

Table 5.2: Proportion of degrees of DR flexibility per retailer's serving population.

- Simulation horizon, which is independently comprised of the months January and July.
- Forecasting ability of end-user agents, which are naive and perfect predictions for the inflexible net-load. The naive forecast uses the amount of  $t - 1$  from the inflexible profile to estimate that of time period  $t$  when constructing the DR ask. The perfect forecast uses the exact amount from the inflexible profile of time period  $t$ . The perfect forecast is used to compare the effect of forecasting regarding DR asks, achievements and penalty schemes.
- The initial NIV of retailers was set to  $\sim \mathcal{N}(0, 1) \times |N_j|$ ,  $\forall j \in M$ ,  $\forall t \in T$ , where  $M$  is the set of three retailers,  $|N_j|$  is the size of the population that retailer  $j \in M$  serves, and  $T$  is the set of time periods in the simulation horizon.
- The imbalance settlement prices per time period were based on ELEXON system prices from year 2014 (Elexon, 2015; Elexon, 2014). Although these prices are not from the same year as the electricity use profiles, for the current study, it

can be safely assumed that electricity use profiles are similar to those of other years due to their strong seasonality (and similar daily and weekly patterns). Moreover, the ELEXON system prices were arbitrarily adjusted to reflect a scenario in which balancing generation is less desirable than DR.

- The system sell price (SSP) was set to  $\frac{1}{2}SSP$ . This assumes a low salvage price for retailers' excess, such that it is more preferable to allocate this excess amongst demand responders, than to sell it back to the balancing market.
- The system buy price (SBP) was set to  $3SBP$ . This assumes a high price for last-second electricity, such that it is more desirable to accommodate the deficit amongst demand responders, than to buy balancing generation.
- The retailers' valuation for a kWh of flexibility was set to the retailer's marginal value for an actual kWh of electricity, given retail and balancing prices.
- Mechanisms:
  - **BAU**: Business-as-usual, when a task arrives to the schedule, it is always set to run without delay.
  - **VCG\_P1**: the VCG-based mechanism specified in Section 3.3 paired with the middle point penalty scheme from Subsection 3.3.5.1. The penalty threshold is  $\delta := 0.5$ , for all retailers.
  - **VCG\_P2**: the VCG-based mechanism specified in Section 3.3 coupled with the slope-based penalty scheme described in Subsection 3.3.5.2. The penalty threshold is  $\delta := 0.8$ , for all retailers.
  - **VCG\_P3**: the VCG-based mechanism specified in Section 3.3 in tandem with exponentially weighted moving average (EWMA) penalty scheme from Subsection 3.3.5.3. The parameters are set to  $\alpha := 0.25$  and  $\delta := 0.9$ , for all retailers.
  - **VCG\_PD**: the VCG-based mechanism specified in Section 3.3 with the penalty scheme from (Dash et al., 2007), which is adapted to the studied setting in Subsection 3.3.5.4. The parameter  $\delta := 0.2\lambda^R$  for all retailers, where  $\lambda^R$  is the retailer's reservation price.
  - **McAf\_P3**: the McAfee-based mechanism from Chapter 4, using a the EWMA-based penalty from Subsection 3.3.5.3. The parameters are set to

$\alpha := 0.25$  and  $\delta := 0.9$ , for all retailers.

### 5.1.3 Dependent Variables

- End-users' monthly electricity bill (January and July), which includes the imported and exported amount of kWh, and DR discounts and penalties.
- Retailers' revenue, which is only expressed by retail trade, DR trade, and imbalance settlements. The retail trade includes the inbound and outbound cash flow resulting from selling and buying electricity to households. The DR trade includes discounts and penalties with relation to allocated DR asks. The imbalance settlements regards to the amount that the retailer pays, or is paid by the market, for correcting its NIV. Transactions from previous wholesale markets, such as futures markets, pool markets, and balancing trade are excluded from this revenue variable. The reason for this is because the study is only focused on the effect of DR in retail trade and imbalance settlements for retailers, thus wholesale trade can be treated as an independent variable, which is excluded in this case.
- Retailers' imbalance settlement, which accounts for opportunity costs and balancing generation procurement. If a retailer's NIV is positive, the retailer faces an opportunity cost since it has to forego the electricity excess at a low price to the balancing procedure. Similarly, if the NIV is negative, the retailer is charged an expensive price for last moment procurement to cover the deficit.
- Retailers' absolute NIV, which is similar to an error measure to denote the whole amount of required intervention by balancing generators. The ISO, depending on the electricity supply organisation, has to estimate and procure the balancing generation capacity in advance, and reducing the zonal NIV would lead to less need for balancing generation.

## 5.2 Simulation Results

The experiments were implemented in Python 2.7.11 and were run on Eddie Mark 3, the university's cluster (University of Edinburgh, 2016), which has about 4,000 cores with up to 2 TB of memory, and uses the Open Grid Scheduler batch system on Scientific Linux 7.

The resulting distribution of each dependent variable is hierarchically plotted by month, retailer, mechanism, and end-users' forecast skill. The box plots show the quartiles from each resulting distribution. The error plots, organised in the same order as the box plots, show the mean and standard error of mean (SEM) with 95% confidence intervals (CI). Finally, the hypotheses regarding the effect of these dependent variables are formulated and tested for statistical significance, at 5% level, using paired samples t-tests over the joint effect of the two simulated months, January and July.

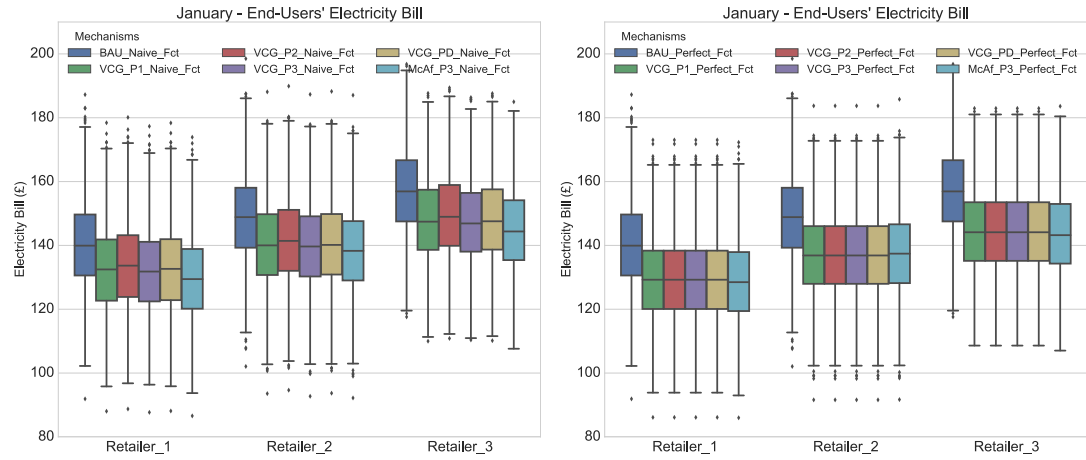
## 5.2.1 End-Users' Electricity Bill

### 5.2.1.1 Comparison of Mechanisms

Figure 5.2 shows the resulting distributions of the monthly electricity bill. The upper half corresponds to January, while the lower half refers to July. The left half corresponds to results that end-users achieve by using a naive forecast for the inflexible net-load, whereas the right half shows these results under a perfect forecast. As previously described in Subsection 5.1.2, retailer 1, 2, and 3 serve populations of 1000, 1350, and 850 households. In each quadrant, the results are grouped by retailer and each mechanism is indicated by a colour. The first distribution for each retailer, showed in blue, corresponds to BAU. It can be seen from these plots that in all the experiments each of the proposed mechanisms on average performed better than BAU, regarding the monthly electricity bill. McAf\_P3 yields a lower bill in most of the cases, except for retailer 2 in January with end-users' perfect forecasts. A potential explanation for the good results of McAf\_P3 is that end-users get to offer DR to more than one retailer, so they have more opportunities to allocate their flexibility and get more discounts, as opposed to the VCG-based mechanisms. In addition, McAf\_P3 uses the EWMA-based penalty scheme, which charges no money, but may prevent end-user agents from the allocation if they repeatedly unfulfill DR offers. Therefore, using this penalty can only yield a weakly lower electricity bill than BAU.

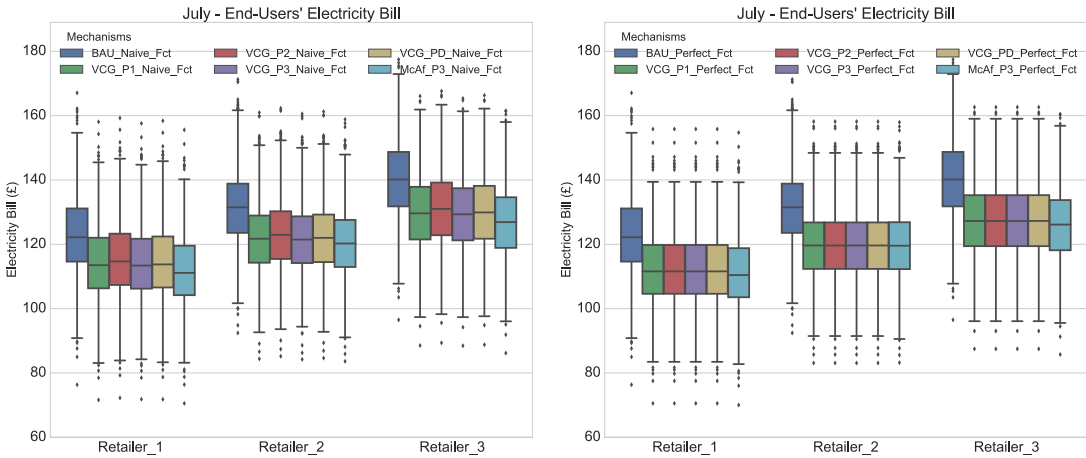
Moreover, the electricity bill is lower for end-users when they use a perfect forecast, because they are never penalised. That is, better forecast methods yield fewer penalties than a naive forecast, because end-users estimate DR offers that they are able to deliver completely and implement allocations accordingly. This can be noticed by comparing the alignment of their interquartile range (IQR), especially the medians on the left and right sides of Figure 5.2. For instance VCG\_P2, in red, is not exactly aligned to the other VCG-based mechanisms, and results in a slightly higher electricity bill due to

charging DR penalties. The penalty threshold for VCG\_P2 is  $\delta := 0.8$ , therefore offers that are not supplied in at least 80% receive a penalty, and given the setting, naive forecast methods are more likely to produce this outcome.



(a) January's electricity bill with naive forecasts.

(b) January's electricity bill with perfect forecasts.



(c) July's electricity bill with naive forecasts.

(d) July's electricity bill with perfect forecasts.

Figure 5.2: Comparative results for each mechanism regarding its effect on the electricity bill.

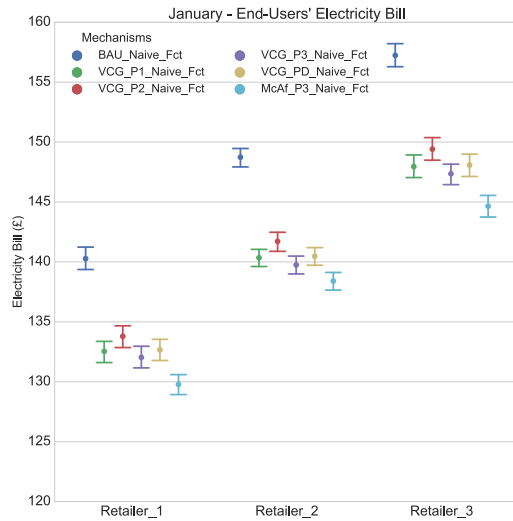
The effect of forecast skill over the electricity bill is small in these plots for several reasons. First, the penalty parameters were not aggressive; if they were, the differences between the left and right sides of the figure would become obvious. Second, the naive forecast is not outrageously bad. Third, the frequency and size of allocated DR offers under uncertainty per end-user, apart from the forecast accuracy, correlates with the likelihood of getting penalties. Last, the length of the simulation horizon is relatively

short, in which a couple of pounds of monthly penalties are hard to visualise, unless they are presented in an additional plot. For instance, the effect of end-users' forecast is more evident in Figure 5.3, and it could be clearer if the two months were summarised into a single plot, so as to show the cumulative effect.

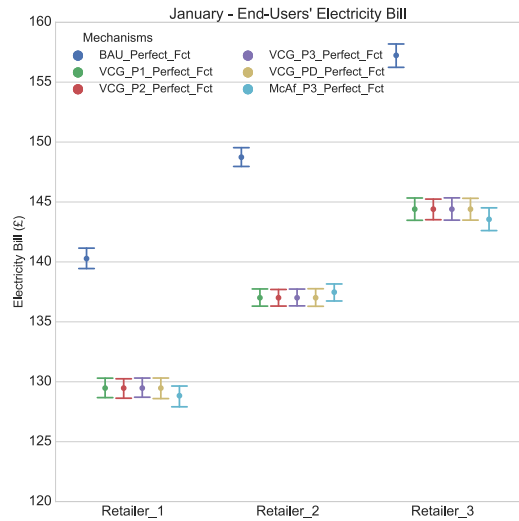
The electricity bills resulting from these simulations are higher than today's average domestic electricity bills in the UK, which according to Department of Energy & Climate Change (2016) is about £50 a month. This discrepancy comes from the modelling and simulation of operational flexibility, described in 5.1.2, that assumes the use of some heavy loads, such as EV recharging, electricity space and water heating (as opposed to gas-based heating). Moreover, the same parameters for operational flexibility were used for January and July; this decision was made for convenience reasons. Although this might not reflect what happens in the UK in July, it might be more representative of countries like the USA, where cooling loads are in high demand during the summer.

#### **5.2.1.2 Confidence Intervals**

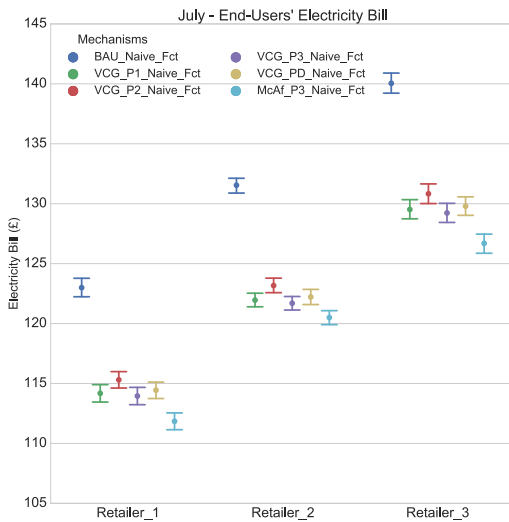
Figure 5.3 is organised in the same manner as the box plots in Figure 5.2, and it shows the distribution means and SEM at 95% CI. In these plots, the effects of end-users' forecast skill on the electricity bill is more evident.



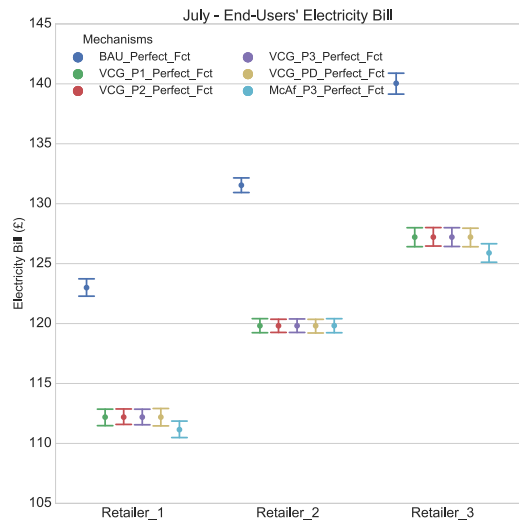
(a) January's electricity bill with naive forecasts.



