Peak reduction in decentralised electricity systems
Markets and prices for flexible planning

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Peak reduction in decentralised electricity systems - Markets and prices for flexible planning

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Proefschrift

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aan de Technische Universiteit Delft,
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voorzitter van het College voor Promoties,
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Changes in generating electricity — as implied by the EU's commitments for reducing CO_2 emissions and increasing the share of renewables in its electricity mix — require that grids become much more flexible than they currently are.

Philip Lowe, Director-General for Energy at the European Commission and Mark van Stiphout, Member of Cabinet of the Commissioner for Energy at the European Commission, in: Responsabilité & Environnement (No. 69), 2013

Capacity, dispatchability or other features that may have a value to the power system are not considered in the current pricing system.

A team comprising individuals from PricewaterhouseCoopers, Potsdam Institute for Climate Impact Research, International Institute for Applied Systems Analysis and the European Climate Forum, in: 100% renewable electricity: A roadmap to 2050 for Europe and North Africa, 2010

SUMMARY

In contemporary societies, industrial processes as well as domestic activities rely to a large degree on a well-functioning electricity system. This reliance exists both structurally (the system should always be available) and economically (the prices for electricity affect the costs of operating a business and the costs of living). After many decades of stability in engineering principles and related economic paradigms, new developments require us to reconsider how electricity is distributed and paid for.

Two well-known examples of important technological developments in this regard are decentralised renewable energy generation (e.g. solar and wind power) and electric vehicles. They promise to be highly useful, for instance because they allow us to decrease our CO_2 emissions and our dependence on energy imports. However, a widespread introduction of these (and related) technologies requires significant engineering efforts. In particular, two challenges to the management of electricity systems are of interest to the scope of this dissertation. *First*, the usage of these technologies has significant effects on how well (part of) supply and demand can be planned ahead of time and balanced in real time. Planning and balancing are important activities in electricity distribution for keeping the number of peaks low (peaks can damage network hardware and lead to high prices). It can become more difficult to plan and balance in future electricity systems, because supply will partly depend on intermittent sunshine and wind patterns, and demand will partly depend on dynamic mobility patterns of electric vehicle drivers. *Second*, these technologies are often placed in the lower voltage (LV) tiers of the grid in a decentralised manner, as opposed to conventional energy sources, which are located in higher voltage (HV) tiers in central positions. This is introducing bi-directional power flows on the grid, and it significantly increases the number of actors in the electricity systems whose day-to-day decision-making about consumption and generation (e.g. electric vehicles supplying electricity back to the network) has significant impacts on the electricity system.

In this dissertation, we look into dynamic pricing and markets in order to achieve allocations (of electricity and money) which are acceptable in future electricity systems. Dynamic pricing and markets are concepts that are highly useful to enable efficient allocations of goods between producers and consumers. Currently, they are being used to allocate electricity between wholesale traders. In recent years, the roles of the wholesale producer and the retailer have been unbundled in many countries of the world, which is often referred to as "market liberalisation". This is supposed to increase competition and give end consumers more choice in contracts. Market liberalisation creates opportunities to design markets and dynamic pricing approaches that can tackle the aforementioned challenges in future electricity systems. However, they also introduce new challenges themselves, such as the acceptance of price fluctuations by consumers.

The research objective of this dissertation is to develop market mechanisms and dynamic pricing strategies which can deal with the challenges mentioned above and achieve acceptable outcomes. To this end, we formulate three major research questions:

First, can we design pricing mechanisms for electricity systems that support two necessary features well, which are not complementary—namely to encourage adaptations in electricity consumption and generation on short notice (by participants who have this flexibility), but also to enable planning ahead of electricity consumption and generation (for participants who can make use of planning)?

Second, the smart grid vision (among others) posits that in future electricity systems, outcomes will be jointly determined by a large number of (possibly) small actors and allocations will be made more frequently than today. Which pricing mechanisms do not require high computational capabilities from the participants, limit the exposure of small participants to risk and are able to find allocations fast?

Third, automated grid protection against peaks is a crucial innovation step for network operators, but a costly infrastructure program. Is it possible for smart devices to combine the objective of protecting network assets (e.g. cables) from overloading with applying buying and selling strategies in a dynamic pricing environment, such that the devices can earn back parts of their own costs?

In order to answer the research questions, our methods are as follows: We consider four problems which are likely to occur in future electricity systems and are of relevance to our research objective. For each problem, we develop an agent-based model and propose a novel solution. Then, we evaluate our proposed solution using stochastic computational simulations in parameterised scenarios. We thus make the following four contributions:

In Chapter 3, we design a market mechanism in which both binding commitments and optional reserve capacity are explicitly represented in the bid format, which can facilitate price finding and planning in future electricity systems (and therefore gives answers to our first research question). We also show that in this mechanism, flexible consumers are incentivised to offer reserve capacity ahead of time, which we prove for the case of perfect competition and show in simulations for the case of imperfect competition. We are able to show in a broad range of scenarios that our proposed mechanism has no economic drawbacks for participants. Furthermore (giving answers to our second research question), the mechanism requires less computational capabilities in order to participate in it than a contemporary wholesale electricity market with comparable features for planning ahead.

In Chapter 4, we consider the complexity of dynamic pricing strategies that retailers could use in future electricity systems (this gives answers to our first, but foremost to our second research question). We argue that two important features of pricing strategies are not complementary—namely power peak reduction and comprehensibility of prices—and we propose indicators for the comprehensibility of a pricing strategy from the perspective of consumers. We thereby add a novel perspective for the design and evaluation of pricing strategies.

In Chapter 5, we consider dynamic pricing mechanisms where the price is set by a single seller. In particular, we develop pricing strategies for a seller (a retailer) who commits to respect an upper limit on its unit prices (this gives answers to both our first and second research question). Upper price limits reduce exposure of market participants to price fluctuations. We show that employing the proposed dynamic pricing strategies reduces consumption peaks, although their parameters are being simultaneously optimised for the maximisation of retailer profits.

In Chapter 6, we develop control algorithms for a small storage device which is connected to a low voltage cable. These algorithms can be used to reach decisions about when to charge and when to discharge the storage device, in order to protect the cable from overloading as well as to maximise revenue from buying and selling (this gives answers to our third research question). We are able to show in computational simulations that our proposed strategies perform well when compared to an approximated theoretical lower cost bound. We also demonstrate the positive effects of one of our proposed strategies in a laboratory setup with real-world cable hardware.

The results obtained in this dissertation advance the state of the art in designing pricing mechanisms and strategies which are useful for many use cases in future decentralised electricity systems. The contributions made can provide two positive effects: First, they are able to avoid or reduce unwanted extreme situations, often related to consumption or production peaks. Second, they are suitable for small actors who do not have much computation power but still need to participate in future electricity systems where fast decision making is needed.

Nicolas Höning
Amsterdam, May 2016

Samenvatting

In de hedendaagse samenleving zijn zowel industriële processen als huishoudelijke activiteiten in grote mate afhankelijk van een goed functionerend elektriciteitssysteem. Deze afhankelijkheid is zowel structureel (het systeem moet altijd beschikbaar zijn) als economisch (elektriciteitsprijzen beïnvloeden de kosten van bedrijfsvoering en van levensonderhoud). Na vele decennia van stabiliteit op het gebied van elektrotechnische principes en de daarmee samenhangende economische paradigma's stellen nieuwe ontwikkelingen ons voor de vraag om opnieuw te bezien hoe elektriciteit moet worden gedistribueerd en afgerekend.

Twee bekende voorbeelden van belangrijke technologische ontwikkelingen op dit gebied zijn decentrale opwekking van hernieuwbare energie (bijvoorbeeld zonne- en windenergie) en elektrische voertuigen. Deze technologieën lijken zeer bruikbaar te zijn, bijvoorbeeld omdat ze het mogelijk maken om zowel onze CO_2-uitstoot als onze afhankelijkheid van energie-invoer te verminderen. Echter, een algemene invoering van deze (en verwante) technologieën vereist aanzienlijke technische inspanningen. Twee uitdagingen voor het beheer van elektriciteitssystemen zijn met name van belang voor het toepassingsgebied van deze dissertatie. *Ten eerste* heeft het gebruik van deze technologieën grote gevolgen voor hoe goed vraag en aanbod (deels) van tevoren kunnen worden gepland en uiteindelijk zelfs exact op elkaar kunnen worden afgestemd. Plannen en afstemmen zijn in elektriciteitssystemen belangrijk om het aantal pieken laag te houden (pieken kunnen netwerk-hardware beschadigen en tot hoge prijzen leiden). In toekomstige elektriciteitssystemen kunnen plannen en afstemmen moeilijker zijn dan nu, omdat het aanbod mede zal afhangen van fluctuerende zon- en windpatronen, terwijl de vraag mede zal afhangen van de mobiliteitspatronen van gebruikers van elektrische voertuigen. *Ten tweede* worden deze technologieën vaak decentraal in laagspanningsnetten geplaatst, in tegenstelling tot conventionele energiebronnen, die zich op centrale posities in hoogspanningsnetten bevinden. Dit zal leiden tot bidirectionele energiestromen in het netwerk, en tot meer actieve gebruikers, waardoor hun dagelijkse besluiten over verbruik en opwek belangrijke effecten op het elektriciteitssysteem hebben (bijvoorbeeld het terugleveren van energie uit elektrische voertuigen naar het netwerk).

In dit proefschrift doen we onderzoek naar dynamische prijsvorming en markten, om aanvaardbare toewijzingen (van elektriciteit en van geld) in toekomstige elektriciteitssystemen mogelijk te maken. Dynamische prijsvorming en markten zijn zeer bruikbare concepten voor een efficiënte toewijzing van goederen tussen producenten en consumenten. Op dit moment worden ze gebruikt om elektriciteit toe te wijzen tussen groothandelaren in energie. In de afgelopen jaren is de rol van grootschalige producent en energieleverancier in veel landen van de wereld opgesplitst. Dit wordt vaak aangeduid als "liberalisering" van de energiemarkt, waarbij wordt verondersteld dat als gevolg hiervan meer concurrentie zal ontstaan en eindgebruikers meer keuze uit contracten zullen hebben. Liberalisering creëert kansen om dynamische prijsvorming en markten te ontwerpen, die de genoemde uitdagingen in toekomstige elektriciteitssystemen kunnen aanpakken. Echter, ze introduceren zelf ook nieuwe uitdagingen, zoals het aanvaarden van fluctuerende prijzen door de consument.

Het doel van dit promotieonderzoek is om marktmechanismen en dynamische prijsvormingsstrategieën te ontwikkelen, die een antwoord zijn op bovengenoemde uitdagingen en die aanvaardbare resultaten bereiken. Daartoe formuleren we drie onderzoeksvragen:

Ten eerste, kunnen we prijsmechanismen voor elektriciteitssystemen ontwerpen die twee noodzakelijke maar niet complementaire functies goed ondersteunen—namelijk het bevorderen van het aanpassen van verbruik en opwek op korte termijn (door deelnemers die over deze flexibiliteit beschikken), en het mogeljik maken van vooruit plannen van elektriciteitsverbruik en opwek (voor deelnemers die van plannen gebruik kunnen maken)?

Ten tweede, de smartgridvisie veronderstelt (onder andere) dat uitkomsten in toekomstige elektriciteitssystemen door een groot aantal (eventueel) kleine actoren gezamenlijk bepaald worden en dat energietoewijzingen frequenter plaatsvinden dan momenteel gebeurt. Welke prijsmechanismen kunnen zonder grote rekenkracht van deelnemers werken, beperken de risico's voor kleine deelnemers en zijn in staat om toewijzingen snel te bepalen?

Ten derde, een geautomatiseerde netwerkbescherming tegen pieken is een cruciale en innovatieve stap voor netbeheerders, maar impliceert ook een kostbaar infrastructuurprogramma. Is het voor slimme apparaten mogelijk om het beschermen van netwerkcomponenten (zoals kabels) tegen overbelasting te combineren met strategisch inkopen en verkopen van electriciteit tegen dynamische prijzen, zodanig dat deze apparaten een deel van hun eigen kosten terug kunnen verdienen?

Onze methode om deze onderzoeksvragen te beantwoorden, is als volgt: We beschouwen vier problemen die kunnen optreden in toekomstige elektriciteitssystemen en die van belang zijn voor het doel van ons onderzoek. Voor elk probleem ontwikkelen we een agentgebaseerd model en stellen we een nieuwe oplossing voor. Daarnaast evalueren we onze voorgestelde oplossing met behulp van stochastische simulaties in geparameteriseerde scenario's. Op deze wijze maken we de volgende vier bijdragen:

In Hoofdstuk 3 ontwerpen we een marktmechanisme voor toekomstige electriciteitssystemen waarin zowel bindende toezeggingen als optionele reservecapaciteit expliciet zijn vertegenwoordigd in de biedwijze. Dit kan de prijsbepaling en de planning van verbruik en opwek faciliteren (en geeft dus antwoorden op onze eerste onderzoeksvraag). We tonen ook aan dat flexibele consumenten in dit mechanisme worden gemotiveerd om reservecapaciteit van tevoren aan te bieden. We bewijzen dit voor het geval van perfecte concurrentie in de markt en tonen dat met behulp van simulaties aan voor het geval van imperfecte concurrentie. We laten in een breed scala aan scenario's zien dat ons voorgestelde mechanisme geen economische nadelen heeft voor de deelnemers. Verder vereist het mechanisme minder rekenkracht van de deelnemers dan een hedendaagse groothandelsmarkt voor elektriciteit die vergelijkbare functies voor het vooruit plannen heeft (we geven dus antwoorden op onze tweede onderzoeksvraag).

In Hoofdstuk 4 beschouwen we de complexiteit van dynamische prijsvormingsstrategieën die detailhandelaars kunnen gebruiken in toekomstige elektriciteitssystemen (dit geeft antwoorden op onze eerste, maar vooral op onze tweede onderzoeksvraag). We stellen dat twee belangrijke kenmerken van prijsstrategieën niet complementair zijn—namelijk het vermogen om stroompieken te verminderen en de mate van begrijpelijkheid van het tarief—en wij stellen indicatoren voor die de begrijpelijkheid aangeven vanuit het perspectief van de consument. Daarmee voegen we een nieuw perspectief toe voor het ontwerp en de evaluatie van prijsstrategieën.

In Hoofdstuk 5 beschouwen we dynamische prijsvormingsmechanismen waar de (dynamische) prijs word gekozen door een enkele verkoper. We ontwikkelen prijsstrategieën voor een verkoper (een energiebedrijf) die zich verplicht tot een bovengrens voor de prijs per eenheid (dit geeft antwoorden op zowel onze eerste als tweede onderzoeksvraag). Prijslimieten beperken de blootstelling van marktdeelnemers aan prijsfluctuaties. We laten zien dat het gebruik van de voorgestelde strategieën voor dynamische prijzen het aantal verbruikspieken vermindert, ondanks dat hun parameters geoptimaliseerd werden voor winstmaximalisatie van de energiebedrijf.

In Hoofdstuk 6 ontwikkelen we algoritmes voor een klein opslagapparaat dat aangesloten is op een laagspanningskabel (dit geeft antwoorden op onze derde onderzoeksvraag). Met hulp van deze algoritmes kan worden besloten wanneer het apparaat energie opwekt of teruglevert aan het netwerk, met het doel om zowel de kabel te beschermen tegen overbelasting als de inkomsten van in- en verkoop van electriciteit te maximaliseren. Wij laten in simulaties zien dat onze voorgestelde strategieën goed presteren in vergelijking met een theoretische benadering van de laagste kosten. We tonen ook de positieve effecten van een van onze voorgestelde strategieën aan in een laboratoriumexperiment onder gebruik van echte distributiekabels.

De in dit proefschrift beschreven resultaten verbeteren de state-of-the-art in het ontwerpen van prijsmechanismen en strategieën die nuttig zijn voor vele toepassingen in toekomstige gedecentraliseerde elektriciteitssystemen. De gemaakte bijdragen kunnen twee positieve effecten tot stand brengen: Ten eerste kunnen ze ongewenste extreme omstandigheden verminderen, die vaak gerelateerd zijn aan pieken in consumptie of productie. Ten tweede zijn ze geschikt voor kleine actoren die niet veel rekenkracht ter beschikking hebben, maar wel deel moeten nemen aan toekomstige elektriciteitssystemen waarin snelle besluitvorming nodig is.

Nicolas Höning
Amsterdam, Mei 2016

Contents

Table 1: Acronyms and Symbols used throughout this dissertation

Acronym/Symbol	Description
SO	System Operator
DSO	Distribution System Operator
TSO	Transmission System Operator
q	quantity (conceptual)
Q	quantity (denoting a specific value)
ρ	price (usually for a unit of electricity per period of time)
t	a period of time
DP	Dynamic Pricing
CP	Constant Pricing

1

INTRODUCTION

1.1. CONTEXT

Almost all economic activities are heavily dependent on the affordable availability of energy. This dependence has become more significant during the industrialisation in recent centuries. Since the introduction of mechanisation, energy can be turned into work more effectively than ever before, using for instance the internal combustion engine. Consequently, the generation and distribution of energy are critical enablers of technological progress. However, in a state that is usable to humans, such as gasoline or electricity, energy is a scarce resource. It is therefore crucial that energy is allocated among demanding actors, using efficient and fair approaches.

The introduction of electricity as an energy carrier revolutionised the distribution of energy. Electricity has become a ubiquitous energy carrier and is still gaining in usage every year. In fact, the European, U.S. and Chinese electrical grids are the biggest man-made synchronous machines on earth - a feat of 20th century engineering. Historically, the growth rate for electricity demand has outstripped that for other energy carriers.

After many decades of stability in engineering principles and economic paradigms, the energy system, and with it the electricity system, is entering into a time of change. We mention several important developments in this context which are relevant for the purpose of this thesis.

First of all, renewable energy sources are being installed on the electricity grid. They are expected to represent a significant share of energy sources within a few decades, but they already begin to have influence on the daily practice of distribution network operators today. Renewable energy sources are influential for two reasons. The first reason is their intermittent nature, e.g. sunshine and wind are not completely predictable. The second reason is the fact that they are often placed in the lower (LV) tiers of the grid in a decentralised manner, as opposed to conventional energy sources, which are located in higher (HV) tiers in central positions. This is introducing bidirectional power flows on the grid.

Second, electricity markets have been liberalised in many countries of the world. The roles of the wholesale producer and the retailer have been unbundled, which is supposed to increase competition and give consumers more choice in contracts. One side effect of liberalisation is the need for more open market designs. Up until recently, government agencies managed the allocation of electricity generation centrally, involving only a few large producers in clearly defined optimisation procedures which aimed to minimise the overall costs of generation. Today, many market designs for the wholesale trade of electricity are being tried out around the world, with varying degrees of openness, decentralisation and success. For the coming years, most market policy designers plan to involve consumers into dynamic markets, as the demand side is still rather static.

A third development of interest in the context of this thesis is that the demand for electricity in industrialised countries currently increases every year, by between 0.5 and 1 percent. However, a more significant increase in demand is on the horizon. The reason for this is that several activities with high energy demands, which were fuelled by a different energy source until now, are about to utilise electricity as their energy carrier - a process traditionally referred to as "electrification". Two examples concern transportation (electric vehicles) and heating (heat pumps).

Fourth, the IT revolution is coming to the electricity systems, as well. More data will be available with the ability to measure the load at points of consumption (with smart meters) and the states of many grid assets (with sensors). The decreasing costs of computing power make it possible that real-time decisions can be made on site by intelligent software. Furthermore, the improving availability and bandwidth of network communication make it possible to integrate these local decisions in real-time mechanisms which allocate electricity among participants. This concept, described by the automation of both local measurement and local decision-making, is often referred to as the "smart grid".

The final relevant recent development concerns households. Today, the set of households is very homogeneous with respect to consumption behaviour. This might change, as a significant number of households will be installing heat pumps or use electric cars over the next decade, while others may even start producing electricity (becoming so-called "prosumers"). With the introduction of dynamic prices for electricity, household behaviour will diversify even further, because households will be able to choose among different economic strategies to manage their energy-related activities.

1.2. MOTIVATION

In recent decades, the energy system has seen an exceptional level of security of supply, and therefore any activities which rely on electricity could be planned with high certainty. In addition, prices have been stable and fair. For most consumers, prices have been fixed by long-term contracts. Furthermore, prices were roughly equal among comparable consumers, i.e. among residential consumers as well as among industrial consumers of comparable size. However, the new developments listed above make it more difficult to keep security of supply high and prices stable, for three reasons: First, the changes in supply and demand patterns in the energy system can result in higher peaks in network utilisation and novel fluctuations in prices, e.g. because dynamic pricing contracts specify that prices may increase on short notice during peak hours. Second, the number of decisions to be made by network operators as well as consumers and suppliers is increasing. The amount of information which is needed to make informed decisions is increasing, as well. Finally, the number of decision makers that are influential to the security of supply and price stability is increasing substantially, based on two trends: Households will become more diverse (as mentioned above), thus the individual behaviour of some households can have more influence than the behaviour of other households, both on the security of supply and on the stability of prices. An example for this is that one household owns an electric car, which significantly increases its electricity consumption, while his neighbours do not. Furthermore, a novel kind of decision maker enters the energy system - smart software will be installed at many locations in the grid, for example in network equipment or in electricity-consuming devices like electric cars. These devices can make autonomous decisions based on signals or local observations. The introduction of these smart devices can increase overall energy efficiency as well as stability of supply, but the design of the distributed architecture in which this takes place is crucial.

In order to keep the security of supply high and price fluctuations within acceptable ranges in these novel circumstances, it is crucial to find suitable methods with which to allocate electricity among participants. Market mechanisms are very useful procedures for such allocations. The main objective of a market mechanism usually is to allocate a good (electricity in our case) to those who want it the most. However, in a complex setting like electricity systems, a suitable market mechanism will need to operate with multiple objectives, for instance to protect expensive network assets, to keep prices stable and to provide some level of fairness.

Furthermore, for a market mechanism to be effective in the settings described above, it needs to assess the flexibility of participants or of their devices to deviate from their natural course of action, for example by shifting actions over time. This flexibility is based on the physical properties of the participant's circumstances (e.g. the ramp-up speed of a power plant determines the amount it can supply on short notice), its ability to plan ahead (e.g. if an electric vehicle which is connected to the grid has a high likelihood of not being used for driving during the next few hours, there exists flexibility to charge and discharge the battery in response to market signals) and finally its willingness to make use of his flexibility in exchange for monetary compensation. We will provide a more formal definition of flexibility in Chapter 2.

When flexible market participants can be incentivised to offer their flexibility, positive effects on security of supply and on overall costs can follow. For example, balancing between supply and demand becomes possible on short notice, congestion management can increase the lifetime of network equipment by re-routing power or delaying either generation or consumption, power quality support (e.g. by voltage regulation) can decrease losses and the likelihood of blackouts and brownouts is lowered substantially. The incentives which flexible participants receive (for making their flexibility available) are paid for by the market participants who demand the flexibility. For example, the operator of a windmill has demand for flexibility in a specific time step if the windmill generates less power than it sold (ahead of time) for that time step

- it thus needs to buy power on short notice to fulfil contractual obligations. Another example is a distribution system operator who requires short-term protection of network equipment, in order to avoid overloading. This could mean that the operator would pay consumers (who are flexible to do so and willing to accept his offer) to decrease their power consumption during the time of overloading.

However, only with such flexibility present and being offered will incentives from market mechanisms lead to desired outcomes. Until now, only a few very large actors are offering their flexibility for economic compensation. These large actors employ trained traders and sophisticated optimisation programs to plan ahead and design bids to use in wholesale markets. In future energy systems, we need to enable small actors who have less sophisticated decision-making capabilities to offer flexibility, as well. First, they represent large parts of the demand side and if they offer their flexibility, the average costs of acquiring flexibility in the market should therefore be reduced for all participants through increased competition. Second, there exist several problems on the lower levels of the grid (e.g. local congestion problems) which can only be addressed if price signals can incentivise small participants to adapt their behaviour.

1.3. RESEARCH QUESTIONS

In this thesis, we consider various settings in lower and middle layers of future energy systems, which are characterised by the trends in supply and demand we discussed above. We distinguish various problems in these settings and provide novel solutions, such as mechanisms and strategies. In particular, we outline the following research questions:

1. Future energy systems will exhibit more intermittent supply and more heterogeneous demand, while storage technology will still be expensive. Consequently, we will require flexible participants and devices to adapt their activities on short notice, in order to balance supply and demand and to protect assets. Existing dynamic pricing mechanisms for smart grid settings are able to achieve balancing of supply and demand by providing monetary benefits for such behaviour. However, in these mechanisms the ability of both flexible and inflexible participants to plan ahead is usually greatly reduced. *Can we design pricing mechanisms that enable adaptations by flexible participants on short notice, but still maintain the ability of participants to plan ahead?*

2. Today, participants in dynamic economic allocation mechanisms for electricity are professional energy traders, who make use of elaborated financial portfolio management techniques and powerful computation facilities to find the best strategies. If many more actors are exposed to dynamic prices, then the level of required sophistication that is needed to take part in pricing mechanisms should be lowered. *Which pricing mechanisms do not require high computational capabilities from the participants, are able to limit the exposure of small participants to risk and are able to find allocations fast (suitable for smart grids)?*

3. Automated grid protection is a crucial innovation step for network operators, but a costly infrastructure program. Smart devices can be programmed to per-

form protective actions, but they can react to dynamic prices as well. *Is it possible for such devices to combine the objective of protecting network assets (e.g. cables) from overloading with applying buying and selling strategies in a dynamic pricing environment, such that the devices can earn back parts of their own costs?*

1.4. RESEARCH METHODOLOGY

In order to capture enough of the complexity inherent to the problem, this thesis studies the questions outlined in Section 1.3 with agent-based models of electricity market settings, which are evaluated in stochastic simulations. We will provide some deeper background on this technique in Section 2.3. Typically, each contribution chapter (Chapters 3 through 6) will consist of three main parts.

First, we will design agents as autonomous decision-makers, that are well-suited to model actors (people, companies, software) in economic allocation mechanisms. This allows us to implement basic economic goals for market participants, e.g. cost reduction or profit maximisation. Agents may be equipped with strategies or optimisation procedures to respond to a given setting with a behaviour that is likely to improve their situation.

Second, we will define the protocols of interaction between agents. In this thesis, this means to implement a market mechanism which is able to collect information from both the supply and the demand side and which responds with an allocation for all parties. This information will often, but not necessarily, come in the form of bids, so that the market mechanism represents a one- or two-sided auction. The contribution we make in order to improve outcomes for a problem setting is either a novel market mechanism (with accompanying strategies of participants being based on reasonable assumptions), strategies for existing mechanisms or indicators which describe how well a given mechanism facilitates strategies of participants.

Third, we evaluate our solutions by measuring economic outcomes, where we make use of economic paradigms like profits, consumer surplus or market power. Most of our measurements concern single agents, for instance the profits made by a bidding agent situated in an electric vehicle or by an electricity retailer company. Other measurements concern a societal perspective, for instance the uneven distribution of market power among agents. We evaluate a range of possible what-if scenarios by employing parameter analysis and Monte-Carlo sampling.

We note that throughout the thesis, multiple perspectives of actors in the energy system are taken - market designer (Chapter 3), Distribution System Operator (Chapter 6), producer (Chapters 3 and 5), consumer (Chapters 3 and 4), or a prosumer (a new kind of player in electricity markets who both buys and sells - Chapter 6).

1.5. OUTLINE AND CONTRIBUTIONS

We summarise now how the remainder of this thesis is organised and what contributions are made. We refer to the research questions which were outlined in Section 1.3. The chapters with novel scientific contributions (Chapters 3 through 6) can be read independently. For a recommended instruction for reading (indicating which chapters require the knowledge of which previous content), see the dependency diagram

1

in Figure 1.1.

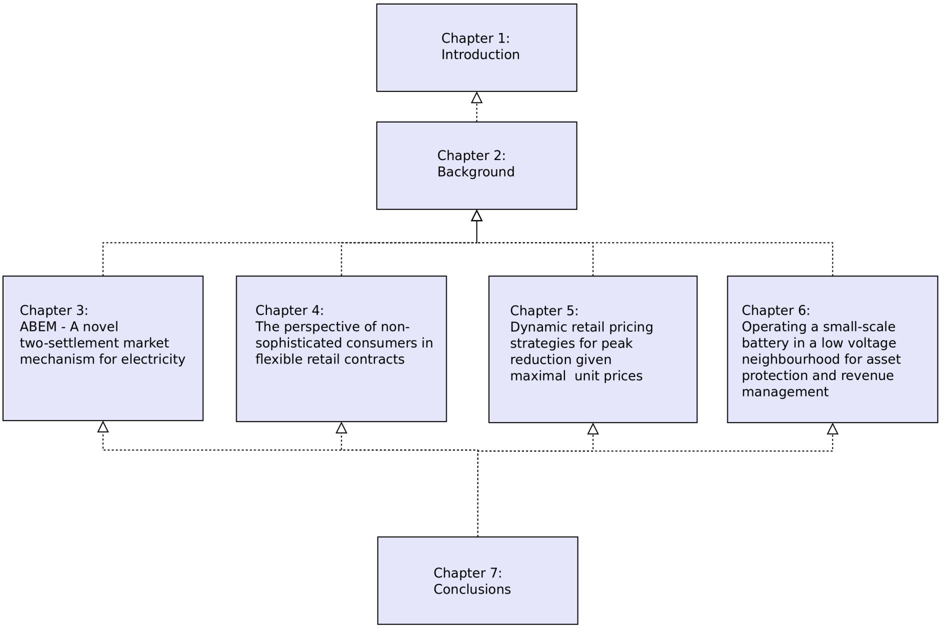


Figure 1.1: Dependency diagram of the chapters of this thesis.

Chapter 2 *provides a closer look at the current developments and challenges in energy systems.* We give an overview over existing literature that deals with these developments and challenges and we provide more insight in the way we address them in this thesis. This information is beneficial to understand the contributions being made in the following chapters (each following chapter also contains a discussion of related work which is specific to the problem being addressed in that chapter). We examine in Chapter 2 relevant technological trends like renewable energy sources and electrification of demand. Then, we outline how this can affect the design of novel electricity market design mechanisms and the strategies being used in them. We also pay special attention to the notion of reserve capacity and define our notion of flexibility in the context of this thesis. Finally, we go into more detail about our chosen method of inquiry, agent-based modelling and stochastic simulation.

Chapter 3 *proposes and evaluates ABEM, a novel market-mechanism.* In order to reach satisfactory levels of efficiency and reliability in future energy systems, it is crucial to include planning-ahead of the energy-involving activities. Market mechanisms are a promising approach for large-scale coordination problems about energy supply and demand, but existing electricity markets either do not involve planning-ahead sufficiently or require a high level of sophistication and computing power from participants, which is not suitable for smart grid settings. We propose a new market mechanism for smart grids, ABEM (Ahead- and Balancing Energy Market). ABEM performs an ahead market and a last-minute balancing market (a so-called "two-settlement procedure"), where planning-ahead in the ahead market supports both binding ahead-commitments and reserve capacities in bids (which can be submitted as price functions). These features of planning-ahead reflect the features in modern wholesale electricity markets. However, constructing bids in ABEM is straightforward and fast. We also provide a model of a market with the features mentioned above, which a strategic agent can use to construct a bid (e.g. in ABEM), using a decision-theoretic approach.

We evaluate ABEM experimentally in various parameterised scenarios. Using stochastic computational simulations, we show that there are no economic drawbacks for bidders in ABEM when compared to a benchmark mechanism. For the System Operator, there are several advantages, as well: Excessive market power of suppliers is reduced (which we show in simulations) and flexible consumers will offer reserve capacity (which we prove for the case of perfect competition and show in simulations for the case of imperfect competition).

In this chapter, we provide answers to the first and second research question.

Chapter 4 *proposes three indicators for the comprehensibility of dynamic pricing in retail contracts.* The long-term business success of an electricity retailer will in the future be determined by two novel factors: First, retailers need to avoid or mitigate consumption peaks by exposing small-scale consumers to dynamic prices, as such peaks lead to high prices on wholesale markets. Flexibility of consumption is becoming a highly valuable contribution in future energy systems, and dynamic pricing is one of the most promising means available to retailers in order to realise its potential. Second, it is important that the dynamic pricing strategy is not too complex - it should be comprehensible to non-sophisticated consumers and the software agents they might employ for day-to-day decision-making.

We argue and demonstrate in this chapter that these two factors are not complementary, and that this development constitutes a novel challenge to systems engineering as well as economics. We propose three novel indicators (Stability, Learnability and Engageability) to measure comprehensibility of pricing dynamics from the consumer's point of view. We then demonstrate these indicators in using stochastic computational simulations, using a parameterisable market model. The indicators are useful for designers of dynamic pricing mechanisms to understand effects of different contract settings and consumer population composition on the consumer perspective. For instance, a rather surprising finding in our model is that there is a limit to how well price dynamics can be learned from one consumer's point of view when populations contain both flexible and inflexible consumers.

In this chapter, we provide answers to the first and second research question.

Chapter 5 *proposes a method for finding well-working strategies for dynamic pricing in retail contracts with upper limits on prices.* Like Chapter 4, this chapter investigates the relation between retailers and electricity consumers, whose relationship is characterised by dynamic prices. However, here the focus is on the decision problem of the retailer. Formulating well-working dynamic pricing strategies is an important research topic, to which we introduce the additional challenge of being able to promise consumers an upper limit on prices. While consumption peaks (with no concurrent peak in generation) incur significant costs (e.g. because of high wholesale market prices during peak times or penalties for overheating network assets), promising price limits will also be crucial for retailers (to attract consumers) as well as regulators (to protect consumers). However, when designing dynamic pricing strategies, peak reduction and price limits can be conflicting goals.

We propose two parametrisable strategies for computing prices dynamically, based on limited information about the current demand for electricity. We employ an evolutionary algorithm to find well-working parametrisations for a strategy in a given setting (given knowledge about the maximal price and expectations about consumer behaviour). These parameterised strategies are then evaluated in multiple what-if scenarios, using stochastic computational simulations. First, we show that this approach is able to find well-working strategies. Furthermore, we show that the peak reduction potential of dynamic pricing strategies depends on the maximal price. Furthermore, we show that retailers do not prefer a constant price strategy (which always charges the maximal price) over our dynamic price strategy. Finally, we show that employing the proposed dynamic pricing strategies reduces peaks, although their parameters are being optimised for the maximisation of retailer profits.

In this chapter, we provide answers to the first research question.

Chapter 6 *develops algorithms to control the charging and discharging behaviour of a battery, for the multi-objective challenge to simultaneously protect low voltage hardware and maximise its revenue in a dynamic market.* The initial motivation for this contribution is the fact that the rated capacity of many currently installed low voltage cables is too low to withstand the increased usage levels which we can expect in future settings (concerning both the overall electricity demand from households and the peaks from intermittent local generation). This can become a problem for the operators of distribution systems. It is too expensive to replace all cables at once.

We propose to let a battery (e.g. a used electric vehicle battery, which will be available in large numbers in the near future) protect such a low voltage cable. Because also used batteries are costly, the battery should, next to performing protective actions, perform revenue management by buying and selling electricity intelligently. It can thus partly earn back its acquisition costs.

We design control algorithms for the battery that combine these two objectives (protection and revenue management) as heuristic strategies. We also model the costs as a set of linear and integer constraints. Given a heuristic strategy for a given scenario (a strategy describes charging and discharging behaviour of the battery), the costs which occur when the strategy is applied can be computed with this model. As a benchmark, we compute a theoretical lower bound for the arising costs with a mixed integer linear programming solver. The solver optimises an objective function that is based on the cost model and we give the solver clairvoyant knowledge of future prices. We evaluate our algorithms in parameterised scenarios, using stochastic computational simulations. We find that our best-performing heuristic strategy, which uses expectations of the future to prepare the battery state for periods that are likely to be overloaded or are of interest for revenue optimisation, performs within 83% of the approximated theoretical lower bound with clairvoyance.

In this chapter, we provide answers to the third research question.

Chapter 7 concludes the thesis. We first evaluate the methodological approach taken in this thesis and outline the added value it has brought to it. Then, we revisit the research questions which were outlined in Section 1.3 and evaluate to what extent this thesis has been able to answer them.

1.6. PUBLICATIONS

The chapters of this thesis are based on peer-reviewed publications [50–56, 104], as follows.

Papers on which the contents of Chapter 3 are based appeared as

- N. Höning, H. Noot and H. La Poutré: "Integrating power and reserve trade in electricity networks", Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2011), pages 1293-1294, 2011
- N. Höning and H. La Poutré: "Reduction of Market Power and Stabilisation of Outcomes in a Novel and Simplified Two-Settlement Electricity Market", Proceedings of IEEE/WIC/ACM International Conference on Intelligent Agent Technology (IAT 2012), IEEE Computer Society, pages 103-110, 2012
- N. Höning and H. La Poutré: "Flexible Consumers Reserving Electricity and Offering Profitable Downward Regulation", Proceedings of the Third IEEE PES Conference On Innovative Smart Grid Technologies (ISGT 2012), IEEE Press, 8 pages, 2012
- N. Höning and H. La Poutré: "An electricity market with fast bidding, planning and balancing in smart grids", Journal of Multiagent and Grid Systems (10), IOS Press, pages 137-163, 2014

A paper on which the contents of Chapter 4 are based appeared as

- N. Höning and H. La Poutré: "Designing comprehensible self-organising systems", Proceedings of the 4th IEEE International Conference on Self-Adaptive and Self-Organizing Systems (SASO 2010), IEEE Computer Society, pages 233-242, 2010

A paper on which the contents of Chapter 5 are based appeared as

- N. Höning and H. La Poutré: "Reducing electricity consumption peaks with parametrised dynamic pricing strategies given maximal unit prices", Proceedings of the Second International Workshop on Intelligent Agent Technology, Power

Systems and Energy Markets (IATEM 2013), IEEE Computer Society, pages 171-175, 2013

Papers on which the contents of Chapter 6 are based appeared as

- S. Ramezani, N. Höning and H. La Poutré: “Fast and revenue-oriented protection of radial LV cables with smart battery operation", Proceedings of the IEEE Symposium Series on Computational Intelligence (IEEE SSCI), Applications In Smart Grids (CIASG 2013), IEEE Press, pages 107-114, 2013
- N. Höning, E. De Jong, G. Bloemhof and H. La Poutré: “Thermal Behaviour of Low Voltage Cables in Smart Grid - Related Environments”, Proceedings. of The 5th IEEE PES Innovative Smart Grid Technologies (ISGT 2014) European Conference, IEEE Press, 8 pages, 2014

2

BACKGROUND

In this chapter, a richer context is provided for the motivation of this thesis, related work and its nature of inquiry. In the first section, the technological trends in energy systems in the near future are explained in more detail. These trends include that both generation and consumption are becoming less predictable and less steerable and hence make it more difficult to plan the allocation of electricity ahead of time. We first discuss changes on both the demand and supply side, where the increasing usage of renewable energy is probably the most important trend. We also give an overview over the “smart grid” concept and provide a short history of research into intelligent electricity networks, which already spans more than two decades. The current focus of this area of research lies on the inclusion of smaller actors in decision-making and to improve balancing of supply and demand across time, in the face of uncertainty. During the discussion of a number of trends, we argue how they make it necessary to increase efforts in the further development of markets for electricity (markets are mechanisms with which electricity and assorted payments can be allocated among suppliers and consumers). Finally, we discuss implications of these trends for the investment planning of networks.

The technological trends discussed in the first section require us to rethink how electricity can be allocated efficiently and in a fair manner. Therefore, the second section highlights the resulting challenges for designing economic mechanisms for the modern trade of electricity. We begin with a brief classification of market structures and trends in bid modelling. Next, we review ingredients for economic mechanisms which enable the trade of flexibility, like dynamic pricing contracts, trading ahead of time and the allocation of reserve capacity. We then look at a few examples of established economic mechanisms and ongoing real-world experiments which include these ingredients.

The problem settings inquired in this thesis are highly complex and stochastic. This is due to the physical requirement to keep supply and demand in balance at all times and (in future energy systems) the combination of intermittent production with many independent decision makers. Proposed solutions should be tested on models that can represent this complexity and be validated against several what-if scenarios. The third section of this chapter therefore introduces our research method of choice, agent-based simulation, and provides some background concerning its recent scientific development.

2

2.1. TECHNOLOGICAL TRENDS IN ENERGY SYSTEMS

2.1.A. INCREASING DEMAND FOR ELECTRICITY

In industrialised countries, the demand for electricity increases in a roughly linear manner, due to economic growth. The European Network of Transmission Operators currently estimates a yearly increase of around 0.8% [27], a pattern which has been very stable since the 1950s[1]. This trend on its own poses a challenge to the planning and maintenance of electrical grids.

However, several technological innovations introduce novel devices which use electricity as an energy carrier, where traditionally a different energy carrier was used. Thus, these innovations lead to an increase in addition to the yearly linear increase in demand for electricity. A similar non-linear increase happened in the last years of the 19th century when technology used for lighting (by the invention of the light bulb) and manufacturing (by the introduction of the electric motor, among others) started to use electricity. Technology transitions of this kind are often described with the term "electrification" and usually go along with significant investments in electricity grid infrastructure, as both average and peak consumption increase.