(b) January's electricity bill with perfect forecasts.



(c) July's electricity bill with naive forecasts.



(d) July's electricity bill with perfect forecasts.

Figure 5.3: End-users' electricity bill, standard error of the mean at 95% confidence interval.

### 5.2.1.3 Paired Samples T-Test

This test was computed for the cumulative electricity bill of January and July, and for the whole population of households subscribed to the three retailers, over ten simulations.

**Hypothesis:** Does any of the proposed mechanisms result in a lower electricity bill for end-users than BAU?



Let  $\mathbb{M}$  be the set of mechanisms including forecast type, i.e.,  $\mathbb{M} := \{BAU, \dots, McAf\_P3\_Perfect\_Fct\}$ . Let  $M$  be the set of three retailers, and  $N_j$  the set of households served by retailer  $j \in M$ . Then, the difference in electricity bills for each household under a pair of mechanisms,  $m$  and  $m'$ , is denoted by  $d_i^{m,m'} := \xi_i^m - \xi_i^{m'} \forall i \in N_j, \forall j \in M, \forall m, m' \in \mathbb{M}$ , where  $\xi_i^m$  is the amount paid for electricity by household  $i$ . Moreover, the size of the overall population of households is  $n := 32,000$ , i.e.,  $10 \sum_{j \in M} |N_j| = 10(1000 + 1350 + 850)$ , where ten is the number of simulations. The mean difference in electricity bills for all end-users between the mechanisms  $m$  and  $m'$  is expressed by  $\mu_d^{m,m'} := \frac{1}{n} \sum d_i^{m,m'}$ .

**Null hypothesis:** BAU yields a lower electricity bill than any of the proposed mechanisms, i.e.,  $H_0: \mu_d^{m,m'} \leq 0$  for  $m := BAU$  and  $m' := \{\forall x \mid x \in \mathbb{M}, x \neq m\}$ . By how the difference is expressed,  $d_i^{m,m'} := \xi_i^m - \xi_i^{m'}$ , the first term  $\xi_i^m$  is the amount in the electricity bill under BAU, and the second term  $\xi_i^{m'}$  is that amount under another mechanism in  $\mathbb{M}$ , that is being compared to BAU. Therefore, a  $\mu_d^{m,m'} \leq 0$  means that in average the electricity bill  $\xi_i^{m'}$  is higher than that of BAU.

**Alternative hypothesis:** Any of the proposed mechanisms yields a lower electricity bill than BAU, i.e.,  $H_A: \mu_d^{m,m'} > 0$  for  $m := BAU$  and  $m' := \{\forall x \mid x \in \mathbb{M}, x \neq m\}$ . A positive  $\mu_d^{m,m'}$  means savings on the electricity bill by mechanism  $m'$ , compared to BAU.

The paired samples t-test was applied to each pair of mechanisms, not only to compare each proposed mechanism against BAU, but also to compare each of them against the others. Therefore, similar hypotheses can be tested for different baselines than BAU. The level of significance was set to 5%, i.e.,  $\alpha := 0.05$ . Table 5.3 shows the resulting pairs of t-statistics and p-values. The first row of the table compares BAU against the other mechanisms. By the t-statistic formula,  $t^* := \frac{\bar{x}_d - \mu_0}{s_d / \sqrt{n}}$ , where the sample mean difference  $\bar{x}_d$  is tested to be significantly different from zero, i.e.,  $\mu_0 := 0$ , a positive t-statistic in this formulation means that the sample mean difference  $\bar{x}_d$  was positive, and thus, there were savings in the electricity bill. Also, the p-value is very small (second value of the pairs in parentheses), thus, there is enough evidence to reject the null hypothesis. Since all the t-statistics in the first row are positive, it can be concluded that each of the proposed mechanisms is better than BAU regarding end-users' electricity bills. Finally, the second to the last rows, in Table 5.3, show the t-test results for the other pairs of mechanisms, so that further hypotheses can be tested.

Table 5.3: Paired T-Test results for end-users' electricity bill.

BAU	VCG_P1_Naive_Fct	VCG_P1_Perfect_Fct	VCG_P2_Naive_Fct	VCG_P2_Perfect_Fct	VCG_P3_Naive_Fct	VCG_P3_Perfect_Fct
BAU	(nan, nan)	(332.67, 0.00)	(380.26, 0.00)	(310.05, 0.00)	(380.26, 0.00)	(363.35, 0.00)
McAf_P3_Naive_Fct	(-345.56, 0.00)	(-145.17, 0.00)	(25.04, 0.00)	(-211.50, 0.00)	(25.04, 0.00)	(-124.85, 0.00)
McAf_P3_Perfect_Fct	(-355.27, 0.00)	(-180.95, 0.00)	(-28.38, 0.00)	(-235.98, 0.00)	(-28.38, 0.00)	(-165.16, 0.00)
VCG_P1_Naive_Fct	(-332.67, 0.00)	(nan, nan)	(270.85, 0.00)	(-369.47, 0.00)	(270.85, 0.00)	(60.70, 0.00)
VCG_P1_Perfect_Fct	(-380.26, 0.00)	(-270.85, 0.00)	(nan, nan)	(-310.66, 0.00)	(nan, nan)	(-227.04, 0.00)
VCG_P2_Naive_Fct	(-310.05, 0.00)	(369.47, 0.00)	(310.66, 0.00)	(nan, nan)	(310.66, 0.00)	(226.67, 0.00)
VCG_P2_Perfect_Fct	(-380.26, 0.00)	(-270.85, 0.00)	(nan, nan)	(-310.66, 0.00)	(nan, nan)	(-227.04, 0.00)
VCG_P3_Naive_Fct	(-363.35, 0.00)	(-60.70, 0.00)	(227.04, 0.00)	(-226.67, 0.00)	(227.04, 0.00)	(nan, nan)
VCG_P3_Perfect_Fct	(-380.26, 0.00)	(-270.85, 0.00)	(nan, nan)	(-310.66, 0.00)	(nan, nan)	(-227.04, 0.00)
VCG_PD_Naive_Fct	(-330.69, 0.00)	(182.44, 0.00)	(300.68, 0.00)	(-298.73, 0.00)	(300.68, 0.00)	(90.73, 0.00)
VCG_PD_Perfect_Fct	(-380.26, 0.00)	(-270.85, 0.00)	(nan, nan)	(-310.66, 0.00)	(nan, nan)	(-227.04, 0.00)

Paired T-Test results for end-users' electricity bill (continued).

BAU	VCG_P3_Perfect_Fct	VCG_PD_Naive_Fct	VCG_PD_Perfect_Fct	McAf_P3_Naive_Fct	McAf_P3_Perfect_Fct
BAU	(380.26, 0.00)	(330.69, 0.00)	(380.26, 0.00)	(345.56, 0.00)	(355.27, 0.00)
McAf_P3_Naive_Fct	(25.04, 0.00)	(-157.15, 0.00)	(25.04, 0.00)	(nan, nan)	(306.23, 0.00)
McAf_P3_Perfect_Fct	(-28.38, 0.00)	(-192.30, 0.00)	(-28.38, 0.00)	(-306.23, 0.00)	(nan, nan)
VCG_P1_Naive_Fct	(270.85, 0.00)	(-182.44, 0.00)	(270.85, 0.00)	(145.17, 0.00)	(180.95, 0.00)
VCG_P1_Perfect_Fct	(nan, nan)	(-300.68, 0.00)	(nan, nan)	(-25.04, 0.00)	(28.38, 0.00)
VCG_P2_Naive_Fct	(310.66, 0.00)	(298.73, 0.00)	(310.66, 0.00)	(211.50, 0.00)	(235.98, 0.00)
VCG_P2_Perfect_Fct	(nan, nan)	(-300.68, 0.00)	(nan, nan)	(-25.04, 0.00)	(28.38, 0.00)
VCG_P3_Naive_Fct	(227.04, 0.00)	(-90.73, 0.00)	(227.04, 0.00)	(124.85, 0.00)	(165.16, 0.00)
VCG_P3_Perfect_Fct	(nan, nan)	(-300.68, 0.00)	(nan, nan)	(-25.04, 0.00)	(28.38, 0.00)
VCG_PD_Naive_Fct	(300.68, 0.00)	(nan, nan)	(300.68, 0.00)	(157.15, 0.00)	(192.30, 0.00)
VCG_PD_Perfect_Fct	(nan, nan)	(-300.68, 0.00)	(nan, nan)	(-25.04, 0.00)	(28.38, 0.00)

## 5.2.2 Retailers' Revenue

The retailers' revenue, as described in Subsection 5.1.3, was defined as the sum of inbound and outbound cash flows from retail trade, DR allocation, and imbalance settlements. The presentation of results regarding this dependent variable follows the same organisation as the previous subsection, thus some explanation is omitted to avoid redundancy. Also, it is important to note that the forecast types correspond to the end-users' ability, not the retailer's, since for the latter only perfect forecast has been assumed. Although this is an unrealistic assumption, this decision was fixed in order to simplify the assessment regarding the end-users' participation as demand responders.

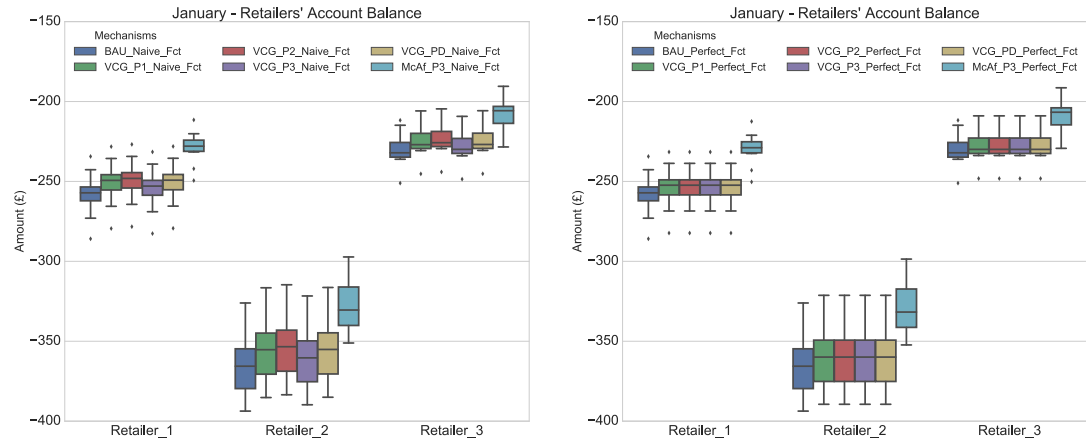
### 5.2.2.1 Comparison of Mechanisms

The y-axis for the set of plots in Figure 5.4 show negative values because of the amount of NIV that was randomly generated, as explained in Subsection 5.1.2, as opposed to real procurement planning. However, since the NIV is being controlled, the mechanisms can be relatively compared against each other.

The revenue is less negative for each of the mechanisms other than BAU. That is, both the VCG-based mechanisms and the McAfee-based DA contribute to reducing retailers' balancing costs, through the allocation of DR offers. This cumulative effect seems relatively small in these plots, mainly due to the short length of the simulation horizon and the small size of the simulated populations. Longer horizons and larger populations would only increase revenue on average w.r.t. BAU under the described dynamics. Nonetheless, the retailers' DR procurement is assumed to be myopic, as described in Subsection 5.1.2, which may lead to suboptimal outcomes in some scenarios.

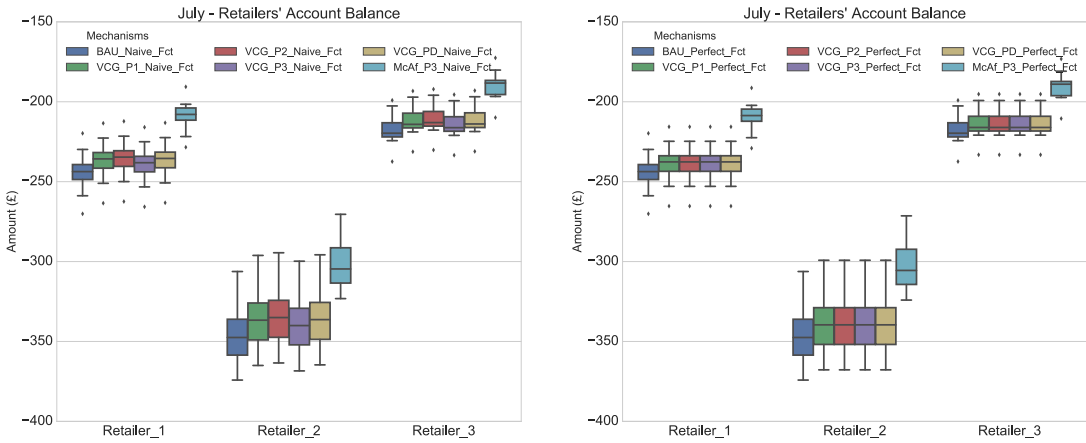
The McAfee-based mechanism, `McAf_P3`, performs consistently better than any other of the studied mechanisms. This happens for two main reasons. First, retailers save on DR discounts because they financially trade their differences first, through the double auction (DA) guided by the ISO's market operator (MO), and only trigger the resulting DR needed in the zone. Second, the stepwise offering methodology, described in Subsection 4.3.1, results in smaller discounts for end-users. This is because each block offer is valued in a  $(k+1)$  second-price fashion w.r.t. the arbitrary size of the block and the first DR offer that no longer fits in, which sets the price, as opposed to pricing a single large block with the most expensive DR offer. This results in more competitive prices for retailers, yet yields lower electricity bills for end-users, as the latter get to participate in more allocations (i.e., DR prices that are lower than retailers'

reservation prices, so they get allocated more often not only to their retailer, but also to the other ones).



(a) January's revenue and end-users' naive forecasts.

(b) January's revenue and end-users' perfect forecasts.



(c) July's revenue and end-users' naive forecasts.

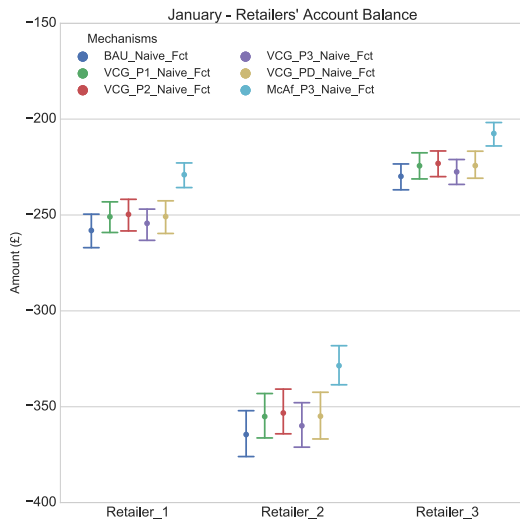
(d) July's revenue and end-users' perfect forecasts.

Figure 5.4: Retailers' revenue as a result of the proposed mechanisms.

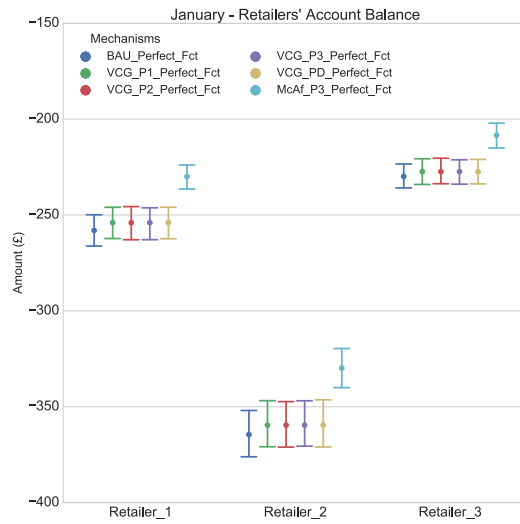
Finally, the effect of end-users' forecast accuracy is rather small to retailers' revenue in these experiments. One potential reason for this, excluding the size of the experiments and a naive forecast that is not too bad, is that some of the forecast errors might be cancelling out across the population of DR end-users.

### 5.2.2.2 Confidence Intervals

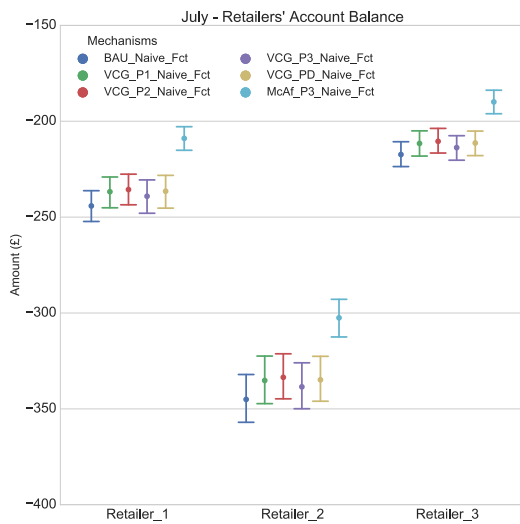
Figure 5.5 is organised in the same manner as the box plots in Figure 5.4, and it shows the distribution means and SEM at 95% CI. In these plots, the effects of end-users' forecast skill is barely noticeable with regard to retailers' revenue.



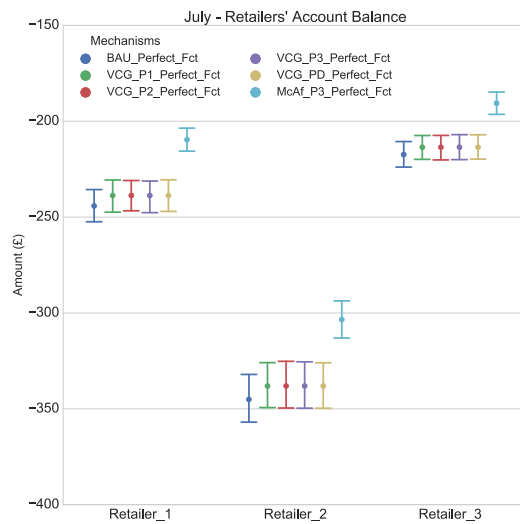
(a) January' revenue and end-users' naive forecasts.



(b) January' revenue and end-users' perfect forecasts.



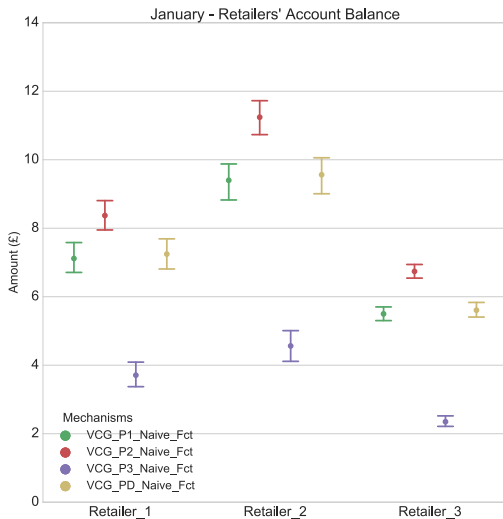
(c) July's revenue and end-users' naive forecasts.



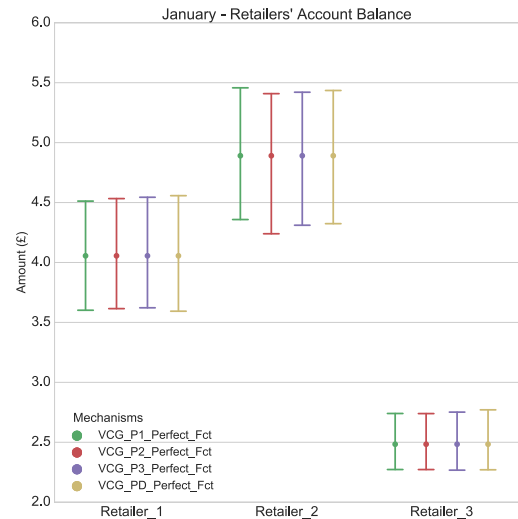
(d) July's revenue and end-users' perfect forecasts.

Figure 5.5: Retailers' revenue SEM at 95% CI.

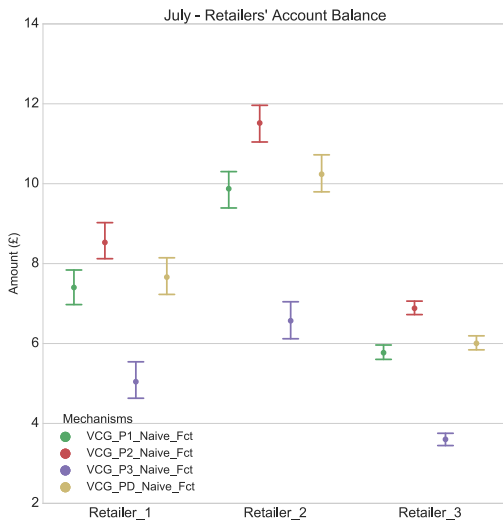
Figure 5.6 shows the difference of the VCG-based mechanisms, which are close together, with respect to BAU so that their contribution can actually be appreciated. These plots shows the distribution means and SEM at 95% CI. The McAfee-based mechanism has been taken out of this plot because its difference is more noticeable from BAU than the VCGs, as shown in Figure 5.5, and it would make the differences amongst the VCGs less clear due to the scale.



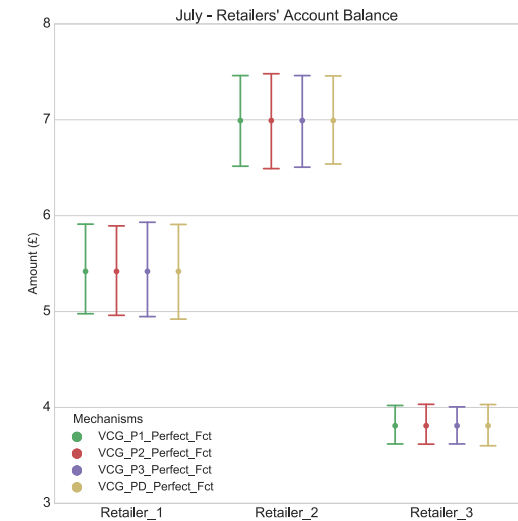
(a) January's revenue and end-users' naive forecasts.



(b) January's revenue and end-users' perfect forecasts.



(c) July's revenue and end-users' naive forecasts.



(d) July's revenue and end-users' perfect forecasts.

Figure 5.6: Contribution of VCG-based mechanisms w.r.t. BAU on retailer's revenue, SEM at 95% CI.

### 5.2.2.3 Paired Samples T-Test

This test was computed for the cumulative revenue of January and July, for the population of three retailers under the proposed mechanisms, over ten simulations.

**Hypothesis:** Does any of the proposed mechanisms result in a higher revenue for retailers than BAU?

Let  $\mathbb{M}$  be the set of mechanisms including forecast type, i.e.,  $\mathbb{M} := \{BAU, \dots, McAf\_P3\_Perfect\_Fct\}$ . Let  $M$  be the set of three retailers. Then, the difference in revenue for each retailer under a pair of mechanisms,  $m$  and  $m'$ , is denoted by  $d_j^{m,m'} := \rho_j^m - \rho_j^{m'} \forall j \in M, \forall m, m' \in \mathbb{M}$ , where  $\rho_j^m$  is the revenue of retailer  $j$ . The size of the population is  $n := 30$ , i.e., three retailers over ten simulations, and the mean difference in revenue for all retailers between the mechanisms  $m$  and  $m'$  is expressed by  $\mu_d^{m,m'} := \frac{1}{n} \sum d_j^{m,m'}$ .

**Null hypothesis:** BAU yields a higher revenue than any of the proposed mechanisms, i.e.,  $H_0: \mu_d^{m,m'} \geq 0$  for  $m := BAU$  and  $m' := \{\forall x \mid x \in \mathbb{M}, x \neq m\}$ . By how the difference is expressed,  $d_j^{m,m'} := \rho_j^m - \rho_j^{m'}$ , the first term  $\rho_j^m$  is the amount of revenue under BAU, and the second term  $\rho_j^{m'}$  is that amount under another mechanism in  $\mathbb{M}$ , that is being compared to BAU. Therefore, a  $\mu_d^{m,m'} \geq 0$  means that in average the revenue  $\rho_j^{m'}$  is lower than that of BAU.

**Alternative hypothesis:** Any of the proposed mechanisms yields a higher revenue than BAU, i.e.,  $H_A: \mu_d^{m,m'} < 0$  for  $m := BAU$  and  $m' := \{\forall x \mid x \in \mathbb{M}, x \neq m\}$ . A negative  $\mu_d^{m,m'}$  means a higher revenue achieved by mechanism  $m'$ , as compared to BAU.

The level of significance was set to 5%, i.e.,  $\alpha := 0.05$ . Table 5.4 shows the resulting pairs of t-statistics and p-values. By inspecting the first row (BAU), it can be seen that each of the proposed mechanisms performs better than BAU, for both naive and perfect forecasts (with negative t-statistics and near-zero p-values). The resulting p-values for this claim are small, thus there is enough evidence to reject the null hypothesis. Therefore, it can be concluded that each of the proposed mechanisms yield higher revenue to the retailer than BAU.

Table 5.4: Paired T-Test results for retailers' revenue.

BAU	VCG_P1_Naive_Fct	VCG_P1_Perfect_Fct	VCG_P2_Naive_Fct	VCG_P2_Perfect_Fct	VCG_P3_Naive_Fct	VCG_P3_Perfect_Fct
BAU	(nan, nan)	(-6.46, 0.02)	(-5.69, 0.03)	(-6.64, 0.02)	(-5.69, 0.03)	(-5.75, 0.03)
McAf_P3_Naive_Fct	(7.75, 0.02)	(8.23, 0.01)	(8.25, 0.01)	(8.20, 0.01)	(8.25, 0.01)	(8.19, 0.01)
McAf_P3_Perfect_Fct	(7.68, 0.02)	(8.14, 0.01)	(8.17, 0.01)	(8.10, 0.01)	(8.17, 0.01)	(8.12, 0.01)
VCG_P1_Naive_Fct	(6.46, 0.02)	(nan, nan)	(7.31, 0.02)	(-7.34, 0.02)	(7.31, 0.02)	(7.31, 0.02)
VCG_P1_Perfect_Fct	(5.69, 0.03)	(-7.31, 0.02)	(nan, nan)	(-7.32, 0.02)	(nan, nan)	(4.59, 0.04)
VCG_P2_Naive_Fct	(6.64, 0.02)	(7.34, 0.02)	(7.32, 0.02)	(nan, nan)	(7.32, 0.02)	(7.33, 0.02)
VCG_P2_Perfect_Fct	(5.69, 0.03)	(-7.31, 0.02)	(nan, nan)	(-7.32, 0.02)	(nan, nan)	(4.59, 0.04)
VCG_P3_Naive_Fct	(5.75, 0.03)	(-7.31, 0.02)	(-4.59, 0.04)	(-7.33, 0.02)	(-4.59, 0.04)	(nan, nan)
VCG_P3_Perfect_Fct	(5.69, 0.03)	(-7.31, 0.02)	(nan, nan)	(-7.32, 0.02)	(nan, nan)	(4.59, 0.04)
VCG_PD_Naive_Fct	(6.49, 0.02)	(7.63, 0.02)	(7.34, 0.02)	(-7.26, 0.02)	(7.34, 0.02)	(7.33, 0.02)
VCG_PD_Perfect_Fct	(5.69, 0.03)	(-7.31, 0.02)	(nan, nan)	(-7.32, 0.02)	(nan, nan)	(4.59, 0.04)

Paired T-Test results for retailers' revenue (continued).

BAU	VCG_P3_Perfect_Fct	VCG_PD_Naive_Fct	VCG_PD_Perfect_Fct	McAf_P3_Naive_Fct	McAf_P3_Perfect_Fct
BAU	(-5.69, 0.03)	(-6.49, 0.02)	(-5.69, 0.03)	(-7.75, 0.02)	(-7.68, 0.02)
McAf_P3_Naive_Fct	(8.25, 0.01)	(8.23, 0.01)	(8.25, 0.01)	(nan, nan)	(9.98, 0.01)
McAf_P3_Perfect_Fct	(8.17, 0.01)	(8.14, 0.01)	(8.17, 0.01)	(-9.98, 0.01)	(nan, nan)
VCG_P1_Naive_Fct	(7.31, 0.02)	(-7.63, 0.02)	(7.31, 0.02)	(-8.23, 0.01)	(-8.14, 0.01)
VCG_P1_Perfect_Fct	(nan, nan)	(-7.34, 0.02)	(nan, nan)	(-8.25, 0.01)	(-8.17, 0.01)
VCG_P2_Naive_Fct	(7.32, 0.02)	(7.26, 0.02)	(7.32, 0.02)	(-8.20, 0.01)	(-8.10, 0.01)
VCG_P2_Perfect_Fct	(nan, nan)	(-7.34, 0.02)	(nan, nan)	(-8.25, 0.01)	(-8.17, 0.01)
VCG_P3_Naive_Fct	(-4.59, 0.04)	(-7.33, 0.02)	(-4.59, 0.04)	(-8.19, 0.01)	(-8.12, 0.01)
VCG_P3_Perfect_Fct	(nan, nan)	(-7.34, 0.02)	(nan, nan)	(-8.25, 0.01)	(-8.17, 0.01)
VCG_PD_Naive_Fct	(7.34, 0.02)	(nan, nan)	(7.34, 0.02)	(-8.23, 0.01)	(-8.14, 0.01)
VCG_PD_Perfect_Fct	(nan, nan)	(-7.34, 0.02)	(nan, nan)	(-8.25, 0.01)	(-8.17, 0.01)



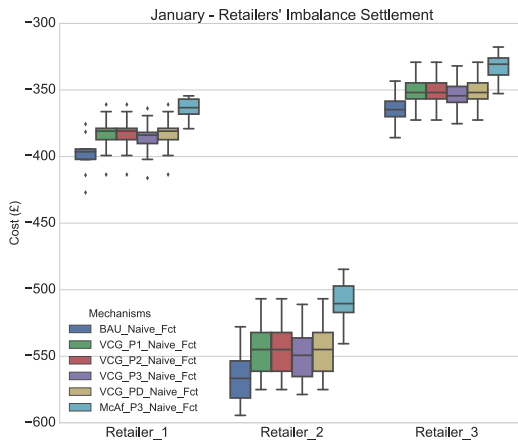
### 5.2.3 Retailers' Imbalance Settlement

The imbalance settlement is computed as the net result from trading in the physical balancing market for the whole simulation horizon. At every time period, if a retailer's NIV is positive, this excess has to be sold to the market at the system sell price (SSP). Similarly, if the NIV is negative, this deficit has to be bought from the balancing market at the resulting system buy price (SBP). In these experiments, SSP is assumed to be low, and SBP high, as described in Subsection 5.1.2.