In this century, we are about to see electrification happening in other fields. The following few decades might see two particular examples: electric vehicles and heat pumps. Electric vehicles are expected to be used widely as they do not require oil and do not pollute cities. They would introduce electricity as an energy carrier for transportation. Heat pumps, which create temperature differences similar to the way a fridge works, are expected to become widely used because they make very efficient use of energy [83]. They would introduce electricity as an energy carrier for heating and cooling.

The continuous and increasing success of electricity as an energy carrier during the last 130 years can be explained if we regard the electricity grid as a driver for technological innovation. One reason for this is that producers of novel energy-consuming devices can reach millions of possible adopters who already have access to a standardised infrastructure (the electricity grid). A second reason is that the electricity grid is a shared transport medium for immediate supply and consumption, which enables grid operators to put those energy sources to use that are most efficient in generating electricity at any given time.

Of course, the electricity grid does not come for free. Building the electricity grid and maintaining its high levels of supply quality leads to high infrastructure costs. A major reason for grid extensions are peaks in consumption or generation. As they most often result in a high difference between demand and supply, peaks require large

[1] However, in western economies there has been a unprecedented consecutive interval of five years with no increases since 2008, due to the economic recession. The future of this trend of slight yearly increases is therefore not certain at this time of writing.

safety margins in grid design and wear out existing infrastructure. If peaks can be flattened (often referred to as “peak reduction"), otherwise necessary upgrades to network components like cables can be postponed, which can save millions in societal investments. In addition, consumption peaks often lead to inefficient economic allocations, e.g. because expensive peak load power plants have to be employed for supply during the peak. The flattening of peaks is a major concern in the design of economic mechanisms for electricity and consequently also in this thesis.

2.1.B. CHANGES ON THE SUPPLY SIDE

FOSSIL ENERGY SOURCES

The generation of energy from fossil fuels (e.g. oil, coal, uranium or gas) has had a major influence on the industrial development in the last 150 years. Currently, the developed world gets 80% of its energy from fossil fuels. However, an end of easy and cheap access to most fossil fuels is foreseeable and energy prices will increase eventually. In addition, CO_2 emissions are becoming a major concern for economic stability in the future, due to climate change [83].

Both oil and coal have been and will remain very important to the world economy, but burning them emits a lot of CO_2. Nuclear power plants emit little CO_2 and can in principle be fuelled by materials more abundant than uranium, for instance thorium or spent nuclear fuel. However, new reactor types will need more time and current implementations are not yet convincing most investors and regulators that they provide reliable service in terms of immediate safety and long-term waste disposal. Gas is a fossil fuel which is used in power plants that start up fast (unlike coal or nuclear power plants) and its CO_2 emissions are also lower, so it will be an important contribution to the energy mix.

THE INTRODUCTION OF RENEWABLE ENERGY SOURCES

In the light of the problems with fossil fuel supply, so-called renewable energy is supposed to constitute a greater part of our energy mix in the future and is exhibiting significant growth rates within the energy mix of many countries over the world[2]. The major novel aspects of this generation technology are of both technical and economical nature.

Technologically, the output of many renewable power generators cannot be steered like it is possible with generators powered by fossil fuels (their output is of “intermittent” nature) and thus their output does often not align with the demand for power[3]. A supply-side response to this problem is that renewable energy sources are accompanied with technologies that can stabilise their supply levels, e.g. a base power plant or energy storage. On the other hand, a demand-side response happens when consumption follows supply, a setting which requires novel solutions for mechanisms to find allocations of electricity and assorted payments.

The predictability of solar and wind power is of high importance to the successful integration of renewables. It can vary substantially between locations. For instance,

[2] Of course, another way to replace fossil fuels is being more efficient while using energy.

[3] There are many methods of renewable power generation, but two of the most popular methods - solar and wind - are both of highly intermittent nature.

2

the North-African desert provides ample and stable solar radiation and wind blows stronger and more consistently a few miles off the coast than on shore. While solar radiation follows predictable patterns over seasons and the time of day, it can vary a lot due to movements of clouds [105]. Wind throughput can often be forecasted surprisingly well hours in advance but exhibits small sudden variations [41].

Another technical challenge to the operation of electricity systems is that many generators of renewable energy are small and will therefore be connected to the grid in a much more decentralised manner than traditional large-scale generators. In the traditional model, large generators are connected to the medium or high voltage grids and electricity is distributed to many small consumers connected to low voltage grids. When generators are also being connected to the low voltage grids, bi-directional power flows have to be managed, which adds significant complexity to the problem of power flow coordination [99].

Economically, renewable energy sources have high investment costs but almost no marginal (fuel) costs. This has strong effects on electricity prices and on the profitability of investments in electricity generation. If an electricity market is dispatching generation in the so-called merit order (ranking available sources of electricity in ascending order of their short-run marginal costs of production, as is the case, for example, in Germany), then electricity prices will be very low when a lot of renewable energy is available [111]. This negatively affects the ability to recover fixed investment costs of generation plants[4].

As was noted earlier, gas is a fossil fuel with low CO_2 emissions. It has the advantage that gas power plants can ramp up quickly and gas would thus be a promising partner technology for renewable energy sources. However, the effects discussed above are stalling investments in gas power plants worldwide, so it is crucial to develop market mechanisms that explicitly assign a monetary value to this flexibility.

2.1.c. Adding intelligence to the electricity grid

Current electricity grid management versus the "smart grid" concept

On the medium and low voltage level of contemporary electricity grids, there is very little real-time information available, which would be needed in order to operate equipment (e.g. generators or transformers) dynamically. Control signals cannot be sent to or received from most equipments either. Thus, the capacity requirements for many assets are estimated before installation and they are usually replaced when they cannot function any more. This approach leads to inefficiencies, which will become even more apparent in the dynamic circumstances that are being expected in the coming decades (due to trends on the demand and supply side that are described in Sections 2.1.a and 2.1.b).

The "smart grid" concept (e.g. [2, 89]) refers to current developmental efforts to add information technology to the electricity grid. It includes both the collection of real-time metering data about electricity usage and the introduction of automated decision-making based on this and other data. These efforts are supposed to increase fault tolerance and efficiency of network maintenance.

[4] Owners of solar panels in Germany are protected against this effect by the German Renewable Energy Act, which increases overall retail prices

An example for improved automated decision-making is a network switch which decides automatically to switch off, in order to protect one part of the connected households from problems in the other part. Furthermore, signals can be sent to connected devices, which enables real-time price communication to domestic consumers, which in turn allows to involve them in market mechanisms for energy, such as dynamic retail contracts. This can be crucial to involve small consumers and generators in peak curtailment (but requires that market mechanisms are designed that allow the participation of many participants with limited computational capabilities). Another large efficiency improvement is that smart meters can send usage data automatically to the utilities or retailers, making manual meter readings unnecessary. The Brattle Group (2009) [32] estimates that the combined advantages of smart meters EU-wide can outweigh the costs of purchase and installation (which are estimated at 51 billion Euros), if the right regulation is put in place.

Critics of this technology are concerned with privacy (asking where the data might be sent and whether it is stored) and the possibility to remotely shut off appliances (a feature which is becoming less and less popular and has been removed from the specification for smart meters in The Netherlands as of 2013). The roll-out of first-generation meters has begun in many countries. For instance, the Dutch government plans to have smart meters installed in 80% of households by 2020.

A SHORT HISTORY OF RESEARCH IN INTELLIGENT ELECTRICITY NETWORKS

The idea that the electricity grid would need to be managed better in order to continue to provide high levels of service dates back to the 1980s. The motivation was that the infrastructure was ageing, which increased the number of blackouts. Efficiency of operation was low, as supply quality was the only major engineering concern. However, the shrinking national budgets during that decade called for more cost-efficient approaches, which were supposed to lead to smarter investment strategies than the approach described in Section 2.1.c. Adding intelligence to the network was regarded as necessary among experts.

Paul Werbos (2011) [135] divides the last two decades of research and innovation (in adding intelligence to electricity grids) into four phases. In the first phase, beginning around 1990, investments in infrastructure increased. The grid needed modernisation, so wires and metering hardware moved into the focus. First fundamental research was done into more intelligent ways to address blackouts and efficiency, mostly by investigating unit commitment problems (the decision problem when which generator should be turned on, e.g. [91, 96, 107]). Many researchers came to the conclusion that the electricity system is a large-scale non-linear system, and that this complexity needed to be taken into account when modelling the problem.

In the second phase, beginning around 1998, concepts from control theory and computational intelligence were utilised in order to address the observed non-linearity [3]. In addition, load shifting began to move into the center of attention and with it the first concepts of dynamic tariffs for domestic consumers, for instance through time-of-day pricing. Finally, new wholesale market regulations introduced new central roles for high-level decision makers, such as the Independent System Operator (ISO). The developments during the second phase opened up a new range of optimisation problems.

During the third phase, which began around 2001, the focus lay on solutions for large-scale, stochastic and global optimisation problems, such as the problems that were conceived of in the second phase. In particular, agreement formed to maximise added value of any solution in the optimisation objective, and thus move away from making stability guarantees. Instead, outages or power quality problems became part of the optimisation objective. However, this discussion also made it clear that planning problems in energy systems are inherently multi-objective. In addition, the problem of formulating strategies for bidders in the recently established wholesale markets received increased attention (e.g. [19, 79, 140]).

The fourth phase began around 2009, and Werbos identifies two main challenges: First, the accommodation of large new loads (for example electric vehicles, refer to Section 2.1.a) and generation facilities (foremost by renewable generation refer to Section 2.1.b) into the distribution network. The wide-spread arrival of these new technologies within the next two decades is by now broadly accepted. Second, better solutions to the balancing challenge are necessary, especially "across time, in the face of uncertainty". This involves forecasting, planning and the coordination of this information. The reduction of peaks, large differences between demand and supply, takes over as the main goal of this phase. For this, demand response mechanisms, more generator ramping capabilities and advances in storage technology are essential.

The main research challenge (which can be addressed by computer science) is, according to Werbos, to improve the optimisation of peak reduction by employing intelligent agents in households: "massive load-shifting can be achieved in a system which allows intelligent agents to be inserted both at the grid level and at the household level". Current research focuses on categorising consumption devices according to the type of flexibility they offer (e.g. curtailable load, shiftable load and storable load [46] or uncontrollable, shiftable and buffer resources [18]) and then finding well-working strategies for each type. Meanwhile, acknowledgement is increasing among smart grid researchers that the goals of individual actors in the energy system do not always align with the system goals (for example to increase overall efficiency) and therefore the integration of market mechanisms with distributed intelligence concepts becomes highly relevant.

2.1.D. CHALLENGES TO INFRASTRUCTURE INVESTMENT PLANNING

Network capacity planning, the planning of investments in power networks, has always been a complicated problem [81, 138]. Assets in electricity grids (like cables, switches and transformers) have a long estimated lifetime and thus they need to be robust against a variety of possible future scenarios. An example is to build strong connections to a certain area because a factory is located there. Should the factory relocate long before the cable's lifetime ends, then the investment was misplaced. In addition, network capacity planning is an inherently multi-objective problem. It deals with deciding on investments at several locations with various types of network components and configurations, as well as different time paths for investing. Important objectives are optimal network capacity (so that future demand and production of electricity can be facilitated), minimal total costs and optimal technical performance of the network (meeting technical requirements with respect to power quality and network stability).

The new technical challenges mentioned in Sections 2.1.a and 2.1.b increase the complexity of this problem. There is currently much diversity in the technologies available for generation as well as consumption. In addition, there is much uncertainty which technologies will be relevant in a few years from now. Thus, it becomes more difficult to forecast where significant production and demand will appear. It is also hard to forecast how and if intermittent energy generation will result in peaks. Finally, the consequences of the resulting (bi-directional) power flows are not fully understood. Currently, modern optimisation techniques such as evolutionary algorithms are being developed to tackle these complexities in distribution network planning (e.g. [45, 80]).

However, the novel possibilities of adding intelligence to devices on the grid (as proposed in the "smart grid" concept outlined in Section 2.1.c) can actually make the planning of investments easier, as the installed hardware can now become more flexible and thus robust against many future developments. In addition, market mechanisms can be used to charge both suppliers and consumers for their usage of the electricity grid and return these charges to investors. Proposed mechanisms for this particular problem are Locational Marginal Pricing (e.g. [78]) and Financial Transmission Rights (e.g. [64]), but no mechanism for the solution of the cost allocation problem has of yet been universally agreed upon.

2.2. ECONOMIC MECHANISMS FOR ELECTRICITY

Electricity is a perishable good. Supply and demand in the system have to match in real time, due to Kirchhoff's laws. In addition, storing electricity is expensive. Thus, it becomes an important task in each time step to allocate electricity, meaning to decide which connections are supplied with how much electricity.

In this thesis, we take the point of view that individual decision-making about electricity can be organised efficiently via economic mechanisms, for example markets. The electricity grid provides a common platform, on which short-term relations between all connected actors can be described by selling and buying. If one actor increases his supply level (as a seller), he increases the frequency on the shared electricity network. Consequently, the overall supply available to all actors (who are interested in buying) increases[5]. Likewise, if one actor increases his consumption level (as a buyer), he decreases the frequency on the network and the overall available supply decreases. Furthermore, the grid is the only economically acceptable method of exchanging electricity between actors who are not within immediate proximity (if it has reached a high connectivity rate and quality of service, as for example in Europe).

[5] This straightforward relation can become more complicated if cable capacity limits are surpassed.

The basic function of an economic mechanism for electricity is to allocate electricity among actors for each delivery time. We define an allocation as follows:

Definition 2.1:
An allocation of electricity assigns, for a given delivery time, to each involved actor a quantity of electricity to produce or to consume and a payment to receive or to pay along with this.

Electricity can be traded in different ways and on different levels. We now provide a short overview. First, electricity can be allocated in long-term forward contracts (for instance, the length of one year is common), which a system operator typically negotiates with the operators of large power plants. Furthermore, there usually exists a wholesale market, which most often operates a day ahead of the time of power flow. In a wholesale market, large suppliers and consumers submit bids and a market operator finds allocations. Because wholesale markets operate ahead of time, ancillary service contracts (which describe options on providing supply on short notice) or balancing markets are needed, in order to equate supply with demand at the time of the actual power flow. On the retail level, retailers have long-term contracts with small-scale consumers and engage in forward contracts, wholesale markets and balancing markets to buy the needed quantities. Retail contracts commonly use fixed, constant prices, but might in the future also describe tariffs with flexible prices.

In this section, we give more details for both contemporary and innovative methods to arrive at allocations as defined in Definition 2.1. We first introduce relevant related work for market design, a field which has a rich history, originally in economics but nowadays equally also in computer science and electricity engineering. Market design is concerned with finding allocations, where both the choice of market mechanism and the format of bids are crucial. Then, we shift our focus to a crucial challenge within modern market design for electricity markets - the challenge of finding adequate monetary compensation for the service of offering flexibility, which is to be able to adapt supply or consumption levels on short notice.

2.2.A. MARKETS FOR ELECTRICITY

The electricity sector has been liberalised in many countries of the world during the recent decades, meaning that regulators move system operation tasks which were previously performed by government agencies to newly formed markets. This phenomenon is not unique to the energy sector, but happened next to the liberalisation of other business sectors, e.g. tele-communication.

The first core idea of liberalisation in the electricity sector has been to move from long-term forward contracts to wholesale markets, where large suppliers compete more often on a regular basis. Another very important idea has been to increase competition among retailers, by enabling contract choice for consumers. Finally, new regulation unbundles roles, meaning that large companies which previously performed several roles are being split up. In many countries, the roles of wholesale producer and retailer have been unbundled. Some countries have also unbundled the role of network owner and operator.

As an effect of liberalisation, the role of domestic consumers becomes more active. Furthermore, as an effect of technological trends, the role of the producer on the distribution level is emerging (see Sections 2.1.a and 2.1.b). It becomes necessary to revisit the design of electricity markets, because interactions between market participants happen more frequently, more trade partners and choices in contracts are available and new roles are created. This section discusses some fundamental properties of electricity markets[6].

BILATERAL AND MEDIATED TRADING

With respect to the trade of electricity, a broad distinction can be made between bilateral and mediated trade. In bilateral trade, buyers and sellers trade with each other directly. The search for the best party to make trade agreements with can be time-consuming, and the outcome of price negotiations can be very one-sided due to market power. In most countries, the government has therefore taken over the role of a mediator in electricity trade and independent spot market operators have begun operation during the last decade (e.g. the European Exchange EEX). A market mediator acts as an intermediate party which collects bids and offers from all other parties and determines an allocation for each participant.

The two most prominent types of mediated wholesale markets for electricity are power pools and exchange markets [86, 114]. The main difference between these two types is that power pools allow for many details to be included in the bids (marginal costs, as well as technical and contractual characteristics, e.g. ramping up and down times or so called "must-run" constraints), while exchange markets limit the level of detail in bids (they require only prices, quantities or functions that map between prices and quantities). This has consequences for both clearing algorithms and bidding strategies.

When we model a mediated market in this thesis, we model an exchange market. Exchanges have grown in popularity for the trade of electricity in recent years [114]. First, this is due to a solid foundation of research. Specifically for spot markets for electricity, Schweppe et al published their seminal work in 1988 [110]. Auctions are currently also popular for the trade of other goods, both in real-world trade and in research into other disciplines and thus, experiences from outside the field of electricity market design can be transferred. A second reason for the success of exchange markets is that requiring less details (than bids in power pools) eases access and thus increases competition. Less details in bids can also decrease the time it takes the mediator to find allocations, which can be crucial in settings like the ones described by the "smart grid" concept (see Section 2.1.c).

TYPES OF BID FORMATS IN ELECTRICITY AUCTIONS

The main types of bid formats used in auctions for electricity are described by the Bertrand model, the Cournot model, and the Supply Function Equilibrium (SFE) model. In *the Bertrand model*, sellers set prices and buyers choose quantities at that price. The Bertrand model works well if there are no capacity limits or transmission costs.

[6] This discussion is inspired by trends in electricity markets found in Europe as well as the U.S. However, most points made here apply to electricity markets in general.

When there are such constraints or costs, prices can rise above the marginal cost and even fluctuate without end [49]. In *the Cournot model*, companies compete on the amount of output they will produce, which they decide on independently of each other and simultaneously. The Cournot model is a more accurate model for contemporary energy markets than the Bertrand model (e.g. [11]). However, studies have shown that electricity prices often lie between what would be predicted on the basis of Bertrand and Cournot models. For this reason, supply functions [71] are used more and more [136].

Supply functions show the prices at which a firm is willing to sell different quantities of output. They combine Cournot and Bertrand modeling approaches [23], and, in addition, allow individual characteristics of costs or utility to be expressed in the function shape. This is a useful property in power markets, as generators sell an interchangeable product but total costs of production are usually non-linear. This is due to portfolios that contain differing generation facilities or to means of generation that operate more costly under high utilisation. Thus, bids often represent cost profiles that map a range of unit prices to the amounts of power which the seller is willing to sell at these prices and times (e.g. the electricity pools modelled in [87, 116] accept piecewise linear bids or several price blocks).

A second reason to use supply functions is given by Klemperer and Meyer (1989) [71]. They describe how supply functions are useful in multi-unit auctions when market outcomes are uncertain. In addition, supply functions are considered to increase competition [114]. It is important to realise that the format of bid functions which is valid in a given market affects the dispatch, revenue, and profit for generators [16]. Typical choices are quadratic functions and piece-wise linear functions. Neither can perfectly model true costs, but quadratic bids are used most commonly, as they allow calculus-based analyses to be performed [16].

2.2.B. ENABLING THE TRADE OF FLEXIBILITY

We have noted earlier (in Sections 2.1.a and 2.1.b) that the difficulty of balancing supply and demand in electricity systems is expected to increase, due to technological trends. Consumption peaks as well as the intermittency on the supply side are increasing. To dynamically store and release energy is still not feasible on a large scale (neither physically nor economically).

In the contemporary discussion of the balancing challenge, the need for flexibility is often mentioned. Future settings in energy systems require that many allocations are created or adapted on short notice (close to the time of consumption). While prices are in principle always negotiable (and thus the willingness of rational actors to offer flexibility services can be assumed to be present if economic conditions increase the expected compensation sufficiently), the physical ability to make such allocations possible is a hard constraint.

Consequently, we define being flexible (in the context of electricity markets) as follows:

Definition 2.2:
An actor can offer the service of flexibility if he is physically able of adapting his energy supply or consumption on short notice, to a level which has not been agreed upon in an earlier allocation.

For instance, a gas power plant is flexible, as it can start up on short notice. A coal power plant is inflexible, as it needs hours to adjust its output level. A wind mill is inflexible, as it depends on the wind speed. In fact, intermittent energy generation like wind power is partly responsible for the need for more flexibility (from other devices). Thus, as the significance of inflexible participants to the operation of electricity systems is on the rise, the value that flexible participants offer to the management of energy systems is increasing.

In their 2030 Framework for climate and energy, the European Union has set the target of “at least a 27% share of renewable energy consumption"[7] overall, which can of course be much higher during certain times of the day. Van Den Bosch et al (2010) [124] write that “present policy is to increase to 30% wind and solar energy, which will introduce larger uncertainties and more demanding arrangements for ancillary services.“

Novel economic allocation mechanisms for electricity should be designed such that the economic value of flexibility can be found and consequently be realised in financial rewards. Compared to current practice, the competition for flexibility should increase (many more flexible actors should be enabled to offer it and inflexible actors should be required to pay for it). Furthermore, prices should be more dynamic and the demand side needs to be included in such mechanisms on a broader basis.

In this section, we will discuss several ingredients to economic mechanisms which can enable the trade of flexibility, namely dynamic pricing contracts, trading ahead of time and the allocation of reserve capacity. We then look at a few implemented economic mechanisms and ongoing experiments.

FLEXIBLE TARIFFS FOR ELECTRICITY CONSUMPTION

The classical market models mentioned in the previous section mostly describe the integration of supply-side bidding, because until now the demand side could reasonably be assumed to be inflexible to changes in price. This is why today almost all consumers are subscribed to long-term contracts with fixed prices. Currently, most market policy designers aim to change this and expose consumers to prices which change throughout the course of a day. This will require more short-term economic decision-making from them. Whereas now the quantity which is consumed by domestic households (which represents around 30% of overall consumption) is an external input to the wholesale markets, it will change in reaction to wholesale market dynamics if domestic consumers are exposed to prices. This is commonly referred to as “active demand" or “demand response".

[7] https://web.archive.org/web/20151022194516/http://ec.europa.eu/energy/node/163

For most consumers, being exposed to wholesale market dynamics is most likely to be achievable if they are aggregated by a third party, whose business model is to buy electricity on the wholesale market on the behalf of their pool of consumers and establishes tariffs for electricity consumption with them. The role of this aggregator can be assumed by several parties, for example the operator of a charging station for electric vehicles. However, traditionally the aggregator role is assumed by the electricity retailers.

In order to incentivise their consumers to act flexibly, aggregators will have to move away from the current model of offering consumption contracts with fixed prices per kilowatt hour. There have been experiments with *time-of-use pricing* (e.g. [131]), where prices are defined, ahead of time, for different times of the day. The most known and technically straightforward example of time-of-use pricing are day/night tariffs, where simply two electricity meters are operated at the customer's premises. Another example is critical peak pricing [120], where a penalty price is applied to some periods which often exhibit consumption peaks. *Dynamic pricing* is a form of optimising revenues for a seller which involves changing the price of goods or services on the spot, based on current conditions like costs of supply or network states. Traditionally, it involves application areas where the capacity is fixed in the short-term and is perishable [25], and thus it is a good fit for electricity retail.

The major difference between dynamic pricing and time-of-use pricing is that dynamic prices are based on real-time information and are announced in real-time, while time-of-use prices are known in advance. An advantage of real-time information being used for pricing is that prices can steer supply and demand more accurately with respect to the system objectives (e.g. peak shaving). A disadvantage is that consumers can plan better with fixed, pre-announced prices (even if consumers are fully aware of a dynamic pricing strategy, they might not have all the information that is used in it). In this regard, we also note that for time-of-use pricing, consumption peaks have been observed that solely result from shared knowledge about an upcoming change in price. For example, a pre-announced drop in prices at 8:00pm leads to a consumption peak during 8:00pm and 8:15pm.

For both time-of-use pricing (with more than two prices, where simply two meters can be installed) as well as for dynamic pricing, more communication infrastructure, e.g. smart meters, are needed. The introduction of consumption contracts with dynamic pricing will of course also be subject to new regulation in order to achieve customer protection. For instance, a maximum price might be mandated such that overall consumption costs will always remain within some bounds.

Trading ahead of time

Currently, most of the electricity that is generated and consumed, is being allocated ahead of the time of actual power flow (also referred to as "time of delivery"). This holds for bilateral trade as well as mediated trade. The time difference between allocation and delivery may vary among market mechanisms between a year to a day ahead and could, in settings such as the smart grid concept (see Section 2.1.c), be even shorter.

Allocations made ahead of time (e.g. in a so-called "ahead market") have been found to increase competition. For example, Kamat and Oren (2004) [69] find that an ahead market decreases market power of generators. Veit, Weidlich, Yao and Oren (2006) [127] conduct a simulation study in which suppliers improve bids by reinforcement learning. They find that an ahead market lowers prices and their volatility. This is confirmed in simulations by Bower and Bunn (2000) [14], who credit this to higher demand elasticity in the ahead-phase. In general, trading ahead facilitates the planning for all involved participants. Inflexible participants can create demand for flexibility, while flexible participants can prepare to deliver flexibility.

Given the uncertainties inherent to energy systems, however, allocations made ahead of time will almost never be perfect. Many actors will find that they have to deviate from the amounts of energy scheduled to them in the allocation made ahead of time. For example, a retailer might need to buy more power, as the consumers who have contracts with him consume more than he had estimated. To match supply and demand close to the time of delivery, at least one more round of allocations (a "settlement") has to happen, in which necessary adaptations to the first settlement can be made. If this settlement is found via a market, that market is often referred to as "balancing market" or "spot market". If quantities of electricity are adjusted (for balancing), then the unit price of electricity might also be adjusted. For instance, the price for power might increase when the time of delivery comes closer. This allows an economic system to approach the true value of offering flexibility.

In addition to the objective to even out overall demand and supply on the grid (which is necessary due to physical laws, such as Kirchhoff's laws), another objective of adding a second settlement close to the time of delivery can be to adjust the flows in the network in order to protect parts of the grid. For example, the second settlement could relieve certain overheated cables by reducing generation in one location and increasing it in another.

A market system with two-settlements, an ahead market and a balancing market, is commonly referred to as "two-settlement procedure" (e.g. [69, 127]). Of course, more settlements can happen, when multiple periodic auctions are held (in a "multi-settlement procedure") or one continuous auction is open for bids at all times until a deadline before the time of delivery. A continuous auction clears two bids with each other whenever possible, while a periodic auction (also called one-shot or clearing house auction) clears all bids at once (after a given period has passed) simultaneously [98].

RESERVE CAPACITY

In order to reach high levels of service quality and efficiency, a system operator should ensure that those adjustments which are necessary to balance supply and demand or to protect the grid are physically possible. This is important if there is no resource (for the purpose at hand) which can be assumed to be limitless on short notice. For example, in a low voltage setting, one can often assume that the connection to the medium voltage grid represents a limitless resource. In a microgrid, however, this assumption can not be made. In addition, such an assurance by the system operator can be important if there is a limitless resource, but it can be assumed that it will ask for very high prices. One traditional approach is to ensure that some flexible actors are able to adapt their pre-planned behaviour on short notice, to some extent that is agreed upon ahead of time. Only if such an explicit agreement exists, can the system operator be certain that adjustments are possible.

The term “reserve capacity” is traditionally used as an umbrella term for several possible ways to implement this method of trading flexibility [36]. The most-used implementation is a supplier who reserves spare generation capacity for balancing out excess demand. The same service (which grid operators call “upward regulation“) can also be provided by a consumer reducing his consumption. Both solutions work against too little supply on the grid. On the other hand, a supplier could reduce his supply or a consumer could consume more than planned on short notice (this service would be called “downward regulation”), to tackle too much supply on the grid.

Because there is one point in time when reserve capacity is allocated and another point in time when it may be used for balancing, the use of reserve capacity integrates well with the two-settlement procedure, which we introduced in this section.

EXAMPLES

In the following, we list three important examples of the trade of flexibility, which are implemented (or are tested) in real-world settings.

- A traditional model is to allocate flexibility on a contractual basis, such that the seller is on stand-by for a longer period of time. These so-called “ancillary services” have traditionally been provided through upward regulation by suppliers, which was accomplished by several layers of services - the fast frequency response (reacts after seconds up until several minutes), the spinning reserves (reacts between 10 and 30 minutes) and operating reserves (reacts after 30 minutes). Ancillary services incurred almost the same cost impacts as transmission in 1998 in the US (12 billion versus 15 billion per year) [48]. The negotiated prices for providing ancillary services available as options are often quite high and their execution is not attached to positive incentives for their providers [123].

- Ancillary services have traditionally been contracts which were negotiated for longer service durations ahead of time (e.g. a year or a week), but it is not clear if this is the economically most efficient way to allocate flexibility. Another main model are periodic auctions, held ahead of time for every upcoming time slot. Compared to long-term service contracts, these auctions can increase competition significantly, because all actors can take part whenever they have flexibility to offer.

  We have mentioned several types of auctions which are implemented as wholesale markets. Many real-world examples are implemented as two-settlement procedures (see above, this section) and also make use of reserve capacity (see above, this section). They add the trade of reserve capacity to their first settlement and then allocate balancing requirements from this reserve capacity in the second settlement, if necessary (e.g. [87, 116]). However, bidding in these advanced two-settlement procedures is quite complex.

- Another important model are flexible retail contracts (see above, this section). Consumers choose a contract from a retailer. If they pick a contract with a dynamic tariff, they assure the retailer some flexibility. When the retailer needs to balance his portfolio, he increases prices to some extent and lowers his aggregated demand. The differences between the classic ancillary service contracts described above are therefore not only that flexible retail contracts deal with consumption, but that the price is dynamic. Flexible retail contracts exist for large industrial consumers, but so far little development has taken place in the domestic consumer retail market. Several real-world trials have been conducted (e.g. [9, 33]), with mixed results.

2.3. THE STUDY OF COMPLEX SYSTEMS WITH AGENT SIMULATIONS

We outlined in Section 1.3 that we aim in this thesis to develop novel solutions, such as mechanisms and strategies, for settings in future energy systems, where small actors will be involved in real-time economic decision-making. Thus, our solutions will have to be evaluated in an electricity engineering context as well as an economic context.

The continental European electricity grid is the largest synchronously working machine in the world [28]. Its operation depends on many independent factors and technological constraints and to operate it with high security of supply and energy efficiency is a major engineering challenge. On the other hand, human economies are commonly counted among the most complex man-made systems [7]. This is due to the wide range of economic allocation mechanisms within which decision makers interact, the limitless set of strategies available to them and the many possible interactions that exist between economic decisions and the rest of the physical world.

Thus, to perform scientific research which should lead to novel solutions applied in both an electricity as well as in an economic context poses a major challenge to modelling. How can our research into these complex settings lead us to valuable insights? More specifically, we have two decisions to make: What method of modelling allows us to include sufficiently many details about problem settings but is still useful for the evaluation of solutions? And by what method should we evaluate solutions in order to generate conclusions? In this thesis, we answer the former question with agent-based modelling and the latter question with stochastic simulations.

2.3.A. AGENT-BASED MODELLING

Ever since Schelling (1971) [109] demonstrated in his work on segregation that surprising macro-effects can be based on continuous individual decision-making, modelling of systems which include many interactions by using the multi-agent metaphor has become an important approach within the social sciences. The trend of increasing computation power in recent decades has enforced this approach, as it became possible to compute many scenarios within acceptable time.

Examples of modern descriptions of agent-based modelling in computer science are given by Wooldridge (1997) [137] and Jennings (2002) [61]. This type of modelling employs separated programs called “intelligent agents” to represent autonomous decision makers and their goals in some environment. These agents receive information about changes to their environment and reach a decision on how to act appropriately with respect to their own goals. Agents can complete their objectives while situated in a dynamic and uncertain environment and can operate within flexible organisational structures. From a computer theory standpoint, an agent can be seen as a Turing machine with added ability to perform input and output actions, supporting dynamic interaction with an environment [133].

A system consisting of several, interacting agents is called a "multi-agent system". Agents in multi-agent systems can be heterogeneous, have a complex model of their environment (including other agents) and make use of a memory about previous interactions with each other. This sets a multi-agent system apart from systems with simpler components, for example from particle-based models, where particles are in different states, but commonly act on precisely the same rules, consider only their own previous state as input and act without (further) memory.

Agent-based modelling is often used in the study of economic systems. Tesfatsion (2002) [118] makes the case for a new branch of economics called "agent-based computational economics (...), a specialization to economics of the basic complex adaptive systems paradigm." Markets for electricity have been studied with the help of multi-agent systems by several researchers during the last decades, amongst which the group of Leigh Tesfatsion herself (e.g [102, 111, 115, 127]). Weidlich and Veit (2008) [134] have compiled an extensive survey on agent-based models of electricity markets.

2.3.B. COMPUTATIONAL SIMULATIONS

In addition to deductive and inductive reasoning, computational simulation is about to become a third pillar of the scientific method [82]. For very complex and dynamic settings like multi-agent systems (see above), where it might be impossible to form closed-form mathematical expressions of the problem at hand, simulation can even be the primary method to reach novel insights. Axelrod (2003) [5] calls simulations "an effective tool for discovering surprising consequences of simple assumptions". Simulations are also very useful to get insights into different scenarios.

Because of the high uncertainties inherent to the problem and its many degrees of freedom, we need to design simulations that repeat the same settings many times, with selected input parameters randomly sampled from statistical distributions. This method, often referred to as the Monte-Carlo method, allows to interpret results with statistics, e.g. by reporting the average over a number of repetitions. The design of stochastic simulations has therefore seen increased attention in recent years (e.g. [65, 72]).

3

ABEM - A NOVEL TWO-SETTLEMENT MARKET MECHANISM FOR ELECTRICITY

3.1. INTRODUCTION

In future energy systems, novel supply and demand patterns pose novel challenges for the economic allocation of electricity. Intermittent renewables increase the uncertainty on the supply side and new consumption technologies, e.g. electric vehicles, enable the demand side to become more flexible. In recent years, centralised mediated markets for electricity, e.g. auction mechanisms, have been developed and employed on the wholesale level to increase competition and find better economic allocations. Another trend to combat these challenges, often referred to as the “smart grid“, is to delegate more decisions on lower levels of the grid to intelligent software, which operates production or consumption devices on their owner’s behalf. This can be especially useful to integrate flexible demand devices.

In a smart grid setting, many actors with limited computational capacities interact. This makes it difficult to re-use market designs which have been developed on the wholesale level, where only a few big players interact who have many capabilities to optimise their bidding behaviour. In this chapter, we present and evaluate a novel market mechanism called ABEM. ABEM is inspired by recent developments in wholesale market design for electricity, but is better suited for smaller, non-sophisticated players. It also addresses some inherent design problems that current implementations have.

ABEM belongs to an important class of multi-settlement market mechanisms (see Section 2.2.b). In particular, this class contains two-settlement markets which integrate the trade of reserve capacity and require simultaneous bidding for the two settlements. Several instances of this class are currently implemented as state-of-the-art mechanisms in wholesale electricity markets. Market mechanisms of this type serve several purposes: They facilitate planning by conducting an *ahead market* (the first settlement) which results in binding commitments. In addition, they allow adjustments to these commitments in a real-time *balancing market* (the second settlement). To improve stability, the first settlement also allocates *reserve capacity* from flexible actors, which can be used in the second settlement if needed. However, current implementations of such mechanisms require bidders who want to achieve success in many different scenarios to conduct complex computations to construct bids. This can become problematic in smart grid settings. In addition, the two bids (which are used in the two settlements) contain no explicit relationship to each other and can not both be price functions. Since both the costs of generating electricity as well as the utility of consuming it are usually described by bidders on non-linear functions, this means that these mechanisms restrict the bidders in efficiently expressing their economic valuation.

ABEM is an abbreviation of "**A**head- and **B**alancing **E**lectricity **M**arket". With the development of ABEM, we address the first two of the research questions we state in Section 1.3, in that it proposes an effective market mechanism that can deal with flexibility and uncertainty in supply as well as demand and is also usable for bidders. The ABEM mechanism has two unique features: First, bids for binding commitments as well as for reserve capacity are combined into one bid. Second, the bid specifies a quantitative relationship between binding commitments and reserve capacity.

ABEM provides several main advantages by design: First, the bid optimisation problem for bidders is reduced in complexity from a two- to a one-dimensional problem, which significantly reduces the time necessary to compute well-working bids. Second, bidders can bid price functions to both markets, potentially their true costs or valuation, which is problematic if two separate bids have to be constructed. Third, the mechanism provides a guarantee for flexible consumers that offering reserve capacity increases their overall surplus (if the marginal valuation is submitted as bid).

Evaluating a market mechanism is a complex undertaking, especially if it serves multiple purposes. This chapter establishes the basic principles of evaluating ABEM. An important question to investigate is whether it makes economical sense for flexible market participants to take part in the ABEM mechanism. Another, equally important question is whether they use the ABEM mechanism as intended, for example whether they exploit settings in which they possibly have excessively high market power. A model for investigating these questions should include as many details as needed, but should also be simple enough to allow conclusions to be drawn. We design a decision-theoretic model, which allows us to vary market settings and the economic situation of one bidder taking part in an ABEM mechanism. We model the bidder both as a flexible supplier and as a flexible consumer. Both are able to provide so-called upward regulation during the second settlement. The supplier is able to supply more power and the consumer is able to consume less power than planned. We perform Monte-Carlo simulations and record the overall outcomes for the bidding agent. We compare ABEM with a benchmark market mechanism, in which bids are also submitted simultaneously and also specify a quantitative relationship between binding commitments and reserve capacity (as in ABEM), but the bidding for both of these goods happens via two independent bids.

In these computational simulations, we are able to answer our questions from above: From the bidding agent's perspective, the same levels of overall economic surplus (on average across all tested settings) can be reached in both ABEM and the benchmark mechanism. The simulations also confirm that the bidding agent's bids are much more efficiently computable if he takes part in ABEM. Furthermore, from the SO's perspective, we show experimentally two advantages of ABEM over the benchmark mechanism. First, overall prices and the bidder's market power are reduced in settings that are highly strategically exploitable by the bidding agent. Second, offered reserve capacity is made available for balancing at affordable prices, whereas the bidding agent in the benchmark mechanism would often prefer to overprice it, in order to avoid costs of lost opportunity.

This chapter proceeds as follows. Section 3.2 provides more details about two-settlement procedures with integrated trade of reserve capacity and simultaneous bidding. We also review some economical concepts of interest to this work. We give a problem statement for the design of a relevant market mechanism in Section 3.3. Section 3.4 introduces the ABEM mechanism - we explain the bid format of ABEM, provide the market clearing procedure and explain the advantages ABEM has by design. We then provide a parametrised decision-theoretic market model in Section 3.5, which a strategic agent can use to model his bid optimisation problem in a two-settlement procedure of the kind we are interested in. In Section 3.6, we evaluate ABEM experimentally. We simulate participation in an ABEM market for the two types of bidders we consider in this work (a flexible supplier and a flexible consumer, providing upward regulation) and discuss the results. The final section concludes and discusses future work.

3.2. BACKGROUND

3.2.A. TWO SETTLEMENT PROCEDURES WITH INTEGRATED TRADE OF RESERVE CAPACITY AND SIMULTANEOUS BIDDING

In this section, we provide background on the subset of market mechanisms we focus on in this work. As was discussed in Section 3.1, many wholesale electricity markets operate with a two-settlement procedure, using an ahead market in combination with a real-time market, in implementations with slightly differing characteristics (e.g. [59, 116]). The term "two-settlement procedure" stems from the Standard Market Design issued by the Federal Energy Regulation Commission (FERC)[24] in the U.S.A. In addition, some two-settlement mechanisms (e.g. [87]) also integrate the trade of reserve capacities. ABEM is a novel market mechanism, which performs a two-settlement procedure while also integrating the trade of reserve capacity. In this section, we give more details on the general bidding procedure in these mechanisms and on procurement of reserve capacity by the System operator (SO). Then, we narrow down the subset of market mechanisms we consider further by arguing for an important design decision - that bids for both settlements are submitted simultaneously.

THE TWO SETTLEMENTS

Two-settlement mechanisms are usually mediated markets. There, the SO acts as a mediator between all market participants, suppliers as well as consumers. He collects their bids and arrives at allocations by a process referred to as “market clearing”, which accepts a number of bids on both sides. On both the supplier’s and the consumer’s side, we differentiate between flexible bidders and inflexible bidders.

First settlement - the *ahead market* First, all bidders submit a bid to buy or sell some quantity on the *ahead market*. If their bid gets accepted, they are allocated a binding commitment to supply or consume at the specified time. To trade in an ahead market enables participants to plan their activities in an uncertain environment. In the wholesale market designs mentioned above, the ahead market is traditionally held one day ahead of time. In more dynamic market settings, e.g. in smart grid settings, shorter intervals are possible.