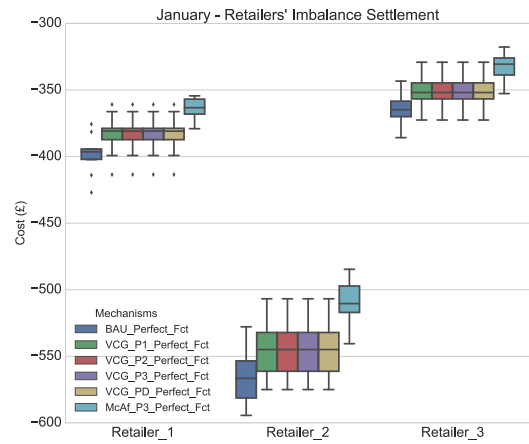
The presentation of results regarding this dependent variable follows the same organisation as the previous subsection, thus some explanation is omitted to avoid redundancy.

#### 5.2.3.1 Comparison of Mechanisms

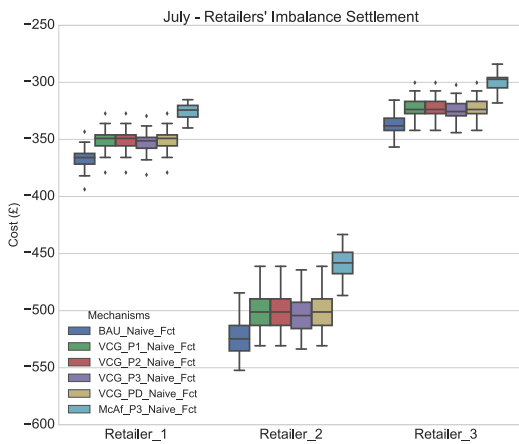
Figure 5.7 shows that the resulting distributions for retailers' total net imbalance settlement turned out to be negative, i.e., costs. The reason for this was that the initial NIV for each retailer was set with a relative high value compared to the population size of households per retailer and their small responsive capacity, as previously specified in Subsection 5.1.2. However, the mechanisms can be relatively compared against each other. Moreover, SSP and SBP were set intentionally low and high, respectively, so as to incentivise retailers to correct their imbalance with DR as opposed to through the imbalance settlement. It can be seen from the resulting distributions that each mechanism on average performs better than BAU at reducing the balancing cost, with an almost negligible effect from end-users' forecast accuracy (under the studied circumstances). McAf\_P3 yields the lowest balancing cost. The magnitude of the effect of forecasts, as discussed in previous sections, is highly correlated to the population size of demand responders and the simulation horizon.



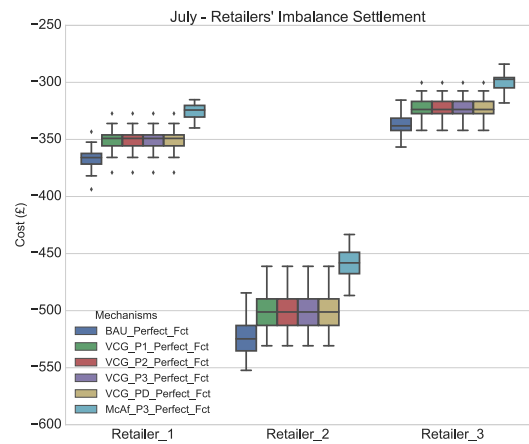
(a) January and end-users' naive forecasts.



(b) January and end-users' perfect forecasts.



(c) July and end-users' naive forecasts.



(d) July and end-users' perfect forecasts.

Figure 5.7: Comparative results for each mechanism regarding their effect on the imbalance settlement.

### 5.2.3.2 Confidence Intervals

Figure 5.8 is organised in the same manner as the box plots in Figure 5.7, and it shows the distribution means and SEM at 95% CI. In these plots, the effects of end-users' forecast skill is barely noticeable regarding retailers' imbalance settlement.

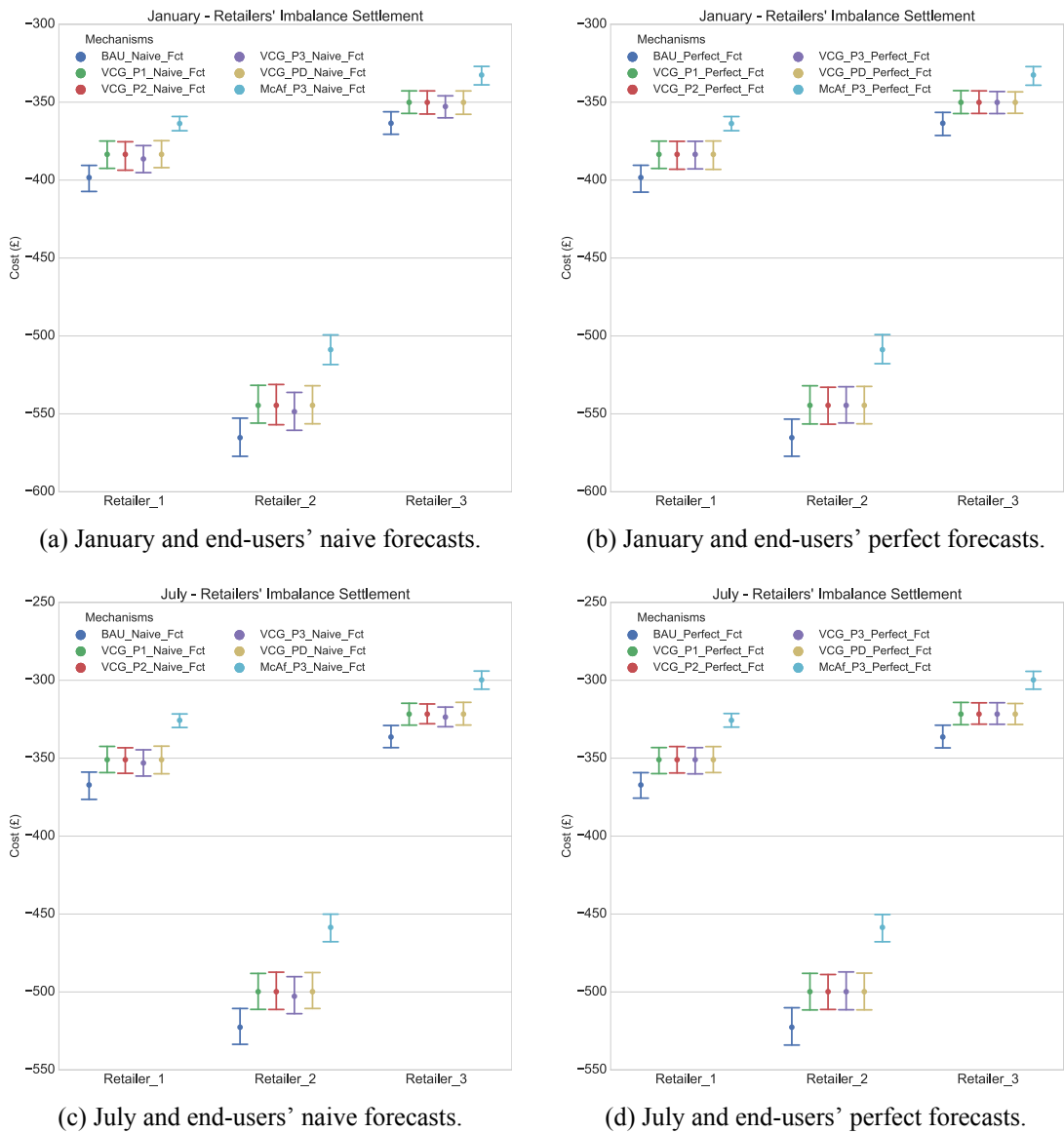
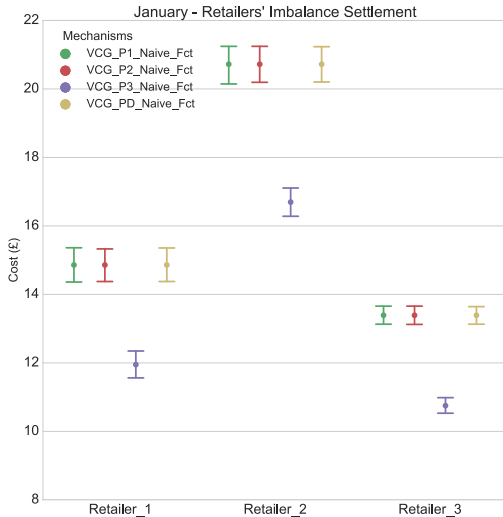
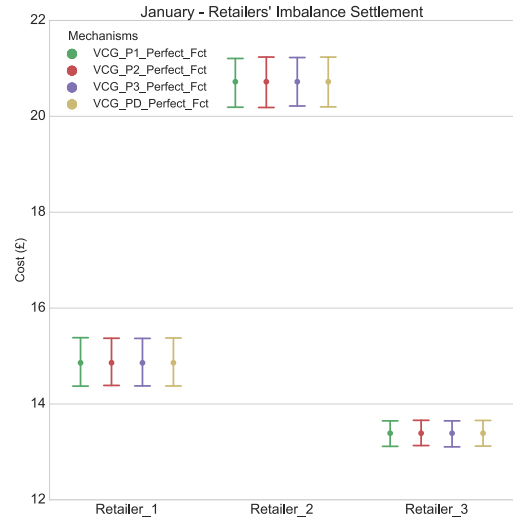


Figure 5.8: Retailers' imbalance settlement SEM at 95% CI.

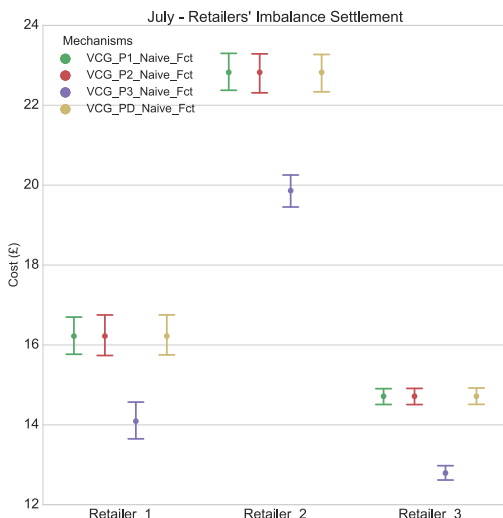
Figure 5.9 shows the difference of the VCG-based mechanisms with respect BAU so that the change can actually be appreciated. It shows the distribution means and SEM at 95% CI. The McAfee-based mechanism has been taken out of this plot because its difference is quite large from BAU, as shown in Figure 5.8, and it makes the differences amongst VCGs unclear due to its scale.



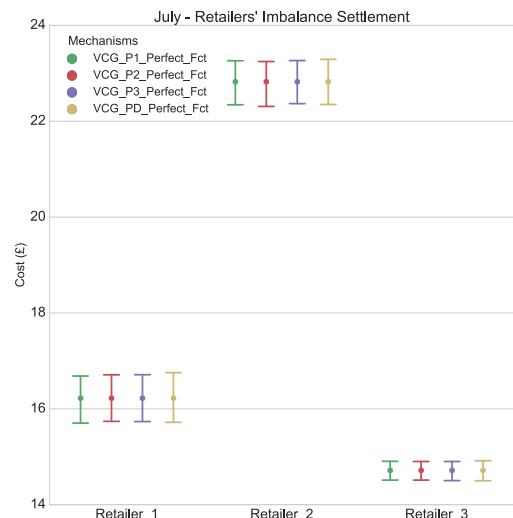
(a) January and end-users' naive forecasts.



(b) January and end-users' perfect forecasts.



(c) July and end-users' naive forecasts.



(d) July and end-users' perfect forecasts.

Figure 5.9: Contribution of VCG-based mechanisms w.r.t. BAU on retailer's imbalance settlement, SEM at 95% CI.

### 5.2.3.3 Paired Samples T-Test

This test was computed for the cumulative imbalance settlement (balancing cost) of January and July, for the population of three retailers under the proposed mechanisms, over ten simulations.

**Hypothesis:** Does any of the proposed mechanisms result in a lower balancing cost for retailers than BAU?

Let  $\mathbb{M}$  be the set of mechanisms including forecast type, i.e.,  $\mathbb{M} := \{BAU, \dots, McAf\_P3\_Perfect\_Fct\}$ . Let  $M$  be the set of three retailers. Then, the difference in balancing cost for each retailer under a pair of mechanisms,  $m$  and  $m'$ , is denoted by  $d_j^{m,m'} := c_j^m - c_j^{m'} \forall j \in M, \forall m, m' \in \mathbb{M}$ , where  $c_j^m$  is the balancing cost for retailer  $j$ . The size of the population is  $n := 30$ , i.e., three retailers over ten simulations, and the mean difference in cost for all retailers between the mechanisms  $m$  and  $m'$  is expressed by  $\mu_d^{m,m'} := \frac{1}{n} \sum d_j^{m,m'}$ .

**Null hypothesis:** BAU yields a lower balancing cost than any of the proposed mechanisms, i.e.,  $H_0: \mu_d^{m,m'} \geq 0$  for  $m := BAU$  and  $m' := \{\forall x \mid x \in \mathbb{M}, x \neq m\}$ . By how the difference is expressed,  $d_j^{m,m'} := c_j^m - c_j^{m'}$ , the first term  $c_j^m$  is the amount of balancing cost under BAU, and the second term  $c_j^{m'}$  is that amount under another mechanism in  $\mathbb{M}$ , that is being compared to BAU. Both,  $c_j^m$  and  $c_j^{m'}$  are negative. Therefore, a  $\mu_d^{m,m'} \geq 0$  means that in average the cost  $c_j^{m'}$  is higher than that of BAU.

**Alternative hypothesis:** Any of the proposed mechanisms yields a lower balancing cost than BAU, i.e.,  $H_A: \mu_d^{m,m'} < 0$  for  $m := BAU$  and  $m' := \{\forall x \mid x \in \mathbb{M}, x \neq m\}$ . A negative  $\mu_d^{m,m'}$  means a lower balancing cost achieved by mechanism  $m'$ , as compared to BAU.

The level of significance was set to 5%, i.e.,  $\alpha := 0.05$ . Table 5.5 shows the resulting pairs of t-statistics and p-values. By inspecting the first row (BAU), it can be seen that all the proposed mechanisms are better than BAU regarding the balancing cost, and they are statistically significant. Therefore, there is enough evidence to reject the null hypothesis, and it can be concluded that each of the proposed mechanisms yields a lower balancing cost than BAU.

Table 5.5: Paired T-Test results for retailers' imbalance settlement.

BAU	VCG_P1_Naive_Fct	VCG_P1_Perfect_Fct	VCG_P2_Naive_Fct	VCG_P2_Perfect_Fct	VCG_P3_Naive_Fct	VCG_P3_Perfect_Fct
BAU	(nan, nan)	(-7.24, 0.02)	(-7.24, 0.02)	(-7.24, 0.02)	(-7.24, 0.02)	(-7.24, 0.02)
McAf_P3_Naive_Fct	(5.37, 0.03)	(4.61, 0.04)	(4.61, 0.04)	(4.61, 0.04)	(4.61, 0.04)	(4.78, 0.04)
McAf_P3_Perfect_Fct	(5.37, 0.03)	(4.61, 0.04)	(4.61, 0.04)	(4.61, 0.04)	(4.61, 0.04)	(4.78, 0.04)
VCG_P1_Naive_Fct	(7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(7.45, 0.02)
VCG_P1_Perfect_Fct	(7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(7.45, 0.02)
VCG_P2_Naive_Fct	(7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(7.45, 0.02)
VCG_P2_Perfect_Fct	(7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(7.45, 0.02)
VCG_P3_Naive_Fct	(7.20, 0.02)	(-7.45, 0.02)	(-7.45, 0.02)	(-7.45, 0.02)	(-7.45, 0.02)	(nan, nan)
VCG_P3_Perfect_Fct	(7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(7.45, 0.02)
VCG_PD_Naive_Fct	(7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(7.45, 0.02)
VCG_PD_Perfect_Fct	(7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(7.45, 0.02)

Paired T-Test results for retailers' imbalance settlement (continued).