In addition to bids for binding commitments, flexible bidders submit a bid to the ahead market for reserve capacity. An actor who offers reserve capacity describes in this bid a range of possible deviations from his binding commitment. One deviation from this range will be allocated in the second settlement. In this work, we consider the (currently) most prevalent form of reserve capacity, namely the provision of “upward regulation”. This entails the supply of more electricity than was sold in the binding commitment (here, deviations are possible even if no binding commitment exists) or the consumption of less energy than was bought in the binding commitment. “Downward regulation”, i.e. supplying less or consuming more electricity, will be increasingly important in future electricity systems, as well.

The first settlement clears both kinds of bids on the ahead market. For each actor with an accepted bid, the SO allocates a number of binding commitments and a range of possible deviations from them as reserve capacity.

Second settlement - the *balancing market* The bidding for optimal deviations happens in the second settlement. Here, inflexible actors can buy power on short notice. They need to make such adjustments to their binding commitments from the first settlement due to imperfect planning, e.g. because less wind blows than an supplier forecasted or because the realised aggregated demand of an retailer’s customers is different than projected. Because these needs for adjustments bring the allocation from the first settlement “out of balance”, the second settlement is often referred to as a *balancing market*. Whether these adjustments happen through the provision of extra supply (by flexible suppliers) or by reduction of consumption (by flexible consumers) is of no importance to inflexible actors.

To summarise, each unit of electricity that is put to use during the time of consumption has either been traded in the ahead market or was reserved in the ahead market and has then been traded in the balancing market. Figure 3.1 illustrates the timeline of the two settlements.

Procurement of reserve capacity

The SO carries the responsibility to balance supply and demand in real time. To be sure that this responsibility can be fulfilled, he requires that reserve capacity is allocate from flexible market participants. Only relying on a real-time balancing market

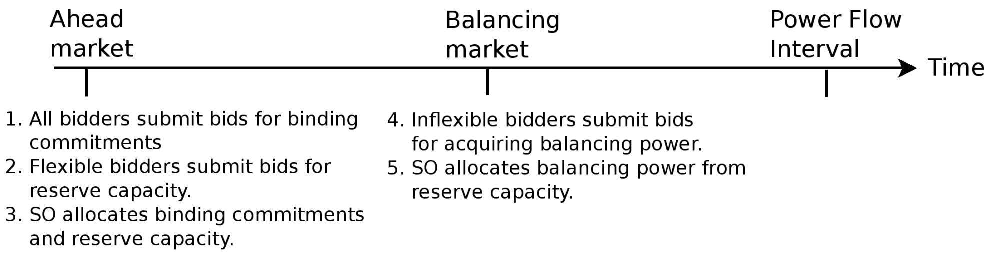


Figure 3.1: Timeline in a two-settlement procedure with integrated trade of reserve capacity and simultaneous bidding.

without reserve capacities could not provide enough certainty that imbalances can be met. While pricing of activated reserve capacity is often dynamic, the SO has often to impose his reserve requirements on flexible market participants to procure as much as reserve capacity as he deems necessary.

Choice of amount - In most real-world markets, the choice how much reserve capacity is acquired is based on static heuristics. For example, one heuristic is to require as much reserve capacity as is the capacity of the largest power plant. Another possibility is to require a certain percentage of historical peak capacity (of a comparable time slot). The Dutch Transmission System Operator TenneT claims all remaining capacity of suppliers with binding commitments and an overall capacity of more than 60 MW [116]. The Midwest System Operator (MISO) in the U.S. calculates an overall amount from forecasted load [87]. Finally, the SO can also choose the amount of required reserve capacity by experience.

Procurement - Having chosen a required amount, the SO needs to procure enough reserve capacity from flexible suppliers and/or flexible consumers. He can negotiate long-term ancillary service contracts or require the actors that are present in the ahead market to offer reserve capacity by some means. For example, refer to the method TenneT is employing or consider that the MISO calculates a reserve capacity obligation for every market participant based on their maximal capacity, which they have to make available themselves or buy from other participants.

Pricing - In the case of ancillary service contracts, the price paid for the service of short-term balancing has been fixed beforehand during contract negotiations. On the other hand, if market participants offer reserve capacity, they can place bids for its execution during the two-settlement procedure, as described above in this section. Including the trade of reserve capacity leads to negotiations about the price of balancing power that happen more frequently and more closely related to the time of power flow in question. Thus, more relevant information should be available during these negotiations, which increases competition.

SIMULTANEOUS BIDDING

Although they are, at the time of consumption, delivered together as an indistinguishable product, power that was sold as a binding commitment in the ahead market and balancing power are priced completely independently in current versions of the two-settlement procedure. An important question for the market design is when to submit the bids for each type. Most scientific literature which discusses this issue (e.g. [63, 139]) favours simultaneous models (submit bids for the first settlement at the same time as bids for the second settlement) over sequential ones (submit bids for the second settlement after the first settlement is over), as the re-commitments in the second auction can lead to inefficient allocations through strategic bidding [48, 95].

For example, Kamat et al. (2002) [68] report that holding back bids in earlier stages becomes a profitable strategy to increase prices. Vandezande et al. (2010) [126] observe that often strong incentives exist to not offer reserve capacity on public markets at all, but rather balance privately owned assets only. An example for a real-world implementation with simultaneous submission of bids is the Midwestern market in the U.S. [87]. ABEM requires simultaneous submission of bids to the ahead- and balancing markets[1].

3.2.B. Economic concepts for models with strategic decision makers

In this section, we provide some background on concepts from the economic sciences, which we make use of in this chapter.

Marginal values and surplus

The marginal value for a given quantity denotes the cost of producing the last unit or the utility of consuming the last unit. It is an important concept used in the economic analysis of bidding strategies in multi-unit commodity markets with unit prices (like ABEM). We will now define the marginal value function as the derivative of the total value function and briefly discuss producer and consumer surplus.

In this work, we assume that the marginal cost function of a supplier is monotonically increasing and that the marginal utility function of consumers is monotonically decreasing. This follows from the economic assumption that those units which cost the least to produce are produced first and that each consumed unit will increase utility less than the one which was consumed before it. We also assume these properties hold for bid functions, which represents that higher prices increase supply and decrease demand. We consider only variable costs and do not model fixed costs explicitly. This leads us to model producer and consumer surplus (which we define below) instead of economic, long-term profit.

Producer's surplus is defined as the revenue that a supplier receives for his delivered quantity minus the variable costs of producing it (where revenue is defined as quantity times unit price). Consumer's surplus is defined as the utility derived from consuming a quantity of goods (which is the highest value that the consumer is willing to pay) minus the price he actually paid for it.

Let a bidding agent a represent his total costs, during an interval of time with fixed length, of generating a quantity q of electricity or, alternatively, his total utility of consuming a quantity q of electricity, by a valuation function V_a. We assume in this chapter that quadratic functions adequately model non-linear dynamics of cost and util-

[1] Note that while bid submission is simultaneous, allocation is still sequential - binding commitments are allocated right after all bids are in, but the allocation for balancing power happens closer to real time, when the need for balancing power becomes apparent.

ity, e.g. as advocated for in [16] and modelled in [115]. V_a and the marginal valuation function V_a' (the derivative of V_a) are given by

$$\begin{aligned} V_a(q) &= v_a q + \delta_a q^2 \\ V_a'(q) &= v_a + 2\delta_a q \end{aligned} \tag{3.1}$$

where $v_a \in \mathbb{R}$ and $\delta_a \in \mathbb{R}$ are coefficients. Furthermore, $\delta > 0$ for cost functions and $\delta < 0$ for consumption utility functions. v_a denotes the value of the first unit in q and δ_a denotes (half of) the change in value of every further unit produced or consumed.

The marginal value function V_a' differs from the average value function V_a^{avg}, which is given by

$$V_a^{avg}(q) = \frac{V_a(q)}{q} = v_a + \delta_a q \tag{3.2}$$

Selling or buying at average value lets a break even. Selling or buying at marginal value yields surplus for a. Sellers sell all units but the last above their production costs (and gain so-called producer surplus) and buyers buy all units but the last below the utility of consuming them (and gain so-called consumer surplus). This surplus can be used to cover fixed costs.

OPTIMAL QUANTITIES FOR SUPPLY AND CONSUMPTION

We now present a property of multi-unit commodity markets with unit prices, which describes the optimal quantity for a bidder to buy or sell. A corollary of this property is that, in a market with perfect competition, the marginal valuation represents the bid which maximises surplus. Refer to above for the definitions of the marginal valuation function V_a' and producer's and consumer's surplus. In the following, we consider a as a supplier, but the discussed property applies in symmetrical fashion to a as a consumer.

Let MR_a be the marginal revenue function for a (see e.g. [100]). MR_a describes additional revenue generated by selling one more unit. Furthermore, let the market demand function D describe the price that consumers in the market are willing to pay per quantity. Under perfect competition, MR_a is equal to D, i.e. a's output level has no influence on the price he can achieve. Under imperfect competition, e.g. an oligopoly, the slope of MR_a is always higher than the market demand price function [88]. For illustration of a's strategic bidding decision, see Figure 3.2.

Economic theory states that, in order to maximise the producer's surplus, a supplier should aim to sell q units, such that $V_a'(q) = MR_a(q)$. This property holds[2] under a wide variety of market conditions (perfect competition, monopoly, monopolistic competition, and oligopoly) [17].

Under perfect competition, a would bid his marginal costs in order to maximise his surplus. Under imperfect competition, e.g. an oligopoly, a would increase his bid from his marginal costs, in order to realise the surplus-maximising output q, such that $V_a'(q) = MR_a(q)$ [106]. This behaviour is of course limited by a's ability to model the

[2]For cases in which more than one intersection of V_a' and MR_a exist (e.g. with non-linear marginal functions), the second-order condition that the slope of V_a' is greater than that of MR at their point of intersection is needed, as well, in order to maximise surplus.

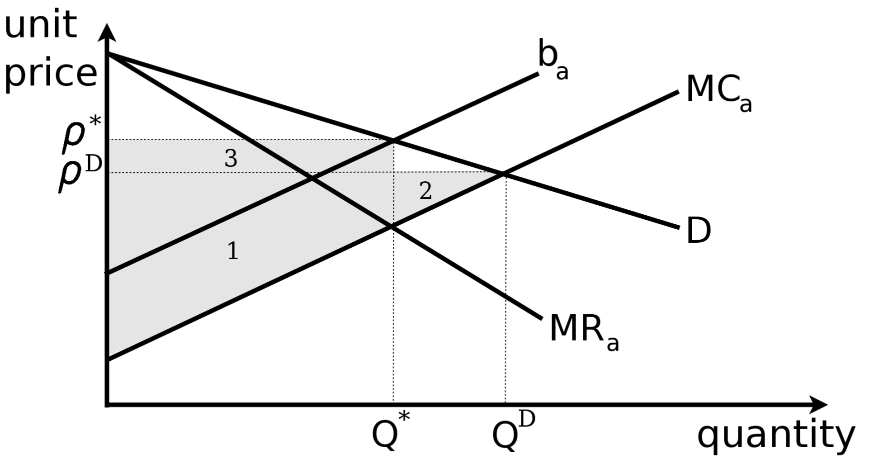


Figure 3.2: Illustration of optimal output of a supplier a. The function MC_a describes a's increasing marginal costs. The marginal revenue function MR_a has a higher slope than the market demand function D, which is the case under imperfect competition. Economic theory states that a aims at selling Q^*, such that $MC_a(Q^*) = MR_a(Q^*)$ to maximise his surplus. If he bids MC_a, a's surplus is given by the areas labelled 1 and 2 (selling Q^D at price ρ^D). Because he bids b_a instead (selling Q^* at price ρ^*), his surplus is given by the areas labelled 1 and 3.

functions MR_a and D appropriately, as well as by the degree of competition (see also below in this section, where we discuss market power).

To conclude, this section describes a property of multi-unit commodity markets with unit prices, which states that the optimal quantity of a bidder is given at the value where the marginal value function equals the marginal revenue function. This allows to make some assumptions about surplus-maximising behaviour of strategic agents in such markets, where one should differentiate between settings with perfect and imperfect competition. In the former case, bidders should bid their marginal valuation. We make use of this property in Section 3.4.c, where we describe a property about bidding behaviour in ABEM, which holds when a is a consumer and bids his marginal utility, i.e. when he takes part in perfectly competitive market setting. We also investigate scenarios with imperfect competition for both suppliers and consumers in ABEM, in the experiments which we describe in Section 3.6.

Uniform versus discriminative pricing in auctions

Two general approaches to pricing in auctions exist [74]. So-called uniform-price auctions (UPA) select only one price for all accepted bids, e.g. all sellers are paid the price of the highest accepted bid. So-called discriminative pricing auctions (DPA) select a unique price for each bidder which is based on their bid (they are also referred to as "pay-as-bid“ auctions). The choice between the two types of auctions has implications on the strategies which bidders select and research into the different effects on market outcomes is ongoing. Generally, UPA designs have been found to result in more efficient allocations, but DPA designs decrease prices and market power (e.g. [21, 30, 39]).

Many electricity market designs in the last two decades have used UPA designs. However, the last decade has also seen some markets in the form of discriminatory pricing auctions, for example the England and Wales wholesale electricity market in March 2001. In Section 3.4.b, we present two versions of market clearing in ABEM, one for a DPA and one for a UPA design.

MARKET POWER

To describe the influence of one actor on the market in the face of competition, economists use the concept of market power. In current electricity markets, market power is concentrated on the supply side. The main reason for this is that demand is currently inelastic and therefore predictable. Demand is the least elastic when allocation decisions are made close to the time of consumption, and thus it is during balancing when market power becomes most visible [114].

Market power is defined as "the ability to alter profitably prices away from competitive levels" [85]. Nicolaisen et al. (2001) [93] distinguish structural market power (which exists in the case where all traders reveal their marginal costs) from strategic market power (which exists in the case where traders misrepresent marginal costs in their bids). To tackle this problem, power market designers have been searching for the best trade-off in bid format design, which allows bidders to freely express their economic preferences, but also restricts them artificially in order to limit the exercise of market power. For instance, Baldick (2002) [6] mentions that quadratic terms in the bids could be limited or bids could be required to be consistent across multiple pricing-periods. The latter method is used in some markets in the U.S.A. (e.g. [24, 87, 115]). There, one bid in the day-ahead market is used to clear all time slots of the following day. Another method is to simply limit allowed price ranges [114].

We measure the market power of the flexible supplier in the experiment in Section 3.6, where we compute the so-called Lerner index $\in [0,1]$, defined by dividing per-unit surplus by unit price (see Section 3.6.a).

3.3. PROBLEM STATEMENT

In this section, we identify four design challenges inherent to the design of any market mechanism from the class of market mechanisms we describe in Section 3.2.a. Problems 3.3.a and 3.3.b stem from the fact that two independent bids are being submitted simultaneously. Challenge 3.3.c and 3.3.d are important in the design of all market mechanisms. Each challenge will be referred to in later sections when we show how ABEM can be a solution for it.

3.3.A. BID OPTIMISATION IS COMPLEX AND DIFFICULT.

Each bidder faces an optimisation problem when constructing bids, which is quite complex in two-settlement mechanisms with two independent bids. The reason is that the evaluation of a bid for the binding commitment has to take into account the effects which this bid has on the performance of all possible bids for reserve capacity, and vice versa. This means that many possible outcomes have to be taken into account. Thus, the computational effort to compute a well-performing bid can be substantial.

In addition, it is difficult to find well-working bids, because a bid in one market cannot explicitly refer to outcomes in the other market. This can become a problem considering that offering reserve capacity leads to (lost) opportunity costs (costs when reserve capacity is not sold during balancing and other opportunities for income from this capacity have not been pursued). To compensate for opportunity costs in the bid for binding commitments is difficult because the amount of reserve capacity is unknown while the bid for binding commitments is formed. Only few proposals to tackle this problem exist. For example, Virag et al. (2011) [129] propose an iterative market design, where in each round the market maker proposes two market prices (for binding commitments and for reserve capacity) and the market participants update the quantities they would sell or buy at those prices. This runs until conversion, but the runtime properties of this dynamic method are uncertain. This can become especially problematic when the time to reach consensus is constrained, for instance in smart grid settings.

3.3.b. The bid format restricts efficient expression of economic value.

We laid out in Section 2.2.a that the Bertrand model (bidding only one price for all possible quantities) is not regarded as the most efficient way to design a power market, where bidders have non-linear value-functions and uncertainty is high. Ideally, both the bid to the ahead market as well as the bid to the balancing market should be functions that map prices to quantities. Current market versions work with bid functions for the ahead market. However, in order to keep the construction of two independent bids reasonably simple (refer to Challenge 3.3.a), they restrict bids for reserve capacity to only a constant unit price.

Furthermore, we explained in Section 3.2.b that in competitive settings, the marginal value function equals the profit-maximising bid. However, if two separate bids are required by the market mechanism, the marginal value function can not be submitted.

3.3.c. Bidders should be economically incentivised to use the mechanism.

A market mechanism can only be successful if bidders make offers. A very important question is therefore whether bidders will use the mechanism. For example, we can only expect participation if a mechanism is individually rational - it should make economical sense for bidders to take part in the mechanism, compared to not taking part in any mechanism at all. We are particularly interested in a question that asks for more than only individual rationality: Are bidders able to make the same amount of surplus as in comparable mechanisms? If not, they will probably decide to use other mechanisms or request that the current mechanism is replaced.

Furthermore, for the scenarios we consider in this work (performance of two-settlement procedures in future energy settings), another question is of importance in comparison to other market mechanisms. Offering reserve capacity can create costs of lost opportunity, if this capacity is not sold. This is especially crucial in market settings with high uncertainty about market outcomes. How does this affect the bid optimisation problem of flexible bidders? Will they offer reserve capacity at affordable prices, or will they overprice it, in order not to only be active on the ahead market?

3.3.D. IN SOME SETTINGS, SUPPLIERS HAVE EXCESSIVELY MUCH MARKET POWER.

We discussed the existence of market power in electricity markets in Section 3.2.b, which is defined as "the ability to alter profitably prices away from competitive levels" [85]. Bidders should have freedom to express their economic preferences, but in settings that allow a small number of bidders to have excessive market power, the mechanism's method to determine prices should limit this ability.

3.4. THE ABEM MECHANISM

3.4.A. BID FORMAT

In this section we define the format in which bids for goods are submitted. Note that from now on, we denote the ahead market (the first settlement) as "market A" and the balancing market (the second settlement) as "market B".

We first define variables for quantities, which are allocated to a as a result of the allocations in market A and market B, and introduce a ratio between binding commitments and reserve capacity per bidder, which is a crucial property of the ABEM bid format. Next, we define components of a bid in ABEM, with special attention to the bid function. Finally, we show how bids which got accepted in market A are put to use in market B.

ALLOCATION VARIABLES AND THE RATIO BETWEEN BINDING COMMITMENTS AND RESERVE CAPACITY

For each bidding agent a, we denote with $Q_a^A \geq 0$ the binding commitment, which is allocated in market A and with $Q_a^B \geq 0$ the usage of reserve capacity which is allocated in market B. If a is not flexible and thus demanding reserve capacity (in the form of upward regulation) in market B, $Q_a^B < 0$. If a is flexible and thus offering reserve capacity, $Q_a^B \in [0, Q_a^R]$, where we denote with $Q_a^R \geq 0$ the amount of reserve capacity which a flexible bidding agent a agrees to hold.

When a is a supplier, he supplies $Q_a^A + Q_a^B$. The maximal amount a could supply is in this case $Q_a^{max} = Q_a^A + Q_a^R$, where $0 \leq Q_a^{max} \leq Q_a^U$. On the other hand, when a is a consumer, a consumes $Q_a^A - Q_a^B$ and the maximal amount a could consume is in this case $Q_a^{max} = Q_a^A$, where $0 \leq Q_a^{max} \leq Q_a^U$.

In the remainder of this section, we explain how the reserve capacity Q_a^R is defined in relation to Q_a^A. Each agent a chooses a ratio $r \in [0, 1]$ per bid $b_{a,r}$. With r, the reserve capacity Q_a^R can be described as a ratio of the binding commitment Q_a^A and is given by:

$$Q_a^R = rQ_a^{max} \tag{3.3}$$

For the case that a is a supplier, we can compute $Q_a^R = \frac{rQ_a^A}{1-r}$ by inserting $Q_a^A + Q_a^R$ for Q_a^{max} (see above). When a is a consumer, this translates to $Q_a^R = rQ_a^A$ (because $Q_a^{max} = Q_a^A$, see also above). Let us consider an example where a submits a bid with

$r = \frac{1}{3}$. For the case when a is a supplier, $Q_a^R = \frac{1}{3}Q_a^A/\frac{2}{3} = \frac{Q_a^A}{2}$. When a is a consumer, then $Q_a^R = \frac{Q_a^A}{3}$.

At $r = 0$, no reserve capacity is offered in market B and a has full certainty how much he sells or consumes after market A has cleared ($Q_a^{max} = Q_a^A, Q_a^R = 0$). Thus, inflexible bidding agents submit bids with $r = 0$ and offer no reserve capacity. For the special case $r = 1$, we define that all of a's capacity up to Q_a^{max} is flexible to be allocated as Q_a^B in market B. Then, if a is a supplier, $Q_a^A = 0$ and $Q_a^{max} = Q_a^R$, and if a is a consumer, $Q_a^R = Q_a^A$.

3

Bid components

A bid in ABEM by a bidder a consists of a function $b_{a,r}$ which maps marginal prices to quantities of power (Q_a^A in market A and Q_a^B in market B). It includes the ratio r (see Section 3.4.a), which is unique for $b_{a,r}$. A bid in ABEM also contains lower and upper quantity limits $Q_a^L \geq 0$ and $Q_a^U \geq 0$, which are unique for a.

We restrict the function in bids to continuous linear functions. This allows for simpler optimisation during market clearing [16], but limits the ability to represent non-continuous costs like the costs of starting up or down a generator or switching from charging to discharging. Thus, ABEM is an exchange market rather than a Pool market (see Section 2.2.a). Furthermore, exchanges can implement continuous or periodic auctions [98]. A continuous auction clears two bids with each other whenever possible, while a periodic auction (also called clearing house auction) clears all bids at once (after a given period has passed) simultaneously. Periodic auctions are considered more efficient, as all bids are cleared together. Giving all actors the same amount of time to compute bids also works towards fairness. In ABEM, periodic auctions are used.

A bid function $b_{a,r}$ in ABEM defines a positive quantity for each price $\rho \geq 0$ and is given by

$$b_{a,r}(\rho) = \delta_a(\rho - v_a) \tag{3.4}$$

where, if a is a supplier, v_a denotes the reservation price below which a is not willing to sell and the slope parameter δ_a is positive. If a is a consumer, v_a denotes the reservation price above which a is not willing to buy and the slope parameter δ_a is negative. Besides being constrained by the reservation price v_a, the set of well-defined outcomes is further constrained by quantities Q_a^L and Q_a^U, so the function $b_{a,r}$ is valid only for unit prices in the interval $[b_{a,r}^{-1}(Q_a^L), b_{a,r}^{-1}(Q_a^U)]$.

Bid translation for market B

After the first settlement (in market A), the SO translates each accepted bid function $b_{a,r}$ into a new bid function b_a^B, which is used on a's behalf in market B. b_a^B is valid for unit prices in the interval $[\rho_{b_{a,r}}^A, \rho_{a,max}^B]$, where we denote with $\rho_{b_{a,r}}^A$ the unit price which bid $b_{a,r}$ describes for the quantity Q_a^A, which is at the time of translation known and fixed. Thus, $\rho_{b_{a,r}}^A = b_{a,r}^{-1}(Q_a^A)$. Furthermore, $\rho_{a,max}^B = b_{a,r}^{-1}(Q_a^A + Q_a^R)$ if a is a supplier. If a is a consumer, $\rho_{a,max}^B = b_{a,r}^{-1}(Q_a^A - Q_a^R)$.

b_a^B is formulated in the same ways as $b_{a,r}$, with v_a in Equation 3.4 replaced by $\rho^A_{b_{a,r}}$. We also introduce a second slope parameter ω. When a is a supplier, $\omega = 1$ and if a is a consumer, $\omega = -1$. Thus, if a is a supplier, b_a^B has the same slope as $b_{a,r}$ and if a is a consumer, the slope of b_a^B is inverted (with respect to the slope of $b_{a,r}$), because a acts as a seller on market B. b_a^B is given by:

$$b_a^B(\rho) = \omega\delta_a(\rho - \rho^A_{b_{a,r}}) \tag{3.5}$$

Figure 3.3 illustrates the bid translation. We note that the slope of b_a^B is always positive and that the reserve price of b_a^B is $\rho^A_{b_{a,r}}$. Thus, this translation ensures that ρ_a^B, the price a is paid for Q_a^B, is higher than ρ_a^A, the price a is paid (when he is a supplier) or pays (when is a a consumer) for Q_a^A:

$$\rho_a^B > \rho_a^A \tag{3.6}$$

This reflects a relation between ahead- and balancing prices which is recommended by economic experts. For example, Oren (2000) [95] argues that balancing power is a good of higher economic quality than day-ahead procurement because of shorter delivery time and should be priced higher.

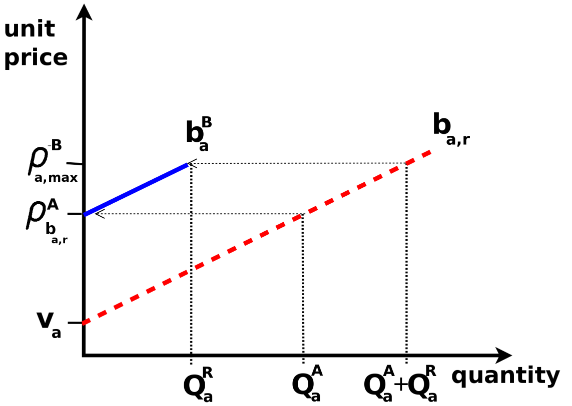
3.4.B. MARKET CLEARING IN ABEM

In this section, we formulate market clearing in ABEM as a constrained optimisation problem. We first introduce the types of actors and then formulate the two parts of the optimisation problem - the first part covers the market clearing in market A (for binding commitments and reserve capacity) and the second part the market clearing in market B (for deviations from binding commitments). Finally, we present two versions of pricing - uniform pricing (UPA) and discriminative pricing (DPA).

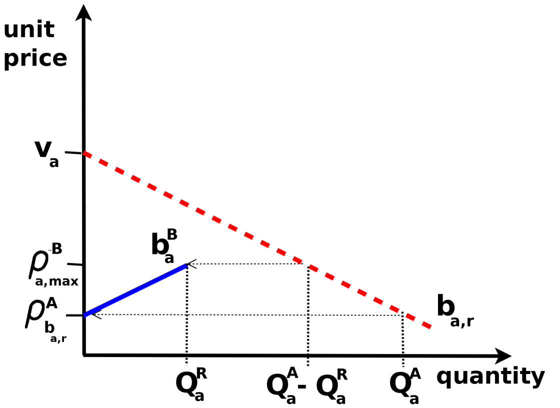
ACTORS AND BIDS

We consider four sets of actors: flexible suppliers FS and flexible consumers FC, as well as inflexible suppliers IS and inflexible consumers IC. Bidders in FS and FC can provide upward regulation - they supply more or consume less, respectively, than was allocated for them as binding commitment in market A. They submit bids with $r \in [0,1]$. Bidders in IS and IC do not provide upward regulation and thus submit bids with $r = 0$. However, they announce extra demand after market A has cleared, because they supply less or consume more, respectively, than was allocated for them as binding commitment in market A. As we explained in Section 3.2.a, it is the responsibility of the SO to secure sufficient reserve capacity in market A, in order to supply all possible extra demand in market B.

For convenience, we consider in this work the case of one submitted bid per bidder. In principle, each bidder can submit more than one bid, which increases the number of market clearings that need to be performed by the SO to find the best clearing solution among all sets of choices of one bid per bidder.



(a) a is a supplier



(b) a is a consumer

Figure 3.3: Bid translation in ABEM from market A (dashed red) to market B (continuous blue). The part of the bid function $b_{a,r}$ which is defined for quantities $q \in [Q_a^A, Q_a^A + Q_a^R]$ (if a is a supplier) or quantities $q \in [Q_a^A - Q_a^R, Q_a^A]$ (if a is a consumer) is translated into a new bid function b_a^B, which is defined for quantities $q \in [0, Q_a^R]$. If a is a consumer, the slope is multiplied by -1.

THE CONSTRAINED OPTIMISATION PROBLEM

The optimisation goal of the SO is to solve the so-called economic dispatch problem, which is to minimise costs of electricity generation. Given all submitted bids (for each bidder a, the bids $b_{a,r}$ and b_a^B), the goal is to find the prices which minimise the overall objective function given by:

$$\arg\min_{P^A,P^B}\Big[\sum_{a\in FS\cup IS}\Big(Q_a^A\rho_a^A+Q_a^B\rho_a^B\Big)\Big] \tag{3.7}$$

3

where P^A and P^B denote the sets of unit prices that all bidders are allocated in market A and market B, respectively, and ρ_a^A and ρ_a^B denote the prices for individual bidders a. It is implied that for each bidder a, $Q_a^A = b_{a,r}(\rho_a^A)$ and $Q_a^B = b_a^B(\rho_a^B)$.

This optimisation problem cannot be solved during the market clearing in market A (the first settlement), because the bids from inflexible actors in IS and IC, in which they describe their extra demand, are not known yet. The outcomes of market B (the second settlement), namely the quantities Q_a^B and the prices ρ_a^B, can only be taken into account once these bids are known. Therefore, we break up this ex-post optimisation problem into two ex-ante optimisation problems, one that can be solved during the market clearing for market A and another that can be solved during the market clearing for market B.

Market A In the optimisation problem for the market clearing in market A (for binding commitments and reserve capacity), the SO minimises the costs which are known for sure at the time of this market clearing and, to an extent which the SO chooses, the costs he expects to occur in the market clearing of market B. This optimisation problem is given by:

$$\arg\min_{P^A}\Big[\sum_{a\in FS\cup IS}Q_a^A\rho_a^A+\gamma E[C^B]\Big] \tag{3.8}$$

where $E[X]$ denotes the expectation of X, C^B denotes costs of using reserve capacity in market B ($C^B = \sum_a^{FS\cup FC} Q_a^B\rho_a^B$) and $\gamma \in [0,1]$ is a weight parameter which the SO can choose. By estimating C^B, the SO estimates costs in market B, but does not include the price set P^B as optimisation variables.

If the SO chooses $\gamma = 0$, there is no need to estimate C^B and the outcomes of market B are not considered during the clearing in market A. If he chooses $\gamma > 0$ and also estimates C^B close to the actual C^B, the SO can improve the solution to the overall economic dispatch problem in Equation 3.7 by buying more power on market A than inflexible consumers ordered, in the expectation that some inflexible actors will have to order more expensive balancing power in market B. This can reduce overall costs because it holds for each flexible actor a that $\rho_a^B > \rho_a^A$ (see Section 3.4.a).

We now list the constraints that every valid solution needs to respect. First, supply needs to equal demand:

$$\sum_{a\in IS}(Q_a^A+E[Q_a^B])+\sum_{a\in FS}(Q_a^A+Q_a^B)=\sum_{a\in IC}(Q_a^A+E[Q_a^B])+\sum_{a\in FC}(Q_a^A-Q_a^B) \tag{3.9}$$

3

If the SO chooses $\gamma = 0$, the SO does not need to consider (expectations of) Q_a^B and this constraint can be simplified to:

$$\sum_{a \in FS \cup IS} Q_a^A = \sum_{a \in FC \cup IC} Q_a^A \tag{3.10}$$

Furthermore, the SO needs to make sure that each supplier a will stay within his capacity constraints:

$$q_a^L \leq Q_a^A \leq Q_a^U (1 - r_a) \tag{3.11}$$

where r_a is the ratio between binding commitment and reserve capacity (see Section 3.4.a) from a's bid. Similarly, each consumer a needs to stay within his capacity constraints:

$$q_a^L + Q_a^A r_a \leq Q_a^A \leq Q_a^U \tag{3.12}$$

Flexible suppliers and consumers are allocated reserve capacity Q_a^R, as described in Section 3.4.a. The overall reserve capacity needs to be at least as high as Q^R, the overall reserve capacity, which is determined by the SO (see Section 3.2.a). Hence, we add the final constraint

$$\sum_{a \in FS \cup FC} Q_a^R \geq Q^R \tag{3.13}$$

We could have used = instead of ≥, but this is not necessary, as the cost optimisation is ensured by minimising costs of supply.

Market B In the optimisation problem for the market clearing in market B, the SO minimises the costs for the use of reserve capacity. Before market B is cleared, inflexible actors $a \in IS \cup IC$ announce their extra demand Q_a^B (flexible actors do not need to do that). The SO translates each accepted bid $b_{a,r}$ from flexible actors (submitted during the first settlement in market A) into a bid b_a^B (to be used in market B), as described in Section 3.4.a. These translated bids are used to minimise the objective function given by

$$\underset{P^B}{\arg\min} \left[\sum_{a \in FS \cup FC} Q_a^B \rho_a^B \right] \tag{3.14}$$

The only constraint to this optimisation requires that all supply equals all demand:

$$\sum_{a \in IS} (Q_a^A - Q_a^B) + \sum_{a \in FS} (Q_a^A + Q_a^B) = \sum_{a \in IC} (Q_a^A + Q_a^B) + \sum_{a \in FC} (Q_a^A - Q_a^B) \tag{3.15}$$

UNIFORM AND DISCRIMINATIVE PRICING

In Section 3.2.b, we discussed uniform pricing auctions (UPA) and discriminative pricing auctions (DPA). Here, we discuss market clearing in more detail, for multi-unit auctions and specifically for ABEM.

If a UPA design approach to market clearing is used, then the price sets P^A and P^B contain the same prices ρ_a^A and ρ_a^B for all actors a. In each of the two markets, the SO adds up (with respect to quantities) all supply functions to one aggregated supply function S. In market A, these are the functions $b_{a,r}$ per bidder $a \in FS \cup IS$ and in market B, these are the functions b_a^B per bidder $a \in FS \cup FC$. The SO also adds up all demand functions to one aggregated demand function D. In market A, these are the functions $b_{a,r}$ per bidder $a \in FC \cup IC$ and in market B, these are the functions b_a^B per bidder $a \in IS \cup IC$.

In both markets, the price ρ for which $S(\rho) = D(\rho)$ is the uniform clearing price. Each actor a buys or sells the quantity which can be looked up on his relevant bid function ($b_{a,r}$ or b_a^B, see above) at price ρ. Should that quantity be lower than 0, a sells nothing. Should that quantity be higher than a maximal limit Q_a^{max} for this bid, a sells Q_a^{max} at price ρ.

Sandholm and Suri (2002) [108] showed that finding ρ is not computationally expensive and always possible, under two conditions. First, all supply functions need to be monotonically increasing and all demand bids need to be monotonically decreasing, which is a condition that the bid functions we describe in Section 3.4.a fulfil. Second, the bid functions should either be linear or piecewise linear. We deal with linear functions, so this condition is fulfilled, as well (capacity constraints like we described in Constraints 3.11 and 3.12 are also used in [108]). However, Constraint 3.13 may render the solution at price ρ invalid. The SO can request that actors with flexibility submit at least one bid with the value for r larger than some minimal r_m which the SO chooses.

Finding prices in a DPA approach is computationally more elaborate, as there is now a distinct price per bidder a in both P^A and P^B. However, in [108] it is also shown that the problem of finding optimal discriminatory prices in a two-sided auction with both supply and demand curves for multiple indistinguishable units can be formulated as a convex quadratic program with linear constraints. The solution to such a program can be found in polynomial time using general techniques, e.g. with the technique described in [42]. The only condition is that curves are linear, which is given in our context, see Section 3.4.a. All the constraints we formulated in Section 3.4.b are linear. As described for the UPA clearing, Constraint 3.13 can make some solutions invalid and the SO might need to request that some bids with minimal values of r are submitted.

3.4.C. ADVANTAGES BY DESIGN

This section describes three advantages which ABEM has by design. In Section 3.3, we listed design challenges, which we refer to here. Following this section, Section 3.6 describes advantages & disadvantages experimentally.

The complexity of bid construction is reduced. In the ABEM mechanism, bidders only submit one bid, whereas other comparable mechanisms (see Section 3.2.a) require the submission of two separate bids, one for binding commitments and one for reserve capacity. This is made possible by the bid translation, described in Section 3.4.a. Thus, the design challenge described in 3.3.a is tackled in the design of the ABEM mechanism. We will show concrete examples of the bidder's optimisation problem in our decision-theoretic experiments later on, where the simplification of the objective function becomes apparent formally.

Bidders can bid price functions to both markets, potentially their marginal costs or valuation. In ABEM, the function which is submitted to market A is resubmitted to market B. The knowledge of the allocation in market A is used in the translation process (see Section 3.4.a). This means that a price function is used in both markets, rather than a constant price in market B (which is the case in some real-world versions of comparable mechanisms).

Being able to submit only one price function also enables bidders to submit their marginal cost or utility function as bid, which is not feasible in mechanisms which require the submission of two independent bids. This addresses the design challenge described in 3.3.b. The expression of the valuation is of course limited by our formal definition of price functions in Section 3.4.a. For example, costs of ramping up or down and switching costs can not be expressed, which has little effect on some flexible technologies (e.g. batteries) and more effect on others (e.g. coal power plants).

Flexible consumers are guaranteed that offering reserve capacity increases their overall utility. Flexible actors should be incentivised to offer reserve capacity. We will show the following proposition holds:

Proposition 3.1:
For a flexible consumer, offering reserve capacity is guaranteed to be profitable, if he submits his marginal utility function.

We refer to Appendix 3.A for the proof. The intuition is that buying Q_a^A and then selling Q_a^B is better for A's utility than both only buying Q_a^A and only buying $Q_a^A - Q_a^B$ in market A. The first reason for this is that the more a buys in market A, the more the price per unit bought decreases (because the slope of $b_{a,r}$ is decreasing). The second reason is that it is profitable to resell a unit in market B which was bought in market A, because $\rho_a^B > \rho_a^A$, a property of ABEM we established in Section 3.4.a. Thereby, we partly address the design challenge described in 3.3.c.

Proposition 3.1 is an important baseline result, especially for markets with high levels of competition (refer to Section 3.2.b). However, we are not able to make a similar claim about a flexible supplier. Let us assume that a has no choice which bid function $b_{a,r}$ to submit (i.e. submitting his marginal costs is one possible scenario given this assumption). Then, a prefers to sell a quantity q on market A over selling q partly on market A and partly on market B. Let ρ_a^A denote the price a is paid for Q_a^A ($b_{a,r}(\rho_a^A) = Q_a^A$) and let ρ_a^B denote the price a is paid for Q_a^B in market B ($b_a^B(\rho_a^B) = Q_a^B$).

Given the way bids in ABEM are translated between market A and market B, ρ_a^B is also the price a would be paid in the case where he sells all of $Q_a^A + Q_a^B$ already in market A ($b_{a,r}(\rho_a^B) = Q_a^A + Q_a^B$)). The difference in a's profits if he sells either $Q_a^A + Q_a^B$ on market A or if he first sells Q_a^A on market A and then Q_a^B on market B is $Q_a^A(\rho_a^B - \rho_a^A)$. Because $\rho_a^B > \rho_a^A$ (see above), a clearly prefers the first option.

This shows that flexible suppliers cannot be guaranteed that offering reserve capacity increases their profits. Offering reserve capacity can, however, be profitable in many market settings and a will have to consider this possibility when constructing his bid.

3.5. A DECISION-THEORETIC MARKET APPROACH FOR AGENTS

In this section, we develop a market model that a bidding agent can use to model his perspective in a two-settlement market with integrated trade of reserve capacity and simultaneous bidding. It includes all other actors in aggregated mathematical functions and is formulated for a discriminatory auction design (refer to Sections 3.2.b and 3.4.b). It is fully parametrised, most importantly with respect to the uncertainty a has about market outcomes. We also provide the bid optimisation problem a faces, given this model, for the case where the choice which value to use for r is fixed.

This market model can be used to implement a strategic agent. In this chapter, we will make use of it in Section 3.6, where we model a as a flexible supplier as well as a flexible consumer and perform various experimental simulations.

3.5.a. Aggregation of other actors

The bidding behaviour of all other market participants besides a is modelled as parametrised functions. For brevity of this market model, these functions are aggregated on both demand and supply side. Aggregating actors in this way is based on the assumption that the average behaviour is sufficiently predictable. Good predictions can be made either when the number of actors is high or individual decision-making of a smaller group of actors can be estimated (for instance by experience).

Following [100], an aggregated bid function is the sum of curves of individual bid functions. Let $D(\rho) \to \mathbb{R}$ be an aggregated demand function and $S(\rho) \to \mathbb{R}$ an aggregated supply function for unit prices ρ. We will use D, S and their parameters with the superscripts ^{A} for market A and ^{B} for market B. If needed for clarification, we might use the subscript $_{-a}$ to denote explicitly that the function does not include a. D and S for markets A and B are given by

$$\begin{aligned} D^A(\rho) &:= \left[D^A_{max} - \alpha^A \rho\right]_{\geq 0} \\ S^A(\rho) &:= \left[\beta^A(\rho - \rho^A_{min})\right]_{\geq 0} \end{aligned} \tag{3.16}$$

$$\begin{aligned} D^B(\rho) &:= \left[D^B_{max} - \alpha^B \rho\right]_{\geq 0} \\ S^B(\rho) &:= \left[\beta^B(\rho - \rho^B_{min})\right]_{\geq 0} \end{aligned} \tag{3.17}$$

where $[X]_{\geq 0}$ denotes the maximum of X and 0, D^A_{max}, D^B_{max} are constants denoting the maximal demand, $\rho^A_{min}, \rho^B_{min}$ are constants denoting the minimal unit offer price and α^A, α^B as well as $\beta^A, \beta^B \in [0,1]$ are slope parameters.