	VCG_P3_Perfect_Fct	VCG_PD_Naive_Fct	VCG_PD_Perfect_Fct	McAf_P3_Naive_Fct	McAf_P3_Perfect_Fct
BAU	(-7.24, 0.02)	(-7.24, 0.02)	(-7.24, 0.02)	(-5.37, 0.03)	(-5.37, 0.03)
McAf_P3_Naive_Fct	(4.61, 0.04)	(4.61, 0.04)	(4.61, 0.04)	(nan, nan)	(nan, nan)
McAf_P3_Perfect_Fct	(4.61, 0.04)	(4.61, 0.04)	(4.61, 0.04)	(nan, nan)	(nan, nan)
VCG_P1_Naive_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(-4.61, 0.04)	(-4.61, 0.04)
VCG_P1_Perfect_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(-4.61, 0.04)	(-4.61, 0.04)
VCG_P2_Naive_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(-4.61, 0.04)	(-4.61, 0.04)
VCG_P2_Perfect_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(-4.61, 0.04)	(-4.61, 0.04)
VCG_P3_Naive_Fct	(-7.45, 0.02)	(-7.45, 0.02)	(-7.45, 0.02)	(-4.78, 0.04)	(-4.78, 0.04)
VCG_P3_Perfect_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(-4.61, 0.04)	(-4.61, 0.04)
VCG_PD_Naive_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(-4.61, 0.04)	(-4.61, 0.04)
VCG_PD_Perfect_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(-4.61, 0.04)	(-4.61, 0.04)

## 5.2.4 Retailers' Absolute NIV

The presentation of results regarding this dependent variable follows the same organisation as the previous subsection, thus some explanation is omitted to avoid redundancy.

### 5.2.4.1 Comparison of Mechanisms

Figure 5.10 shows that domestic DR reduces the absolute NIV in all cases. The McAfee-based mechanism reduces this variable more substantially than the other proposed mechanisms, because it also trades differences amongst retailers as opposed to the VCG-based mechanisms, which only procure domestic DR to cover the retailers' individual NIV. Moreover, the forecast comparison side by side does not yield large differences, because of the scale and simulation parameters.

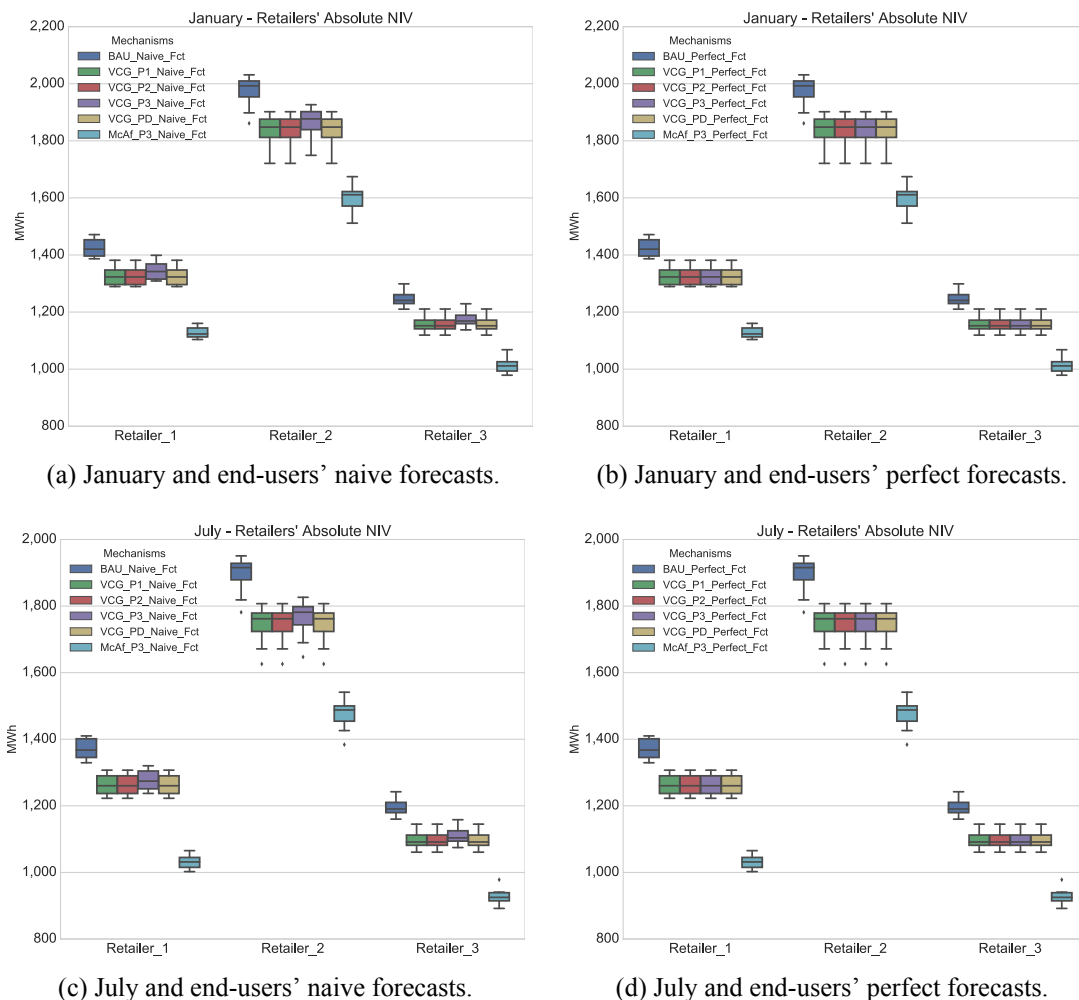
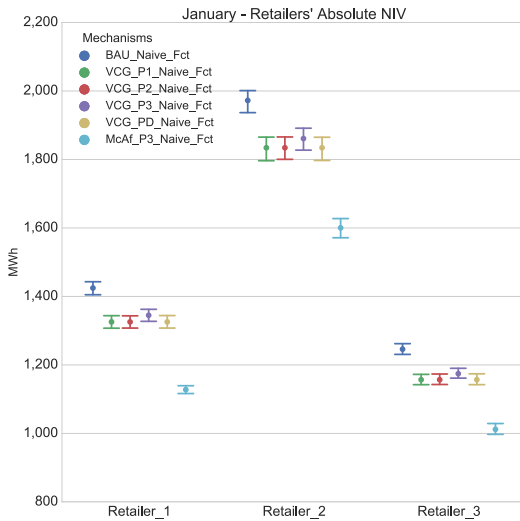


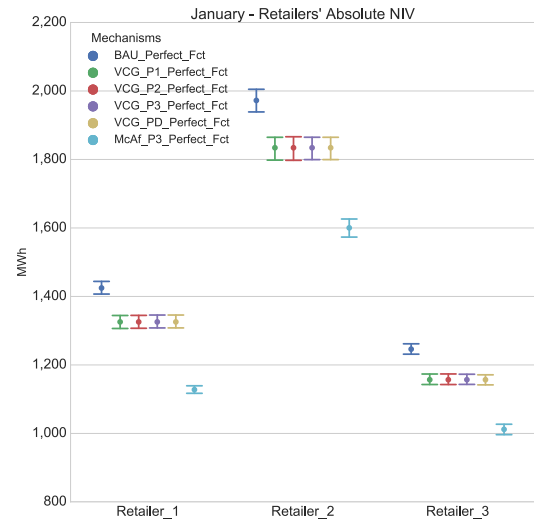
Figure 5.10: Retailers' absolute NIV as a result of the proposed mechanisms.

5.2.4.2 Confidence Intervals

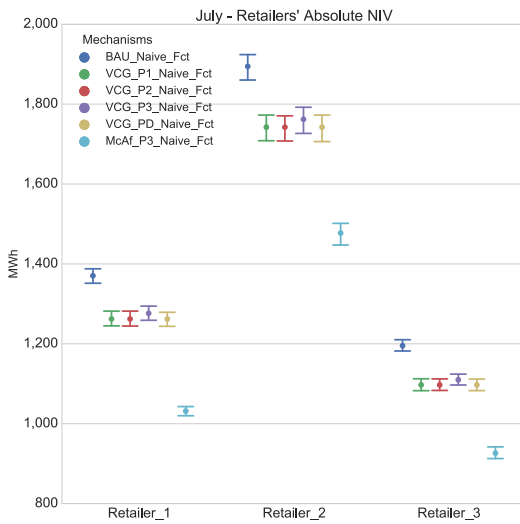
Figure 5.11 is organised in the same manner as the box plots in Figure 5.10, and it shows the distribution means and SEM at 95% CI. In these plots, the effects of end-users' forecast skill is barely noticeable regarding retailers' absolute NIV.



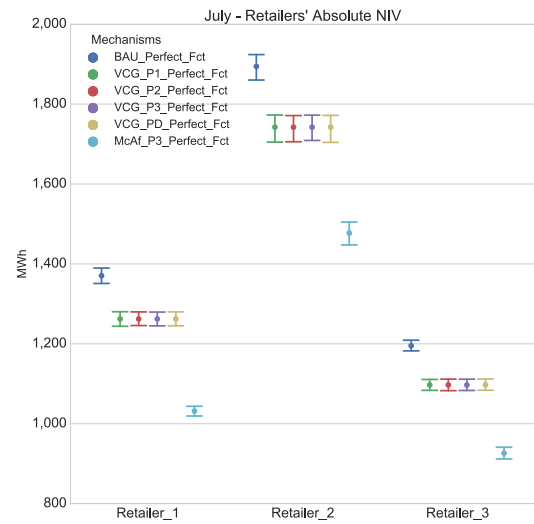
(a) January and end-users' naive forecasts.



(b) January and end-users' perfect forecasts.



(c) July and end-users' naive forecasts.

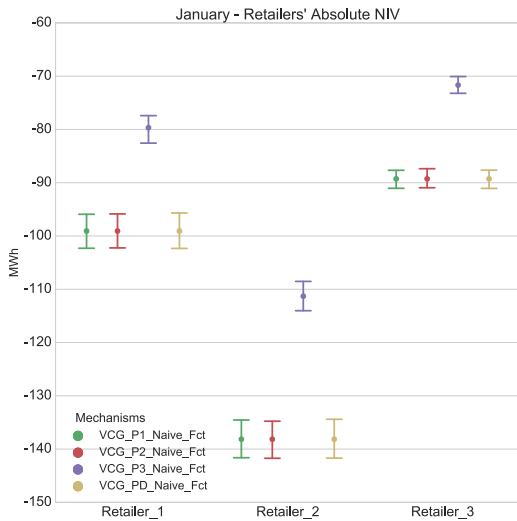


(d) July and end-users' perfect forecasts.

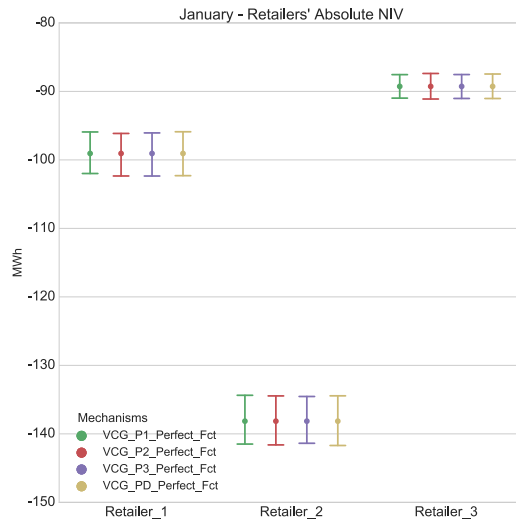
Figure 5.11: Retailers' absolute NIV SEM at 95% CI.



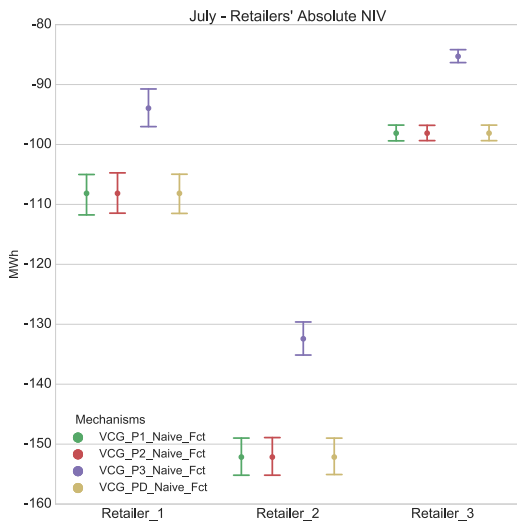
Figure 5.12 shows the difference of the VCG-based mechanisms with respect BAU so that the change can actually be appreciated. It shows the distribution means and SEM at 95% CI. The McAfee-based mechanism has been taken out of this plot because its difference is quite large from BAU, as shown in Figure 5.11, and it makes the differences amongst VCGs unclear due to its scale.



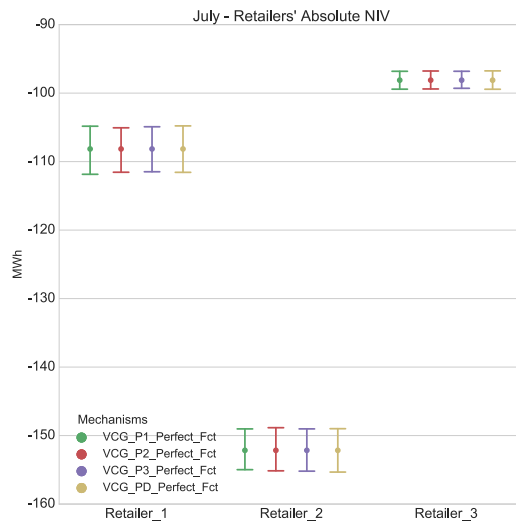
(a) January and end-users' naive forecasts.



(b) January and end-users' perfect forecasts.



(c) July and end-users' naive forecasts.



(d) July and end-users' perfect forecasts.

Figure 5.12: Contribution of VCG-based mechanisms w.r.t. BAU on retailer's absolute NIV, SEM at 95% CI.

### 5.2.4.3 Paired Samples T-Test

This test was computed for the cumulative absolute NIV of January and July, for the population of three retailers under the proposed mechanisms, over ten simulations.

**Hypothesis:** Does any of the proposed mechanisms result in a lower absolute NIV for retailers than BAU?

Let  $\mathbb{M}$  be the set of mechanisms including forecast type, i.e.,  $\mathbb{M} := \{BAU, \dots, McAf\_P3\_Perfect\_Fct\}$ . Let  $M$  be the set of three retailers. Then, the difference in absolute NIV for each retailer under a pair of mechanisms,  $m$  and  $m'$ , is denoted by  $d_j^{m,m'} := \eta_j^m - \eta_j^{m'} \forall j \in M, \forall m, m' \in \mathbb{M}$ , where  $\eta_j^m$  is the absolute NIV of retailer  $j$ . The size of the population is  $n := 30$ , i.e., three retailers over ten simulations, and the mean difference in absolute NIV for all retailers between the mechanisms  $m$  and  $m'$  is expressed by  $\mu_d^{m,m'} := \frac{1}{n} \sum d_j^{m,m'}$ .

**Null hypothesis:** BAU yields a lower absolute NIV than any of the proposed mechanisms, i.e.,  $H_0: \mu_d^{m,m'} \leq 0$  for  $m := BAU$  and  $m' := \{\forall x \mid x \in \mathbb{M}, x \neq m\}$ . By how the difference is expressed,  $d_j^{m,m'} := \eta_j^m - \eta_j^{m'}$ , the first term  $\eta_j^m$  is the amount of NIV under BAU, and the second term  $\eta_j^{m'}$  is that amount under another mechanism in  $\mathbb{M}$ , that is being compared to BAU. Therefore, a  $\mu_d^{m,m'} \leq 0$  means that in average the absolute NIV  $\eta_j^{m'}$  is lower than that of BAU.

**Alternative hypothesis:** Any of the proposed mechanisms yields a lower absolute NIV than BAU, i.e.,  $H_A: \mu_d^{m,m'} > 0$  for  $m := BAU$  and  $m' := \{\forall x \mid x \in \mathbb{M}, x \neq m\}$ . A positive  $\mu_d^{m,m'}$  means a lower revenue achieved by mechanism  $m'$ , as compared to BAU.

The level of significance was set to 5%, i.e.,  $\alpha := 0.05$ . Table 5.6 shows the resulting pairs of t-statistics and p-values. By inspecting the first row (BAU), it can be seen that all the proposed mechanisms are better than BAU regarding the absolute NIV, and they are statistically significant. Therefore, there is enough evidence to reject the null hypothesis, and it can be concluded that each of the proposed mechanisms yields a lower absolute NIV than BAU. In addition, these results are in line with those of the paired t-tests for the imbalance settlement, where the NIV plays an important part along with the balancing prices.

Table 5.6: Paired T-Test results for retailers' absolute NIV.

	BAU	VCG_P1_Naive_Fct	VCG_P1_Perfect_Fct	VCG_P2_Naive_Fct	VCG_P2_Perfect_Fct	VCG_P3_Naive_Fct	VCG_P3_Perfect_Fct
BAU	(nan, nan)	(7.24, 0.02)	(7.24, 0.02)	(7.24, 0.02)	(7.24, 0.02)	(7.24, 0.02)	(7.20, 0.02)
McAf_P3_Naive_Fct	(-7.77, 0.02)	(-7.76, 0.02)	(-7.76, 0.02)	(-7.76, 0.02)	(-7.76, 0.02)	(-7.76, 0.02)	(-7.80, 0.02)
McAf_P3_Perfect_Fct	(-7.77, 0.02)	(-7.76, 0.02)	(-7.76, 0.02)	(-7.76, 0.02)	(-7.76, 0.02)	(-7.76, 0.02)	(-7.80, 0.02)
VCG_P1_Naive_Fct	(-7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(-7.45, 0.02)
VCG_P1_Perfect_Fct	(-7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(-7.45, 0.02)
VCG_P2_Naive_Fct	(-7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(-7.45, 0.02)
VCG_P2_Perfect_Fct	(-7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(-7.45, 0.02)
VCG_P3_Naive_Fct	(-7.20, 0.02)	(7.45, 0.02)	(7.45, 0.02)	(7.45, 0.02)	(7.45, 0.02)	(7.45, 0.02)	(nan, nan)
VCG_P3_Perfect_Fct	(-7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(-7.45, 0.02)
VCG_PD_Naive_Fct	(-7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(-7.45, 0.02)
VCG_PD_Perfect_Fct	(-7.24, 0.02)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(nan, nan)	(-7.45, 0.02)

Paired T-Test results for retailers' absolute NIV (continued).

	VCG_P3_Perfect_Fct	VCG_PD_Naive_Fct	VCG_PD_Perfect_Fct	McAf_P3_Naive_Fct	McAf_P3_Perfect_Fct
BAU	(7.24, 0.02)	(7.24, 0.02)	(7.24, 0.02)	(7.77, 0.02)	(7.77, 0.02)
McAf_P3_Naive_Fct	(-7.76, 0.02)	(-7.76, 0.02)	(-7.76, 0.02)	(nan, nan)	(nan, nan)
McAf_P3_Perfect_Fct	(-7.76, 0.02)	(-7.76, 0.02)	(-7.76, 0.02)	(nan, nan)	(nan, nan)
VCG_P1_Naive_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(7.76, 0.02)	(7.76, 0.02)
VCG_P1_Perfect_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(7.76, 0.02)	(7.76, 0.02)
VCG_P2_Naive_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(7.76, 0.02)	(7.76, 0.02)
VCG_P2_Perfect_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(7.76, 0.02)	(7.76, 0.02)
VCG_P3_Naive_Fct	(7.45, 0.02)	(7.45, 0.02)	(7.45, 0.02)	(7.80, 0.02)	(7.80, 0.02)
VCG_P3_Perfect_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(7.76, 0.02)	(7.76, 0.02)
VCG_PD_Naive_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(7.76, 0.02)	(7.76, 0.02)
VCG_PD_Perfect_Fct	(nan, nan)	(nan, nan)	(nan, nan)	(7.76, 0.02)	(7.76, 0.02)

## 5.3 Discussion

The results in this chapter were mostly limited by the length of the simulation horizon and the number of participants in the experiments. All the proposed mechanisms performed better than BAU in all the studied economic effects. However, the greedy policy followed by retailers to allocate DR is suboptimal. A more realistic setting would include a non-myopic procurement policy for DR allocation, that determines the pursued amounts of DR per time period. Furthermore, an interesting research question, that is not pursued in this thesis, would be to find the retailers' trading strategy for the wholesale market given that one of these DR mechanisms is available.

## 5.4 Summary

This chapter evaluated the effects of the VCG-based and McAfee-based mechanisms, proposed in Chapters 3 and 4, for end-users, retailers and, to some extent, the ISO. The simulations were based on domestic electricity-use profiles from the UK and the imbalance settlement prices prescribed by the UK National Grid that are managed by Elexon. Some variation was introduced in order to fit the purpose of this study, such as the variation imposed in the profile generation procedure based in the original profiles, and the proportional increase and decrease of imbalance prices so as to foster DR. Moreover, the used retail prices are comparable to those of the UK; however, these were overly simplified into two controlled prices as opposed to the complex pricing structures available in the UK (Office of Gas and Electricity Markets (OFGEM), 2016b), where suppliers offer several types of contracts and the FIT tariffs depend on the type of generator (Office of Gas and Electricity Markets (OFGEM), 2016a), and both change often.

The effects of these mechanisms were compared in order to assess the DR impact on the end-users' electricity bill, and retailers' revenue, balancing cost, and absolute NIV. For end-users, the electricity bill was lower than BAU, in all proposed mechanisms. For retailers, revenue was higher, and the balancing cost and absolute NIV were lower than BAU, in all proposed mechanisms. Finally, the results show that the McAfee-based DA achieves on average the best balance of interests amongst end-users, retailers, and the ISO; although it reduces the market share of balancing generators, which is an implicit effect.



# Chapter 6

## Forecasting of the Household's Inflexible Net-Load

In this chapter, some forecast methods are explored and empirically benchmarked so that end-user agents are able to predict their one-step-ahead household's inflexible net-load. The mechanisms developed in Chapters 3 and 4 expect, to a certain degree, that end-user agents are able to submit accurate DR offers that they will provide, or incur in penalties otherwise. The computational model used to estimate the operational flexibility assumes that schedulable tasks can be easily and accurately measured. However, DR offers integrate both the inflexible net-load and the operational flexibility. Therefore, end-users that are able to reasonably forecast the inflexible net-load have a lower risk of penalties and face less opportunity costs, resulting in a lower electricity bill as showed in Chapter 5.

### 6.1 Introduction

Accurately forecasting the inflexible domestic net-load can be challenging. Electricity use is correlated with variables such as human behaviour, number of simultaneous end-users at the household, weather temperature, a wide variety of available technologies and trends. Therefore, adaptive data-driven methods are essential for this problem. Also, it is well-known that a combination of forecasts is usually more robust and often leads to higher accuracy than any of its single forecasters, as described by J. M. Bates and Granger (1969). Therefore, some approaches for the combination of univariate time series regression methods are empirically tested.

## 6.2 Experiment Design

The 50 inflexible net-load profiles from Chapter 5 have been used to assess a set of univariate forecast methods. Of these profiles, 25 have no generation technologies, while the remaining 25 correspond to those same profiles including a synthetically generated PV output, as previously described in Subsection 5.1.1. The forecast methods that have been used and their training time frames are described next.

### 6.2.1 Forecast Methods

Multiple types of univariate forecast methods were selected for this problem. These include four naive methods, four specialised time-series prediction methods, and two artificial neural networks. In addition, four measures of central tendency were explored as methods to combine the previous forecasts into a more accurate and resilient forecaster. Finally, an exponentially weighted average forecaster is examined so that the forecasting methods, excluding the measures of central tendency, are weighted according to their past performance.

#### 6.2.1.1 Naive Methods

These simple methods are described in (Hyndman and Athanasopoulos, 2014) as initial benchmarks, since they might be surprisingly effective in some cases, and their computation is inexpensive.

- **NAIVE:** This method returns the value of the previous time period. That is, the inflexible net-load  $\hat{y}_{t|t-1} := y_{t-1}$ .
- **MEAN\_L3T:** This forecast returns the arithmetic mean value of the last three time periods. That is,  $\hat{y}_{t|t-h} := \frac{1}{h} \sum_{i=t-h}^{t-1} y_i$ , where  $h := 3$ . The time window was set to three by trial and error over exploring some profiles.
- **SNAIVE:** This forecast is a seasonal naive method that gives the value from the last season at the requested time period. In this case, the season was set to one week. For instance, the value on Monday at 5pm is predicted using exactly that amount from the previous Monday. Since time is discretely modelled as half-hourly time periods, the seasonal period is 336 (i.e., 48 time periods per day, times 7 days a week) and  $\hat{y}_{t|t-s} := y_{t-s}$ .

- **DRIFT**: This method returns the value from the previous time period plus the average change, which is given by  $\hat{y}_{t|t-1} := y_{t-1} + \frac{y_t - y_1}{t-2}$ .

### 6.2.1.2 Specialised Time-Series Methods

These sophisticated methods have been estimated using the standard Holt-Winters implementation from the R `stats` package (R Core Team, 2016), and the other three from the R `forecast` package (Hyndman and Khandakar, 2008). These methods have been trained on a weekly basis, starting with one month of history and cumulatively adding new data. The standard Holt-Winters estimates the parameters by minimising the squared predicted error, whereas in the other methods the best model is given by minimising the Akaike information criterion (AIC), that yields a measure of relative quality.

- **HW**: This method corresponds to the well-known standard Holt-Winters (HW) triple exponential smoothing (Holt, 1957; Winters, 1960; Holt, 2004). The additive seasonal model was arbitrarily selected.
- **DSHW**: This is a double seasonal Holt-Winters (DSHW) exponential smoothing method proposed by (Taylor, 2003), with additive trend and multiplicative seasonality. According to Taylor (2003), the widely used standard HW method can only accommodate one seasonal pattern. Therefore, he proposes DSHW to allow for two seasonalities, for instance, daily and weekly seasonalities in electricity use. Later, Taylor (2010) extends his method to allow three seasonal components, but this one has not been considered for the study in this chapter.
- **STL+ARIMAX**: This combination of methods has been proposed by Hyndman and Athanasopoulos (2014) as an alternative approach that is less computationally expensive than seasonal ARIMA(X), specially in high resolution time series. It uses the seasonal and trend decomposition by Loess (STL) proposed by Cleveland et al. (1990), and the autoregressive integrated moving average with exogenous regressors (ARIMAX)<sup>25</sup> (Box and Jenkins, 1970; Box and Tiao, 1975; Pankratz, 1991). This approach first decomposes the time series into seasonal, trend, and error components. Then, it fits the ARIMAX to the errors, with the outside temperature as a covariate. In order to predict, the ARIMAX model takes the weather forecast (that was assumed as perfect), predicts the inflexible net-load,

<sup>25</sup>ARIMAX is also known in the literature as dynamic regression (Pankratz, 1991).



and finally the seasonal component of the last cycle is added to it (similar to a seasonal naive). The seasonal component does not account for prediction errors, but it is generally a reasonable approximation.

- **TBATS:** This method, proposed by De Livera et al. (2011), is an exponential smoothing state space model with Box-Cox transformation (Box and Cox, 1964), ARMA errors, trend and seasonal components, where complex seasonality is decomposed by a trigonometric formulation. This method is complex and computationally demanding, but it works well in practice; further details can be found in (De Livera et al., 2011).

### 6.2.1.3 Artificial Neural Networks

Two well-known artificial neural network (ANN) architectures were trained using Keras (Chollet, 2015) with a Theano (The Theano Development Team, 2016) backend. Both ANN were trained on a sequence of three time periods, minimising the mean square error with the Adam method for stochastic optimisation (Kingma and Ba, 2014). They were retrained each week during 20 epochs, starting with a history of four weeks and cumulatively adding new data.

- **MLP:** A multilayer perceptron architecture (Rosenblatt, 1961; Rumelhart et al., 1985) of a single fully connected hidden layer of eight neurons with rectified linear units (ReLU).
- **LSTM:** A long short-term memory architecture (Hochreiter and Schmidhuber, 1997) of four neurons.

### 6.2.1.4 Measures of Central Tendency

These measures provide simple averaging approaches to creating robust predictions from the previous forecast methods.

- **E\_MEDIAN:** Ordinary median of the predictions made by the previous forecasters.
- **E\_MEAN:** Arithmetic mean of forecasters' predictions.
- **E\_T-MEAN:** Trimmed mean of forecasters' predictions. It discards the two lowest and two highest predictions before computing the mean, so as to remove outliers.

- **E\_W-MEAN**: Winsorised mean of forecasters' predictions. It replaces the two lowest and two highest predictions with the prediction by their closest non-replaced prediction, in order to replace outliers with values closer to the centre, and finally it computes the mean prediction.

### 6.2.1.5 Exponentially Weighted Average Forecaster (EWAFF)

EWAFF is computational inexpensive, only depends on the forecasters' weights for the last prediction, and can be computed online (Cesa-Bianchi and Lugosi, 2006). Let  $F$  be the set of forecasters excluding the above measures of central tendency so as to avoid correlation amongst methods, which is a common practice to get a more resilient forecast. Let the weights be expressed by  $w_{i(t-1)}$ ,  $\forall i \in F$ , which are democratically initialised at  $\frac{1}{|F|}$ . Then, the prediction is computed as  $\hat{p}_t := \sum_{i \in F} w_{i(t-1)} \hat{y}_{it}$ , where  $\hat{y}_{it}$  is the prediction given by forecaster  $i \in F$  at time period  $t \in T$ , where  $T$  is the ordered set of discrete time periods in the simulation horizon. Finally, the forecasters' weights are updated online at every time period as the following.

$$w_{it} := \frac{w_{i(t-1)} e^{-\eta \ell(\hat{y}_{it}, y_t)}}{\sum_{j \in F} w_{j(t-1)} e^{-\eta \ell(\hat{y}_{j(t-1)}, y_t)}}, \quad \forall i \in F \quad (6.1)$$

In Equation 6.1,  $e$  is the Euler's constant,  $\eta$  is a weighting parameter that was set to  $\eta := 0.8$  in order to give more importance to recent errors,  $\ell(\cdot)$  is a nonnegative loss function, which in this case was set to the root-mean-square-error (RMSE),  $\hat{y}_{it}$  is the forecaster  $i$ 's prediction, and  $y_t$  is the actual realisation of inflexible net-load. More information about EWAFF, as well as other methods for combining multiple forecasts, can be found in (Cesa-Bianchi and Lugosi, 2006).

### 6.3 Forecast Results

Each forecast method was tested on the 50 profiles using the out-of-sample RMSE. Figure 6.1 shows the quartiles for each resulting distribution of RMSE. Moreover, Figure 6.2 shows the mean and standard error of mean (SEM) with 95% confidence intervals (CI) for each method. Overall, as it can be seen from these figures, EWAF is a resilient method that end-users can use into their DR offering strategy so as to take the forecast error into account and hedge against penalties.