We thus have eight parameters to describe this market model. Some relations between parameters, however, might be assumed. For example, D^B_{max} is probably related to D^A_{max}, ρ^B_{min} is probably not lower than ρ^A_{min} and the slopes of these accumulated functions can probably assumed not to change significantly between market A and market B. We will make specific assumptions for such relations when we make use of this market model in experiments.

3.5.B. RESIDUAL FUNCTIONS

Given D^A, D^B, S^A and S^B, we model the residual functions that a faces in markets A and B. In economic theory, residual supply is the full market supply minus the quantity bought by other actors at each unit price ρ and residual demand is the full market demand minus the quantity supplied by other actors at each unit price ρ. Following [100], Equation 3.18 first shows the residual demand function D^A_{res} (for when a is a supplier) and then the residual supply function S^A_{res} (for when a is a consumer). Finally, the residual demand function D^B_{res} is shown, which a faces in market B.

$$\begin{aligned} D^A_{res}(\rho) &= D^A(\rho) - S^A_{-a}(\rho) \\ S^A_{res}(\rho) &= S^A(\rho) - D^A_{-a}(\rho) \\ D^B_{res}(\rho) &= D^B(\rho) - S^B_{-a}(\rho) \end{aligned} \tag{3.18}$$

3.5.C. MARKET CLEARING

We can now discuss how supply and demand bids are cleared in our decision-theoretic market model representation. The prices ρ^A_a and ρ^B_a, which allocate from a the quantities Q^A_a and Q^B_a, respectively, are found at the intersection of a's bid with the residual functions. Similar to Equation 3.18, Equation 3.19 first shows clearing in market A, for the two cases of a being a supplier or a consumer, and then clearing in market B, where a acts as a supplier:

$$\begin{aligned} Q^A_a &= D^A_{res}(\rho^A_a) = b_{a,r}(\rho^A_a) \\ Q^A_a &= S^A_{res}(\rho^A_a) = b_{a,r}(\rho^A_a) \\ Q^B_a &= D^B_{res}(\rho^B_a) = b^B_a(\rho^B_a) \end{aligned} \tag{3.19}$$

3.5.D. UNCERTAINTY

a approximates the residual supply and demand functions D^A_{res} (if a is a supplier), S^A_{res} (if a is a consumer) and D^B_{res} (in both cases) with some uncertainty. We model this by noise parameters k^A and k^B, with which we multiply the minimal price of suppliers in S^A_{-a} and S^B_{-a} (refer to Equations (3.16) and (3.17)). Functions D^A_{res}, S^A_{res} and S^A_{-a} prescribe an additional parameter k^A and functions D^B_{res} and S^B_{-a} prescribe an additional parameter k^B. S^A_{-a} and S^B_{-a} are then given by:

Table 3.1: Summary of market parameters - we use superscripts ^{A} or ^{B} to denote usage in market A or B, respectively.

Parameter	Description
D_{max}	maximal demand of demand functions D^A_{-a} and D^B
α	slope of demand functions
ρ_{min}	min. price of supply functions S^A_{-a} and S^B_{-a}
β	slope of supply functions
k	noise parameter

$$\begin{aligned} S^A_{-a}(\rho, k^A) &= \beta^A(\rho - \rho^A_{min} k^A) \\ S^B_{-a}(\rho, k^B) &= \beta^B(\rho - \rho^B_{min} k^B) \end{aligned} \tag{3.20}$$

For the likelihood of individual value of k^A and k^B, a needs to model two probability distributions $prob^A : \mathbb{R} \rightarrow [0,1]$ and $prob^B : \mathbb{R} \rightarrow [0,1]$, respectively.

3.5.E. SURPLUS FUNCTIONS FOR AGENT A AS FLEXIBLE SUPPLIER AND CONSUMER

We now model surplus functions for a, given market outcomes. Refer to Section 3.2.b for a definition of surplus with marginal bid functions. Section 3.5.f uses these functions to formulate the bid optimisation problem for this model.

***a* as a flexible supplier:** The surplus in each market (refer to Section 3.2.b) is the revenues minus the total variable costs of generation. In market A, revenues are $Q^A_a * \rho^A_a$ and the total costs of producing Q^A_a are given by $V_a(Q^A_a)$. In market B, revenues are $Q^B_a * \rho^A_a$ and the total costs of generating Q^B_a are the costs for generating the last Q^B_a units in $Q^A_a + Q^B_a$. Therefore, we introduce a total cost function V^B_a for Q^B_a that calculates the costs on $V_a(Q^A_a + Q^B_a)$ for $Q^B_a \in [0, Q^R_a]$. V^B_a is given by:

$$\begin{aligned} V^B_a(Q^A_a, Q^B_a) &= V_a(Q^A_a + Q^B_a) - V_a(Q^A_a) \\ &= (v_a + 2\delta_a Q^A_a) Q^B_a + \delta_a (Q^B_a)^2 \end{aligned} \tag{3.21}$$

Then, the surplus functions are given by:

$$\begin{aligned} surplus^A_a(b_{a,r}, k^A) &= \rho^A_a Q^A_a - V_a(Q^A_a) \\ surplus^B_a(b^B_a, b_{a,r}, k^B) &= \rho^B_a Q^B_a - V^B_a(Q^A_a, Q^B_a) \end{aligned} \tag{3.22}$$

where b^B_a is either the result of the translation of bid function $b_{a,r}$ for market B in the ABEM mechanism (see Section 3.4.a) or the price ρ^B_a, chosen by a in the BENCH mechanism (see Section 3.6.a). Q^A_a and ρ^A_a, as well as Q^B_a and ρ^B_a, are determined through market clearing (see Section 3.4.b), and thus $b_{a,r}$ and k^A, as well as b^B_a and k^B, are implicit in the right-hand formulae. Note that $surplus^B_a$ is coupled to the results of market A (and thus needs to consider $b_{a,r}$), as Q^A_a is used in V^B_a as well as in the determination of Q^R_a.

a as a flexible consumer: a's overall utility U_a is the valuation of the electricity he actually consumes, minus the price he pays for his initial allocation in market A, plus revenues through providing reserve capacity in market B. U_a is given by:

$$U_a = V_a(Q_a^A - Q_a^B) - Q_a^A \rho_a^A + Q_a^B \rho_a^B \tag{3.23}$$

For $surplus_a^A$, we consider a's valuation of consuming Q_a^A and the costs of buying Q_a^A. For $surplus_a^B$, we consider the economic reward for reducing demand and subtract the costs of a's provision of reserve capacity by the (lost) utility of the last Q_a^B units in Q_a^A. We model this lost utility via the function V_a^B, which is given by:

$$V_a^B(Q_a^B, Q_a^A) = V_a(Q_a^A) - V_a(Q_a^A - Q_a^B) \tag{3.24}$$

Then, the surplus functions are given by:

$$\begin{aligned} surplus_a^A(b_{a,r}, k^A) &= V_a(Q_a^A) - Q_a^A \rho_a^A \\ surplus_a^B(b_a^B, b_{a,r}, k^B) &= Q_a^B \rho_a^B - V_a^B(Q_a^B, Q_a^A) \end{aligned} \tag{3.25}$$

3.5.F. THE BID OPTIMISATION PROBLEM

As we explain in Section 3.2.b, a has a positive surplus (considering only variable costs and utilities) when selling or buying a quantity q at his marginal value $V_a'(q)$. However, a maximises his surplus when his production or consumption q is such that $V_a'(q) = MR_a(q)$, where MR_a is the marginal revenue function for a (see Section 3.2.b). The surplus maximisation problem for a is given by:

$$\begin{aligned} \arg\max_{b_{a,r}, b_a^B} \Bigg[\int_{k^A = k^A_{min}}^{k^A_{max}} & prob^A(k^A) * \Bigg(surplus_a^A(b_{a,r}, k^A) \\ + \int_{k^B = k^B_{min}}^{k^B_{max}} & prob^B(k^B) * \; surplus_a^B(b_a^B, b_{a,r}, k^B) \, dk^B \Bigg) \, dk^A \Bigg] \end{aligned} \tag{3.26}$$

Note that in the ABEM mechanism, b_a^B is not a choice to be made by a, but is translated from $b_{a,r}$ and therefore the optimisation problem is considerably reduced in complexity, when compared to a mechanism where bids $b_{a,r}$ and b_a^B are independent (this addresses the problem we discuss in Section 3.3.a).

3.6. EXPERIMENTS

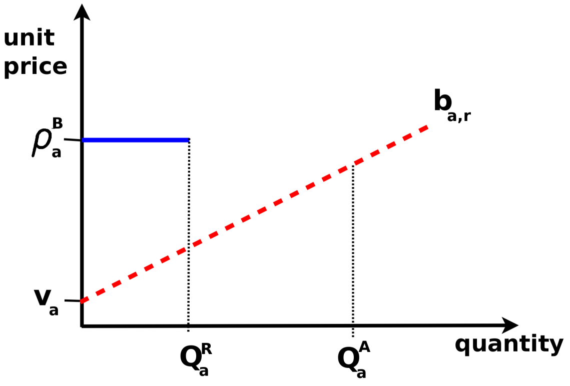
In this section, we describe two experiments, in which we model a as a flexible supplier and a flexible consumer. a uses the decision-theoretic approach we laid out in the previous section and we model the market accordingly in a stochastic two-settlement model. Section 3.6.a introduces some necessary modelling concepts, most importantly the benchmark mechanism BENCH. We also show how a constructs bid functions mathematically and explain how we measure market power when a is a supplier. Section 3.6.b then explains the experimental setup. We discuss results in Section 3.6.c.

3.6.A. EXPERIMENT MODELS

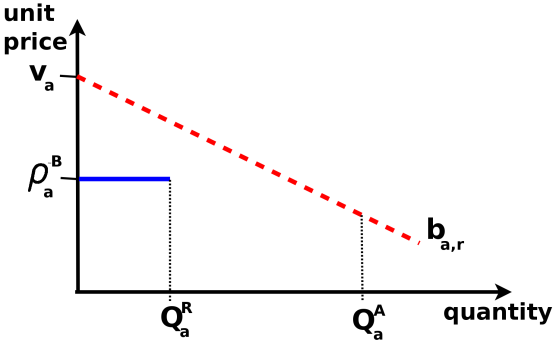
THE BENCHMARK MECHANISM BENCH

We model a benchmark mechanism (which we will refer to as BENCH from now on) for a to take part in, which is modelled in resemblance to existing real-world implementations of electricity markets (e.g. [87] or [116]). Like ABEM, the BENCH mechanism is a two-settlement mechanism with integration of the trade of reserve capacity and simultaneous bidding. Unlike ABEM, BENCH requires from a two separate bids to market A and market B.

Furthermore, BENCH also requires from a a price function $b_{a,r}$ as bid to market A (like ABEM), but only allows b_a^B, the bid to market B to represent a constant price ρ_a^B (unlike ABEM). In both mechanisms, the reserve capacity Q_a^R is determined by a bid parameter, and the allocation in market A, as described in Section 3.4.a. Figure 3.4 illustrates the bids to BENCH for both cases (a representing a supplier or a consumer).



(a) a is a supplier



(b) a is a consumer

Figure 3.4: Bids in the BENCH format. Bid $b_{a,r}$ to market A (dashed red) is a function and the bid ρ_a^B to market B (continuous blue) is a constant price. Note that ρ_a^B is independent from the bid $b_{a,r}$, besides being constrained in quantity by Q_a^R. For bids in ABEM, see Figure 3.3.

Both the ABEM and the BENCH mechanism can be used for a within the market model described in Section 3.5, without changes to the modelling of other actors.

TRANSLATION OF a'S VALUATION OF ELECTRICITY INTO BIDS

We now show how the bidder agent a translates V'_a, his marginal value function for electricity (refer to Section 3.2.b) into a bid function to either the ABEM or BENCH mechanism. We also show how a can alter this bid function for surplus optimisation.

Bid functions in both the ABEM and the BENCH mechanism map unit prices to quantities (see Section 3.4.a). The bid of marginal valuation, b_a^{mar}, is therefore given by the inverse of V'_a:

$$b_a^{mar}(\rho) = V_a'^{-1}(\rho) = \frac{1}{2\delta_a}(\rho - v_a) \tag{3.27}$$

In order to construct a bid that maximises his surplus, a can submit a bid that deviates from b_a^{mar} - in particular, a could deviate from both his v_a and δ_a values. For simplicity, we fix δ_a and restrict a to adapt only the parameter v_a. In [6], this restriction of the function parametrisation in a market mechanism is called "c-parametrisation" (because they used "C" as a parameter name where we use "v_a") and previous literature in which this restriction was also used is described. In a bid $b_{a,r}$, we denote the adapted v_a as v_a^*. $b_{a,r}$ is given by:

$$b_{a,r}(\rho) = \frac{1}{2\delta_a}(\rho - v_a^*) \tag{3.28}$$

In the BENCH mechanism, a has, next to v_a^*, also to choose ρ_a^B, his constant price bid for balancing power (see Section 3.6.a).

MARKET POWER OF a AS A FLEXIBLE SUPPLIER

We measure a's market power by calculating the Lerner index $\in [0,1]$, defined by dividing per-unit profits by unit price. As the index is defined for a monopolist, we multiply it by a's market share to compute the Lerner index for an oligopoly [114]:

$$lerner(Q_a^A, Q_a^B) = \frac{\rho_a(Q_a^A, Q_a^B) - costs_a^{avg}(Q_a^A, Q_a^B)}{\rho_a(Q_a^A, Q_a^B)} s_a(Q_a^A, Q_a^B) \tag{3.29}$$

where ρ_a denotes the average unit price which a earns when selling the quantities Q_a^A and Q_a^B, $costs_a^{avg}$ is the average production costs per unit and s_a is a's market share. In our case:

$$\begin{aligned} \rho_a(Q_a^A, Q_a^B) &= \frac{Q_a^A \rho_a^A + Q_a^B \rho_a^B}{Q_a^A + Q_a^B} \\ costs_a^{avg}(Q_a^A, Q_a^B) &= \frac{costs_a^{full}(Q_a^A + Q_a^B)}{Q_a^A + Q_a^B} \\ s_a(Q_a^A, Q_a^B) &= \frac{Q_a^A + Q_a^B}{Q_a^A + Q_{-a}^A + Q_{-a}^B + Q_a^B} \end{aligned} \tag{3.30}$$

where $costs_a^{full}$ denotes the full production cost function of a and Q_{-a}^A denotes the amount which all suppliers but a sold in market A (when a is a supplier) or the amount which all consumers bought (when a is a consumer) in market A. Q^B_{-a} denotes the amount which all suppliers but a sold in market B.

Note that this way of modelling market power works well for a supplier, but is not defined for the perspective of a flexible consumer who also acts as a supplier in market B. We will thus use it only for the use case of modelling a flexible supplier.

3.6.B. EXPERIMENT SETUP

MARKET SCENARIOS

In this section, we model two market scenarios for our experiments. They describe two important market configurations which are relevant to the future of energy systems. We explain how we find values for all relevant market parameters which were introduced in Section 3.5 (refer to Table 3.1).

The values we choose for both scenarios are based on realistic settings from a wholesale power market simulation study by Sun & Tesfatsion (2007) [115]. In addition, we use a survey report by Lafferty at al (2001) [76] that aggregates several demand responsiveness studies, in order to model the slope of the demand functions.

Oligopolistic market scenario First, we define an oligopolistic market scenario, which could for instance resemble the situation in a microgrid. Both microgrids and wholesale markets resemble oligopolistic markets, because they are dominated by a small number of players.

Supply side in market A - In [115], several generators and a generic buyer profile are modelled for a simulation of 24 hours. From this study, we model an average generator g and the sum of aggregated demand. Our chosen settings correspond to hour 8am in [115]. We chose that hour as it is similar to most other hours and not an outlier. As was noted earlier, our experiments perform a one-shot auction. Note also that, because we use settings from a wholesale market study, the prices in our model are in \$/MWh. However, the general findings of this model can also hold for markets which trade kWh, as we only use settings to model relative quantities and slopes of cost functions.

The average generator g has a maximal production of $Q^U_g = 300$ units, a minimum unit cost $v_g = 18.8$ and δ_g, the slope parameter of g's marginal cost function, is given by $\delta_g = 0.008$. The model in [115] includes five generators. Thus, to arrive at the average slope of S^A, we multiply the slope of g's marginal costs by five: $\beta^A = \frac{5}{2\delta_g}$. When we model a as a supplier, then S^A_{-a}, the aggregated function without a, has the slope $\beta^A = \frac{4}{2\delta_g}$. Finally, we assume that the minimal unit price of S^A_{-a} is 10% higher than g's minimal unit costs: $\rho^A_{min} = 1.1\, v_g$.

Demand side in market A - The sum of the demand of all buyers in [115] is 900, or $3Q^U_g$. We set $D^A_{max} = 3Q^U_g(1 - r_m)$. All studies in [76] measured the price elasticity of demand, which denotes the percentage change in quantity demanded in response to a one percent change in price. [76] distinguishes between “long-run” and “short-run” demand. At the time when he considers the price, a consumer with long-term demand has more time until the time of consumption than a consumer with short-term demand. Thus, having short-term demand allows for less substitution of demanded power with any alternative (e.g. shifting demand to a later time), similar to the situation in a balancing market. The survey reports price elasticities between 0.7 and 2.1 for “long-run” scenarios (which we use for market A) and between 0.03 and 0.5 in “short-run” scenarios (which we use for market B). We take $\alpha^A = 1.0$ and $\alpha^B = 0.2$.

Coupling of market B - Two parameters of market B are determined by the outcome of market A: the minimum price ρ^B_{min} and the maximal reserve capacity D^B_{max}. ρ^B_{min} is determined as the price at which demand and supply in market A (without a taken into account) intersect ($D^A_{-a}(\rho^B_{min}) = S^A_{-a}(\rho^B_{min})$). We assume that D^B_{max} is related to demand in market A via a ratio r_m, such that $D^B_{max} = \frac{r_m Q^A_C}{1-r_m}$, where Q^A_C denotes the sum of all binding commitments of consumers in market A (without a taken into account, if he is a consumer).

Reserve capacity - The *SO* needs to allocate sufficient reserve capacity from all market participants in market A, such that $Q^R \geq D^B_{max}$. For this, he might approximate r_m from experience (refer to Section 3.2.a for a discussion of current practice). We assume he is successful in this. For the purposes of this decision-theoretic model, we need to decide which level of reserve capacity agent a bids on[3], i.e. which r is set in his bid $b_{a,r}$. For the simplicity of our setup, we assume that the *SO* can approximate r_m perfectly and requires a to use r_m in his bid $b_{a,r}$ with $r = r_m$. This modeling choice assumes that r is technically feasible with the generation or consumption devices that a has. We will use two values for r, 0.1 and 0.3 (see our method description below). While the smaller value of $r = 0.1$ should be feasible with almost all devices, the higher value of $r = 0.3$ is mainly possible with devices that have little costs of switching between states, e.g. batteries. Of course, a more detailed model would assume that bidders have individual preferences which values for r they prefer, e.g. based on their devices or previous history. In such a market clearing mechanism, bidders can submit several bids with different values for r. We discuss this possibility in Section 3.4.b and also propose it for future work (see Section 3.7).

Competitive market scenario We also design a second scenario (using the oligopolistic scenario as a starting point), in which we model two trends that are considered very important for smart grids. First, we make the scenario more competitive: we increase both the number of suppliers and demand responsiveness tenfold (which affects α^A and β^A). Second, we add demand (e.g. to model increasing market penetration of electric vehicles and heat pumps) by doubling the overall demand for electricity (which affects D^A_{max}).

Table 3.2 lists all default parameter values for the two scenarios. Note that the parameters for market B depend on the parameters of market A.

SETTINGS FOR BIDDING AGENT a

In order to model *a as a flexible supplier*, we parametrise a as an average generator, according to [115] (we discuss our concept of an average generator in this context below). We set $v_a = v_g$, $\delta_a = \delta_g$ and $Q^U_a = Q^U_g$.

[3] All inflexible actors use $r = 0$ in their bids. As all market participants other than a are modelled by unconstrained functions, we do not need to decide which values of r the flexible participants bid.

Table 3.2: Default settings for parameters in the oligopolistic and competitive scenario.

Name	oligopolistic scenario	competitive scenario
D^A_{max}	$3Q^U_g(1-r_m)$	$6Q^U_g(1-r_m)$
α^A	1.0	10.0
ρ^A_{min}	$1.1v_g$	$1.1v_g$
β^A	$\frac{5}{2\delta_g}$	$\frac{50}{2\delta_g}$
D^B_{max}	$\frac{r_m Q^A}{1-r_m}$	$\frac{r_m Q^A}{1-r_m}$
α^B	$\frac{\alpha^A}{5}$	$\frac{\alpha^A}{5}$
ρ^B_{min}	ρ^A_{-a}	ρ^A_{-a}
β^B	β^A	β^A
r_m	0.1 or 0.3	0.1 or 0.3

We model *a as a flexible consumer* in the following way: His maximum capacity is $Q^U_a = Q^U_g$, same as for our average generator g. For the slope of the valuation function of a flexible consumer, literature does not provide us with helpful pointers. For this work, we choose $\delta_a = -0.008$, mirroring δ_g, the slope of the cost function of g. Finally, we aim at modeling a's utility function V_a such that a's valuation is close to the market valuation and set $v_a = \rho^{AB}_{-a} * 1.1$. ρ^{AB}_{-a} is the average price over markets A and B, under given parameter settings, if a is not present. The multiplication by 1.1 roughly compensates for the slope δ_a.

METHOD

In the experiments, we evaluate both the oligopolistic and the competitive market scenario using a Monte-Carlo simulation. We now describe the generation of specific parameter settings, the method of sampling traces in them, and which steps bidding agent a follows to find optimal bid parameters.

Parameter settings - We create several relevant settings in both market scenarios by varying the value of one parameter a a time, where the other parameters remain at the default setting from Table 3.2. In both scenarios, $\phi \in [0,3]$ (ϕ is the uncertainty scaling parameter and will be explained below), $\rho^A_{min} \in [\frac{2}{3}v_g, \frac{3}{2}v_g]$ and $D^A_{max} \in [\frac{2}{3}D^{A,base}_{max}, \frac{3}{2}D^{A,base}_{max}]$, where $D^{A,base}_{max}$ denotes the default setting for D^A_{max} from Table 3.2. Note that ρ^B_{min} and D^B_{max} are formulated in relation to ρ^A_{min} and D^A_{max}, respectively. Finally, we run simulations with $r_m = 0.1$, which is a reserve level observed often in current markets, as well as $r_m = 0.3$, a setting that is not unrealistic in the market scenarios we can expect in the upcoming 10 years, at least for the actors that can offer significant reserve power (for example if they operate batteries or gas power plants).

Sampling - We sample the outcomes for each setting 100 times. Each sample contains a new pair of the noise parameters k^A and k^B, which influence the position of the residual functions that a faces with respect to quantity (see Section 3.5.d). Each pair is generated by the Mersenne twister pseudo-random number generation algorithm. We assume that the two probability distribution functions $prob^A$ and $prob^B$

are independent from one another. Also, we assume they model normal distributions and we thus have to make two choices: how to set means and standard deviations for the distribution functions of both k^A and k^B. First, we set both means to 1, which is the value for which there is no noise, compare Equation 3.20. Second, we define the standard deviations s^A and s^B such that the position of the residual function for a in the given market is changed by a certain amount (the amount is specific to the market setting). We explain this definition using k^B in market B as an example. At a noise value of $k^B = 1$, no noise is present. Residual demand is not willing to buy from a above the price ρ^B_{-a} ($D^B_{res}(\rho^B_{-a}, 1) = 0$). We define s^B such that $D^B_{res}(\rho^B_{min}, 1-3s^B) = 0$. Thus, a value of $k^B = 1-3s^B$ repositions D^B_{res} downwards along the quantity axis such that residual demand is not willing to buy from a above the price ρ^B_{min}. Finally, in order to model varying degrees of noise, we create additional parametrised settings, where we vary s^A and s^B. To create these settings, we multiply both s^A and s^B with a scaling parameter $\phi \in [0,3]$ (in default settings, $\phi = 1$).

Finding optimal bid parameters - in Section 3.6.a, we describe that bidding agent a has to optimise one (in the ABEM mechanism) or two (in the BENCH mechanism) bid parameters. He does this in two steps. First, a performs a brute-force search on parameter settings for his bid(s). a evaluates 100 evenly-spaced values for v^*_a (in his bid to market A) in the range $[v_a, \rho^A_{max}]$ when a is a supplier or $[\rho^A_{min}, v_a]$ when a is a consumer. Furthermore, when participating in the BENCH market, a evaluates, for each of the 100 values he evaluated for v^*_a, 100 evenly-spaced values for ρ^B_a (his bid to market B) in the range $[p^A_{min}, \rho^B_{max}]$. Here lies the main difference in the time it takes to compute a bid with optimal expected value. In our experiments, optimising a bid in the ABEM mechanism took around a minute, while optimising bids to the BENCH mechanism took up to around one hour on a standard desktop PC.

The second step of the bid optimisation is to refine the best solution from the brute-force search. Starting with the most promising bid(s) found so far (with respect to his expected surplus), a applies a downhill simplex algorithm [92] to maximise the expected surplus further.

During the evaluation of each value setting, a sets $k^A_{min} = 1-3s^A$, $k^A_{max} = 1+3s^A$, $k^B_{min} = 1-3s^B$ and $k^B_{max} = 1+3s^B$ (refer to Equation 3.26).

3.6.c. Results and Discussion

Let us first note that a first important difference between ABEM and the BENCH mechanism is the time it took us to compute bids with optimal expected values (see previous section). Bids for us in ABEM were computed much faster. We now pay attention to economical outcomes.

Agent a as a flexible supplier

We begin with confirming that, for several general economic properties, the market model behaves as expected in reality. First, a has positive surplus in both mechanisms and across all settings. a's surplus also correlates with settings like one would expect. It is positively correlated to changes in δ_a, D^A_{max} and ρ^A_{min} and negatively correlated to r_m, α^A and β^A. Second, a's presence increases competition as he can offer electricity below market price. We simulated the markets without a (thus decreasing the number of suppliers by one). As should be expected, the aggregated unit price (the sum of all sold units in both markets divided by the sum of money paid by consumers) is significantly higher in these settings than it is with a's presence. Finally, in comparison to the oligopolistic scenario, the competitive scenario has a lower aggregated market price, as well as lower market power and surplus for a.

We now turn to two important observations, concerning notable differences or similarities in outcomes when a takes part in either the ABEM or the BENCH mechanism:

3

Observation 1: Agent a reaches comparable surplus in both mechanisms across a wide range of market conditions, but shows different bidding behaviour. The outcomes for a are different, between both mechanisms, in terms of quantities a supplies and prices a is paid. The differences are most prominent in market B and we now note two notable ones. First, the results for a in market B vary mostly in price in ABEM, while in BENCH, they vary mostly in quantity (see Figure 3.5 for two examples). Second, a in the BENCH mechanism does not sell any Q_a^B in settings with high uncertainty ($\phi > 1.5$), because he charges a price that is too high for the market.

However, a's surplus does not differ significantly[4] across all settings when we let a take part in the ABEM or BENCH mechanism. The only exceptions are in the oligopolistic scenario when the setting has high values for D_{max}^A (where a has higher surplus in ABEM) or in both scenarios when the setting has high values for ρ_{min}^A (where a has higher surplus in BENCH).

Observation 2: The ABEM mechanism substantially reduces market prices and market power in exploitable settings. In the default settings, market power measurements for agent a in the ABEM and BENCH mechanism show no significant differences. The biggest opportunities for a to exercise market power exist in settings with larger values for ρ_{min}^A, because then the difference between offer prices of S_{-a} and a's costs is high and a can thus increase his surplus. The settings in which $\rho_{min}^A \geq 24$ show by far the highest aggregated market prices, as well as market power and surplus for a. In these settings, a exploits this opportunity less when he uses the ABEM mechanism (see Figure 3.6 for an example). The differences in a's market power between the ABEM and the BENCH mechanism in these settings are significant, with the exception of the oligopolistic scenario where $r_m = 0.1$. This observation also aligns with some differences in surplus which we reported in observation 1 (in settings with high values for ρ_{min}^A).

Specifically, a in ABEM is lowering the price ρ_a^A on market A, and as a result the aggregated market prices are lower than in the BENCH mechanism. Note that the most quantity is sold on market A and thus lowering ρ_a^A has a strong effect. See Figure 3.6a for the most substantial case, where the presence of a when using the ABEM mechanism has an impact on aggregated market prices which is up to 2.7 times larger as when a takes part in the BENCH mechanism. The results also show a clear reduction in market power. In the default settings ($\rho_{min}^A = 20.68$), a has the same market

[4]We performed Student's T-Tests and tested for $p \leq 0.01$.

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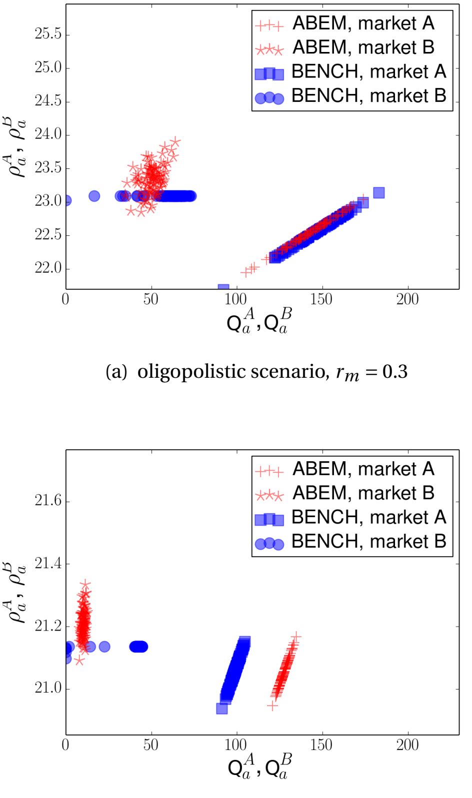
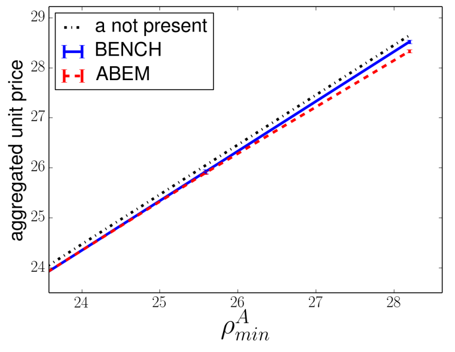


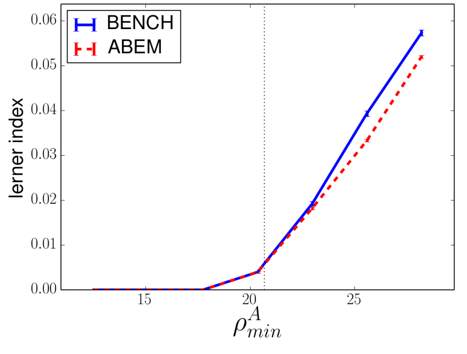
(a) oligopolistic scenario, $r_m = 0.3$

(b) competitive scenario, $r_m = 0.3$

Figure 3.5: Sampled outcomes for a in default settings



(a) Aggregated unit prices across both markets.



(b) Market power of a.

Figure 3.6: Effects of increasing prices of a's competition in the competitive scenario, $r_m = 0.3$. Results shown with ± 1 standard deviation.

power in both mechanisms. However, in settings with $\rho^A_{min} \geq 24$, a gains substantially less market power with respect to the default setting when taking part in the ABEM mechanism and therefore has less market power than when taking part in the BENCH mechanism. See Figure 3.6b for the most substantial case, where a has up to 11% less market power in the ABEM mechanism.

Discussion: First, the mechanisms ABEM and BENCH prescribe different bid formats for market B. This leads to different bidding behaviour by a in both markets (see observation 1). In market B, agent a in BENCH bids a constant price ρ^B_a and thus the results differ only along the quantity axis (for Q^B_a). Agent a in ABEM, on the other hand, bids a supply function to market B, and thus results for both Q^B_a and ρ^B_a differ (depending on δ_a, the slope of a's bid).

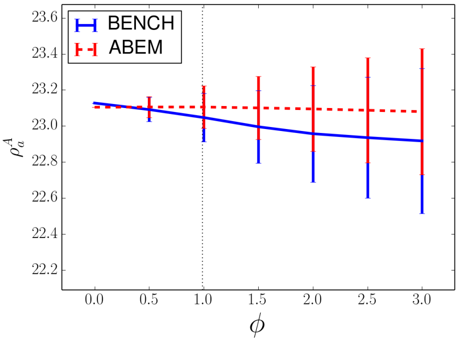
Most important, however, is the confirmation that a reaches the same level of surplus in ABEM and in BENCH. This shows that using ABEM is economically as rewarding as our benchmark mechanism BENCH, by which we address the design challenge we describe in Section 3.3.c. The observation that a in the BENCH mechanism does not sell any Q^B_a in settings with high uncertainty is more prevalent when a is a flexible consumer, so we will discuss this behaviour in Section 3.6.c.

We now turn to observation 2 and discuss bidding behaviour under exploitable market settings (here modelled by large values for ρ^A_{min}). In most settings we simulated, multiple near-optimal combinations of quantities and prices exist. Though bids in the ABEM mechanism are less flexible than in the BENCH mechanism (because only one bid function can be submitted), a is likely to find a bid $b_{a,r}$ that realises one of them, as is evident in the good performance across all settings (see observation 1). However, the market settings in question (with $\rho^A_{min} \geq 24$) are so favourable for a that he can sell all capacity on both markets ($Q^A_a = Q^U_a(1 - r_m)$ and $Q^B_a = Q^R_a$). This means that there exists only one pair of optimal quantities (because bid functions are monotonically increasing) and the optimisation problem is reduced to finding the optimal prices for this pair of quantities.

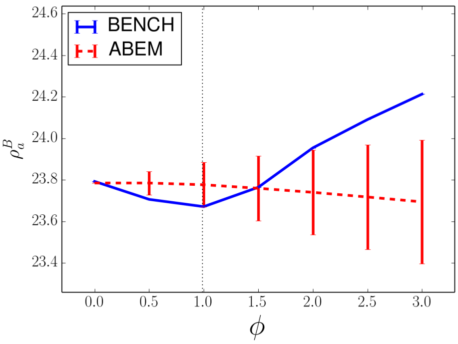
However, in the ABEM mechanism the following restriction is in place: Let the quantity Q^A_a be fixed. Then, the distance between bids $b_{a,r}$ and b^B_a with regard to the price is fixed as well (because the minimum price of b^B_a is $v^*_a + 2\delta_a Q^A_a$). Thus, in ABEM it becomes highly unlikely that a can bid optimal prices in both markets in this situation. We conclude that in conditions with excessive market power for a, the ABEM mechanism restricts a from realising the full potential market power. In effect, a in the ABEM mechanism lowers bid $b_{a,r}$ substantially, in order to not overprice on market B. This result addresses the design challenge we describe in Section 3.3.d. It makes the ABEM mechanism appealing to market makers, as it protects vulnerable consumers from unnecessarily high prices.

Agent a as a flexible consumer

As we do in Section 3.6.c, we begin by validating the market model for several important properties: a's overall surplus is positive in both mechanisms across all settings and, in comparison to the oligopolistic scenario, the competitive scenario has lower market prices and a lower surplus for a. We now discuss two major observations, where observation 1 is similar to observation 1 in Section 3.6.c.



(a) Effects on ρ_a^A



(b) Effects on ρ_a^B

Figure 3.7: Effects of increasing uncertainty on prices for a (oligopolistic scenario, $r_m = 0.3$). The dotted line shows the default setting $\phi = 1$.

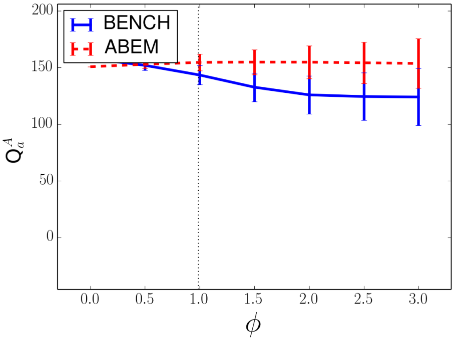
Observation 1: Agent a reaches comparable surplus in both mechanisms across a wide range of market conditions, but shows different bidding behaviour. The outcomes for a show distinct patterns between both mechanisms, most prominently in market B. If a sells electricity in both markets, this resembles outcomes we showed in Figure 3.5 and described in Section 3.6.c. However, in many settings, a in the BENCH mechanism sells no Q_a^B at all (see observation 2 for more details on this).

Despite such differences in market outcomes, a's surplus does not differ significantly[5] across all settings when we let a take part in the ABEM or BENCH mechanism. This observation is present in all our parametrised market settings, with the only exception for low values of ρ_{min}^A (where a has higher surplus in the BENCH mechanism).

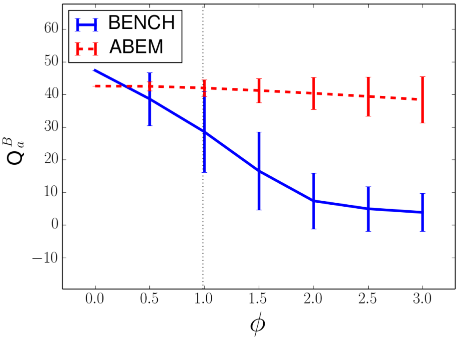
[5]We performed Student's T-Tests and tested for $p \leq 0.01$.

3

Observation 2: Agent a offers and sells reserve capacity at affordable prices in the ABEM mechanism, but not in the BENCH mechanism. In the ABEM mechanism, a consistently sells balancing power across most market settings, at prices which inflexible actors are willing to pay. a in BENCH, however, will in many settings bid a price ρ_a^B which is too high in the given market setting. As a consequence, he sells, when compared to the ABEM mechanism, very little Q_a^B or even none at all. In fact, a in BENCH only sells Q_a^B in the oligopolistic scenario, when $r_m = 0.3$, neither ρ_{min}^A nor D_{max}^A are low and ϕ is not high. Figures 3.7 and 3.8 illustrate what is happening when the uncertainty parameter ϕ (a's uncertainty about market outcomes increases with ϕ, refer to Section 3.6.b) is varied. a in the BENCH mechanism increases the price ρ_a^B and sells less Q_a^B when $\phi > 1$. At the same time, he decreases the price on market A and thus buys Q_a^A cheaper than a in ABEM.



(a) Effects on Q_a^A



(b) Effects on Q_a^B

Figure 3.8: Effects of increasing uncertainty on quantities for a (oligopolistic scenario, $r_m = 0.3$). The dotted line shows the default setting $\phi = 1$.

Discussion: The fact that agent a reaches comparable surplus in both mechanisms (see observation 1) confirms observation 1 in our first experiment (see Section 3.6.c) where a is a flexible supplier and the same discussion applies here. The only exception is given in settings with low values for ρ^A_{min}. We will discuss this exception in our discussion of observation 2.

Observation 2 describes that a in BENCH is only in a few settings willing to offer his reserve capacity at prices which are acceptable to inflexible actors in market B (and thus does not sell Q^B_a in other settings). This observation addresses the design challenge we describe in Section 3.3.c and makes the ABEM mechanism attractive to market operators.

Agent a in BENCH does offer and sell Q^B_a at affordable prices in the default settings of the oligopolistic scenario. In the remainder of this section, we will discuss the three settings noted in observation 2 (low values for ρ^A_{min}, low values for D^A_{max}, high values for ϕ), which lead a in BENCH to overprice Q^B_a in the oligopolistic scenario and also explain why he does not sell Q^B_a at all in the competitive scenario. Keep in mind, however, that settings with low values for ρ^A_{min} are the only ones where surplus for a differs significantly between the ABEM and BENCH mechanisms (see observation 1). In all other settings, the difference from a's point of view is merely one of bidding strategy choices, which a makes, not of financial outcomes for a. This is significant for the design challenge we defined in Section 3.3.c, which requires that bidders should be able to make the same amount of surplus as in comparable mechanisms.

In general, a in BENCH behaves as observation 2 describes, in order to avoid costs of lost opportunity (see Section 3.3.c). In particular, there are two reasons these costs exists. First, if a is uncertain about market outcomes, the financial risk of buying electricity in market A with the goal of offering it as reserve capacity in market B becomes too high for him when he bids a constant price ρ^B_a (as prescribed by the BENCH mechanism). Second, in some settings, a in the BENCH mechanism can buy electricity at a very low price ρ^A_a in market A and the price difference between ρ^A_a and possible prices ρ^B_a in market B is not attractive enough. We now begin by discussing settings where the latter reason for not selling ρ^B_a holds.

In *settings with low values for* ρ^A_{min}, supply prices are low in market A and thus an opportunity exists for buyers to raise their surplus considerably. a buys Q^A_a far under his reserve price v_a. In the BENCH mechanism, a does not need to sell any Q^B_a (he can overprice, as observation 2 describes), while a in the ABEM mechanism is required to sell Q^B_a at a price related to the price he paid for Q^A_a. *Settings with low values for* D^A_{max} are similar - Q^A_a can be bought cheaply in market A (in this case, because there is little competition from other buyers) and a in BENCH prefers not to offer it in market B at the prices he could achieve there. Finally, in *the competitive scenario*, the number of suppliers is increased tenfold, which decreases prices in both markets. As a consequence, buying on market A becomes more attractive and selling on market B becomes less attractive, which leads to a in BENCH to not sell Q^B_a.

We now turn to *settings with high values for* ϕ, in other words, with high uncertainty a has about market outcomes. In the BENCH mechanism, both the bid to market B (ρ^B_a) and the residual demand function for balancing power (D^B_{res}) react only very little to changes in price: The former is a constant price, and the latter has a low slope. The intersection of both varies strongly along the quantity axis. Figure 3.8b) illustrates this. Consider for example the default setting, where $\phi = 1$ (a base level of noise exists) and a still sells Q_a^B in BENCH. This variation of possible quantities for a means that, in the BENCH mechanism, a is facing a higher risk than in the ABEM mechanism, if he follows the strategy of increasing his bid to market A (i.e. to pay a higher price for Q_a^A), in order to be able to offer reserve capacity Q_a^R and sell Q_a^B. The negative outcome a risks in this case is that he might sell too little or no Q_a^B due to noise in market B. This would strongly lower a's overall surplus. Therefore, a lowers his bid $b_{a,r}$ to market A, in order to optimise surplus there, and overprices his bid price ρ_a^B in market B, in order not having to sell any Q_a^B.

This is not the case in the ABEM mechanism. Here, a submits a positively-sloped bid function to market B, which reduces variation along the quantity axis. This result relates to the original paper about supply function equilibria by Klemperer and Meyer (1989) [71], where the authors note that, when faced with exogenous uncertainty about residual demand, "a supply function provides valuable flexibility, because it can be chosen to coincide with the set of optimal price-quantity pairs“. By using supply functions in market B rather than a constant price (a Bertrand model), the ABEM mechanism provides a solution to the design challenge we defined in Section 3.3.b.

3.7. CONCLUSIONS

Future energy systems will contain many dynamic patterns on both the supply and demand side. To allow for stable operation, market mechanisms are needed that allow for planning by making binding commitments ahead of time. In addition, they should trade reserve capacity, such that flexible actors are explicitly involved in the System Operator's challenge to balance out supply and demand in real time.

Existing versions of such mechanisms can be found on the level of wholesale markets. However, it is hard for bidders taking part in them to compute well-performing bids, both because it takes much computational effort and because their bid representation restrict efficient expression of economic value. This problem is highly relevant in so-called "smart grid" settings, where numerous computers make automated decisions for supplying or consuming energy on behalf of their owners situated on lower levels of the grid. In addition, it is uncertain whether bidders will use an existing mechanism as intended. First, bidders should be able to achieve sufficient surplus, when compared to other mechanisms. Second, flexible bidders should choose to offer reserve capacity at affordable prices. Finally, all mechanisms in energy systems face the problem that suppliers have excessive market power in certain market settings.

In this chapter, we propose and evaluate ABEM. ABEM is a novel two-settlement market mechanism which includes the trade of reserve capacity. To the best of our knowledge, no market mechanisms with these capabilities have been proposed so far, which are also suitable for small-scale and non-sophisticated actors, like for instance in smart grid settings. For bidders, ABEM allows for quick construction of bids and we show experimentally that there are no economic drawbacks when compared to a benchmark mechanism. For the System Operator, there are several advantages, as well: Excessive market power of suppliers is reduced (which we show in computational simulations) and flexible consumers will offer reserve capacity (which we prove for the case of perfect competition and show in simulations for the case of imperfect competition, where the flexible consumer needs to choose a profit-maximising bid strategically).

Future work could evaluate the ABEM mechanism in a setting with more than one strategic bidding agent. By including the decision-making of multiple actors, the social efficiency improvements can be studied in more detail. In addition, it can be useful to allow bidders to bid on several reserve ratios r at the same time, with several bids to the same market mechanism. This would enable the SO to increase market efficiency by increasing the number of alternative market clearing solutions. The design challenge here is to allow bidders some freedom on their choice of values for r, but also to give the SO a way to ensure that he will be able to allocate sufficient reserve capacity. The explicit notion of r which ABEM prescribes is a good foundation for solving this problem, as opposed to the static heuristics which are in use today.

3

3.A. APPENDIX: PROOF THAT OFFERING RESERVE CAPACITY INCREASES THE UTILITY OF A FLEXIBLE CONSUMER

In this section, we provide a proof that for a flexible consumer a, offering reserve capacity is guaranteed to be profitable, if he submits his marginal utility function. As a benchmark, we consider a as an inflexible consumer, who buys Q_a^A and does not sell anything on market B. His surplus $SUR_a^{'}$ is given by:

$$SUR_a^{'} = \int_{q=0}^{Q_a^A} \left(\rho_a(q) - \rho_a^A\right)\, dq \tag{3.31}$$

where $\rho_a(q) = b_{a,r}^{-1}(q)$ denotes the unit price at which a's bid $b_{a,r}$ describes the quantity q.

Now we consider the case in which a is flexible and active on market B, selling any $Q_a^B \in [0, Q_a^R]$ at price ρ_a^B. Let us denote a's utility in this case by $U_a^{'}$. We calculate $U_a^{'}$ by subtracting from $SUR_a^{'}$ the loss of utility for selling Q_a^B less than Q_a^A and adding the revenues from selling Q_a^B. For illustration, Figure 3.9 shows in a grey area both the lost utility (on the right) and the revenues from selling Q_a^B (on the left). $U_a^{'}$ is given by:

$$\begin{aligned} U_a^{'} &= SUR_a^{'} - \int_{q=Q_a^A - Q_a^B}^{Q_a^A} \rho_a(q)\, dq + Q_a^B \rho_a^B \\ &= SUR_a^{'} + \int_{q=0}^{Q_a^B} \left(-\rho_a(q + Q_a^A - Q_a^B) + \rho_a^B\right) dq \end{aligned} \tag{3.32}$$

$U_a^{'}$ is guaranteed to be larger than $SUR_a^{'}$, if we can show that $\rho_a(q + Q_a^A - Q_a^B) \le \rho_a^B$ for all $q \in [0, Q_a^B]$. This is the case, because $\rho_a(0 + Q_a^A - Q_a^B) = \rho_a^B$ and the slope of $b_{a,r}$ is negative. □

Finally, we can now show that the ABEM bid mechanism guarantees that offering reserve capacity increases a's utility, compared with an inflexible consumer that buys

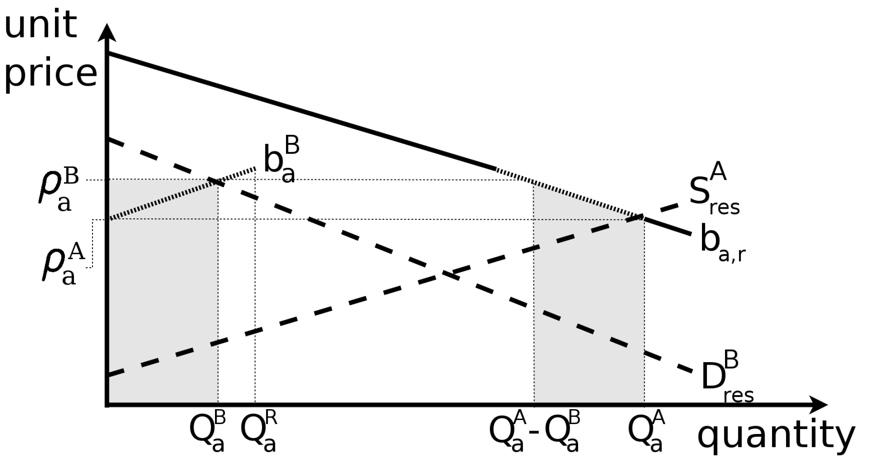


Figure 3.9: a's bid $b_{a,r}$ and the residual functions S^A_{res} and D^B_{res}. The dotted part of bid b_a is translated into bid b^B_a. Q^A_a and Q^B_a are determined by intersection of $b_{a,r}$ with S^A_{res} and D^B_{res}.

the same amount of electricity. As a benchmark, let us again assume that a is inflexible and offers nothing to market B (and thus $Q^R_a = 0$). Here, we assume that a buys exactly $Q^A_a - Q^B_a$ in market A. We denote the surplus for a in this case by SUR^*_a, given by:

$$SUR^*_a = \int_{q=0}^{Q^A_a - Q^B_a} \left(\rho_a(q) - \rho^B_a\right) \, dq \tag{3.33}$$

where in this example, $\rho^B_a = \rho_a(Q^A_a - Q^B_a)$ denotes the price a pays for $Q^A_a - Q^B_a$ on market A (refer also to Figure 3.9).

Let us now consider that a acts as a flexible consumer and offers Q^R_a on market B. To make this case comparable to our benchmark case (which led to SUR^*_a), we assume that a first buys Q^A_a and then sells $Q^B_a \in [0, Q^R_a]$. This leaves a with $Q^A_a - Q^B_a$ for his own usage, just as in the benchmark case. We denote the utility a has in this case with U^*_a. There are two differences in U^*_a with respect to SUR^*_a: First, a pays a lower unit price for his consumption of $Q^A_a - Q^B_a$, namely ρ^A_a instead of ρ^B_a, and if the price difference of $\rho^B_a - \rho^A_a$ is positive, a's utility will increase. Second, a sells Q^B_a instead of consuming it himself, and thus adds $U'_a - SUR'_a$ to his utility (see above). U^*_a is given by:

$$U^*_a = SUR^*_a + (\rho^B_a - \rho^A_a)(Q^A_a - Q^B_a) + U'_a - SUR'_a \tag{3.34}$$

We have shown above that $U'_a - SUR'_a$ is positive. We now show that also $(\rho^B_a - \rho^A_a)(Q^A_a - Q^B_a)$ is positive. This is the case because $Q^A_a - Q^B_a \geq 0$ and $\rho^B_a \geq \rho^A_a$ (see Section 3.4.a). $\square$

4

THE PERSPECTIVE OF NON-SOPHISTICATED CONSUMERS IN FLEXIBLE RETAIL CONTRACTS

4.1. INTRODUCTION

Most electricity consumers are small-scale households, who currently have long-term contracts with electricity retailers. These contracts prescribe a constant unit price per consumed kWh (see also our discussion of current retail contract models in Section 2.2.b). As a result, retailers completely shield their consumers from the risk of price dynamics on the wholesale markets. This situation will probably change in the near future. Retailers will begin to expose their consumers to wholesale price dynamics, as both supply and demand become more volatile and less predictable (we discuss these trends in Section 2.1). Flexibility of consumption is becoming a valuable contribution in future energy systems, and dynamic pricing is needed to realise its potential.

In this chapter, we propose novel indicators to evaluate the perspective of flexible as well as inflexible consumers for settings in which electricity retailers use novel retail contracts which allow them to use dynamic pricing. Our analysis for this purpose is positioned in economics and market design, and we use agent-based modelling to demonstrate the indicators in a future electricity retail setting. The proposed indicators measure comprehensibility of a pricing system from the standpoint of one consumer, thus the resolution of the consumer model is no limiting factor for their usage. By taking averages of the measured indicator values across the whole population or across selected groups of participants, statements can be made about the pricing system as a whole. This kind of analysis is useful for designers of dynamic pricing systems, where the strategic choice of pricing strategy and the response of consumers to it is crucial to the objectives of the designer.

Flexible consumers (who are flexible to changes in prices) exist in today's electricity systems, but they mostly represent large facilities (e.g. an aluminium-producing factory). In so-called smart grid settings, many consumers, for example domestic households, can be expected to be small and non-sophisticated, i.e. they do not possess elaborate strategic intelligence to optimise their behaviour when facing dynamic prices. In future settings, consumers might employ decision-making software to govern their devices on their behalf. However, we should not expect that this software has large amounts of computational power nor should it be assumed that it uses an algorithm which is fine-tuned to the market situation it is operating in. Finally, we should also expect that, at least for a considerable amount of time, many consumers will remain inflexible with respect to prices, out of necessity or indifference, and make no use of software to optimise decisions.

A short description of a likely future setting is thus as follows. Retailers will offer contracts with dynamic pricing. In effect, a retailer sets up and mediates a local market, in which he acts as a monopolistic supplier and the consumers with whom who he has contracts represent the buyers. Using this definition of the relation between a retailer and his consumers, this chapter views the business strategy challenge for the retailer as a market design problem. He has to decide which contract settings to offer and which pricing strategy to use in real time to arrive from wholesale market prices (where he has to buy electricity) to prices for consumers. Furthermore, we can expect that contracts restrict the range in which prices can vary, as a consequence of regulation for consumer protection or as a marketing strategy to attract consumers. Finally, consumer populations will likely be mixed, with one part of the population being flexible and the other part being inflexible. It is unclear how decision-making will develop. Current research investigates how humans react to dynamic pricing, but probably most consumers will employ automated software to decide on their behalf, which probably differs in the decision-making with respect to a human.

To the best of our knowledge, a setting in which contracts allow prices to vary within pre-defined bounds and where consumer populations contain both flexible and inflexible consumers, has not been explored in detail in scientific modelling so far.

The long-term success of an electricity retailer will in the future be determined by two novel factors: First, retailers need to avoid or mitigate consumption peaks, as they lead to high prices on wholesale markets. *Dynamic pricing can incentivise consumers to avoid or delay consumption during peaks.* Second, it is important that the pricing strategy is not too complex. *The price dynamics should be comprehensible to non-sophisticated consumers and to software agents they employ.* Consumers want to make informed decisions whether to sign a retailer contract and software needs to make local consumption decisions based on the dynamic prices. Both of these reasons are important to reduce customer retention.

These two factors are not complementary, however, as we will show in this chapter. The price with the lowest complexity is a constant price, as in today's retail contracts. If, however, prices become dynamic, they become more difficult to comprehend, which increases the effort necessary to participate in the retailer's market and to objectively compare the contract to the contracts of other retailers. In effect, the retailer faces a trade-off when he designs his contracts and pricing strategy.

With the contributions of this chapter, we address the second research question of this thesis (which we stated in the introduction, see Section 1.3). This research question states the need for simple, fast and fair mechanisms, involving non-sophisticated actors. We propose novel indicators to measure comprehensibility of pricing dynamics from the consumer's point of view. We then demonstrate these indicators in a stochastic market model, using Monte Carlo simulations. Note that in Chapter 5, we will address a similar setting, but concentrate on the dynamic pricing strategy of the retailer. In particular, this chapter proceeds as follows.

In Section 4.2, we will motivate why we believe retailers should put more focus on the consumer's point of view, compare our approach with other modern approaches to market design and provide some discussion about complexity in markets and its visibility to market participants. Section 4.3 formulates the problem statement for this chapter. Then, in Section 4.4, we define our concept of Comprehensibility. We propose three dimensions of Comprehensibility, which we formulate as straightforward and generic statistical indicators: *Stability* (the variance in prices over time), *Learnability* (correlations between prices and other observable information) and *Engageability* (correlation between changes in price and demand response by consumers). In Section 4.5, we describe the model of a basic example market, in which a retailer has contracts for dynamic pricing (with upper and lower price limits) with a population of non-sophisticated consumers (who are either flexible or inflexible). We perform stochastic Monte-Carlo simulations in Section 4.6, where we evaluate several scenarios. We vary the maximal price deviation in contracts (to give more or less space for the retailer to adapt prices) and the ratio of flexible consumers in the population.

In Section 4.7, we demonstrate the dynamics in this model and then show that the Comprehensibility indicators are useful to understand effects of different contract settings and consumer population composition on the consumer perspective. In particular, we can demonstrate two properties of our model. First, *designing dynamic pricing retail contracts for both stable and engageable prices is a trade-off problem*. Second, *there is a limit to how well a consumer can learn price dynamics when populations are mixed*. Finally, section 4.8 concludes and discusses future work.

4.2. CONSUMERS AND COMPLEXITY IN MARKET DESIGN

In this chapter, we propose a novel way to analyse the contract settings and dynamic pricing strategy of a retailer and this section provides some background for this purpose. In the previous section, we viewed the retailer's decisions in this respect as a market design problem (for a local market, in which the retailer sets some boundary rules in contracts and then acts as a monopolist supplier for consumers in his own market, as long as they maintain a contract with him). Consequently, this section looks at the background from a market theory standpoint.

We first argue that consumer behaviour is an essential ingredient to the success of the retailer's strategy. It is important to design the local market such that flexible consumers can react to price dynamics (despite the complexity inherent to the market) and that few consumers leave the market (i.e. do not leave to join another retailer). We then briefly review methods of market analysis from the field of mechanism design, which are available to designers of markets and bidding strategies. There are, to the best of our knowledge, no methods of analysis that focus on the complexity of the decision problem from the point of view of the electricity consumer in a modern energy system. There are, however, several discussions of the general amount of complexity in markets and how much of this complexity should be shown to consumers. We review this discussion at the end of this section.

4.2.A. DECISION-MAKING CAPABILITIES OF NON-SOPHISTICATED MARKET PARTICIPANTS

When dynamic pricing is used in future retail markets for electricity, it is essential for retailers that non-sophisticated consumers can comprehend the pricing dynamics. We mentioned this already in Section 4.1. In particular, consumers will more often than today compare retail contracts with one another. In order to make informed decisions, it is necessary for them to comprehend the pricing dynamics. Consumers will probably let software agents react to prices in real time on their behalf. We can assume that these software solutions will not be high end, customised solutions, but need to operate with limited computational capabilities and that their decision-making processes will probably not be fine-tuned to the contract and pricing strategy of a specific retailer.

Thus, the real-time strategies of consumers should form an essential consideration during the design of the retailer's contract offerings and pricing strategy. In literature about market design, not many considerations of such interdependence between market operator and market participants exist. One example from economic literature is the property of markets called "Dynamic Efficiency" (e.g. [1]), which denotes how well a market policy prepares its participants for possible future states, rather than (statically) optimising the present.

Another interesting viewpoint comes from system theory. Several authors have paid attention to systems which depend on the actions of their users. Users make their decisions in autonomous fashion, but the system depends on these decisions to fulfil its objectives. In our case, the retailer depends on decisions of flexible consumers. They can lower their electricity consumption during peak load times, which is important for the retailer's objectives. However, the retailer can only indirectly control the actions of flexible consumers by contract settings and his pricing strategy. Such systems have been described with the term "socio-technological system" [26] or "co-constructive systems" [60]. Kroes et al (2006) [75] state that in socio-technical systems "agents within the system, who perform a sub-function, may change or redesign the system 'from within'. In other words, the (re)design of the system no longer takes place from a central point outside the system, as is the case in traditional engineering, but becomes decentralized".

Recently, there is more and more research from the field of human-computer-interaction (HCI) to study how users respond to and interact with complex autonomous systems. For example, Cramer (2010) [20] conducts usability experiments with human subjects to study their response to autonomous and adaptive systems which have some inherent complexity. Semi-automated decision making in complex environments is a relatively new field in HCI, which combines the fields of computer science and psychology. For instance, Hindriks et al (2008) [47] propose a decision support system (the "pocket negotiator") for humans to use in negotiations.

However, in this work we focus on ways to evaluate how automated decision-making fares in a given situation. Here, the field of Decision Theory (e.g. [35]) can be useful. It is concerned with the question how better decision making can be enabled for actors in complex, uncertain and inter-temporal environments. For instance, given a market mechanism, Decision Theory can be used by bidders to model automated bidding strategies that are likely to maximise their revenues.

4.2.B. RELATION OF THIS WORK TO MARKET MECHANISM DESIGN

In order to react to prices in accordance with the retailer's objectives, consumers have to be offered the correct incentives. Much work to analyse incentives in economic mechanisms has been done in the field of mechanism design (e.g. [57]). The basic idea of mechanism design theory is that an incentive-compatible mechanism receives truthful reports about utilities from market participants, because, given that mechanism, truthfulness is their optimal strategy. This result is often achieved by side payments or discounts. However, mechanism design has to make strong assumptions (e.g. market participants are rational, their utilities are known to them, no budget constraints for payments, no consideration for repeated interactions).

The main purpose of mechanism design is to choose a market mechanism. This is not the focus of this chapter, as we aim at evaluating existing mechanisms. Furthermore, the assumption that their utility function is known to consumers can often not be supported in reality. The utility which non-sophisticated consumers derive from their consumption of electricity is not very well researched. One reason for this is that electricity is an economic good that is always complementary to the achievement of some other activity (i.e. consuming electricity has no utility in itself). Finally, retail pricing strategies often use uniform pricing, i.e. side payments to achieve incentive compatibility might not always be possible.

During the last decade, the field of algorithmic mechanism design [94] has developed analysis techniques within traditional mechanism design. This development has been inspired by the disciplines of discrete mathematics and theoretical computer science. Algorithmic mechanism design aims to design mechanisms and to arrive at statements about them, regarding the computational feasibility of computing outcomes. To this end, it conducts a worst case analysis and uses approximation algorithms to evaluate computational efficiency. This is ongoing work, as the computational feasibility of algorithms in some domains is still unclear (e.g. [77, 113]). Algorithmic mechanism design is a useful tool for some economic settings (see for example Singer (2001) [113], who shows a class of problems for which mechanism design can approximate solutions in polynomial time and also avoid overpayments). In this chapter, we are also interested in the computational feasibility of using a market mechanism, but rather from the market participant's point of view (specifically, their algorithmic challenge to take part successfully), not from the market operator's point of view.

4.2.C. HIDDEN COMPLEXITY IN MEDIATED MARKETS

Markets are complex systems. One way to describe the complexity in a market is to describe the amount of information that is contained in prices. For example, Bonanno et al (2001) [10] describe three levels of complexity that are useful for the statistical interpretation of financial time series. Such interpretation requires advanced intelligence, both if humans compare markets with each other or software makes real-time decisions in reaction to price dynamics. In settings where, as in this chapter, most market participants can be assumed to be non-sophisticated, it is necessary to take a closer look at complexity in markets.

Complexity makes it difficult for market participants to properly plan their actions. Complexity also increases the differences between sophisticated and non-sophisticated participants in their abilities to optimise their outcomes. In recent years, arguments have been made that there is a complexity constraint (e.g. [34, 101]), in that strategies of participants can only handle a limited amount of complexity in the market. If a market is saturated with complexity in this regard, strategies of consumers will become less effective and they might leave the market (in our case, this means they leave the local market which the retailer runs, by cancelling their contract).

On the other hand, complexity is also viewed as necessary for the long-term success of a market. Potts (2001) [101] argues that some amount of structural complexity is needed in an economic system, such that the possible allocations enable market participants to adapt to a current state and also to prepare for an uncertain future.

Most of the economic literature agrees that the inherent complexity in markets is not visible to all market participants. The "efficient-market hypothesis" claims that the information in prices reflects the true value of products. However, there is growing evidence against the hypothesis in its strong form (e.g. [62]), which claims that prices reflect even private information. As an example, consider mediated markets (see Section 2.2.a) like auctions or the local retailer markets, which we focus on in this chapter. Market participants (i.e. bidders, consumers, etc) only interact with one central mediator, e.g. an auctioneer or the retailer. They might not know how the mediator computes prices (e.g. a retailer does not publish his pricing strategy). More important, however, is that market prices are always to some degree based on the activities of other market participants (e.g. other consumers), who act autonomously. The goals, constraints and contracts of these other market participants are private information, and also their behaviour, such as bids or consumption, is often not visible to other participants. Finally, various other systemic features (e.g. transaction costs) prevent hidden information from being represented in prices.

Designers of market mechanisms face a trade-off situation between making the decisions of participants easier (by hiding the complexity from them) and enabling them to make more informative decisions (by showing them much available information and enabling more complex bids). As markets are employed for more and more use cases, often involving non-sophisticated users and automated decision making, it becomes more and more important to make the right choice for the given market setting.

It appears that market design researchers are not in agreement how to handle this trade-off. Many lean towards either of the two extremes. For instance, Pagano and Roell [97] state that transparency about prices decreases trading costs and conclude "that if policy makers want to reduce trading costs for uninformed traders, they should publicly disseminate order flow information as promptly as possible". They claim that their findings “may also help to understand why lately dealer markets are under increasing pressure from the more transparent automated auction systems.” On the other hand, some researchers in computational economics want to hide as much complexity as possible from actors, in order to decrease the barrier of participation. For instance, Seuken et al. (2010) [112] advocate “Hidden Market Design", which hides complexities and semantic aspects from the user. Teschner and Weinhardt (2012) [117] claim that “one reason for market failure is the inherent complexity excluding non-sophisticated users.”

4.3. PROBLEM STATEMENT

In this section, we summarise the problem this chapter is addressing. In Section 4.1, we outlined the upcoming challenges for the business models of future electricity retailers. In order to compete with other retailers, retailers will have to offer dynamic pricing contracts and operate pricing strategies. This makes them designers and operators of local markets, where a retailer acts as a monopolistic supplier to the consumers (as long as they maintain a contract with him). The contracts describe some market rules for allowed price ranges. Consumers can not be expected to own sophisticated decision-making facilities, and the consumer population can have any mix of inflexible and flexible consumers. Furthermore, we discussed in Section 4.2 that comprehensibility (from a consumer’s point of view) should be an integral concern when analysing local retail markets. Finally, we argued that markets are complex systems and that decision-makers can have limited capacity to deal with the inherent complexity.

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However, if comprehending the price dynamics is too complex for non-sophisticated humans or decision-making software which acts on their behalf, the quality of their decisions suffers. To design for comprehensibility constitutes a trade-off, as we described in Section 4.2.c. On the one hand, the information contained in prices should be reliable and not too complex; on the other hand it should enable understanding and the forming of informed decisions, using simple, non-sophisticated techniques. A comprehensible market reduces the overhead costs that arise by using it.

The point of view that comprehensibility is important to the success of markets is gaining support (see Section 4.2.c). However, few proposals exist how comprehensibility can be formalised and measured, such that it can become a relevant feature of the market analysis. We propose a three-fold view on comprehensibility in markets. Consumers want **stable prices** with small volatility. In their new role (representing so-called “active demand”), they also want to be able to **learn patterns** and they want to know that their **actions will be rewarded** (i.e. being flexible lowers costs). These goals might not be completely compatible with each other. For example, constant (completely stable) prices contain few patterns that could be learned.

There is a need for standardised indicators to make markets with dynamic pricing comparable to each other, with respect to comprehensibility. Such comprehensibility indicators would formalise a universal set of interests inherent to most consumers who are interested in reducing their overhead costs of taking part in the market. This is commonly not captured by objective measures such as average costs of contracts. If the indicators are used in market analysis, the applicability of automated bidding strategies can become more comparable between markets, which could be useful for the development of general-purpose bidding algorithms. In effect, the retailer can design his contracts and pricing strategy such that he attracts consumers, benefits from consumer flexibility and decreases customer retention.

Most market settings are too complex for a full description and analysis of all interactions to be feasible. Also, markets will differ among each other in several aspects. For these indicators to be applicable to different market designs and to enable comparison among them, they should be of general nature and make use of information which is available in most markets. For example, prices are signals of scarcity in all markets and can therefore serve as information in the indicators. Furthermore, the information used in the indicators, e.g. prices and quantities that consumers consume, should be accessible to the market operator who computes them.

4.4. COMPREHENSIBILITY INDICATORS TO ANALYSE THE PERSPECTIVE OF CONSUMERS ON PRICE DYNAMICS

We propose three comprehensibility indicators which are formulated for one consumer at a time. For simplicity of this work, we begin by measuring indicators one day at a time. In general, all indicators are an interpretation of the market prices announced to the consumer. We conclude this section by proposing three methods of evaluating the indicators in an aggregated manner, i.e. collecting the average values for all consumers or groups of consumers, in order to evaluate the pricing system as a whole.

4.4.A. PRELIMINARY CONCEPTS

We make use of two well-known statistical measurements for series of data measurements. The first one is variance, given by

$$v_P = \frac{1}{T-1}\sum_{t=1}^{T}\left(\rho^t - \bar{\rho}\right)^2 \tag{4.1}$$

where P is the series of prices (e.g. all prices during one day), T is the length of the series, $\rho^t \in P$ denotes an individual price at time t and $\overline{\rho}$ is the population mean over all prices in P. $v_P \geq 0$, where high values indicate that prices are spread out far from the mean and from each other. The magnitude of variance depends on the values in the series (the square root of variance is called the standard deviation).

The second measurement is the sample Pearson correlation coefficient, which computes the correlation between two measurement series X and Y. It is given by:

$$r_{X,Y} = \frac{1}{T-1}\sum_{t=1}^{T}\left(\frac{x^t - \bar{x}}{s_X}\right)\left(\frac{y^t - \bar{y}}{s_Y}\right) \tag{4.2}$$

where $s_X = \sqrt{v_X}$ and $s_Y = \sqrt{v_Y}$ are sample standard deviations. Note that $r_{X,Y} \in [-1,1]$, where $r_{X,Y} > 0$ means that the series are positively correlated (values change together and in the same direction), and $r_{X,Y} < 0$ means that the series are negatively correlated (values change together, but in different directions). $r_{X,Y} = 0$ does not allow to make any such statement.

4.4.B. STABILITY

One aspect of comprehensibility is Stability. A market which exhibits low variance in price series is more reliable for consumers and thus the resources needed to participate in it can be reduced (or be put to use less frequently). Of course, Stability usually works against some desirable attributes of dynamic pricing in markets, such as responsiveness to price differences.

We measure Stability with the standard deviation (which is the square root of variance), such that the values are given in the same units as the price data. Furthermore, we want Stability to be high when variance is low, thus we multiply the standard deviation in the series of prices by -1 (and let the Stability indicator report values ≤ 0, where 0 indicates maximal Stability). Our Stability indicator is given by:

$$Stability = -1 \cdot \sqrt{v_P} \tag{4.3}$$

where v_P is the variance (see Equation 4.1) in the series of prices P which were billed to consumers.

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4.4.C. LEARNABILITY

It is important that smart software can detect recurring patterns in price data, e.g. by machine learning techniques. We propose a second indicator, Learnability, which measures how well the likelihood of transitions between prices can be learned by a consumer. Specifically, the indicator measures how well an algorithm can be expected to perform a simple linear regression on behalf of the consumer, given previous series of prices and other observable information.

The term learnability is also used in several other contexts. For instance, it is also used in computational linguistics with respect to languages. The indicator discussed here is more similar to the concept of learnability in computational learning theory (e.g. [70]), where the term denotes the mathematical analysis of machine learning. A well-known theory in computational learning theory is Probably Approximately Correct (PAC) learning [121], with which the complexity of a wide range of learning tasks can be described, e.g. concept learning or classification. However, we are (for this indicator) interested in a specific learning task, namely how well one continuous variable (prices) can be forecasted, given one other continuous, so-called "explanatory", variable. In machine learning, this class of problems can be solved by so-called simple linear regression and the relation between the two series of data is modelled with a correlation coefficient.

For our use case this means that, in order to predict the likelihood of the next price transition, the consumer needs to correlate price series with series of other information that is available to him. For example, a consumer in a market in which power is predominantly generated from solar panels could learn patterns by correlating sunshine intensity with prices. However, Learnability can be quite low in some markets due to their inherent hidden complexity, which we discussed in Section 4.2.c.

Learnability, as an indicator how likely a simple linear regression is to succeed, is thus formulated as a correlation coefficient (see Section 4.4.a) and is given by:

$$Learnability = \frac{1}{T-1}\sum_{t=1}^{T}(\frac{\rho^t - \bar{\rho}}{s_P})(\frac{\iota^t - \bar{\iota}}{s_\Upsilon}) \tag{4.4}$$

where ρ^t denotes a price at time t in the series of prices P, and $\bar{\rho}$ is the mean price in P. $\iota^t \in \Upsilon$ denotes the value at time t from the series of information Υ which is used to correlate prices with (e.g. sunshine intensity). $\bar{\iota}$ denotes the average value in Υ.

4.4.D. ENGAGEABILITY

Engageability measures how well the market price dynamics incentivise consumers to react to them. The market design should encourage consumer reactions which help the operator reach his objectives and discouraging those that do not. This also works towards the reduction of customer retention in future markets for electricity, as flexible consumers might come to expect Engageability, in order to monetise their flexibility.

To measure Engageability for a time step t, we assume that there exists a way to quantify a consumer reaction as the difference between his initial intention for t (to consume a certain quantity) and his actual consumption during t. Likewise, we also assume there exists a way to quantify a price change as the difference between an initially assumed price for t and the actual price for t. In the following, we will first formulate the indicator and then discuss possible ways to quantify initially intended consumption and initially assumed prices.

Engageability assesses whether the reactions from consumers correspond to changes in price. More formally, Engageability measures how much a change $\triangle q_c^t$ in behaviour of consumer c for time step t relates to the change $\triangle\rho^t$ in price. Then, Engageability can be formulated as a correlation coefficient:

$$Engageability = \frac{1}{T-1}\sum_{t=1}^{T}(\frac{\triangle\rho^t - \bar{\triangle\rho}}{s_{P\triangle}})(\frac{\triangle q_c^t - \bar{\triangle q_c^t}}{s_{Q_c^\triangle}}) \tag{4.5}$$

where $\triangle\rho^t$ denotes changes in price (e.g. $\rho^t_{init} - \rho^t$, where ρ^t_{init} is an initially assumed price for t and ρ^t is the actual price). We denote with $P_\triangle$ the series of price changes for all t and with $\bar{\triangle\rho}$ the mean value in $P_\triangle$. $\triangle q_c^t$ denotes a consumption change by consumer c (e.g. $q^t_{c,init} - q_c^t$, where $q^t_{c,init}$ is the initially intended consumption by c during t and q_c^t is his actual consumption). We denote with $Q_\triangle$ the series of quantity changes for all t and with $\bar{\triangle q}$ the mean value in $Q_c^\triangle$.

Quantifying the initial values $q_{c,init}$ and ρ^t_{init} is crucial to make statements about the value of flexibility in a system and whether it is priced correctly. In a market system without explicit announcements of such initial values, expected values can be used which are based on experience (e.g. ρ^t_{init} is the usual price during t on previous comparable days). However, such assumptions are inexact. Another alternative are market designs in which these initial values are made explicit. The model we use in this chapter (see Section 4.5 for details) follows this approach. In this market design, the retailer lets consumers know about a price peak in an upcoming time step t (based on the aggregated consumption which consumers announced as their intention for this time step). In response to this price announcement, flexible consumers consume less than they intended. Then, the amount of demand that one consumer refrains from during t denotes the consumption change $\triangle q_c^t$ and the price reduction (per unit) during t denotes the price change $\triangle \rho^t$.

4.4.E. EVALUATION

An evaluation of the indicators can take place on data that is collected in a real-world market setting or from a computational simulation. As we noted above, the indicators are formulated for one consumer at a time. In order to evaluate the pricing system as a whole, it is useful to be able to evaluate the indicators in an aggregated manner, i.e. collecting the average values for all consumers or groups of consumers. For any indicator I, we thus compute

$$I_C = \frac{1}{|C|} \sum_{c \in C} I_c$$

where I_c is the indicator value for one consumer c, and C denotes a class of consumers, e.g. all flexible consumers or the whole population of consumers. In the following, we propose three methods of evaluating aggregated outcomes:

- *System configuration analysis:* It is important to see how the indicators respond to different market settings. Therefore, some important parameters to the market should be systematically changed, if possible, to evaluate the average effects on the indicators across all consumers.
- *Pareto front analysis:* As we stated before, the objectives expressed by the indicators are not necessarily compatible with each other. For the comparison of market designs in multi-objective optimisation problems like these, pareto fronts can be a meaningful tool to study how much the objectives compete with each other. Pareto fronts allow us to state if the outcome for an indicator could be increased under a different market setting without decreasing the outcome for another indicator in the process. If this is possible, the new configuration "pareto-dominates“ the current one.
- *Inner-consumer-group analysis:* Not all consumers are alike. In order to take this fact into account, one should compare the outcomes for one indicator for distinct groups of the consumer population with each other.

4.5. PROBLEM MODEL

In this section, we model a stylised market example. Consumers continuously consume electricity and pay for it according to dynamic retail contracts. The retailer buys electricity for the consumers from the wholesale market and calculates a uniform unit price in order to recoup his costs. Consumers can be either inflexible, meaning that they do not react to prices (they consume in each time step what they intended to consume) or flexible, meaning that they react to high prices by delaying demand to a time with lower prices.

4.5.A. AGENT INTERACTIONS

There are C consumers c. Each consumer c has a demand profile d_c, which indicates his original intent (independent of his expectations of costs and not adapted by previous delays of consumptions) to consume an amount of electricity d_c^t in 96 time steps $t \in T$. Each time step lasts 15 minutes. The retailer has a contract with each consumer. A contract specifies a minimum price ρ_{min} per kWh and the maximal price deviation factor $\delta > 1$ (the maximal unit price is $\rho_{min} \cdot \delta$). We assume in this work that all consumers have the same contract. See Figure 4.1 for an overview of the involved agents.

To match the consumer demand for the current time step, the retailer buys the needed amount of electricity from the wholesale market. To model the wholesale market and the retailer's interaction with it, we use the pricing function ρ_w^t. ρ_w^t maps the aggregated demand of all consumers (in kWh) to a unit price on the wholesale market (in €), which the retailer has to pay when the consumers demand this amount. We assume ρ_w^t is known to the retailer. When we refer to the wholesale market price at time step t, we use ρ_w^t as a shorthand for $\rho_w^t(d^t)$, where d^t is the aggregated demand of all consumers.

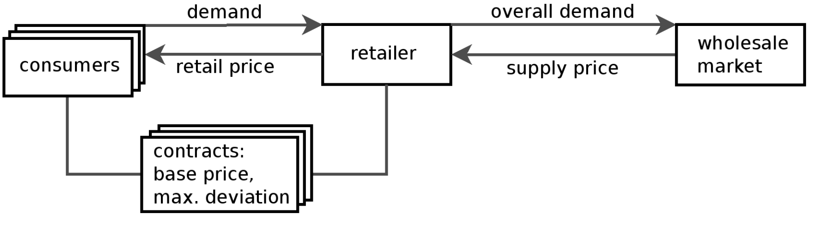


Figure 4.1: Agents and their interactions

The retailer finds prices to bill consumers as follows. At some agreed time $t - x$, all consumers announce their intended consumption to the retailer, based on which the retailer computes an expected unit price ρ_e^t. At this point in time, flexible consumers have time to adjust their consumption plans for t if they find the price estimation too high. Shortly before t, all consumers again announce their intended consumption for t to the retailer. Based on this second announcement, the retailer computes an actual unit price ρ^t. Consumers are ensured that both ρ_e^t and ρ^t remain within $[\rho_{min}, \rho_{min} \cdot \delta]$. To ensure that the actual unit price ρ^t will not be higher than the expected unit price ρ_e^t, consumers are not allowed to consume more than the amount they announced as intended consumption. We assume that the final announced amount is equal to the actual consumption during t by the consumer[1].

4.5.B. PRICE CALCULATIONS BY THE RETAILER

We now turn to the method which the retailer uses to compute uniform unit prices for electricity consumption. He uses this method both to compute the expected unit

[1]In a more elaborated model, consumers might use more than they announced, for which the retailer would bill them at a unit price higher than the regular unit price for t. If they use less, they have no advantage anyway, as the unit price for t was based on higher estimations.

price and the actual unit price. We assume the retailer needs to cover costs in addition to the costs of buying on the wholesale market, for instance administration and advertising. We model this by an overhead factor $H > 1$, by which we multiply the wholesale market costs. Thus, the retailer's target earnings per kWh (to cover his expenses) are $\rho_w^t \cdot H \cdot C$. The retailer offers contracts to consumers which allow him to adapt the price he charges for each time step t. Every time step t, the retailer bills all consumers with a uniform unit price ρ^t (per consumed kWh), where $\rho^t \geq \rho_{min}$ and $\rho^t <= \rho_{min} \cdot \delta$ (where $\delta > 1$). Equation 4.6 shows in detail how ρ^t is computed. In Section 4.6, we illustrate an example, see Figure 4.3.

$$\rho^t = max(\rho_{min}, min(\rho_{min} \cdot \delta, \rho_w^t \cdot H)) \tag{4.6}$$

4.5.C. BEHAVIOUR OF FLEXIBLE CONSUMERS

We call consumers inflexible who will never change their demand in response to ρ_e^t. Other consumers, who we call flexible, can delay consumption to a later time. They make the decision to delay if they deem ρ_e^t too high.

However, we do not assume that demand can disappear completely. A flexible consumer c will delay ϕ% of d_c^t (his demand in time step t) to the night if $\frac{\rho_e^t}{\rho_{min}} > \gamma$ (demand, and thus prices, can be expected to be low during the night in the consumption profiles we simulate, which are based on recent realistic data, see Section 4.6 for details). Thus, the parameter γ determines the price above which consumers deem ρ_e^t as high enough to delay their consumption, and the parameter ϕ determines how much of their current consumption they delay. The full amount that a flexible consumer delays in one day is spread out evenly over the hours from 00:30am to 06:00am of the following day. We thus assume that it is physically possible for ϕ% of demand of flexible consumers to be postponed on short notice. Furthermore, we assume for the simplicity of the model (preventing the so-called "bullwhip effect") that flexible consumers do not perform delays in response to high prices during the night.