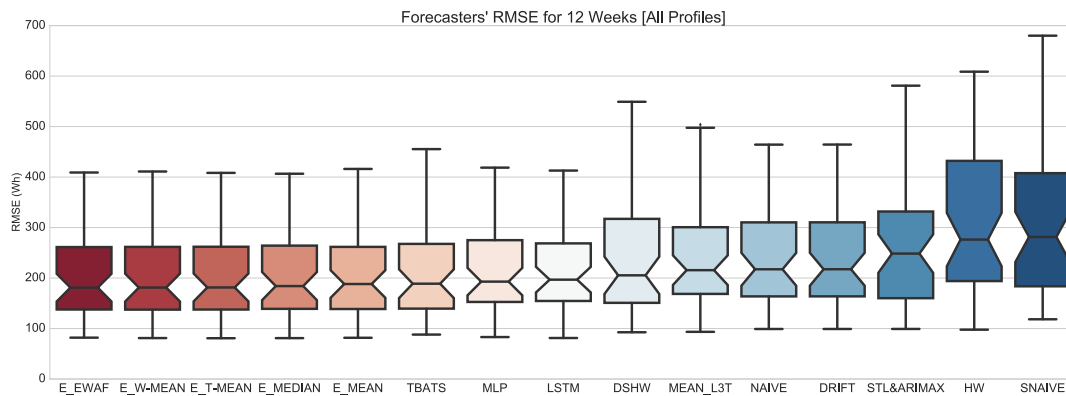


Figure 6.1: Comparative results of inflexible net-load forecasters.

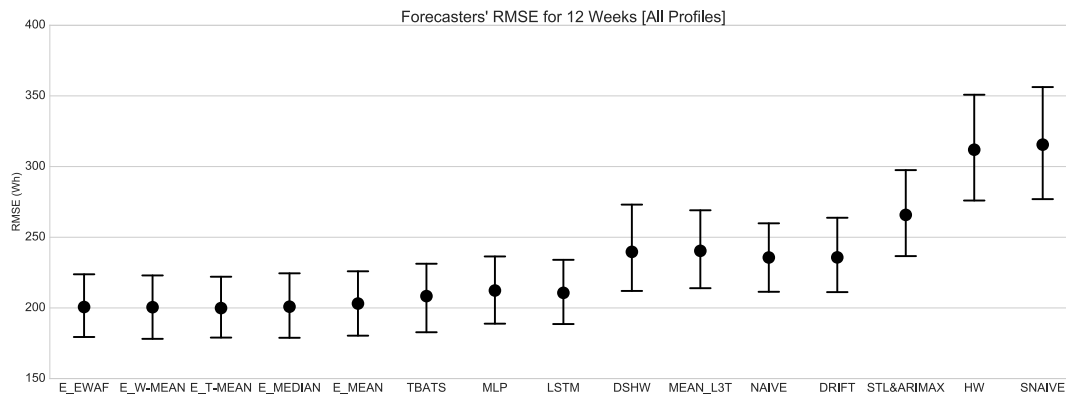
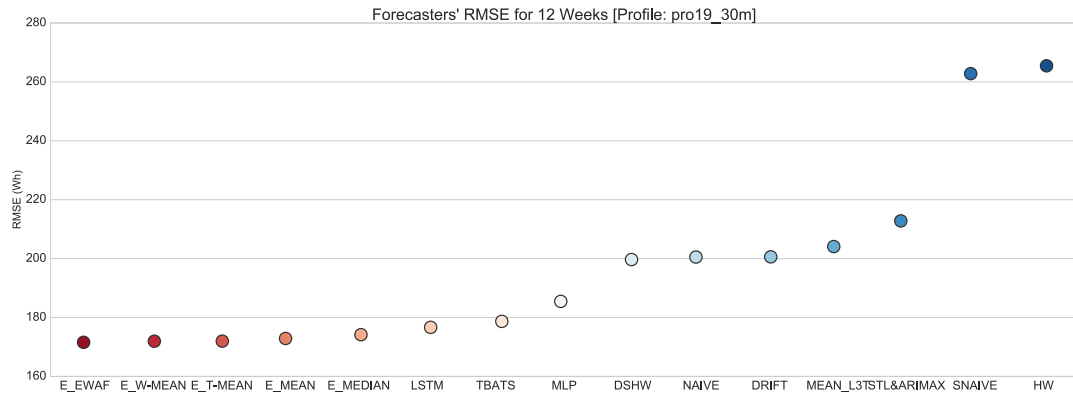
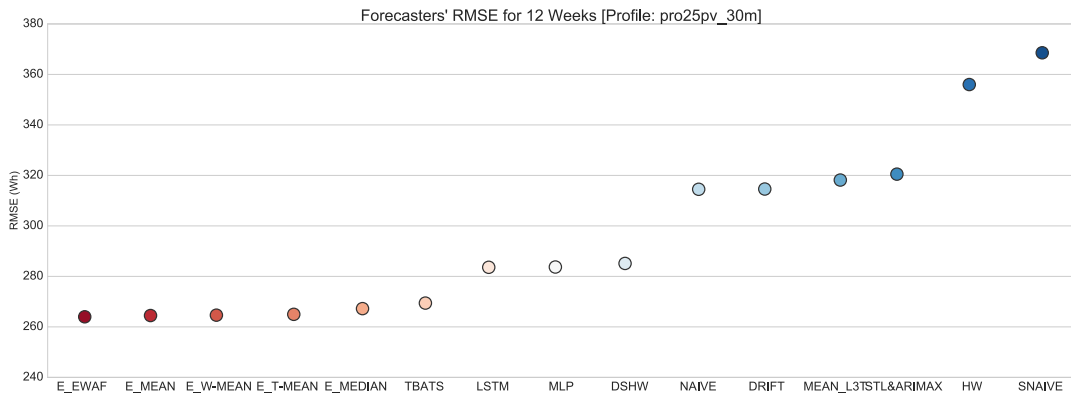


Figure 6.2: Forecasters' RMSE, standard error of the mean at 95% confidence interval.

The results from two individual profiles that were arbitrarily selected for the purpose of exposition are shown in Figure 6.3.



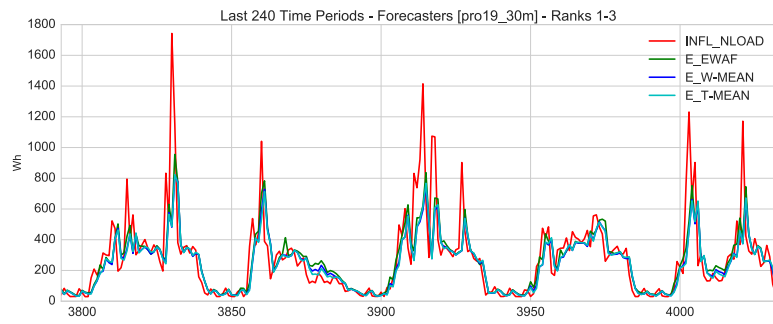
(a) Forecasters' RMSE for an exemplary profile without DG.



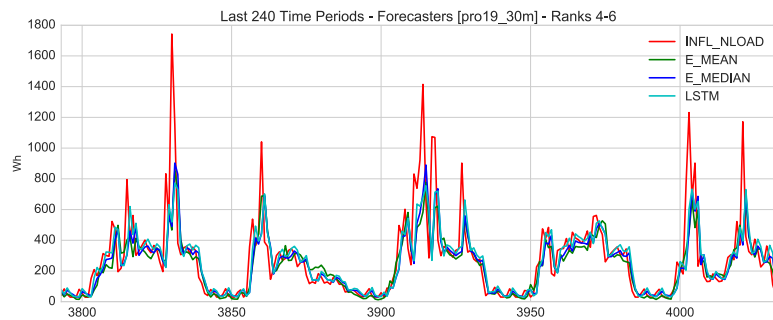
(b) Forecasters' RMSE for an exemplary profile with solar PV.

Figure 6.3: Forecasters' RMSE for two exemplary profiles.

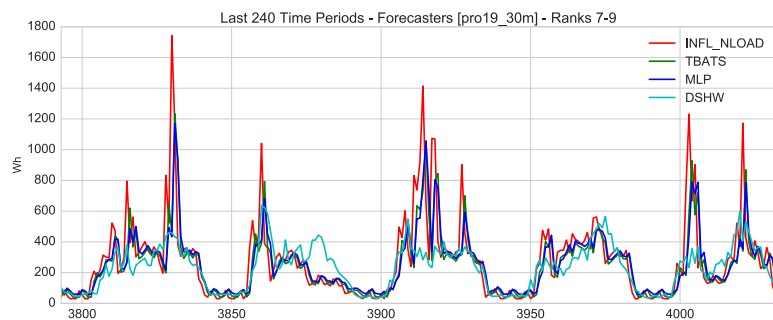
Similarly, the ranking of forecast methods for the same two profiles are shown in Figures 6.4 and 6.5, separated by groups of three and only for the last 240 time periods for clarity reasons.



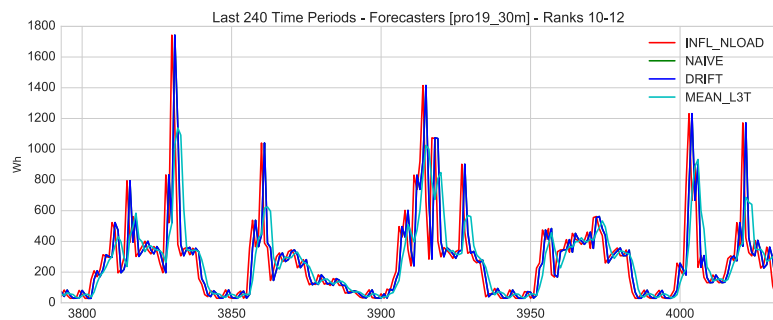
(a) Top 3 forecasters for this profile.



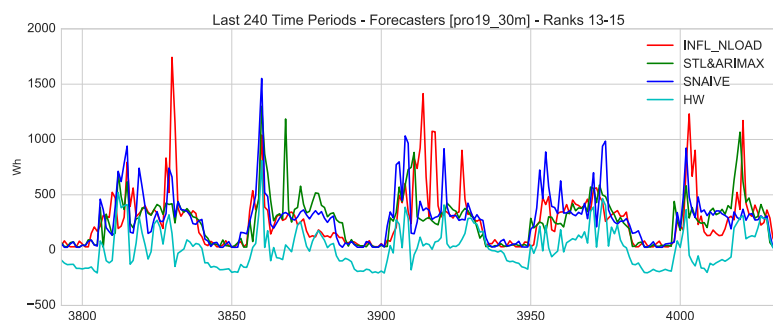
(b) Ranks 4–6 forecasters for this profile.



(c) Ranks 7–9 forecasters for this profile.

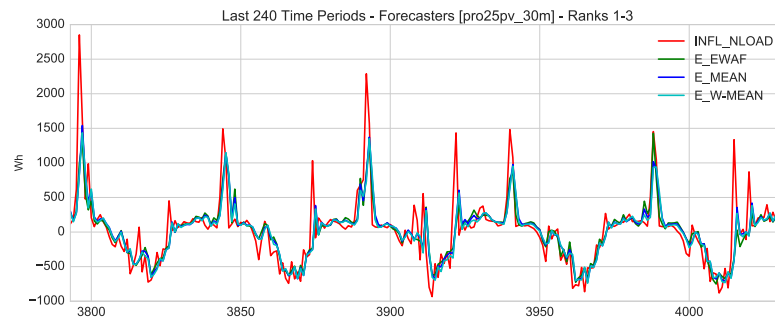


(d) Ranks 10–12 forecasters for this profile.

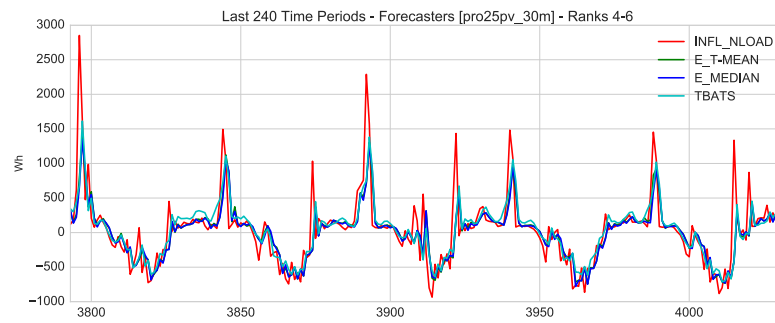


(e) Bottom 3 forecasters for this profile.

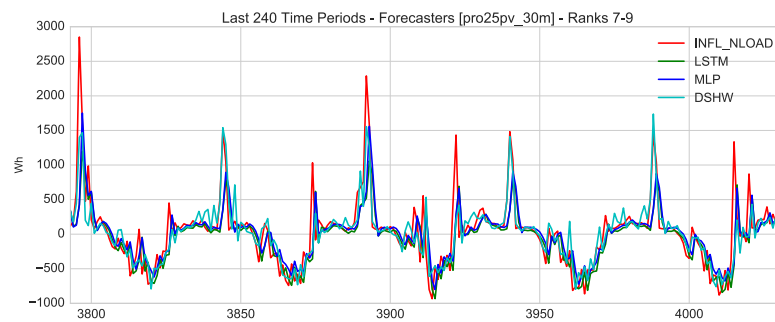
Figure 6.4: Ranking of forecast methods for an exemplary profile without DG.



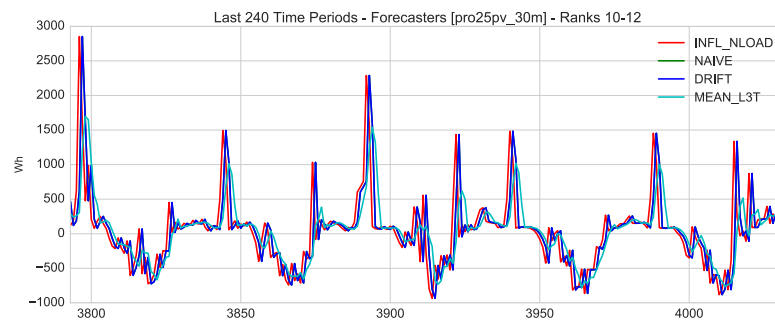
(a) Top 3 forecasters for this profile.



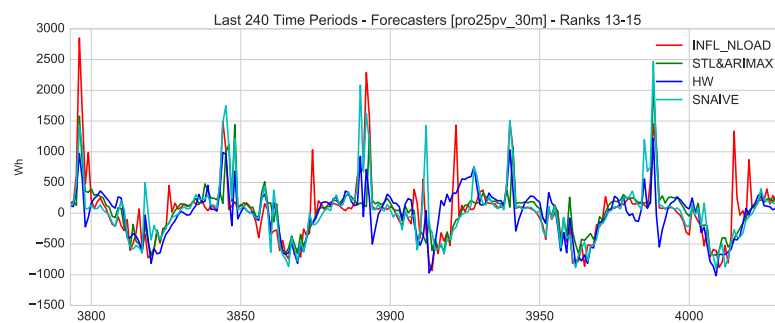
(b) Ranks 4–6 forecasters for this profile.



(c) Ranks 7–9 forecasters for this profile.



(d) Ranks 10–12 forecasters for this profile.



(e) Bottom 3 forecasters for this profile.

Figure 6.5: Ranking of forecast methods for an exemplary profile with solar PV.

Moreover, the exponential weights from these two profiles are shown in Figures 6.6 and 6.7.