Algorithm 4.1 explains how the model proceeds in detail. In addition, Table 4.1 lists the relevant model parameters.

The retailer announces an expected uniform unit price, based on the intentions of all consumers. Possible deviations from this price are bound by the retail contract (between ρ_{min} and $\rho_{min} \cdot \delta$). These intended states (demand d_c^t per consumer) and the possible price deviations (from the expected unit price ρ_e^t) are known only when the consumers have announced their intended consumption and the retailer has computed ρ_e^t, see lines 2-3 in Algorithm 4.1. Flexible consumers can reduce their demand (if they choose to), which can lead to a price reduction. This happens in lines 4-9.

4.6. EXPERIMENTAL SIMULATIONS

In this section, we perform computational experiments. We begin by describing the experimental setup, with which we model several scenarios for our Monte-Carlo simulations. Then, we explain results in two steps. We first present several outcomes from the perspective of both retailer and consumers over time, in order to illustrate the model dynamics to the reader and to illustrate that important model properties

Algorithm 4.1 Demand negotiations

while $t < runtime$ **do**
  Consumers announce their intended consumption for t to the retailer.
  The retailer computes and announces the expected unit price ρ_e^t.
  for all c **do**
    if c is flexible and $\frac{\rho_e^t}{\rho_{min}} \geq \gamma$ **then**
      c delays ϕ% of d_c^t to the night
    end if
  end for
  Consumers announce their updated intended consumption for t to the retailer.
  The retailer calculates ρ^t and bills consumers.
  Consumers consume according to their most recent announcement during t.
  $t \leftarrow t+1$
end while

Table 4.1: Summary of model parameters

Parameter	Description
C	number of consumers
T	number of time steps
ρ_w^t	wholesale supply unit price for time step t
ρ^t	uniform retail unit price for time step t
ρ_{min}	minimum unit price in contracts
γ	consumer price limit factor
δ	max. price deviation factor (max. price is $\rho_{min} \cdot \delta$)
d_c^t	intended demand of consumer c during time step t
ϕ	percent of delayable demand (for flexible consumers)
H	retailer overhead cost factor

behave according to our expectations. We then evaluate the Engageability indicators we proposed in Section 4.4.

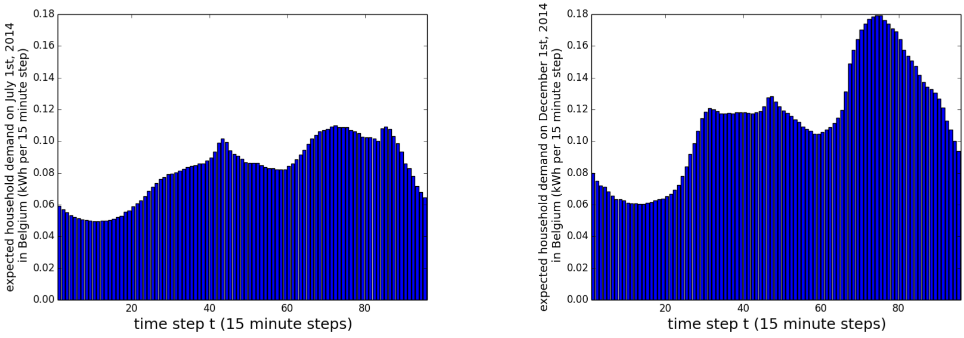
4.6.A. SETUP

In this section, we provide details on our choices for household demand, wholesale market pricing, retail contract settings and the consumer population composition. The flexibility of prices in contracts and the consumer population composition are systematically varied to create experimental settings.

In our experimental model, there are 24 **consumers**. To model their consumption profiles, we make use of domestic household demand profiles[2] which are based on historical consumption data and have been provided by the Flemish energy regulator VREG to serve as an expectation for the year 2014. From this set, we have removed

[2] https://web.archive.org/web/20140707232324/http://www.vreg.be/sites/default/files/uploads/slp_2014.xls

weekends. Two examples of such demand profiles over the course of one day are shown in Figure 4.2, with two peaks, one in the morning and one in the evening. In our system, the consumption profile for a consumer c, d_c, corresponds to the forecasted average profile d for a simulated day (where d was taken from the VREG dataset, see above), but with individual noise added to each time step (the noise is uniformly distributed within the range $[-7.5\% * d^t, 7.5\% * d^t]$ around each consumption value d^t at time t). Furthermore, we parametrise the delay decisions of flexible consumers by setting $\gamma = 1.1$ and $\phi = 30$.



(a) July 1st, 2014

(b) December 1st, 2014

Figure 4.2: The average expected consumer demand profile of two days in 2014

Wholesale market prices are modelled by a function ρ^t_w (see Section 4.5). Our implementation of ρ^t_w is inspired by wholesale day-ahead market data from the APX energy exchange[3] in the Netherlands from 2002-2013. The wholesale price per unit increases with average demand q, because generators get allocated to satisfy demand in order of ascending costs per generated unit. A positive slope has the effect that the unit price (and thus the average costs of all consumers) is high during time steps with high overall consumption.

However, the price dynamics in future energy systems can be expected to differ from the dynamics contained in the APX data: prices in our model are allocated much closer to the time of consumption than prices in a day-ahead market, the consumption in future energy systems is likely to be less predictable than today, and the supply during consumption peaks will be more costly in the future than today. Thus, we make two adjustments to the function which is given by the APX data. First, we multiply the slope of the historic APX supply curve by five. Second, we model a peak penalty which the retailer has to pay (e.g. for activation of balancing reserves) if $q > 0.25$ kWh, where q is the average demand of his consumers. Note that we use 15 minute time steps - the threshold would be 1 kWh if the time step length were 60 minutes. ρ^t_w is given by:

$$\rho^t_w(q) = \begin{cases} 0.019 + 0.6q & \text{if } q \leq 0.25 \text{ kWh} \\ 0.019 + 0.6q + 0.01 & \text{otherwise.} \end{cases} \quad (4.7)$$

[3]http://www.apxgroup.com/market-results/apx-power-nl/dashboard/

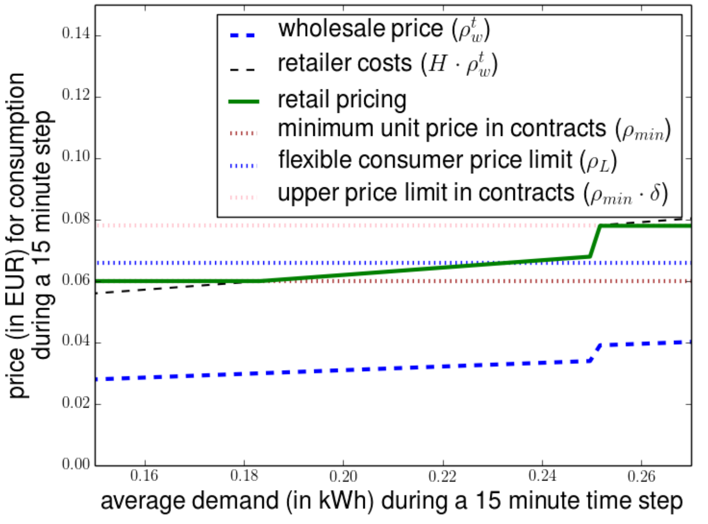


Figure 4.3: Illustration of the retailer's pricing model

For **the retailer**, we set the cost overhead factor $H = 2$ and choose ρ_{min} =0.06€ as the minimum price in his contracts. Figure 4.3 shows the resulting target retail price per kWh, which is bound from below by ρ_{min} and from above by $\rho_{min}\cdot\delta$ (in the Figure, $\delta = 1.3$). To create experimental settings, we vary $\delta \in [1.0, 1.075, 1.15, 1.225, 1.3]$.

For **the composition of the consumer population**, we vary C_f, the number of flexible consumers, $\in \{1, 6, 12, 18, 23\}$ (out of 24 consumers overall).

By varying δ and C_f as described above, we thus create $5 * 5 = 25$ settings. Per setting, we conduct 10 stochastic runs. In each run, we randomly select one day to start with and simulate 30 consecutive days (if December 31 is passed, we continue with January 1).

4.6.B. MEASURING THE INDICATORS

We now describe what data series are used to compute the indicators we propose in Section 4.4. We compute the indicators at the end of each simulated day, so all data series have a length of 96 time steps.

To measure Stability, we set the price series P to the uniform unit prices the consumers are billed. For Learnability, we set the price series P to the unit prices the retailer assessed in the beginning of a time step (ρ_e^t). We set Υ to the consumption values in the original demand profile of the consumer, on which the price expectation is (partly) based. For Engageability, we set $P_\triangle$ to the series of $\rho_e^t - \rho^t$. Furthermore, we set $Q_\triangle$ to the series of the quantities of electricity which the consumer delayed in each considered time step.

4.7. RESULTS AND DISCUSSION

This section presents results. We first present insights into the model dynamics of quantities, prices and accumulated monetary accounts. Then, we look at the Comprehensibility indicator results, where we make use of the evaluation methods we laid out in Section 4.4.e. If not stated otherwise, we take all measurements once per simulated day and report the averages.

4.7.A. ILLUSTRATION OF MODEL DYNAMICS

In this section, we illustrate the inner workings of our dynamic pricing model. The goal of this illustration is to increase understanding of the inner workings, which can be of help to interpret the indicator analysis results, which are presented in the next section. Although the model might seem not very intricate, the resulting dynamics are more complex than one would initially expect.

4

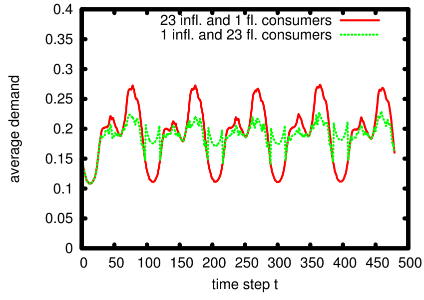
We use example settings for this illustration, where $\delta = 1.3$ (maximal flexibility in pricing) and only one ($C_f = 1$) or all but one ($C_f = 23$) consumers were flexible. Results from this example are averaged over 10 stochastic runs.

Figures 4.4(a) and 4.4(b) show the detailed dynamics (one tick on the x-axis per time step of 15 minutes) of demand d_c^t and retail prices ρ^t, respectively, over a course of five days. In the case where $C_f = 1$, all but one consumers are inflexible and thus demand spikes are high, which also leads to higher retail price peaks (given that the wholesale price function is positively sloped and we modelled a peak penalty, see Section 4.6.a). The case where $C_f = 23$ demonstrates how flexible consumers spread their demand and thus partly avoid price peaks. However, this increases prices during the night.

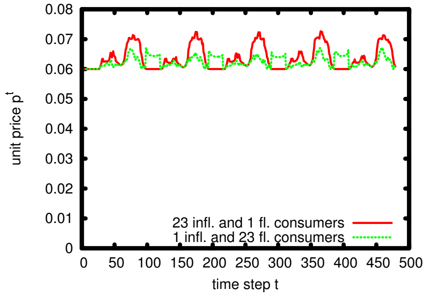
Figures 4.4(c) and 4.4(d) show accumulated monetary accounts of consumers and retailer, respectively. Both show averages from the simulations which run 25 experimental settings with 10 stochastic runs (each running for 30 days). In Figure 4.4(c), it can be seen that inflexible and flexible consumers are financially almost equally well-off after 30 days. Only when there are few flexible consumers (low values for C_f), are inflexible consumers notably worse off. The accounts of both groups are similar because the price reductions achieved through the actions of flexible consumer are beneficial to all consumers, as prices are uniform. In addition, the price during the night is (in the settings we evaluate) above ρ_{min}, so flexible consumers increase the price during the night by delaying parts of their demand there (this effect is visible in Figure 4.4(b)). Accounts of both groups decrease with increasing values of δ (because the retailer exposes them to wholesale price dynamics).

In Figure 4.4(d), we show the retailers' financial account under dynamic pricing (DP), for the two scenarios with $C_f = 1$ and $C_f = 23$. It can be seen that the retailer has the same average account in both scenarios. This is because he saves peak costs when many consumers are flexible, but on the other hand, he makes profits during the night in settings with many inflexible consumers (because they consume so little electricity that he can buy it at a price $\rho_w^t < \rho_{min}$).

For reference, we also show in Figure 4.4(d) the retailer account if he charges constant prices (CP), once for the minimum price ρ_{min} and once for the maximal price allowed by the contracts, $\rho_{min} \cdot \delta$. This shows that our scenario setup allows the re-



(a) Demand dynamics within five days



(b) Price dynamics within five days

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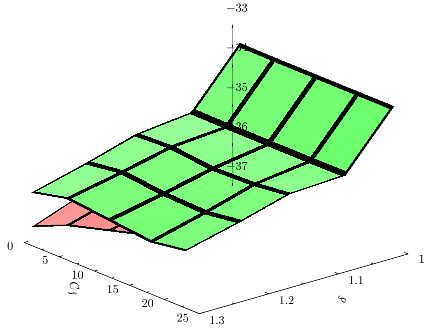
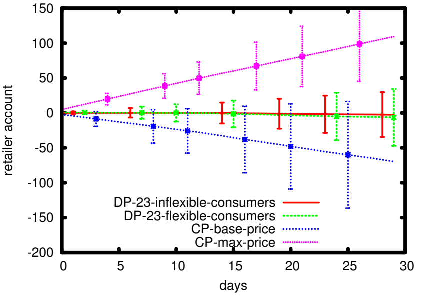


(c) Monetary account (z-axis) of flexible (green) and inflexible consumers (red) after 30 days. Shown for different scenarios where maximal price deviation (δ) and number of flexible consumers (C_f) are varied.



(d) Monetary account of the retailer in different settings over a 30 day period

Figure 4.4: Model dynamics of quantities, prices and accumulated monetary accounts. Values are averages across all consumers, for two different scenarios (four in Figure 4.4(d).)

tailer to roughly break even with dynamic pricing, other than the CP scenarios with the minimum price (where he makes high losses) and the maximal price (where he has high profits, but probably increases customer retention and makes losses in the long run). DP scenarios also lead to less noise in outcomes than CP scenarios.

4.7.B. COMPREHENSIBILITY INDICATOR ANALYSIS

In this section, we use the indicators we described in Section 4.4 to evaluate the comprehensibility in the dynamic pricing model described in Section 4.5. We demonstrate the usage of the indicators and are in the end able to draw some conclusions about dynamic pricing systems with mixed populations. The analysis shows that several properties of a complex dynamic pricing system can be analysed with the help of the indicators and the concept of comprehensibility from a consumer standpoint becomes more clear.

SYSTEM CONFIGURATION ANALYSIS

Figures 4.5(a) and 4.5(b) demonstrate the illustrative results which the indicators make possible: *Stability and Engageability are influenced by both δ and C_f*. Retail prices are fixed and thus maximally stable when δ (the maximal price deviation factor) is 1.0. With higher values for δ, they can fluctuate and thus Stability decreases. Regarding different settings for C_f, Stability is slightly lower in settings where the population has a majority of inflexible consumers.

Engageability is zero if $\delta \leq \gamma$, because flexible consumers do not delay demand during peaks to the night when the price is lower than $\rho_{min} * \gamma$ (γ is the price deviation factor, which flexible consumers use to decide whether to delay consumption). If $\delta > \gamma$, Engageability increases proportional to C_f. This is because the retailer uses a uniform price for all consumers. The more consumers are flexible (with higher values for C_f), the larger will be the price difference they can achieve.

The Learnability indicator (not plotted) has high values throughout all scenarios, with the exception of scenarios with $\delta = 0$, where Learnability is zero. This is a straightforward result, given the economic assumptions we used. All consumer profiles follow similar patterns, so when prices can vary to some degree, they are correlated to consumer's demand profiles throughout the day. This indicator might become more informative if a consumer population is modelled which contains consumer profiles of various kinds, e.g. with electric vehicle or heat pump owners present.

PARETO FRONT ANALYSIS

In order to investigate trade-offs between indicators, we plot pareto fronts. A planner of our example market could make use of such trade-offs for design decisions. As indicators should ideally be maximised, it is desirable to look for solutions which are situated towards the right (on the x-axis) and towards the top (on the y-axis). As is to be expected, *a pareto front, and thus a design trade-off, is visible between Engageability and Stability* (see Figure 4.5(c)). However, the trade-off given in our model seems acceptable: settings can be changed for increasing Engageability (e.g. by increasing the share of flexible consumers, see the System configuration analysis above), without decreasing Stability significantly. As an indication, the outcome outlined in blue has $\delta = 1.15$ and $C_f = 23$. The pareto plots involving Learnability are not of interest (in our model), as the Learnability indicator has similar values across almost all settings (refer to the System configuration analysis above).

INNER-CONSUMER-GROUP ANALYSIS

In order to get more insight into the Learnability indicator, we now look at the Learnability for flexible and inflexible consumers distinctively. We are interested in how much Learnability differs among them and how much the Learnability for each group changes if the ratio between the groups in the population is varied. Note that in our model, neither flexible nor inflexible consumers conduct any learning. However, Learnability indicates how well consumers understand their current situation and whether they have the opportunity to implement strategies which are based on learning. For this analysis, we fixed $\delta = 1.3$. Figure 4.5(d) shows that *both flexible and inflexible consumers perceive the highest Learnability of the pricing system when they are among consumers that behave just like them.* This result shows the kind of deeper insight which becomes possible with the indicators. It can be explained as a consequence of the retailers method of billing all consumers with a uniform price, without regard to their contribution in delaying demand.

4.8. CONCLUSIONS

In this chapter, we have described a challenge to the design of retail electricity markets. In future settings, retailers will offer dynamic pricing contracts in order to expose flexible consumers to price dynamics on the wholesale markets. These contracts will bound the range within which prices can vary. Retailers should expect consumers that are non-sophisticated in their decision-making. Furthermore, populations can be mixed, by which we mean that they can contain both flexible and inflexible consumers. We state that, given the complexity inherent to such economic settings, the comprehensibility from the consumers' point of view is crucial to a retailer's business strategy.

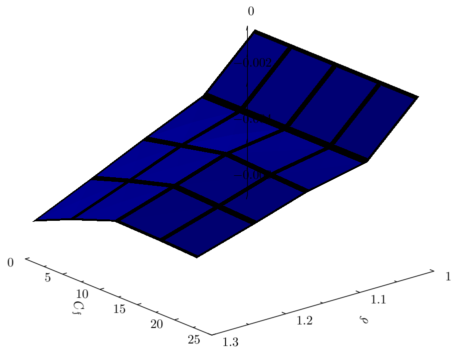
We offer three quality indicators for Comprehensibility: Stability, Learnability and Engageability. We propose ways of computing the indicators using basic statistic measures. These indicators measure comprehensibility from the standpoint of one consumer, thus the resolution of the consumer model is no limiting factor for their usage. By taking averages of the measured indicator values across the whole population or across selected groups of participants, the indicators can be useful tools for designers of electronic markets to evaluate their system, e.g. for designers of retail contracts. We conduct simulations in a retail market model with dynamic pricing and mixed populations in order to demonstrate their evaluation.

The results are helpful to demonstrate two properties of the dynamic pricing system we model. First, as can be expected, *designing dynamic pricing retail contracts for both stable and engaging prices can be a trade-off.* If prices can vary a lot, they are not stable. But only if prices vary, flexible consumers get incentives to make use of their flexibility, which flattens peaks. Second, we found that *there is a limit to how well a consumer can learn price dynamics when populations are mixed.* If other consumers behave differently, price dynamics makes less sense to them. For instance, if a flexible consumer is adapting, but no one else is, his influence on the uniform price is small.

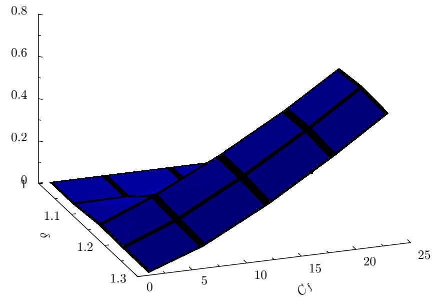
In future work, the models of consumers could be more differentiated, in order to gain more insight into the usefulness of the indicators when they are used to make statements about groups of market participants (as we did to some degree in Section 4.7). For instance, as we already mentioned in Section 4.7.b, consumer demand profiles could be modelled for different types of consumers. Furthermore, our classification between flexible and inflexible consumers could become more fine-grained, e.g. by introducing a degree of flexibility or by devising a set of strategies that consumers use to react to prices.

In addition, indicators could be enhanced for comparison between days. For instance, it could be helpful to measure Learnability by comparing the current time series with a time series of previous days.

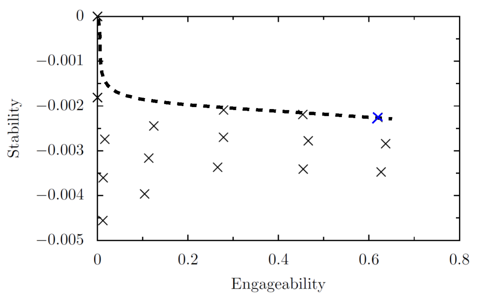
Finally, a promising route of further investigation would be to model an expanded setting in which several retailers compete with each other for consumers, who continuously decide which contract they could switch to. In such a setting, it could be studied if and how the Comprehensibility indicators are aligned with the long-term success of retailer strategies.



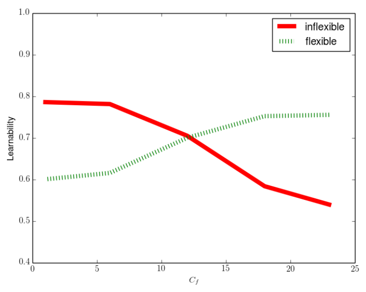
(a) Stability (average across all consumers) in different scenarios



(b) Engageability (average across all consumers) in different scenarios



(c) Engageability vs Stability (average across all consumers) in different scenarios, plus pareto front



(d) Learnability, separately plotted for inflexible and flexible consumers

Figure 4.5: Comprehensibility indicator analyses, outcomes from 25 scenarios (five in Figure 4.5(d)). a)+b): *System configuration analysis* - Results of varying C_f, the number of flexible consumers, and δ, the maximal deviations in retail prices, for Stability and Engageability - note that the graphs have been rotated for best visibility of the plot; c): A *Pareto front analysis* - scatter plot of all simulated settings and a manually illustrated pareto front for Engageability versus Stability; d): An *Inner-consumer-group analysis* - Learnability shown separately from the standpoint of all flexible versus all inflexible consumers - plotted for varying representations of flexible consumers in the population.

5

DYNAMIC RETAIL PRICING STRATEGIES FOR PEAK REDUCTION GIVEN MAXIMAL UNIT PRICES

5.1. INTRODUCTION

By employing dynamic pricing (DP) towards end consumers, electricity consumption can be distributed more evenly across time. This can shave consumption peaks, and thereby avoid high costs and CO_2 emissions. We already discussed dynamic pricing for electricity in smart grids in Section 2.2.b and we also mentioned the potentials of peak reduction in Section 2.1.a. In addition, we have paid close attention to the decision problem of consumers in Chapter 4. However, the implementation of this approach not only requires consumers who react to price changes, but also intelligent strategies for sellers to select prices.

This chapter considers the important topic of pricing electricity dynamically for end consumers (with the goal to reduce consumption peaks), where the focus lays on the selection of effective pricing strategies. This task is typically given for electricity retailers, who buy on the wholesale markets and sell to consumers who have contracts with them. In future smart grid settings, this task may also be given for other actors, e.g. a smart energy management system in a large office building, which aims to reduce local peak consumption by dynamic pricing. However, in this chapter, we will use the term "retailer".

We propose two model-based parameterised strategies for dynamic pricing. The parameters describe how a uniform unit price for each time step is computed as a response to the state of currently ongoing tasks of consumers. To employ such a strategy, the retailer needs a model of consumers and limited real-time knowledge. We show how sets of parameters which can be expected to perform well in a given scenario can be obtained from the large space of possible parameterisations through offline optimisation.

In both Chapter 4 and this chapter, we are interested in the effectiveness of dynamic pricing when the range of possible prices is constrained. Being able to promise an upper bound on prices is of interest to both retailers (to attract consumers) and government policy (to protect consumers). Then again, limiting the possible range of prices reduces the effectiveness of dynamic pricing. Thus, we are dealing with a trade-off in this problem of selecting pricing strategies. To the best of our knowledge, we are the first to introduce a maximal price into dynamic pricing problems for energy in smart grids.

For the evaluation of our proposed strategies, the effect of parameter sets needs to be computed based on a multi-agent model. The retailer's objective is to maximise profits, while he also has to pay penalties for consumption peaks. Consumers can buy energy per time step and have stochastically arriving jobs with a deadline (e.g. to charge a car or to run some factory equipment). They decide in which time steps to buy electricity, in order to minimise their expected costs and satisfy their deadlines. Similar to Chapter 4, consumers differ in their flexibility to react to prices on short notice.

This setup represents a stochastic and decentralised online scheduling problem under scarcity conditions. Dynamic pricing serves as the means to achieve good global outcomes when consumers can make scheduling decisions autonomously. Scarcity is given because peaks are costly and consumers have to respect deadlines for their jobs. Furthermore, as discussed earlier, a maximal price introduces a limit to the effectiveness of dynamic pricing solutions to minimise peak penalties for the retailer. Finding good dynamic pricing strategies for this problem is a complex task.

Retailers could use our approach to find a pricing strategy, along with a maximal price, with which they can expect to achieve some profit margin and also promise their consumers that prices will only vary to some extent (in order to set themselves apart from other retailers). Regulators could use the approach to mandate a maximal price, in order to protect consumers, while being able to argue to retailers that the price range should suffice to operate profitably.

This chapter contributes to the state of the art in the following ways. After Section 5.2 discusses related work, Section 5.3 offers a formalised model for the distributed online scheduling problem described above, which includes the novel aspect of a maximal price. In Section 5.4, we propose two novel, parametrisable strategies to set prices dynamically, based on available real-time knowledge about running jobs. In this work, we compute parameter sets which perform well for the retailer, through offline optimisation, for which we use a model of decision-making of consumers and an evolutionary algorithm. In Section 5.5, we perform computational experiments with simulated scenarios. We show the peak reduction effects of the dynamic pricing (DP) strategies with max. prices. Furthermore, we show that lowering the maximal price also lowers the peak reduction potential of dynamic pricing. We also show that a constant price (CP) strategy is not preferable over our (DP) strategies for the retailer (in terms of expected profits). Finally, we show that peaks are being reduced if the retailer employs our DP approach, even if he used profit maximisation as an objective to parameterise his pricing strategy.

5.2. OPTIMISATION OF SCHEDULING WITH DYNAMIC PRICING

In this section, we provide some background for the approach taken in this chapter. Because we model the consumer demand as a distributed scheduling problem, we briefly visit the rich history of scheduling in the energy domain. We pay special attention to scheduling via dynamic pricing. Finally, we introduce the technique of offline optimisation of online scheduling problems and our optimisation method of choice for the problem in this chapter.

5.2.A. SCHEDULING IN THE ENERGY DOMAIN

In this chapter, we consider consumer demand with a view that is slightly different from the previous chapter. Here, consumers not only have time-dependent demand, but their demand is modelled in the form of jobs, which have a deadline. In between their arrival and their deadline, jobs can be run when the consumer chooses to. This part of our model therefore falls into the domain of scheduling. Scheduling is a process that is used to make the decision when to commit one or more limited resources to one or more tasks. In the energy domain, scheduling has traditionally involved power generators, as consumption was less in the focus of optimisation in energy systems.

Yamin (2004) [141] provides a review of traditional approaches to the scheduling of generators. He distinguishes between two paradigms. The first paradigm is security-constrained unit commitment (SCUC), where a system operator plans generator schedules such that forecasted demand is met, system constraints are satisfied in real time and operating costs are minimised. The second paradigm is price-based unit commitment (PBUC), which arose with the advent of markets in energy systems. The common feature of PBUC systems is (according to Yamin) decentralised competitive bidding. While security has to be maintained by contracts (similar to SCUC systems) or balancing markets, meeting demand and minimising costs are, in PBUC systems, achieved by the market mechanism, which determines the schedule based on bids.

Yamin (2004) also provides an overview over the many different optimisation methods which have been employed to find good solutions for generator scheduling since the 1960s. The range of methods covers early techniques like integer or linear programming (e.g. [38]) and lagrangian relaxation (e.g. [90]), as well as later techniques for more complex problems, e.g. particle swarm optimisation [4] or genetic algorithms [96]. The complexity in the problem of scheduling generators increases with the amount and the nature of constraints. For instance, traditional generators do not only have variable costs (e.g. fuel input), but also fixed costs that are influenced by the schedule (e.g. ramping up and down has costs). Ramping up and down also requires a certain amount of time, which adds hard constraints to the scheduling problem.

5.2.b. Decentralised scheduling of consumption with dynamic pricing

If we model a scheduling problem for consumers, we also find various constraints. For instance, consumers have costs of delaying or interrupting their jobs. As the tasks that consumers perform with the help of electricity are more diverse than the traditional methods of electricity generation, it is not as straightforward to describe such constraints for the scheduling of consumption. Often, surveys are the only tool available. For example, Bertazzi et al (2005) [8] report, from a survey among consumers in Italy, the estimated direct costs of interruptions in electricity supply. The consumers were inquired about their willingness to accept (WTA) a specific compensation for service failures and their willingness to pay (WTP) a higher regular fee to increase the service quality. The authors concluded that WTA is higher than WTP.

PBUC systems (see Section 5.2.a) can use dynamic pricing instead of markets. In this case there is no bidding or market clearing. Instead, the system operator employs a pricing strategy, to which local decision-makers react. The scheduling is still a decentralised process, as consumers decide when to buy based on the current price. We have discussed dynamic pricing in previous chapters 2 and 4. In short, dynamic pricing selects prices on short notice, based on conditions found in the current situation.

In this chapter, the operator of a dynamic pricing system selects a pricing strategy offline (before the fact), which determines his prices online (while time progresses) automatically. A pricing strategy is a function or an algorithm, which maps conditions of the environment to a price for the current time step. For example, a mathematical function can be used to translate a numerical representation of the conditions in the environment to a price. A more powerful approach to model more complex functions are pricing algorithms. A robust example for such an algorithm is the derivative follower algorithm (e.g. [22, 43]), which changes the price in the same direction (increasing or decreasing) as long as the revenue keeps increasing, otherwise it changes the direction. However, the complexity of analysing outcomes also increases substantially if an algorithm is used. In addition, in the case that the pricing strategy should be communicated to consumers, most algorithms are less likely to be understood well by consumers than a mathematical function with a simple form (e.g. linear, quadratic or exponential) [1].

The design of well-working pricing strategies for scheduling in complex settings (like the one we describe in this chapter) is often a hard problem. It is possible that a pricing strategy which simply defines a constant price turns out to be a profit-maximising strategy [37] (although not necessarily a good solution to the scheduling problem). We will use a constant price as a benchmark in our simulations.

Offline optimisation of online scheduling problems

For complex domains, scheduling strategies (e.g. dynamic pricing strategies) can be optimised offline when a proper model is used. For instance, an algorithm might be parametrised and the offline optimisation selects values for the parameters which

[1] This aspect of understandability of a pricing strategy complements the concept we used in Chapter 4, where the understandability of actual price series was studied, rather than the strategy itself.

perform well on a problem model. In stochastic settings, it then makes sense to evaluate parameter value combinations in a Monte-Carlo simulation of the model (a Monte-Carlo simulation means to evaluate the same solution parameters multiple times, where selected input parameters to the model are randomly sampled from statistical distributions, see Section 2.3). Online, the parametrised scheduling strategy then can make choices quickly and without much computational overhead. Examples of this approach can be found in Vermeulen et al (2009) [128] and Hutzschenreuter et al. (2009) [58] for the application to hospital scheduling or in Ramezani et al (2011) [103] for general research into revenue management.

We also employ this approach for the complex setting of decentralised scheduling of energy consumption. We define pricing strategies for the retailer to use, for which we need to identify suitable parametrisations (which can be expected to perform well) from a value space with several dimensions. To this end, we have chosen to use evolutionary algorithms (EAs). In particular, we use Estimation-of-Distribution Algorithms (EDAs). EDAs are a type of EA but differ from conventional EAs in that they generate new solutions by estimating a probability distribution in the solution space from the last generation, from which then new solutions are drawn via random sampling. One of the advantages of EDAs over other EAs is that they can achieve good performance with little custom configuration.

5.3. MODEL

This section describes our problem model. First, we provide an outline. Then, we give details on the task of the retailer and describe consumers and their jobs. Finally, we outline a greedy algorithm to model the purchasing decisions of consumers.

5.3.A. OUTLINE

Several consumer agents $c \in C$ are consumers of electricity who each have one electricity-consuming job to run. Each job has a distinct arrival time and a deadline. After its arrival, it can be delayed by starting later than planned or by interrupting its execution (thus, we assume interruptable loads in this model - applicable examples for this are electric car charging or heating/cooling).

We measure performance over one day at a time, and thus consider a set of days $D \in T$. Each day is partitioned into time steps $t \in \mathbb{N}$ of 15 minutes, so one day has $24 * 4 = 96$ time steps.

The retailer buys electricity at current wholesale market prices ρ_w^t and has to pay penalties if peaks occur. He sets uniform unit prices ρ^t for each time step. Given ρ^t, the consumers decide before each time step whether to purchase electricity at price ρ^t for their job. If a consumer c decides not to buy, his job is delayed, which is unwanted, as consumers would prefer to finish their job as fast as possible. We assume that all jobs have to be supplied with energy until they are done and that supply is limitless.

5.3.B. THE RETAILER

The retailer sells electricity to consumers, which he buys on the wholesale market at the unit price ρ_w^t. For each time step t, the retailer announces a unit price ρ^t for the

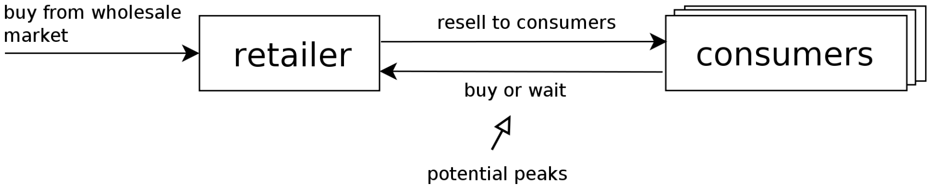


Figure 5.1: Agents and their interactions

supply of electricity. We assume that unit prices are bound by the maximal unit price ρ_{max}. The goal of the retailer is to minimise his costs of daily operation (for which he needs a well-working pricing function, see Section 5.4).

We assume for simplicity of our mechanism that ρ_w^t, the unit price on the wholesale market for time step t, is constant, so we can from now on refer to it as ρ_w. We also assume that consumers cannot switch to a competitor, so the retailer acts as a monopolist towards the consumers who have a contract with him. With these assumptions, we can focus on the problem of peak pricing in this chapter.

Considering ρ_w and the state of the jobs of consumers, the retailer decides on a unit price ρ^t. The actual supply which the retailer has to buy on the wholesale market for time step t follows from consumer purchasing decisions which are in turn based on the state of their job at time t and the announced price ρ^t. We denote this supply by $q(t, \rho^t)$.

5.3.c. Peaks

Let Q_{max} be the maximal capacity above which the aggregate consumption is considered a peak in our model[2]. The retailer is aware of a cost function $peak(t, \rho^t) \in \mathbb{R}$, which calculates the magnitude of a consumption peak in time step t. We model $peak$ for simplicity of this work as a linear function of overloading above Q_{max}. It is given by

$$peak(t, \rho^t) = \begin{cases} q(t, \rho^t) - Q_{max} \text{ if } q(t, \rho^t) - Q_{max} > 0 \\ 0 \text{ otherwise} \end{cases} \tag{5.1}$$

We assume that the retailer has to pay for those costs that are caused by peaks. We discussed in Section 2.1.a that the prevention of consumption peaks is crucial for several reasons. For instance, if the consumers share the same infrastructure, cables and transformer may overheat if all jobs are supplied right away, reducing their lifetime. Consumption peaks also lead to higher supply costs, i.e. on the wholesale market.

5.3.d. The consumers

We model a population of consumer agents $c \in C$ (we denote the size of the population with $|C|$), who all have one energy-consuming job, e.g. charging the battery of an

[2] In today's reality, there exists a second threshold $Q_{cut} > Q_{max}$, above which supply has to be cut off. In this case, high penalties have to be paid for every household that was cut off. We assume that Q_{cut} is not breached in our scenarios.

electric vehicle or heating up a house. They aim to minimise the costs of running their job. Consumers differ among each other in two aspects: the arrival times of their jobs and their reluctance to react to a price difference, i.e. to shift job execution away from the earliest possible slots (which they would do in order to achieve lower unit prices in later slots). This reluctance can take many forms. We model it as a general delay cost $\delta_c \in [0, \delta_{max}]$ per consumer c for the purpose of this work, which is applied for each delayed time step.

JOBS

The number of time steps for which all jobs need to be supplied in order to be finished is denoted as W. Because each consumer agent $c \in C$ has exactly one job, we will use the subscript $_c$ when we denote unique properties of the consumer's job. Each job can start after a unique arrival time t_c^s, and $t_c^e = t_c^s + L$ is the job's mandatory deadline, the time step at which it has to be finished. Thus, $L \geq W$ is the maximal number of time steps available to finish a job. Consequently, we constrain arrival times $t_c^s \in [0, 96 - L]$. Arrival times t_c^s are drawn anew every day from a Gaussian probability function. This probability function is used for all jobs and remains the same over all days $D \in T$. The retailer only learns about the job of consumer c at time t_c^s. Figure 5.2 illustrates a job which is supplied without delay and one with one delay in the supply.

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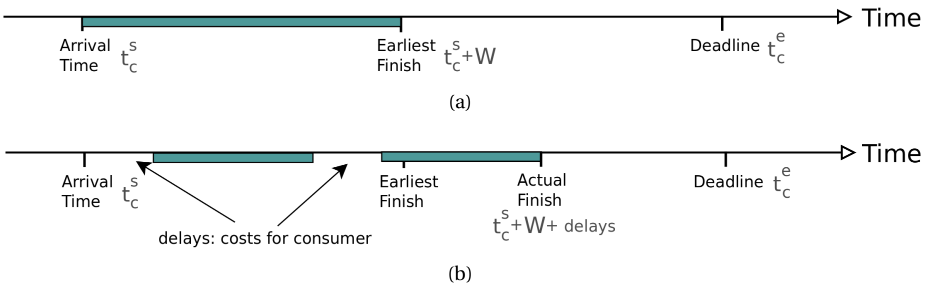


Figure 5.2: A job without and with delays.

If a consumer c supplies his job with energy in time step t (and buys the necessary electricity from the retailer), we denote this by $Q_c^t = 1$; if he does not supply his job, we denote this by $Q_c^t = 0$. For simplicity of our mechanism, we make the assumption that if a job is supplied during time step t, it requires and receives the exact, constant input of 1 kW for the duration of t (thus, c consumes 0.25 kWh per 15-minute time step). We thus assume that physically, both consumption and supply can, within one time step, happen constant over time.

To describe the state of c's job in a time step t, we denote with $rmng(c,t) \in \mathbb{N}$ the amount of electricity which c still needs to buy *before* time step t begins. The function $rmng$ subtracts the supply already bought before t from the overall needed supply for the job and is given by

$$rmng(c,t) = W - \sum_{i=t_c^s}^{t-1} Q_c^i \tag{5.2}$$

If $t + rmng(c,t) < t_c^e$, then c has flexibility of when to buy electricity: c can choose not to supply the job for up to $t_c^e - t - rmng(c,t)$ time steps by delaying to supply it. Note that all jobs have (the same) flexibility on arrival, as for all c, it holds that $t_c^e - t_c^s = L$ and $rmng(c, t_c^s) = W$.

Furthermore, we use the function $dlyd(c,t) \in \{0,1\}$ to denote whether c is not supplying an active job *during* t. The function $dlyd$ is given by:

$$dlyd(c,t) = \begin{cases} 1 \text{ if } t > t_c^s \wedge rmng(c,t) > 0 \wedge Q_c^t = 0 \\ 0 \text{ otherwise} \end{cases} \tag{5.3}$$

THE CONSUMER'S COST MINIMISATION PROBLEM

Each consumer c needs to make an informed decision in a rational manner whether to buy or not in each time step t if their job is active (i.e., if $t \in [t_c^s, t_c^e]$). For this, he needs some kind of expectation over future costs. In this section, we provide a simple algorithm for c to approximate an estimation of these costs and thus model consumer behaviour.

The cost minimisation problem faced by a consumer c in each time step t is given by:

$$\begin{aligned} \arg\min_{Q_c^t} &\left[Q_c^t \rho^t + dlyd(c,t)\delta_c + EC(c,t,Q_c^t) \right] \\ s.t. \quad & Q_c^t \in \{0,1\} \\ & Q_c^t = 1 \text{ if } t + rmng(c,t) \geq t_c^e \end{aligned} \tag{5.4}$$

where EC is a function which c uses to estimate costs in future time steps $i \in [t+1, t_c^e]$, given Q_c^t.

An important criteria to choose the algorithm which implements EC is that it can be performed in polynomial time, in order to keep the computation time in the simulation within acceptable bounds. This allows our optimisation method to perform many evaluations of solutions in acceptable time. We therefore provide a greedy algorithm (see Algorithm 5.1), i.e. consumer c only delays in a step if this decision appears already profitable immediately, given the next step. This assumes c to be a myopically optimising consumer, i.e. c only considers limited horizons in order to make decisions.

Furthermore, we assume that consumers learn which prices are to be expected in the upcoming time steps based on experience in previous days. Algorithm 5.1 can make use of $\vec{\rho}^E$, a vector of expected prices. $\vec{\rho}^E$ contains, for each time slot of the current day, a weighted running average[3] of the prices that have been announced in previous days for this time slot. We denote with $\rho_e^i \in \vec{\rho}^E$ the unit price that c expects in time step i. The outcomes of the state functions $rmng$ and $dlyd$ for any future time steps $i > t$ are based on purchasing decisions Q_c^j which c made in time steps $j \in [t_c^s, t]$ and which the algorithm is assuming to be made for time steps $j \in [t+1, i-1]$.

[3] A weighted running average is defined such that prices from more recent days have a higher weight in the average than prices from less recent days. It is recomputed daily, always taking the same number of recent days into account.

Algorithm 5.1 For a given t, estimate EC_c^t, the costs of completing the job of customer c in future time steps $> t$.

```
EC_c^t = 0
for all i ∈ [t+1, t_c^e] do
    if rmng(c,i) > 0 and t_c^s ≤ i ≤ t_c^e then   // If the job needs supply ...
        if i + rmng(c,i) ≥ t_c^e                   // and if no time is left ...
        or ρ_e^i < dlyd(c,i)δ_c + ρ_e^{i+1} then   // or waiting is more expensive:
            EC_c^t += ρ_e^i                         // Buy now.
        else
            EC_c^t += dlyd(c,i)δ_c                  // Otherwise, buy later.
        end if
    end if
end for
```

Table 5.1: Summary of model variables

Variable	Description
t	current time step
L	length of time window for a job
W	workload of a job
δ_c	delay costs of consumer c
Q_c^t	if $Q_c^t = 1$, c consumes 1 kW during time step t, otherwise $Q_c^t = 0$
ρ_w	wholesale market price
ρ^t	local unit price in time step t
ρ_{max}	maximal unit price for consumers

5.4. MODEL-BASED STRATEGIES FOR DYNAMIC PRICING

In this section, we propose two strategies for dynamic pricing (DP). The strategies are a mathematical function, mapping a state of consumer's jobs to a unit price. They are parameterised by a vector $\vec{x}$, which is optimised offline (considering the consumer model) and the maximal unit price ρ_{max}. We discuss the important design choices we made, formulate the strategies mathematically and introduce two possible objective functions, which the retailer could use in order to find well-working parameter sets.

5.4.A. DESIGN CHOICES

This work deals with uniform prices, i.e. a unit price is set for a following time step t which is valid for all consumers. Furthermore, we make two design choices:

1. Dynamic pricing: The price in each time step is a function of the state of active jobs (only jobs with $t_c^s \leq t \leq t_c^e$ are known to the retailer). We suppose the retailer can assess how much work each active jobs still has to do and knows the job deadline.

2. Offline optimisation: Given that finding successful parameter sets is hard in a complex setting like this, we optimise the parametrisation of strategies offline. A parameter set, once chosen, is employed by the retailer unchanged for a number of days (until he updates his model of consumers or the maximal price and re-optimises the parametrisation).

5.4.B. MATHEMATICAL FORMULATION OF STRATEGIES

We are interested in formulating pricing strategies which compute prices online (per time step t) without the need for extensive computation, using only a stylised mathematical function (as opposed to an algorithm, refer to Section 5.2.b).

Our strategies for pricing electricity are characterised by what we refer to as a parameter set in this chapter. A parameter set consists of a parameter vector $\vec{x}$, which is used to determine price responses, and a maximal price ρ_{max}. A pricing strategy $DP_{\vec{x},\rho_{max}}(\omega^t) \in \mathbb{R}$ computes the price ρ^t for the current time step t, given a state of the environment ω^t. The environment in this case refers to the consumers. We will describe both $DP_{\vec{x},\rho_{max}}$ and ω^t in more detail below.

5

The DP pricing strategies should achieve good results (over a range of days $D \in T$) on an objective function O of the retailer. The optimisation problem needs to find well-working parametrisation (values for $\vec{x}$ and ρ_{max}). Its general form is given by:

$$\arg\min_{\vec{x},\rho_{max}} \sum_{D\in T} O(D,\vec{x},\rho_{max}) \tag{5.5}$$

We now provide more details on the DP strategies. First, $DP_{\vec{x},\rho_{max}}$ is given by:

$$\rho^t = DP_{\vec{x},\rho_{max}}(\omega^t) = min(\rho_{max}, \Lambda_{\vec{x}}(\omega^t)) \tag{5.6}$$

where $\Lambda_{\vec{x}}(\omega^t) \in \mathbb{R}$ is a stylised mathematical function to compute a price. We propose two implementations for $\Lambda_{\vec{x}}$, thus two strategies. The first models quadratic functions (denoted by $\Lambda_{\vec{x}}^{quad}$) and the second models exponential functions (denoted by $\Lambda_{\vec{x}}^{exp}$):

$$\begin{aligned} \Lambda_{\vec{x}}^{quad}(\omega^t) &= x_0 + x_1\omega^t + (x_2\omega^t)^2 \\ \Lambda_{\vec{x}}^{exp}(\omega^t) &= x_0 + (x_1\omega^t)^{x_2} \end{aligned} \tag{5.7}$$

where the parametrisation vector is $\vec{x} = \{x_0, x_1, x_2\}$. We denote our two strategies by DP-Q $\in \mathbb{R}$ (which uses $\Lambda_{\vec{x}}^{quad}$; DP-Q is an abbreviation for DP-$Q_{\vec{x},\rho_{max}}$) and DP-E $\in \mathbb{R}$ (which uses $\Lambda_{\vec{x}}^{exp}$; DP-E is an abbreviation for DP-$E_{\vec{x},\rho_{max}}$).

Finally, the state descriptor ω^t is an approximation of the likelihood of consumers with active jobs to buy electricity in t, given the state of their job. ω^t is given by:

$$\omega^t = \sum_{c\in C} \frac{rmng(c,t)}{t_c^e - t} \tag{5.8}$$

The term $\frac{rmng(c,t)}{t_c^e - t}$ is initially $\frac{W}{L}$ for all jobs and can increase up to 1 if c has no more time to delay his job. Thus, $\omega^t \in [0, |C|]$.

As we noted above, the parameter set $\{\vec{x}, \rho_{max}\}$ is optimised offline, using an accurate model of the population, which includes the buying strategy of consumers (see Algorithm 5.1), the statistical distribution of values for arrival times t_c^s and delay costs δ_c (see Section 5.3). We note, however, that ω^t does not include values of δ_c, which is private information. Thus, in the online setting, the retailer uses only the pricing strategies and does not need to know actual values for δ_c.

Figure 5.3 illustrates the problem space between ω^t (the input to the dynamic pricing problem) and ρ^t (the output of the problem). The figure also shows a few example instances of pricing strategies.

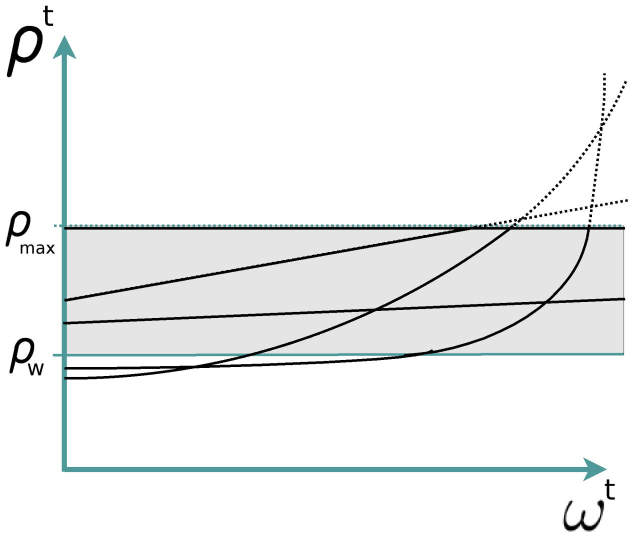


Figure 5.3: Problem space for determining a dynamic price ρ^t from the current state of consumers ω^t. The black lines represent graphical examples of pricing strategy instances, where the dotted parts are outside the restricted pricing range (which is depicted with grey background).

5.4.C. OBJECTIVE FUNCTIONS

There are two possible implementations for the objective function O. First, we are interested in **reducing peaks** by dynamic pricing. We would thus aim to minimise:

$$O_{PK}(D, \vec{x}, \rho_{max}) = \sum_{t \in D} peak(t, \rho^t) \tag{5.9}$$

where D denotes one full day, the $peak$ function was introduced in 5.1 and $\vec{x}$ and ρ_{max} are implicit in the unit price ρ^t (see Equation 5.6). Alternatively, we can **maximise the profit of the retailer**. We would thus aim to maximise:

$$O_{PR}(D, \vec{x}, \rho_{max}) = \sum_{t \in D} \sum_{c \in C} Q_c^t(\rho^t - \rho_w) - \sum_{t \in D} \phi \cdot peak(t, \rho^t) \tag{5.10}$$

where Q_c^t is derived by the consumers solving their purchasing decision problem

Table 5.2: Experimental settings

Parameter	Description	Setting
$\lvert C\rvert$	number of consumer agents	20
T	number of days	20
L	length of time window for a job	8 (2 hours)
W	workload of a job	4 (1 hour)
ρ_w	wholesale market price	0.1 € / kWh
Q_{max}	peak threshold	$\{8,4,2\}$
δ_{max}	max. delay cost factor per delayed time step	0.05 €/15 min
J_{mean}, J_{std}	mean and st. dev. of t_c^s (job arrival time)	20, 2

outlined in Equation 5.4 and ϕ is a multiplication parameter, used to compute the true costs to the retailer, which are caused by peaks.

5

5.5. Simulations

This section describes computational experiments. We first describe our choices for general parameter settings and three scenarios, which differ in Q_{max} (the available capacity below which aggregated supply is not considered a peak). We then explain how we find well-working parameterisations. In order to evaluate the effectiveness of our chosen method of optimisation, we compare its results to the results of a brute-force approach to finding well-working parameterisations. Then, we discuss what could be meaningful benchmark values for our objective functions, which is of interest to interpret results. Finally, we discuss the results of our dynamic pricing (DP) strategies against a constant pricing (CP) strategy.

5.5.a. Scenarios

In all three scenarios, we model a setting of 20 consumers, which we run for 20 days. Consumers need four time steps (of 15 minutes) to complete their job (because the supply is assumed to be constantly 1 kW, each job requires 1 kWh in total) and has two hours (8 time steps) to complete the job. The wholesale market price for 1 kWh is assumed to be 0.1 € (recall from Section 5.3 that we assume a constant price for simplicity of our mechanism - we chose for the higher end from APX UK[4] wholesale market traces from 2012, where prices ranged from 0.04 € to 0.1 €). Thus the price for one time step is ρ_w =0.025 €. Each customers reluctance to react to a price difference, i.e. to shift job execution away from the earliest possible slots (δ_c), is drawn from a uniform distribution in [0 €, 0.05 €]. Recall that we model one job per customer. So, in order to keep the problem concise, we focus on the late afternoon/evening consumption peak in our simulations for the simulation of a day. Job starting times are drawn from a normal distribution with mean 20 (i.e. the mean is set to time step number 20 of each day, which is the time step with duration from 5:00pm to 5:15pm) and a

[4] http://www.apxgroup.com/market-results/apx-power-uk/dashboard/

standard deviation of 2 (i.e. 30 minutes). The detailed parameter settings can also be read from Table 5.2.

We now propose a simple indicator β, which describes the scenario-specific scarcity of the cable capacity. In this context, we refer to an allocation as the act of supplying 1kW of electricity to one consumer for the duration of one 15-minute time step. We describe β as the ratio between the number of allocations which are *needed* to run all jobs and the maximal number of allocations that are *available* in the scheduling problem without causing peaks. Based on our formalisation for β, we will choose three scenarios based on three different values for Q_{max}).

Specifically, the number of needed allocations is given by:

$$|C| \cdot W \tag{5.11}$$

Furthermore, we set the number of *available* allocations to an optimistic approximation based on the time that jobs are active. Our approximation is given by:

$$Q_{max}(6 \cdot J_{std} + L) \tag{5.12}$$

5

$6 \cdot J_{std}$ is the length of a time window which includes 99.7% of the distribution of job starting times. We add one job length L, so that $6 \cdot J_{std} + L$ denotes our approximation of the length of a time window in which jobs are active, even if the starting time of some jobs might be three standard deviations after the mean starting time. Then, we multiply this approximation by the peak threshold Q_{max}. Thus, the scarcity indicator β is given by:

$$\beta = \frac{\text{needed}}{\text{available}} = \frac{|C| \cdot W}{Q_{max}(6 \cdot J_{std} + L)} \tag{5.13}$$

When we insert values from Table 5.2 into Equation 5.13, we arrive at $\beta = \frac{4}{Q_{max}}$. If $\beta = 1$ (and thus $Q_{max} = 4$), the available time steps could in most cases suffice to solve the allocation problem without causing peaks, given that the needed redistribution of consumption and, if necessary, job starting times, were achievable. We note that the normal distribution of job starting times and delay costs limit the solvability of this problem (more details are given in Section 5.5.b). However, the given formulation of β allows us to anchor a scenario at a solvable setting. If β is increased (and thus Q_{max} is lowered), the resulting scenario has more scarcity than the scenario with $\beta = 1$. If β is decreased (and thus Q_{max} is increased), the resulting scenario has less scarcity than the scenario with $\beta = 1$.

We run three scenarios, with $\beta \in \{0.5, 1, 1.5\}$, thus $Q_{max} \in \{8, 4, 2\}$.

5.5.B. SETUP

OPTIMISATION OF PARAMETERS

We now explain how we find promising parameter sets (values for $\{\vec{x}, \rho_{max}\}$). The following is conducted for both dynamic pricing strategies DP-Q and DP-E (which we introduced in Section 5.4).

In each scenario (see Section 5.5.a), we optimise two problems, each of which uses one of the two objective functions we described in Section 5.4.c. One population is optimised for O_{PK} (peak reduction, see Equation 5.9), the second for O_{PR} (profit maximisation for the retailer, see Equation 5.10).

We use an evolutionary algorithm (EA) to evolve populations of parameter sets, from which the retailer can choose one to employ. In principle, well-working values for $\vec{x}$ can be found with a single-objective EA (where the objective function is either O_{PK} or O_{PR}) when ρ_{max} is fixed (for instance for the case where ρ_{max} is known, or when the retailer repeats the optimisation for several values for ρ_{max}). In this work, we use the minimisation of ρ_{max} as an additional objective, so that we avoid having to repeat the optimisation process and also are not restricted by our choices of specific values for ρ_{max} (as the EA will explore the space of possible values).

We use the iMAMaLGaM-X+ algorithm (which is an abbreviation for “incremental Adaptive Maximum-Likelihood Gaussian Model miXture +"), a version of EDAs (see Section 5.2.b) for multi-objective problems (e.g. [12, 13]), for which EAs have shown to be highly effective (e.g. [15, 31]). Like any optimisation technique for multi-objective problems, iMAMaLGaM-X+ builds a pareto front of solutions. The pareto front built by a multi-objective optimiser shows for any solution if the outcome for one objective could be increased (by choosing a different solution) without decreasing the outcome for another objective. If this is possible, the new solution ”pareto-dominates“ the current one.

iMAMaLGaM-X+ estimates the distribution of the fitness function incrementally, over multiple generations, effectively reducing the population size required to perform this task. Furthermore, it clusters the current population of solutions, which spreads the search intensity along the Pareto front in an effective manner. Finally, iMAMaLGaM-X+ runs, in parallel, an instance of the single-objective optimisation algorithm iAMaLGaM for each objective, in order to arrive at robust results for the edges of the pareto front. These single-objective results are used within the overall search process of iMAMaLGaM-X+.

We parametrise iMAMaLGaM-X+ according to guidelines from literature [12], among others population size and maximum number of subsequent generations without an improvement. We run each market in each scenario for 1500 generations. The computation time to evolve 1500 generations on each of these problems was around 48 hours on a 16-core PC with a 2.26 GHz processor (iMAMaLGaM-X+ is able to evaluate solutions in parallel across all available CPUs). We used 5 clusters of solution populations (which the algorithm uses to model the pareto front, see above). Values in $\vec{x}$ are constrained to $[0,5]$. We thus maintain that price functions are positively sloped, i.e. ρ^t positively correlates with ω^t. ρ_{max} is constrained in [0, 0.75 €].

For all optimisations performed, we use the population (of evolved parameter sets) from the 1500th generation as the final outcome and we report as results the values obtained by evaluating this population again on the model in Section 5.3, independently from the optimisation procedure. We average outcomes over ten runs of T days on the model per parameter set, where δ_c and t_c^s values are drawn anew before the start of each run. These ten runs are always (for every evaluated parameter set) performed with the same set of ten seeds, which are used to initiate the random number generator.

Finally, outcomes are averaged over the last $\frac{T}{2}$ days of a simulation, to account for warm-up effects. As a result, we report for both DP-Q and DP-E the results given by:

$$\frac{\sum_{D=T/2}^{T} O_{PK}(D, \vec{x}, \rho_{max})}{T - T/2}$$

when O_{PK} is the objective function, and the results given by:

$$\frac{\sum_{D=T/2}^{T} O_{PR}(D, \vec{x}, \rho_{max})}{T - T/2}$$

when O_{PR} is the objective function.

A BRUTE-FORCE BENCHMARK FOR THE OPTIMISATION METHOD

It is crucial to evaluate whether the EA optimisation is a suitable method to find good solutions. We preform a brute-force approach on one scenario ($\beta = 1$, thus $Q_{max} = 4$) with 600,000 randomly generated parameter sets. We also evaluate these parameter sets on the model in Section 5.3. We were interested in comparing the best-performing parameter sets from the brute-force approach with the performance of the final population of parameter sets which had been optimised by the EA for the strategy DP-Q, using O_{PK} as the objective function (for peak minimisation). Figure 5.4 shows that the results from the dynamic pricing optimisation are at least as good as the results from the brute-force analysis, when plotting the results for average peaks per day on the y-axis as discussed in Section 5.5.b. In particular, we can also see that only few parameter sets of the brute-force approach are close to the pareto front which is formed by parameter sets optimised with DP-Q. This indicates that this optimisation problem is indeed hard, from a computational perspective.

5

BENCHMARK FOR THE OBJECTIVE FUNCTIONS

We are interested in benchmark values for evaluating the performance of our dynamic pricing strategies, for both objective functions O_{PK} and O_{PR} (see Section 5.4.c).

As benchmark for O_{PK} (for the peak reduction potential), an optimal lower bound of peaks would be useful, but the computational effort to compute this lower bound is high. For every time step, each consumer has $\binom{L}{W}$ possible schedules. An indication of the size of the search space, i.e. the number of possible combination of all possible schedules of consumers across the running time of our simulation, is given by:

$$T \cdot 96 \binom{L}{W}^{|C|} = 20 \cdot 96 \binom{8}{4}^{20} \tag{5.14}$$

However, the DP-Q strategy (and probably also the DP-E strategy) can serve as a good approximation, as we showed in the brute-force simulation (see Section 5.5.b).

As a benchmark for O_{PR} (profit maximisation for the retailer), we implement a simple constant-price strategy (CP). When he uses CP, the retailer always charges ρ_{max}:

$$CP_{\rho_{max}}(\omega^t) : \rho_{max} \tag{5.15}$$

Among all possible constant prices, ρ_{max} is a reasonable choice, as the amount of peaks will be the same, no matter what constant price is used. This is because

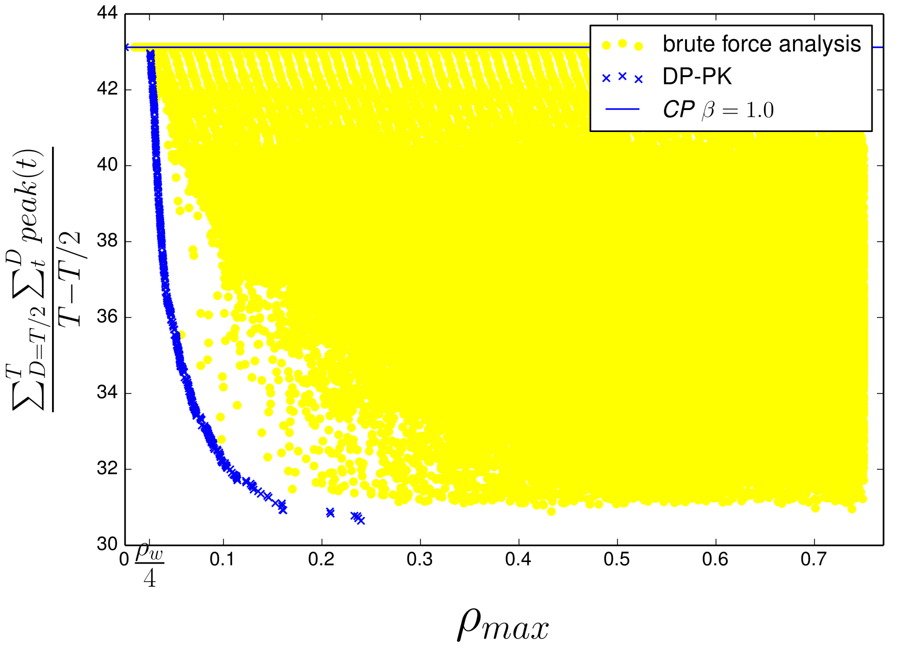


Figure 5.4: Peak costs of brute-force analysis against EA optimisation of dynamic pricing (DP-Q), when optimised for peak reduction.

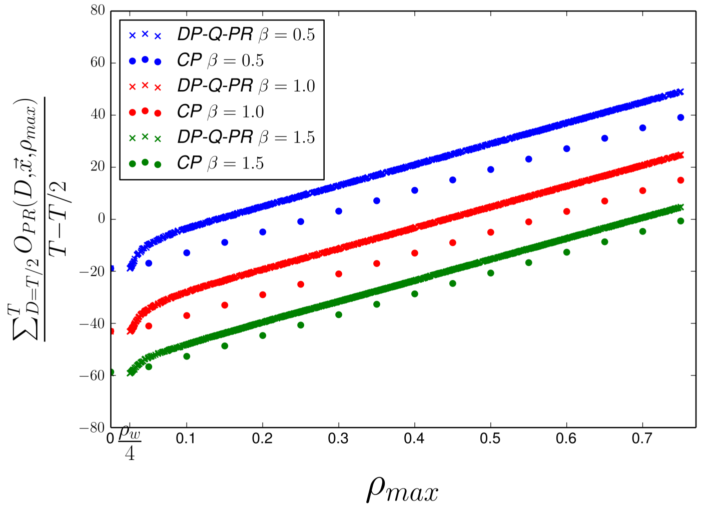
there are no price differences, and consumers will all supply their jobs directly upon arrival, in order to avoid delay costs. This also means that the peaks caused by the CP strategy can be considered a practical upper benchmark for peaks[5]. Note that the DP strategies can also model the CP strategy, as the mathematical formalisations allow to charge any constant price, as well.

5.5.c. Results

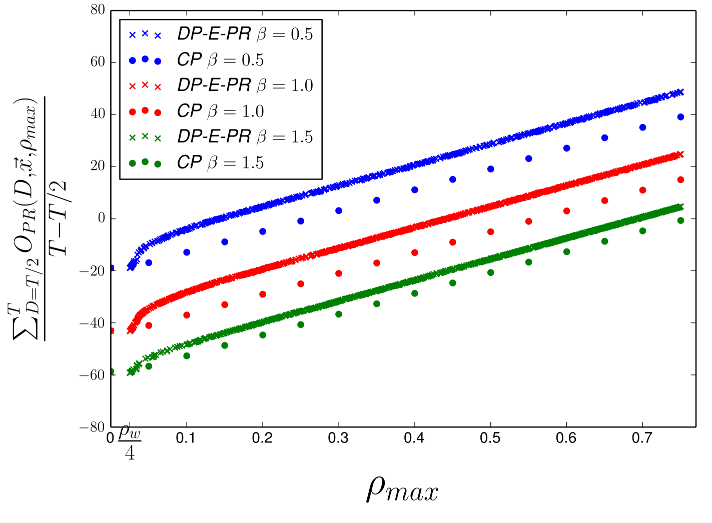
Profits

Figure 5.5 shows the average daily profits (as defined by objective function O_{PR}) of the retailer for different values of the maximal unit price ρ_{max}. We compare profits which the CP strategy makes (we used 16 values for ρ_{max}, chosen with equal distance from the range [0, 0.75 €]) with profits made by the DP-Q and DP-E strategies (which have been optimised for profit maximisation (O_{PR}) and are thus labelled DP-Q-PR and DP-E-PR in the figure). ϕ (the multiplication parameter to determine the impact of peaks on costs for the retailer) was set to 1. Each subfigure shows results for CP and either one of the DP strategies. Furthermore, all three scarcity scenarios (values for β) are

[5]Theoretically, more peaks than produced with a CP strategy might be possible, by setting prices that can make consumers consume during peaks. We do not allow this in our simulation, as values in $\vec{x}$ are constrained to be positive.



(a) Using DP-Q (quadratic pricing functions)



(b) Using DP-E (exponential pricing functions)

Figure 5.5: Average daily profits of the retailer against maximal prices ρ_{max} when employing the CP strategy or the DP strategies (optimised for retailer profits). For orientation, the wholesale unit price per 15-minute time step ($\frac{\rho_w}{4}$) is displayed on the x-axis.

plotted per subfigure. The resulting patterns, which we discuss below, are similar in all three scarcity scenarios. There is no significant difference in the results of the DP-Q and DP-E strategies.

In both cases, profits increase with ρ_{max}. From the results, it is possible to estimate the value for ρ_{max}, below which the retailer should expect to be making losses. For very small values of ρ_{max} (when there is little room for dynamic pricing), the level of profits of the CP strategy and the DP strategies are comparable. In these settings, profits for the retailer are negative, as the costs incurred by peaks are higher than revenues made by selling electricity. For higher values of ρ_{max}, **the DP strategies generate higher profits than the CP strategy**, as they can lower unit prices in peak times, whereby more peak costs are saved than revenue is lost (we will discuss reduction of peak costs in more detail in the next section).

PEAKS

In Figure 5.6, we show the average occurrences of peaks per day (as defined by objective function O_{PK}), when the retailer uses the CP or DP strategies. Again, each subfigure shows one of the two DP strategies and includes the three scarcity scenarios (values for β). We compare peaks incurred by the CP strategy with peaks incurred by DP strategies, which have been optimised for peak minimisation (for the objective function O_{PK}, and thus we label them DP-Q-PK and DP-E-PK). In addition, we now include peaks incurred by DP strategies which have been optimised for profit maximisation (for the objective function O_{PR}, and thus we label them DP-Q-PR and DP-E-PR), where ϕ was again set to 1.

First, we can again conclude that there is no significant difference in the results when either the DP-Q or DP-E strategy is used.

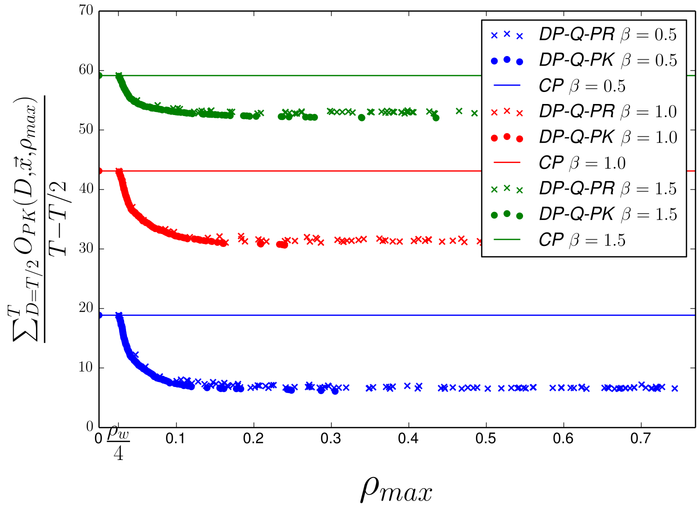
Second, when considering the results of the DP strategies optimised for peak reduction (DP-Q-PK and DP-E-PK), **the peak reduction potential of the DP strategies is clearly visible as a pareto front**. There is a trade-off between the price range in which DP strategies can operate (limited by ρ_{max}) and the peak reduction that can be achieved. If $\rho_{max} \leq 0.1$ € and is approaching 0, the possibilities for the retailer to reduce peaks decrease, as there is too little room to affect consumer choices with differences in prices[6]. If $\rho_{max} \geq 0.1$ €, the slope of the pareto front is low, as the peak reduction potential does not increase much further. We can also observe from Figure 5.6 that the percentage of peaks that either DP strategy (having been optimised for peak minimisation) can avoid increases when the scenario has lower scarcity (lower values of β, and thus higher peak thresholds Q_{max}).

Third, DP strategies which have been optimised for profit maximisation (O_{PR}) achieve much fewer peak than the CP strategy. Thus, we can conclude that **if the retailer optimises dynamic pricing strategies to maximise profits, peak reduction still occurs, as avoiding peak costs is an important part of how the retailer maximises profits**. As is expected, even fewer peaks are recorded with DP strategies which have been optimised for peak minimisation (O_{PK}).

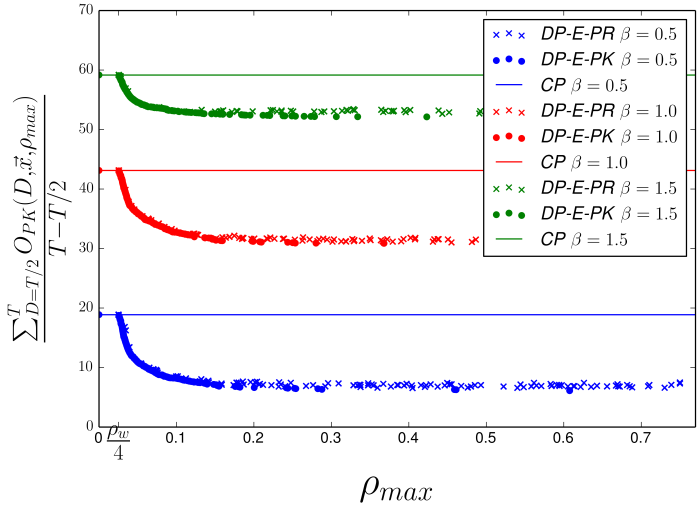
THE INFLUENCE OF PEAK COSTS

An important parameter for the difference in peaks which are achieved under the two optimisation objectives is ϕ, the weighting parameter for the impact of peaks on costs for the retailer. ϕ affects how much the retailer considers peak reduction a priority

[6]Note that the wholesale unit price to supply one job in one time step of 15 minutes is $\frac{\rho_w}{4} = 0.025$ €.



(a) Using DP-Q (quadratic pricing functions)



(b) Using DP-E (exponential pricing functions)

Figure 5.6: Average daily peaks against maximal prices ρ_{max}, when employing the CP strategy or the DP strategy, optimised for profit-maximisation (DP-Q-PR, DP-E-PR) or peak-reduction (DP-Q-PK, DP-E-PK). For orientation, the wholesale unit price per 15-minute time step ($\frac{\rho_w}{4}$) is displayed on the x-axis.

when choosing a profit-maximising strategy. So far, we have used $\phi = 1$. This means that we have so far assumed that the peak costs which the retailer has to pay amount to the accumulated magnitude of peaks (refer to Section 5.3.c). In this section, we investigate outcomes for different values for ϕ, in order to demonstrate its effect.

It is straightforward to assume that, if $\phi = \infty$ (peaks cause infinitely high costs), a profit-oriented retailer would make peak reduction its sole objective, which would lead to strategies similar to DP-Q-PK and DP-E-PK. Furthermore, one would assume that if $\phi = 0$ (peaks cause no costs for the retailer), a profit-oriented retailer would use the CP strategy and always charge ρ_{max}.

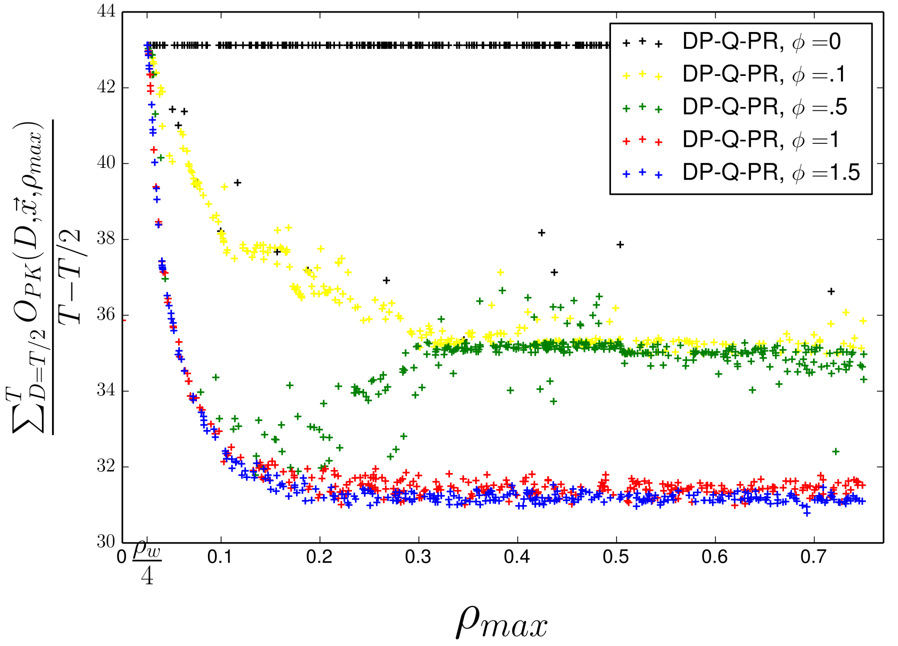


Figure 5.7: Average daily peaks given different values of ϕ, for $\beta = 1$ and the strategy DP-Q, being used for profit maximisation

To evaluate the effect of ϕ, we run simulations (for one scenario, in which $\beta = 1$) of the DP-Q strategy. Parameter sets are optimised for profit maximisation (O_{PR}), but we report the amount of average peaks (we thus label the graphs DP-Q-PR, as we do for the same approach in Figure 5.6). We use values for $\phi \in \{0, 0.1, 0.5, 1, 1.5\}$.

The results in Figure 5.7 assert our initial assumptions about high and low values for ϕ. First, for both $\phi = 1$ and $\phi = 1.5$, the average peaks per day (y-axis) plotted against maximal unit prices (x-axis) describe a pareto front and these two pareto fronts are very similar. We showed in Section 5.5.b that this outcome appears to approximate a lower benchmark for average peaks per day. Second, for $\phi = 0$, the average peaks per day are constant with respect to ρ_{max} and roughly similar to the average peaks per day incurred by the CP strategy in this scenario (compare with the graph labelled "CP $\beta = 1$" in Figure 5.6). As we argued before, the level of average peaks per day incurred by the CP strategy can be assumed to be representative for an upper scenario-specific benchmark.

For $\phi \in \{0.1, 0.5\}$, average peaks stabilise at an intermediate level when $\rho_{max} \geq 0.3$. This level (at around 35) probably is a scenario-specific plateau between lower and upper benchmarks for average peaks per day. For $\phi = 0.5$ we see an additional effect: For values of $\rho_{max} < 0.3$, average peaks are below 35, often close to the lower benchmark. In these settings for ϕ, the retailer finds it profitable to avoid peaks. With $\rho_{max} \geq 0.3$, it is more profitable to always charge constant prices and accept all eventual peak costs.

5.6. CONCLUSIONS

Dynamic pricing is an important tool for reducing peaks in future electricity grids, where scheduling decisions are made online by independent actors and retailers face high costs during consumption peaks. Retailers for electricity need to choose pricing strategies, which dynamically create incentives for consumers to delay their demand during peaks. Furthermore, mandating an upper constraint on unit prices is an important ingredient for consumer protection.

In this chapter, we offer a formalised model for such a distributed online scheduling problem and propose two meta-strategies for dynamic pricing. We show how to find suitable strategies through offline optimisation, for which we use an evolutionary algorithm. We show in computational simulations that both quadratic as well as exponential pricing functions can be parameterised by offline optimisation to perform well. This holds with respect to both the objective to reduce peaks and the objective to maximise profits of the retailer. In computational simulations, we demonstrate that the peak reduction potential of dynamic pricing strategies depends on the maximal price. Furthermore, we show that retailers do not prefer a constant price (CP) strategy over our proposed dynamic pricing (DP) strategies. Finally, we show that employing the proposed dynamic pricing strategies reduces peaks, even if they are optimised for the maximisation of retailer profits.

In future work, the model could be made more realistic (but also more complex) by letting the wholesale unit price ρ_w vary or by requiring the retailer to plan ahead, which adds the challenge to balance his announced consumption with his actual consumption. Finally, the fairness of dynamic pricing strategies can be formulated as an additional objective. One approach to implement fairness could be to offer electricity for several consecutive time steps at a constant unit price, which would improve the ability of less flexible consumers to plan ahead.

6

Operating a small-scale battery in a low voltage neighbourhood for asset protection and revenue management

6.1. Introduction

The use of electricity as an energy carrier is still increasing in importance, in particular in domestic settings. A new generation of powerful appliances is being connected to our power grids in the upcoming decade. These appliances often have stronger consumption needs than traditional appliances (e.g. electric vehicles (EVs)) or they even supply power to the grid (e.g. solar panels). This trend can be expected to threaten network assets (such as cables) on the low voltage level (LV) much earlier than on medium or high voltage levels[1]. Consequently, distribution network operators (DSOs) face the necessity of huge investments. Finding solutions that can prolong the life of these assets, even if only for a few years, can result in significant cost reductions.

In particular, damage to LV infrastructure happens because too much aggregated load or generation can surpass the maximum capacity of assets. LV cables connect domestic households to the electricity grid and their capacity has not been designed to accommodate the novel household appliances mentioned above. Violations of network asset capacity constraints, e.g. by overloading, can reduce the expected lifetime of these assets through overheating of the material. During the ongoing transition to a

[1] A topic of discussion in industry at the moment, e.g. http://www.technologyreview.com/news/518066/could-electric-cars-threaten-the-grid/

next-generation energy system, it is crucial that our current energy infrastructure remains able to support stable operations. However, major updates of network assets in order to tackle problems like the ones above are very expensive. A recent report suggests that asset investment costs of up to 800 million EUR might be necessary within the next 35 years to only accommodate EVs in The Netherlands [130]. With the arrival of such devices in the distribution grid, DSOs thus face large investments over the next one or two decades. The direct need for these investments could, given that no capacity for asset protection is in place, occur in a short period of three to five years. Dynamic and cost-efficient solutions like the one proposed in this chapter can enable DSOs to react fast to overloading challenges, as well as flatten out the investments across a longer time span, which is crucial for the financial health of DSOs.

Electricity storage provides flexibility of operation and can thus perform LV network support functions, such as the protection of assets. In this work, we develop the idea of using batteries to protect low voltage network cables. Local storage solutions like batteries can postpone expensive major grid updates, but it is challenging to operate batteries successfully in a setting as described above. One reason for this difficulty is that the domestic LV setting is a multi-actor environment, where future activities and prices are uncertain. Another reason is given by physical limitations, e.g. the battery's maximal charging rate and energy capacity place unique constraints on the problem to design effective control strategies for battery operation.

A control strategy represents a recipe which the agent that controls a device can use to achieve his goal under uncertain conditions. In this chapter, we represent control strategies in algorithmic form. By applying a strategy, a software agent controlling a battery can compute actions for each time step (where an action consists of either charging or discharging the battery by some amount). The design of strategies for these control agents begins with choosing appropriate objectives. We identify two important objectives for future settings. A multi-objective approach enables control strategies to be more effective in reducing costs, but further increases the challenge to design well-working strategies. So, *the first objective* for the efficient operation of batteries is to protect network assets from overloading. For this, computational strategies need to optimise charging and discharging schedules of the batteries, given limited knowledge about future states of the network. These strategies need to enable agents to compute actions for the upcoming time step fast (i.e. within a few seconds). We tackle this problem by formulating robust heuristic strategies, which can be installed by the DSO or by a battery operator who is paid by the DSO for protection services[2] and controls one (or more) batteries in a low-voltage neighbourhood. *The second objective* for battery operation is to maximise revenues from buying and selling electricity. This is relevant because batteries have high fixed costs. Given a real-time market for electricity, the purchase costs of the batteries can partly be recovered. In addition, if batteries adapt their charging and discharging activity to market prices, their activity is likely to have a positive effect on the balancing challenge of the whole grid.