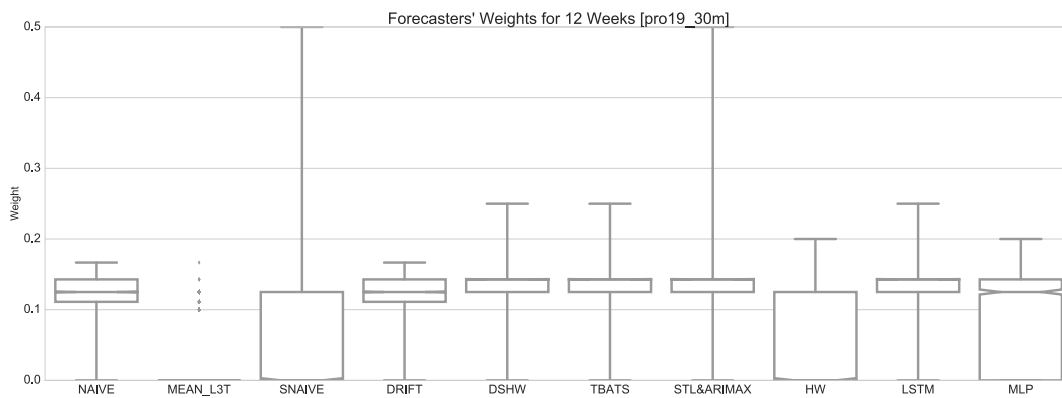


Figure 6.6: EWAF weights for an exemplary profile without DG.

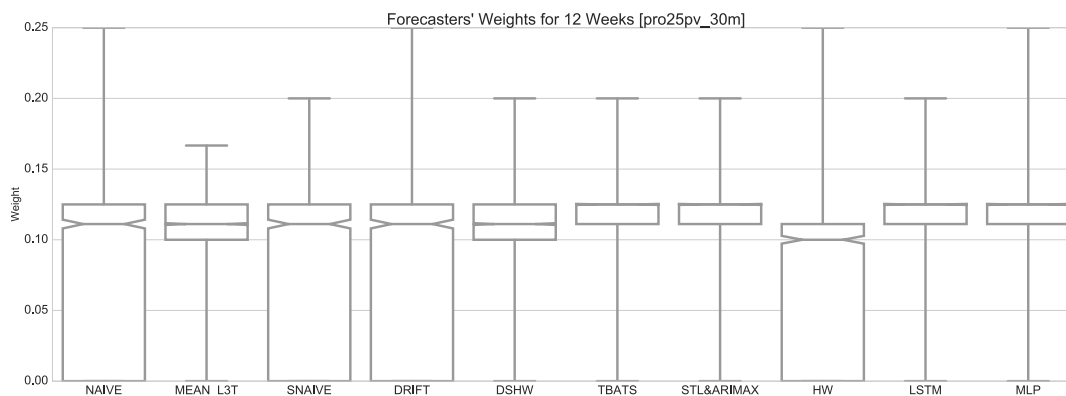


Figure 6.7: EWAF weights for an exemplary profile with solar PV.

## 6.4 Discussion

It is important to note that, while there are several methods to predict sequences and multiple approaches to combine them, only a small set of both were empirically tested. Future work might consider higher resolution time series, as well as other methods for forecast aggregation, such as online gradient descent (OGD), ridge regression, polynomially weighted average forecaster (PWAFF), Bernstein online aggregation (BOA),

ANN, clustering variations, and others. Furthermore, other independent forecast methods for time series, such as support vector machines for regression (SVR), and more optimised ANN architectures for this type of problem could also be considered. Alternatively, other covariates apart from temperature might help improve the accuracy of single predictors.

Given the mechanisms from Chapters 3 and 4, a more accurate forecast of the inflexible net-load, such as the one predicted by EWAF, can only improve the ability of rational end-user agents to maximise their benefit from DR offers. This also reduces the uncertainty on the retailers' side as DR offers are more reliable.

## **6.5 Summary**

This chapter has empirically evaluated the effectiveness of independent forecast methods on the 50 inflexible net-load profiles that are based on the Household Electricity Survey (HES) from the UK. Moreover, it is not surprising that a forecast combination based on several independent methods yielded, in general, a higher accuracy than each of the single forecasts. Even simple measures of central tendency amongst the individual forecasts resulted in higher accuracy. Moreover, a simple and elegant combination method that can be updated online, such as EWAF, is reasonably effective for the presented task.





# Chapter 7

## Conclusion

The research in this thesis has dealt with the problem of electronic market design for domestic DR in low-carbon electricity systems. It introduced a computational model of operational flexibility for schedulable household appliances along with a compact representation of DR offers. Two auction protocols were designed to coordinate DR in single- and multi-retailer settings: a VCG-based mechanism, and a McAfee-based double auction (DA). Several considerations were taken into account in order to achieve computational efficiency and DSIC implementations for these mechanisms. In addition, three penalty schemes were designed, and another one was adapted from the literature, in order to incentivise honest reporting. Moreover, a method was developed to form stepwise offering blocks that integrate DR and can be traded amongst multiple retailers. The theoretical properties of these mechanisms were proved and their economic effects were empirically evaluated. The evaluation chapter shows that, under reasonable conditions, the electricity bill is lowered for end-users, revenue is increased and imbalance settlement decreased for retailers, and the absolute NIV is reduced in a zone. Finally, a set of diverse forecast methods was explored to predict a household's electrical net-load, excluding scheduled appliances, and simple ensembles of predictors performed consistently better than each of the single methods. This allows for better estimation of DR offers and it reduces their uncertainty. The work in this thesis extends the state-of-the-art in DR characterisation and coordination through an algorithmic mechanism design perspective, so as to improve the supply and demand balance in low-carbon electricity grids.

## 7.1 Contributions Revisited

- **Characterisation of operational flexibility:** The concept of DR flexibility in the domestic setting has been formally modelled as the capacity of households to drive the meter up or down at a single time period in line with scheduling constraints of appliance use. This characterisation has considered realistic automation at the end-users' side that can be delegated to a HEMS, such as the scheduling of heating and EV recharging. Furthermore, flexibility from these schedules is extracted and quantified so that a specific DR offer can be made to retailers. These offers are tied to the meter readings so they can be verified. One of the considerations taken into account was to be able to express DR offers in a compact format that would not reveal much regarding end-users' behaviour (appliance use). This was achieved by an ask format that only reveal the offered meters for DR operations of peak-shaving and valley-filling, w.r.t the intended electricity use, with the restriction that only one would be allocated. The format is yet expressive so that end-user agents can indicate different costs.
- **Single-sided VCG-based DSIC mechanism for DR coordination between a retailer and its customers:** This mechanism has been designed to be integrated within the meter reading process, which can be facilitated by the use of smart meters. Apart from the meter readings, the DR offers are collected and the VCG-based mechanism determines the allocation and discounts. The allocation procedure was tailored to deal with the structure of DR offers, so as to prevent insincere exploitation by end-user agents. Moreover, the allocation is solved by a greedy algorithm that results in a monotonic allocation, and payments are determined by Myerson critical payments, which replicates Vickrey's auction payment rule. These properties yield a DSIC mechanism on reported costs, but not in DR amounts. Therefore, the mechanism required verification in order to measure actual DR achievements and settle differences. For this reason, three penalty schemes have been designed to deter dishonest reporting on DR amounts, yet to keep rational end-user agents committed to their offers. These penalty schemes, i.e., middle-point, slope-based, and EWMA-based penalties, provide a means to encourage end-users to report their preferences truthfully and forecast their offers accurately. Moreover, by design, DR extra achievements are not rewarded so that end-user agents have an incentive to estimate offers accurately. This designed under the previous considerations yielded properties such as DSIC, individual ra-

tionality (in the case of EWMA-based penalty), balanced budget, computational efficiency, robustness to uncertainty regarding end-users' DR skill, and privacy protection. Furthermore, simulations show that this mechanism yields a lower electricity bill for end-users, increases revenue for retailers while decreases their NIV, resulting in a lower balancing cost, as compared to BAU.

- **Double-sided McAfee-based DSIC mechanism for multi-retailer DR coordination in a zone:** This mechanism has been designed with the focus on balancing a geographical zone rather than a retailer's trading schedule. It provides a means of DR cooperation amongst competing retailers within a single zone. That is, the DR from one retailer could ameliorate the schedule of another retailer, however, the deviation from the former should not impose a negative externality on it. For this reason, retailers are modelled as virtual generators with respect their schedules, and offer their expected imbalances along with DR blocks. The mechanism is chained in two levels, in the first echelon the interaction between end-users and retailers is managed, while in the second echelon retailers trade both their expected imbalances and DR offer blocks. This mechanism provides an advantage for retailers as opposed to the single-sided VCG-based mechanism, because in some cases retailers trigger fewer DR offers. For instance, two retailers may independently procure DR in opposite directions, while their expected deviations cancel out most of the zonal imbalance, where less DR is really needed. A method to form stepwise block offers has been developed so that DR offers from the first echelon can be grouped into blocks of more meaningful magnitudes amongst retailers. This method collects DR offers and allocates them into sell blocks and buy blocks of a size determined by the market operator (MO). By how flexibility is characterised, these DR offers are present in both type of blocks, however, only one type of block is allocated in the second echelon. The discounts for those offers are determined in a second-price style. The first echelon includes the same verification process as the VCG-based mechanism, and it is paired with the EWMA-based penalty (although one of the other penalty scheme can also be used). In the second echelon, the (ISO-controlled) retailer agents submit the imbalance offers along with DR sell blocks and buy blocks to the DA. The MO estimates the zonal imbalance first and then allocate DR offers to correct that imbalance. Feasible trade allocated by the DA, and the clearing prices are determined by McAfee's DA pricing rule. DR offers are triggered according to

the resulting allocation from the second echelon and verified in the first echelon as in the VCG-based mechanism. The first echelon inherits the properties from the VCG-based mechanism, while the second echelon achieves DSIC, individual rationality, a weak balanced budget, and polynomial-time computation. Furthermore, simulations show that this mechanism yields a lower electricity bill for end-users and generate more revenue for retailers, also the NIV and balancing cost are considerably decreased. Finally, this chained mechanism yields more competitive DR prices that contribute to solve the balancing problem more effectively.

- **Forecasting of the household's inflexible net-load:** In line with the proposed characterisation of operational flexibility, the largest portion of uncertainty in DR offers comes from the inflexible net-load. Higher forecast accuracy allows for better estimation of DR offers, and thus less penalisation due to incorrect allocated offers. The simulations from Chapter 5 has showed that end-users achieve lower electricity bills in the presence of perfect forecasts as compared to naive ones. It seems unlikely that a single method can predict the inflexible net-load with high accuracy. Therefore, a set of diverse forecast methods have been examined to benchmark their ability to predict the inflexible net-load in the 50 household profiles used in Chapter 5. As expected, higher accuracy comes from a combination of these methods rather than from any single one of them. Also, the simple central tendency measures that were used (i.e., mean, trimmed mean, winsorised mean, and median) performed relatively well compared to each single method. Nonetheless, these measures does not account for the out-of-sample error by these forecasts. A weighted average that adjust the weights online according to the out-of-sample error is more resilient in this regard. Therefore, an exponentially weighted average forecaster (EWAFF) was used to combine the forecast methods, excluding the central tendency measures, so that the methods could be weighted according to their performance (i.e., out-of-sample error). EWAFF showed the highest accuracy in most of the 50 profiles, it is computationally inexpensive, and it can be computed online. In fact, this method is related to the EWMA-based penalty used for the end-user agents to measure their performance on their DR offers. There are several other methods for this problem of matching several forecast outputs to a combined output. Those include, a polynomially weighted average forecaster, online gradient descent, online ridge regression, and

ensemble learning approaches, such as stacking. Online adaptive methods should be preferred, given the nature of this problem, and the amount of data required to train them should be considered as well.

## 7.2 Future Work

Several directions have been identified for the further understanding of DR coordination amongst self-interested agents, so as to make this coordination practical for end-users and retailers, and advance the automation of this process with intelligent autonomous agents that continuously improve their results. The list is far from complete, but hopefully will provide some avenues for future research on market-based DR coordination for low-carbon electricity systems.

- **Non-myopic DR procurement:** This is a non-trivial problem. It requires not only a reasonable estimation of the retailer's market position, but also a plausible measurement of the collective DR at different reservation prices, over the time horizon of interest. Some forecast methods can provide reasonable approximations. However, finding the value of flexibility over time requires online price-finding dynamics, for instance by multi-armed bandit approaches. A similar approach could be used to establish dependencies over time regarding the impact of scheduling of non-interruptible tasks. That is, the starting time of these tasks could be scheduled within a time window, however, once they start, they will run for several time periods. Furthermore, multi-stage stochastic programming could be used to model the sequential decision making, given a set of scenarios previously simulated and estimated regarding the collective DR.
- **Wholesale electricity trading under DR:** This is not a trivial problem either. Once a non-myopic DR procurement is achieved some scenarios could be simulated and varied under a range of parameters. These scenarios, along with the modelling of market prices and demand quantities, can be used to derive an optimal wholesale trading strategy in the stochastic programming sense. Similar to DR procurement, this problem could be modelled with multi-stage stochastic programming, however, accurately quantifying the probability of a representative set of scenarios might result challenging.
- **Continuous-time DR coordination:** An natural extension to the mechanisms proposed in this thesis is to allow DR offers to be submitted at any time, not only

at periodic intervals. This may result in a smoother effect of DR on electricity use. Nonetheless, these types of offers should be restricted to, an otherwise calibrated, time window that is in line with market dynamics and imbalance settlements. In addition, the optimal reservation prices would have to be tuned more often than in the periodic case. Moreover, the offers would need to include some expiration time, and the modelling of this type of mechanism is interesting and more challenging at the zonal level.

- **Non-myopic strategies for end-user agents:** This research direction would try to answer when is the best time to submit DR offers for end-users. This could be modelled by using online learning, such as multi-armed bandit algorithms. Furthermore, it would be interesting to assess the systemic effects when all responsive end-user agents follow other strategies as opposed to the greedy strategy followed in this thesis.
- **Large-scale dynamics:** This would include the modelling of inter-zonal market forces in the electricity grid. It may also model the effect of larger participants, such as industrial and commercial customers, universities, hospitals and other municipalities.
- **Simulation of government policies:** This area of research would use agent-based modelling and simulation (ABM/S) to derive organisational and public policies regarding DR. Also, these simulations could provide some insights on different organisational models for the electricity grid organisation, including instrumentation and reinforcement in the presence of a large number of more active end-users.
- **Online mechanism design:** This would require multi-dimensional offers so that other considerations, such as a time window availability or technical constraints, are included in the offers. For instance, the DR offers could be expressed as a tree spanning a horizon of more than one time period. That is, the minimum and maximum meter thresholds can be subsequently offered in time, including dependencies when either is selected, (e.g.,  $m_{i(t+2)}^u$  and  $m_{i(t+2)}^d$  from agent  $i$  at time  $t + 2$ , given that  $m_{i(t+1)}^d$  and  $m_{it}^u$  are selected, etc.), from the private information in each household's schedule. Some pre-commitment notions could be implemented on the retailer's side, similar to the notion implemented in the EV recharging problem in (Stein et al., 2012; Ströhle et al., 2014), but with a different type

structure (i.e., preferences).

- **Selective targeting of households:** Given certain constraints on communication and computing power, a subset of responsive customers could be queried according to some measure, e.g., willingness to offer DR (Holyhead et al., 2015), reliability (Ma et al., 2016), etc.

### **7.3 Concluding Remarks**

Overall, this thesis has provided a framework to study DR through direct market-based mechanisms with autonomous software agents. The proposed mechanisms were designed taking into account a liberalised organisation of the electricity supply, and some of their complex dynamics. The characterisation of operational flexibility allowed for expressing specific DR offers, which were used to financially balance the supply and demand from retailers' trading positions. Moreover, the empirical evaluation showed that, under reasonable assumptions, these mechanisms yielded a lower electricity bill for end-users, reduced the absolute NIV and its balancing cost, and yielded higher revenue to retailers. Finally, this work can serve as a basis for studying more approaches for integrating active end-users into smarter grids.





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