We also address the issue of high fixed costs for batteries in another way. We pur-

[2] In several countries, e.g. in The Netherlands, DSOs are not allowed to buy or sell energy at the time of writing, but problem settings as the one discussed in this chapter are raising concerns about this constraint amongst regulators.

posely model a small-scale battery, because these batteries can be expected to become more affordable: the second-life market for EV batteries is expected to form an integral part of the EV product life cycle. At the beginning of its second life, a battery can still have "up to 70 percent capacity remaining after 10 years of use in an automotive application“[3]. Small-scale batteries are also easy to replace without interruptions to electricity supply.

This chapter proceeds as follows. Section 6.2 discusses the expected challenge of low voltage grid protection and gives a brief overview of related work on battery operation in electricity grids. Section 6.3 then describes the model of the relevant parts of the low-voltage network and the domestic households. We formulate cost functions and provide a mixed integer linear program which can be used to compute the offline theoretical optimum, or a close approximation of it, given advance knowledge of household activity before the fact. In Section 6.4, we propose two heuristic real-time battery control strategies, H_1 and H_2. With these strategies, control agents can compute actions very fast, which is crucial in the electricity domain. While H_1 reacts to current conditions, H_2 plans real-time and ahead, based on (uncertain) expectations about price developments and household behaviour. In Section 6.5, we assess the performance of our control strategies in stochastic simulations. We model two what-if scenarios of low-voltage neighbourhoods, where consumption and generation activity leads to overloading of the cable and a dynamic price for electricity is available to the local actors. We assume, however, that households are not adapting their behaviour in real-time based on price information. The results of the simulations enable us to compare the effects of the solutions of H_1 and H_2 to the effects given in the cases of having no battery or having a battery which pre-computes actions for the upcoming day with the mixed integer linear program mentioned above. In the latter case, we use two fictitious settings - we assume the control agent has either perfect knowledge of future events (during the upcoming day) or has only expectations available. We find that the H_2 strategy performs within 83% of the approximated upper bound which is computed with the assumption of perfect advance knowledge. Finally, in Section 6.6, we also describe laboratory experiments where we could show that even a battery with small capacity can make a significant contribution to avoiding overheating if it employs our H_2 strategy. [4]

6

6.2. BACKGROUND

In this section, we describe some related work which is of relevance to this chapter. We discuss advantages of storage technology in future energy systems and then pay special attention to the challenge of protecting assets in distribution networks.

[3]https://web.archive.org/web/20160420093755/
http://www.abb.nl/cawp/seitp202/a2b2d2aff96520bec1257989004e62ae.aspx

[4]The author of this thesis collaborated in equal parts with Sara Ramezani on the design of the heuristic algorithms and the computational experiments. He is mainly responsible for the implementation of the models, algorithm and experiments. Sara Ramezani is mainly responsible for the mathematical problem model. The laboratory experiments are the sole responsibility of the author of this thesis.

6.2.A. THE ROLE OF STORAGE TECHNOLOGY IN FUTURE ENERGY SYSTEMS

Recent years have seen increased attention to energy storage technology, which can deal with many contemporary and future challenges on the electricity grid. One example is how batteries can buffer the output of intermittent renewable energy generation, a topic which has (mostly for batteries with large capacity) received a lot of attention in the last decade (e.g. [29, 73]). Of course, storage is flexible in charging as well as discharging, so also the reduction of consumption peaks is an important application. On the other hand, we are interested in small-scale batteries. In regions or settings where intermittent local energy generation or the activity of novel consumption devices cause operational problems, such small-capacity batteries can reduce local generation or consumption peaks. Thus, electricity storage (i.e. batteries) is a technology which complements other technologies, that are considered primary drivers in our energy systems, such as solar cells, wind turbines, heat pumps and electric vehicles.

Manz et al (2012) [84] provide a comprehensive list of other advantages of storage technology, namely revenue management (monetising the differences between on- and off-peak prices by purchasing and selling), equipment capacity (relieve temporary overload conditions), line congestion (resolving transmission constraints) and frequency regulation (keeping system frequency in safe ranges). In this chapter, we consider two of these advantages explicitly, namely revenue management and equipment capacity. In the advantages listed in [84], the usefulness of storage for buffering intermittent generation or reduction of consumption peaks is implicitly reflected. If generation or consumption peaks occur on the global grid level, market prices are very high or very low and intelligent storage control strategies would react to this fact by charging or discharging energy, if possible, in the course of revenue management. If these peaks occur locally, they are the reason why the local equipment needs local protection from overloading and thus the local battery control strategy reacts to these peaks as well, if possible.

The operation of batteries on lower levels of the grid has only recently begun to attract attention. A notable area of application are electric vehicles (EVs), which are expected to represent higher shares of the car fleet in upcoming years. Most work in this field has discussed decentralised mechanisms of scheduling the charging of fleets of EVs (e.g. Vandael et al (2011) [125], Gerding et al (2011) [40], Kahlen et al (2014) [67]). Furthermore, Vytelingum et al (2010) have studied the effect of large-scale penetration of batteries for smart home management on the overall grid [132]. Finally, there is a growing body of work dealing with algorithms for the control of batteries in an economic context. For example, Grillo et al (2012) [44] propose a dynamic programming algorithm for a battery that is coupled to a windmill in a distribution network and exploits the differences between on- and off-peak prices, given an optimisation time horizon. Valogianni et al (2014) [122] propose an algorithm which plans EV charging for a week ahead and accounts for the preferences of the car owner by applying Reinforcement Learning.

6.2.B. PROTECTION OF ASSETS IN DISTRIBUTION NETWORKS

This chapter looks into the interplay of storage with a rather novel and important technological challenge. This challenge relates to the possible advantage of storage technologies which is described by Manz et al (2012) [84] as “equipment capacity" (relieving temporary overload conditions, see above) and has not yet received much attention from researchers. Electrical engineers have only recently begun to model the problem of increased expected activity on low voltage levels, where cables have not been designed for this novel usage. For example, Trichakis et al (2008) [119] provide methods to predict the technical impacts of small-scale generators on low-voltage networks.

Kadurek et al. (2011) [66] describe this challenge for the operation of low voltage cables in more detail, highlighting that conventional protection schemes will not be able to tackle overloading. They note that different segments of a cable can be in different states and that only a more sophisticated measuring infrastructure (e.g. by smart meters) can allow the DSO to identify the critical segments and in which state they exactly are. They thus make the case for a novel use case for sensory data, in which intelligent actions based on these data are of high societal benefit (because the lifetime of an expensive underground cable can be prolonged). Their proposed protection scheme operates in two phases, where the first phase assumes some (to be further determined) method of preventive action and the second phase involves protection (disconnection of customers).

To the best of our knowledge, this chapter is the first work which includes this protection challenge explicitly in the objective function and also offers a dedicated solution. Referring to the work by Kadurek et al we described above, we concentrate on the preventive action in this chapter, which they had stated as future research challenge.

6.3. MODEL

This section describes our modelling of network assets (batteries and cables). We also formalise the offline optimisation problem as a mixed integer linear program.

A short overview of the involved components is as follows: We consider a street with a radial low-voltage (LV) cable, with a battery at the end. This location was chosen because the battery’s charging and discharging activity affects all of the cable in front of it. We model time as a finite number of time steps $t = 1, 2, \ldots, T$ and are interested in how the batteries’ charging and discharging actions in each time step can reduce the costs associated with overloading of the network assets.

6.3.A. THE BATTERY

The capacity of the battery is B and it can be charged at a rate of at most R^c or discharged at a rate of at most R^d units of energy per time unit. The battery has an efficiency factor α: for every unit the battery is charged with, it can only discharge α units ($\alpha \in [0,1]$) at a later time. We denote the actual rate at which the battery is charged in time t as c_t and the actual rate it is discharged d_t, where $c_t, d_t \in \mathbb{R}_0^+$, so $0 \le c_t \le R^c$ and $0 \le d_t \le R^d$. In practice, the battery can either be charged or discharged in each time step. So at time t, the battery is charged c_t units if $c_t > 0$ and discharged d_t units if

$d_t > 0$. We thus assume that in all time steps t, $c_t \cdot d_t = 0$[5].

Finally, we designate by b_t the level of charge present in the battery at the beginning of time step t, so $0 \leq b_t \leq B$. We also assume that the charge level of the battery is already b_1 at the beginning of the first time step (for some $b_1 \geq 0$).

6.3.b. The cable

The cable has a sequence of N consuming and producing households attributed to it. The maximum power capacity of the cable is $C \in \mathbb{R}^+$. The cable is radial - one end is connected to the grid (which provides all consumed power that is not generated locally and also consumes all locally generated power that is not locally consumed), and the other end of the cable is not. The battery is located at the end of the cable which is not connected to the grid, and all the households are in between the battery and the transformer. The cable is divided into a number of segments, each segment is between two consecutive households, or has an household on one side and the substation or the battery on the other.

We represent the power flow on the cable using real numbers. The flow on each cable segment is given by the aggregated demand and supply (by households or the battery) on the segments it services, i.e. the segments between it and the end of the cable. It is thus represented by a positive number if there is more demand than supply on these serviced segments, and by a negative number if there is more supply than demand. So in any time step, if a household or the battery starts to consume one kW of power more, the power flow in all segments located before it (i.e. between it and the transformer) will increase by 1. By the generation of one kW (or by the battery discharging one kW), power flow in all segments before it decreases by 1. See Figure 6.1 for an illustration.

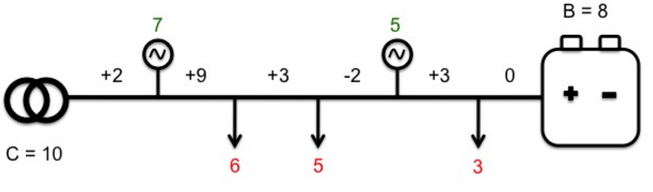


Figure 6.1: Example problem when in a non-overloaded time step and without battery activity.

To model the overloading problem in a given time step t, we are only interested in the load on the most overloaded segment. Given the above mathematical formulation of power flow, we call the flow of the segment on the cable with the lowest flow f_t^{low} and the flow of the segment with the highest flow f_t^{high}. Note that both f_t^{low} and f_t^{high} are computed by a linear program, given the demand and supply of the households and the battery activity.

If $f_t^{low} < -C$ or $f_t^{high} > C$, then the cable is *overloaded* in time t. The amount of

[5] Note that this assumption does not introduce any constraints on solutions. A theoretical solution where both $c_t > 0$ and $d_t > 0$ has less revenue than a solution with the same net flow but where either $c_t = 0$ or $d_t = 0$. This is because a factor of α of the energy is lost by storing it on the battery and then discharging.

overload is then $\max(f_t^{high} - C, -f_t^{low} - C)$. The battery may be able to "resolve" an overloaded time step by charging when the overloaded segments have negative flow and discharging when the overloaded segments have positive flow. By "resolving", we mean that this results in a configuration that is not overloaded any more. See Figures 6.2 and 6.3 for examples of overloaded time steps resulting, respectively, from excess consumption and production, and how the battery can resolve them.

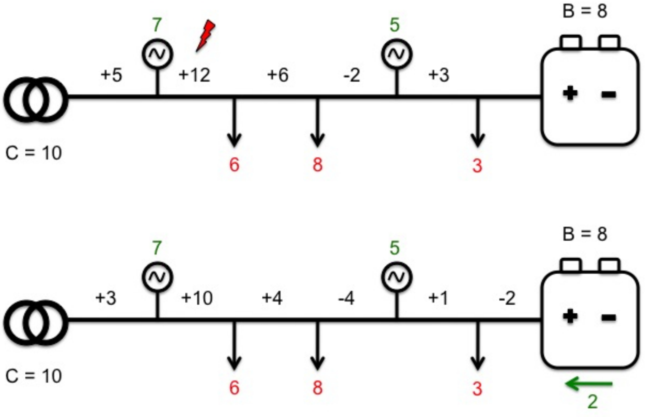


Figure 6.2: Example of resolving overload from excess consumption. Top: An overloaded time step, resulting from excess consumption. Bottom: The battery discharges 2 units of energy to resolve the overloaded time step.

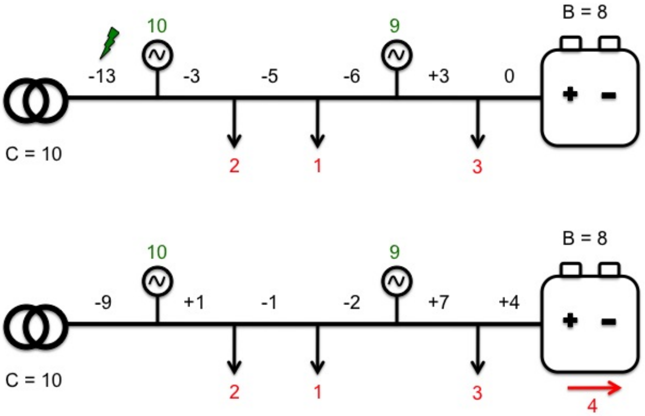


Figure 6.3: Example of resolving overload from excess production. Top: An overloaded time step, resulting from excess production. Bottom: The battery charges 4 units of energy to resolve the overloaded time step.

Note that it is not always possible to completely resolve an overloaded time step using a battery, no matter how much charge or capacity the battery has. For instance, it is not possible to resolve an overload if there are both overloaded segments with a positive flow and overloaded segments with a negative flow, since resolving one will intensify the other. Furthermore, it is also not possible to resolve an overloaded time step if the amount of overload is more than the cable capacity, or more than what would result in an overload in the opposite direction.

6.3.c. Overload cost functions

In this section, we consider the damage, in economical terms, which a time step with overloading causes to the cable. There is currently no consensus among engineering experts about a standard cost function that represents economic losses experienced by overheating a cable. However, it is commonly agreed that some are more realistic than others. A useful assumption is that the cable is damaged most when it is being overheated for long periods of time, so consecutively overloaded intervals result in the most damage. We use this assumption to construct the following cost function v for each time step t:

$$v(x_t, k_t) = \begin{cases} \omega \cdot (c_O)^{k_t} & x_t \geq C \\ 0 & \text{otherwise.} \end{cases} \tag{6.1}$$

In this function, $x_t = \max(|f_t^{high} + c_t - d_t|, |-f_t^{low} - c_t + d_t|)$, i.e. the maximum amount of flow in the cable at time step t. Furthermore, k_t denotes how many consecutive time steps the cable has been overloaded at time t, i.e. $k_t = l$ s.t. $(x_{t-l} \leq C) \wedge \forall j = 0, \ldots, l-1 : [x_{t-j} > C]$. Furthermore, $c_O > 1$ is a constant coefficient used to compute the cost of consecutive overloads. c_O is larger than one to reflect that in a consecutive set of overloaded time steps, each time step becomes more costly than the last. Finally, ω is a weight to scale the costs of cable overheating.

6.3.d. The offline Optimisation Problem

The offline optimisation solution aims to find the amounts that the battery should be charged and discharged in all time steps (which we model with the solution variables c_t and d_t, see Section 6.3.a), such as to minimise overall costs. Costs represent wear-out of the cable, as described by Equation 6.1. The revenues made by the battery through buying and selling electricity are subtracted from the costs. For this offline problem formulation, we assume (for all time steps t of the day in question) perfect foresight of household activity, and thus of f_t^{low} and f_t^{high}, because they are easily computed from household activity (see Section 6.3.b). Furthermore, we assume the possibility for the battery to buy and sell electricity at a unit price ρ_t, which can also perfectly be foreseen. This problem can be formulated as:

$$\min_{c_t, d_t} \sum_{t=1}^{T} v(x_t, k_t) - \sum_{t=1}^{T} \rho_t (d_t - c_t)$$

such that: $\forall\ t \in \{1, \ldots, T\}$:

$$0 \leq c_t \leq R^c, \quad 0 \leq d_t \leq R^d$$

$$0 \leq b_1 + \sum_{j=1}^{t} (\alpha c_j - d_j) \leq B$$

For more information on the internal variables x_t and k_t, see Section 6.3.c. Note that because of the exponential factor in the cost function v and the structure of k_t, this problem is difficult to compute as a closed function. However, we can formulate a mixed integer linear program (MILP) that computes the optimal solution, assuming at most K consecutive overloaded time steps for a given constant K. The MILP yields an approximation to the solution if this is not the case. In order to obtain this MILP, we reformulate the optimisation problem as follows:

$$\min_{c_t,d_t} \sum_{t=1}^{T} v_t - \sum_{t=1}^{T} \rho_t(d_t - c_t)$$

such that $\forall t \in \{1,\ldots,T\}, k \in \{1,\ldots,K\}$:

$$x_t >= 0$$
$$x_t >= f_t^{high} + c_t - d_t, \quad x_t >= -f_t^{low} - c_t + d_t$$
$$x_t >= -f_t^{high} - c_t + d_t, \quad x_t >= f_t^{low} + c_t - d_t$$
$$0 \le c_t \le R^c, \quad 0 \le d_t \le R^d$$
$$0 \le b_1 + \sum_{j=1}^{t} (\alpha c_j - d_j) \le B$$
$$v_t \ge e_k \times O_t^k$$
$$O_t^k \in \{0,1\}, \;\; O_t^1 \ge (x_t - C)/(Maxx - C)$$

and $\forall t \in \{2,\ldots,T\} \wedge \forall k \in \{2,\ldots,K\}$:

$$O_t^k \ge O_{t-1}^{k-1} + O_t^1 - 1.5$$

Where $e_k = \omega(c_O)^k$ and $Maxx$ is a constant number that is larger than all flows we are dealing with. Also, v_t is a variable inspired by $v(x_t, k_t)$ and O_t^k is a binary variable that specifies whether t is at least the k^{th} consecutive overloaded time step; it is equal to 1 if it is, and equal to zero otherwise.

6.4. HEURISTICS

In this section we present two heuristic strategies for solving the online problem (deciding which charging or discharging action to take for the current time step). Both make two general assumptions about overloaded time steps, namely that avoiding overloading takes precedence (also over revenue optimization) and that resolving overloading as much as possible is worthwhile (even if the cable would still be overloaded during this time step). With these assumptions, we are able to create algorithms which are robust and offer the assurance to never increase an overload, a property that does not necessarily hold for the solutions which are computed by the mixed integer linear program defined in Section 6.3.d. Furthermore, the two algorithms we present in this section have a low computation time. The first strategy, H_1, is purely reactive and does not rely on expectations of future household behaviour or prices. H_1 involves only rule-based decisions concerning the current time step. The second strategy, H_2, uses such expectations to prepare for future overloads as well as to maximise its revenue. H_2 will make at most two iterations through the remaining time steps to compute a solution for the current time step.

The algorithms make use of the decision function $overloaded : \mathbb{N} \rightarrow \{true, false\}$, which is comparable to O_t^1 in the model (see Section 6.3.d) or the truth value of the statement $\max(f_t^{high}, |f_t^{low}|) > C$. The function computes whether the cable (in its current state as a result of the behaviour of households) would be in an overloaded condition for the time step given as argument (assuming no action of the battery).

6.4.a. Strategy H_1

Our first heuristic strategy, H_1, is designed for robustness only and therefore does not base its decisions on the current price. It also does not use information on expectations of future developments (neither household behaviour nor prices). Algorithm 6.1 describes H_1 in detail.

The basic idea of this heuristic algorithm is that if the current time step is overloaded, H_1 resolves it as much as is feasible given the battery charge level and charge and discharge rates. If the interval is not overloaded, H_1 always tries to bring the charge in the battery to half of its capacity, in order to be prepared to resolve both overloaded intervals that call for charging and overloaded intervals that call for discharging as much as possible (assuming the control agent does not know which one of these events is more likely than the other).

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In more detail, the first objective of the H_1 strategy is to always contribute to resolving overloaded time steps, as far as possible. The battery will attempt to contribute an action in the direction opposite to the highest power flow (e.g. it charges when the highest flow on the cable is caused by local generation). The maximally possible contribution to the opposite of the highest power flow is computed in line 2 of Algorithm 6.1. This contribution is limited by the highest flow which already exists on the cable in this direction (e.g. when the battery resolves overload by charging, its possibilities for doing so are limited by the existing charging activity of households). The battery can at most contribute $(f_t^{high} + f_t^{low})/2$, because contributing more would increase the overload in the opposite direction of the original overload[6]. For example, if $C = 10$, $f_t^{high} = 13$ and $f_t^{low} = -9$, then $x_t = 3$ (for the definition of x_t, the maximum absolute amount of flow on the cable, see Section 6.3.c). If the battery discharges any amount $\in [-2, 0]$, x_t decreases. For example, if $A_t = -2 = (13-9)/-2$, then $x_t = 1$, because the highest flow on the cable is now equal to $f_t^{high} - 2 = 11$. With $A_t < -2$ however, x_t would increase again because the battery discharge leads to the lowest flow on the cable being equal to $f_t^{low} + A_t < -11$. Finally, in lines 3 through 7, H_1 makes sure that the contribution to resolve overloading is only as high as necessary when taking the cable capacity C into consideration.

In all non-overloaded time steps, the H_1 strategy aims to adjust its current charge level, b_t, towards half of its maximum charge level ($\frac{B}{2}$), see line 9. In line 11, α, the efficiency factor of the battery is taken into account, in order to reach the target level

[6] f_t^{high} and f_t^{low} denote the highest and lowest flow on the cable, respectively, during t, see Section 6.3.b

(note that α is only applied during charging in our model, see Section 6.3). Lines 13 and 14 make sure that this action does not lead to overloading.

Each chosen action is, of course, restricted by the maximal charging rates R^c and R^d (see line 16), the available space in the battery when charging (capacity B minus level b_t, see lines 17 through 19) and the available level b_t when discharging (see line 20).

Algorithm 6.1 Strategy $H_1(t)$ computes an action A_t for the battery in time step t.

1: **if** overloaded(t) **then** // **The cable is overheating:**
2:     $A_t \leftarrow (f_t^{high} + f_t^{low})/-2$ // Maximal contribution to opposite of highest flow
3:     **if** $f_t^{high} \geq |f_t^{low}|$ **then**
4:         $A_t \leftarrow \max(A_t, C - f_t^{high})$ // Discharge only as much as necessary; $A_t \leq 0$
5:     **else**
6:         $A_t \leftarrow \min(A_t, -C - f_t^{low})$ // Charge only as much as necessary; $A_t \geq 0$
7:     **end if**
8: **else** // **The cable is not overheating:**
9:     $A_t \leftarrow \frac{B}{2} - b_t$ // Go towards half charge
10:     **if** $A_t > 0$ **then** // If charging, adjust A_t for efficiency losses
11:         $A_t \leftarrow A_t * \frac{1}{\alpha}$
12:     **end if**
13:     **if** $A_t > C - f_t^{high}$ **then** // Limit A_t to avoid overheating
14:         $A_t \leftarrow C - f_t^{high}$
15:     **end if**
16:     **if** $A_t < -C - f_t^{low}$ **then**
17:         $A_t \leftarrow -C - f_t^{low}$
18:     **end if**
19:     $A_t \leftarrow \max(A_t, -C - f_t^{low})$
20: **end if**
21: $A_t \leftarrow \min(\max(A_t, R^d), R^c)$ // Limit A_t w.r.t. max. charge rates
22: **if** $A_t > 0$ **and** $\alpha A_t > B - b_t$ **then**
23:     $A_t \leftarrow B - b_t$ // If charging, limit A_t w.r.t. battery capacity
24: **end if**
25: **if** $A_t < 0$ **and** $A_t < -b_t$ **then**
26:     $A_t \leftarrow -b_t$ // If discharging, limit A_t w.r.t. existing charge
27: **end if**
28: **return** A_t

6.4.B. STRATEGY H_2

Our second heuristic strategy, H_2, also (like H_1) computes a battery action for the current time step t. However, H_2 differs from H_1 in that it plans ahead and adds revenue maximisation from buying and selling as a second objective next to cable protection. To take future steps into account is crucial for a storage control problem due to the limited capacity of the device, which should be put to the most optimal use under uncertainty about future events. However, it is challenging to devise storage control problems which are able to plan ahead and have a low computation time, as well. The schedule which H_2 creates is influenced by thresholds for hardware (the rated cable capacity C and the battery capacity B, maximal charging rates R^c and R^d and efficiency α, see Section 6.3), but also by a price threshold ρ_a, which denotes the average expected unit price for the current month. Algorithm 6.2 describes H_2 in detail.

In short, H_2 works as follows. If the current time step is overloaded, the situation is handled according to strategy H_1. Otherwise, H_2 creates a schedule for charging and discharging actions during the remainder of the day. The creation of this schedule proceeds in two phases. In the first phase, H_2 plans a protective action if the time step is expected to be overloaded (according to H_1), but otherwise H_2 plans an action with profit maximisation in mind (by buying at low prices and selling at high prices). In the second phase, H_2 adjusts the schedule from the first phase to stay within battery constraints and to avoid negative effects of the planned actions, with respect to future cable overloading. The steps in which these adjustments are made are chosen such that the profit maximisation effects from the first phase are preserved, as far as possible.

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We will now explain strategy H_2 in more detail. *In the first phase*, H_2 plans an initial action for each time step $t \in T$: If the cable is overloaded during t, H_2 plans to resolve the overload (lines 3-6), exactly in the way that H_1 deals with overloads, with one difference: H_2 assumes in this first phase that the battery capacity B is infinite. If, on the other hand, there is no overload during t, the default action is to sell or buy in order to maximise revenues (lines 8-14). H_2 plans to buy if ρ^e_t, the expected unit price for t, is lower than ρ_a. Accordingly, H_2 plans to sell if ρ^e_t is higher than ρ_a. To speed up computation, no interaction between time steps is considered in the first phase.

In the second phase, H_2 aims to adjust the schedule with consideration of interaction between time steps. The goals of these adjustments are to achieve feasibility (with respect to the battery capacity limits $[0, B]$, in lines 18-25) and to avoid negative effects of the battery actions on overloading (lines 26-36). These adjustments have to be accomplished by an advanced computational procedure. However, to keep the time complexity of the algorithm within acceptable bounds, adjustments only consist in reducing actions which were planned in the first phase, e.g. to buy less or to sell less than planned.

Algorithm 6.2 Strategy H_2 computes an action A_t for the current time step t (as described in Section 6.4.b). b_i denotes the charge at time i and is given by the sum of actions up until and including step i (see Algorithm 6.3). ρ_a is the expected average unit price of the simulated day and ρ_t^e is the expected unit price for time step t. We denote as I an "interval", a sequence of steps. We also denote with I_{first} the first and with I_{last} the last step in I. Algorithm 6.4 describes the reduction of actions from the first phase.

for all $t \in T$ **do** // **First phase: initial schedule**
  if overloaded(t) **then**
    $A_t \leftarrow$ compute A_i according to strategy H_1 (Algorithm 6.1)
    if t is current time step **then**
      stop // No need to plan ahead
    end if
  else
    $A_t \leftarrow 0$
    if $\rho_t^e > p_a$ **then**
      $A_t \leftarrow -min(R^d, C + f_t^{low})$ // Sell at high prices
    end if
    if $\rho_t^e < p_a$ **then**
      $A_t \leftarrow min(R^c, C - f_t^{high})$ // Buy at low prices
    end if
  end if
end for
Compute all uniform intervals with maximal length $I = [I_{first}, \cdots, I_{last}]$, such that
$\Big[[\forall_{i \in I} overloaded(i)] \vee [\forall_{i \in I} \neg overloaded(i)]\Big] \wedge \Big[[\forall_{i \in I} \rho_i^e > p_a] \vee [\forall_{i \in I} \rho_i^e \leq p_a]\Big]$
for all uniform intervals I **do** // **Second phase: Adjust initial schedule**
  if not overloaded(I_{first}) **then**
    if $A_{I_{first}} > 0$ and $b_{I_{last}} > B$ **then** // Buying planned in I, final charge $> B$:
      Reduce($b_{I_{last}} - B, I$) // Reduce buying in I
    end if
    if $A_{I_{first}} < 0$ and $b_{I_{last}} < 0$ **then** // Selling planned in I, final charge < 0:
      Reduce($b_{I_{last}}, I$) // Reduce selling in I
    end if
  end if
  $H \leftarrow$ the uniform interval preceding I (if it exists, otherwise **stop**)
  if overloaded(I_{first}) and not overloaded(H_{first}) **then**
    $P_I \leftarrow b_{I_{last}} - b_{H_{last}}$ // P_I is the cumulative result of planned actions in I
    if $P_I < 0$ and $b_{H_{last}} < -P_I$ **then** // Not enough energy in battery
    // for the planned discharge in I
      Reduce($b_{H_{last}} + P_I, H$) // Reduce selling in H by $b_{H_{last}} - -P_I$
    end if
    if $P_I > 0$ and $b_{H_{last}} + P_I > B$ **then** // Actions in I would exceed
    // the battery capacity B.
      Reduce($b_{H_{last}} + P_I - B, H$) // Reduce buying in H by $b_{H_{last}} - -P_I - B$
    end if
  end if // Note: Reduce decides to reduce selling or buying by the sign of r
end for

Adjustments in the second phase are applied on "uniform intervals". A uniform interval I is a sequence of time steps which is defined by three conditions: First, the steps in I are expected (given the expectations used by H_2) to be all overloaded or all non-overloaded. Second, the steps in an interval have an expected unit price either all below or all above ρ_a (and thus H_2's initial schedule from the first phase plans for the non-overloaded steps in the uniform interval to either all buy or all sell). The third and last condition is that I is maximal according to the previous two conditions. H_2 plans adjustments on non-overloaded uniform intervals, as the actions during overloaded uniform intervals can be expected to be guided by the need for cable protection. Each non-overloaded uniform interval is adjusted if the battery capacity is expected to be violated by the planned battery actions during the uniform interval (recall that the first phase did assume that the battery capacity is infinite). Furthermore, H_2 plans adjustments to those non-overloaded uniform intervals which precede an overloaded uniform interval. Reducing planned actions during the non-overloaded uniform interval can be useful to avoid negative effects for the overloaded uniform interval.

H_2 uses the function $Reduce(r, I)$ for reductions on the initial actions planned in the first phase (see Algorithm 6.4). $Reduce$ takes as arguments r, the amount of reduction, and I, the uniform interval during which the reduction of r is needed. First, the steps in I are sorted by their expected unit price - in descending order if buying is being reduced and in increasing order if selling is being reduced. Then, H_2 begins reducing actions A_i for all $i \in I$. Action A_i is reduced to $max(0, A_i - r)$ if buying is being reduced and to $min(0, A_i + r)$ if selling is being reduced. The reduction which took place on A_i is subtracted from r and then $Reduce$ moves on action A_j, which is the next action in the ordering, or stops if $r = 0$.

Algorithm 6.3 Compute b_i, the battery level at time step i (after action A_i took place). According to our model (see Section 6.3), we take into account the battery efficiency α when the battery is charged. Note that if $j > t$ (t being the current time step), then A_j describes a planned action.

```
b_i ← 0
for all j ∈ [0, i] do
    if A_j > 0 then
        b_i ← b_i + α · A_j
    else
        b_i ← b_i + A_j
    end if
end for
```

6.5. COMPUTATIONAL SIMULATIONS

In this section, we perform computational experiments, which we performed to evaluate the H_1 and H_2 strategies in several stochastic what-if scenarios. We first describe the experimental setup. Then, we discuss the results.

Algorithm 6.4 The *Reduce* algorithm computes absolute reductions on the initial actions planned in the first phase. *Reduce* takes as arguments r, the amount of reduction, and I, the interval during which the reduction of r is needed. If the initial plan from the first phase is to buy during I, then r is increased, such that $r = \frac{r}{\alpha}$, since in our model a reduction by one unit affects the battery level by only α units.

if $r > 0$ **then** // Buying is planned and should be reduced
    $r \leftarrow \frac{r}{\alpha}$
    sort steps $i \in I$ by ρ_e^t, descending
else // Selling is planned and should be reduced
    sort steps $i \in I$ by ρ_e^t, ascending
end if
for all $i \in I$ **do**
    $A_i^{orig} \leftarrow A_i$
    if $r > 0$ **then** // Note: $A_i \geq 0$
        $A_i \leftarrow max(0, A_i - r)$
        $r \leftarrow r - (A_i^{orig} - A_i)$
    else // Note: $A_i \leq 0$
        $A_i \leftarrow min(0, A_i - r)$
        $r \leftarrow r + (A_i^{orig} - A_i)$ // Note: as $r < 0$, its absolute value is reduced
    end if
    if $r = 0$ **then**
        stop
    end if
end for

6.5.A. SETUP

We construct two scenarios. In each scenario, we systematically vary ω, the weight of costs in the evaluation of the battery performance. The detailed settings can also be read from Table 6.1 [7].

Network element specifications

The cable settings which we modelled in the simulations are inspired by settings that are common in Europe, but most of these also apply to grids in other parts of the world. We assume an LV feeder that can carry a current of 200 Ampere (I) and that has a potential difference of 230 Volt (V). The capacity for power P is given by $P = V * I$, so we assume a value of 46kW for the cable capacity C. On each of the three phases, 20 households are equally distributed. We consider one phase on the feeder, and thus the number of households, N, is 20, of which we model 10 as identical consumers and 10 as identical generators[8].

To model the connected customers, we base values on currently common settings, but also extrapolate to future settings with more devices (which could pose problems

[7] We made the code we use to run the simulations available online at https://github.com/nhoening/battery-heuristics

[8] Households being identical keeps our model simple and has no large drawbacks with respect to this work, because here we are only interested in their cumulative effect with respect to the cable segment with the highest power flow.

for LV cables). The maximal demand of a consumer household, D^{max}, is assumed to be 4kWh per hour. In addition, we assume that consumers own electric vehicles, the batteries of which are being charged by up to 1kWh per hour, between 7pm and 7am. If a household produces electricity, we assume a maximally possible supply S^{max} of 5kW, assuming that such a household has installed a common photovoltaic array of 20x250W[9]. In our scenarios, the PV cells produce electricity only during 12am and 4pm, which we assume to be strong sunlight hours, but during this time they produce constantly at maximum capacity (thus, in each of these hours they produce 5kWh).

Furthermore, we assume that the battery capacity B is 31kWh. The maximum charging rate R^c is 5kW and the maximum discharging rate R^d is 5kW, as well[10]. These values are inspired from specifications of the EV battery of the Coda electric car which was brought to market in 2012[11]. We also assume that the battery has an efficiency factor α of 0.8 (only 80% of charged electricity can be discharged due to conversion losses).

For the simplicity of our mechanism, we will in this work assume that the power flows remain constant over the duration of one time step (we use time steps of 30 minutes length). We also do not consider reactive power or losses by distributing power over distances. We have chosen for the time step length of 30 minutes because we use real-world price data from the UK wholesale market (see below) from 2012, which is given in half hour intervals. A more realistic setting for a future smart grid setting might be 15 minutes or even 5 minutes. As a consequence of the step length being half an hour, only half of the energy (of consumption or generation) that we have described above in kWh will get delivered per time step in our model. For instance, in our model each array of solar panels (installed by one household) produces only 2.5kWh of energy in each of the 16 half-hour time steps between 12am and 4pm.[12]

We model two ways of placing consumers and producers along the cable (here, we describe placement from the perspective of the substation). The first option is that they are situated alternately along the cable, beginning with a consumer. This is the most optimistic setup for the magnitude of possible overloading. The other option is the most pessimistic one, meaning that first all consumers are situated on the cable next to each other, followed by all generators, who are situated next to each other, as well.

Economic assumptions about demand

In order to model realistic pricing dynamics, we obtained half-hour spot market prices from the UK wholesale power market[13] for the first ten months of 2012 (example traces for May 2012 are shown in Figure 6.4). We removed weekend days from the data (leaving us with 219 days), in order to ease predictions for algorithms that have to

[9] compare https://web.archive.org/web/20150228223707/http://www.eurosolar.com.au/5-kw-solar-system/

[10] Modern EV batteries usually are able to discharge much faster but in this work we are interested in the basic principle of the algorithm.

[11] see http://en.wikipedia.org/wiki/Coda_(electric_car)

[12] Of course, the instantaneous power output at any given moment (given in kW) remains unchanged, because x kW of continuous instantaneous power output are required to produce $\frac{1}{2}x$ kWh in only half an hour.

[13] http://www.apxgroup.com/market-results/apx-power-uk/dashboard/

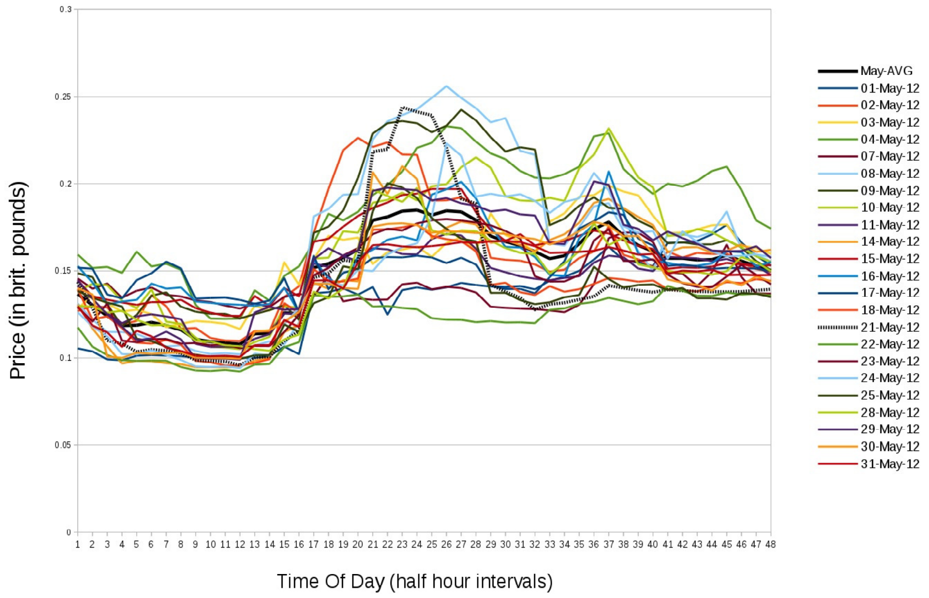

Figure 6.4: Retail market prices (inspired by APX wholesale prices for the UK) for all weekdays in May 2012. "May-AVG“ denotes the average price during these days.

work with expected prices. In order to enable algorithms to make use of price expectations, we computed an average price profile for each month, which is the average of the price profiles of all days in that month. Making good predictions is not the focus of this work and the above preprocessing seems reasonable for investigating the effectiveness of planning ahead. The wholesale market prices in this data set lie roughly in the range between 0.03 to 0.07 £/kWh. We multiplied these wholesale prices by $3\frac{1}{3}$ to arrive at a price range that reflects prices on contemporary retail markets. Our resulting prices lie roughly in the range between 0.10 and 0.23 £/kWh. Those prices are appropriate for the UK and Europe in general[14].

Consumers in our model behave uniformly. We assume they do not have the possibility and/or interest to adapt their behaviour based on the market price, but instead act according to their needs. We assume that they act in accordance with the majority of other consumers in the market. Furthermore, we assume that the aggregated behaviour of the majority of consumers in a market determines the dynamic retail market price ρ_t. Thus, ρ_t is high when the consumers in our model consume the most of their energy and ρ_t is low when they consume only little energy. In order to determine the demand of one household in our model, we model a stylised demand function d with the market price ρ_t as argument. Because d is based on the assumption that high prices are correlated with high demand, its price elasticity[15] is positive.

[14] compare http://www.parliament.uk/briefing-papers/SN04153.pdf

[15] Price elasticity describes the percentage change in quantity demanded in response to a one percent change in price.

Table 6.1: Default settings

Parameter	Definition	value(s)
T	(half-hour) time steps	48
C	cable capacity	46kW
N	number of customers on cable	20
B	battery capacity	31kWh
R^c, R^d	max. (dis)charging rates	5kW
α	efficiency factor	0.8
γ	slope of demand functions	0.5
D^{max}	maximal demand per consumer per step	5.0kWh (7pm to 7am) 4.0kWh otherwise
S^{max}	maximal supply	5kWh (12am to 4pm)
ω	weight of cost-consideration	.05, .2, .5, 1, 2
c_h	cost factor for consecutive over-heating	1.2

The demand function d is given below (where we assume that the maximal price ρ^{max} occurs at maximal quantity D^{max}, where ρ^{max} is the maximal price from our data set, i.e. $d(\rho^{max}) = D^{max}$).

$$d(\rho_t) = (D^{max} - \gamma\rho^{max}) + \gamma\rho_t \tag{6.2}$$

Besides household demand, two more relevant parameters for the wholesale price come to mind: (flexible) consumers adapting their behaviour based on prices and balancing needs based on volatile generation on the overall grid. Both would have increased the complexity in our model significantly. While the presence of flexible consumers probably would decrease the battery's profit margins, it might also constitute a scenario in which a battery is not needed in the first place. Volatile generation influencing wholesale prices can be both positive or negative for battery profits, depending on the local situation and the differences between local conditions for generation (e.g. the weather) and the conditions for the rest of the grid. This would require further research.

Scenarios

We create two scenarios, one with optimistic placement of customers and one where placement is pessimistic. Each scenario is evaluated for the duration of one day, so $T = 48$. We initially drew a random set of 20 daily price series from our set of 219 non-weekend days in our 2012 UK power market price series (see Section 6.5.a). Each scenario is simulated 20 times, using the same 20 randomly drawn days from this set. Furthermore, we evaluate five strategies in each scenario: The first strategy is to use no battery at all (*None*). Furthermore, we employ the optimal offline solution (see Section 6.3) with either clairvoyant knowledge about future prices (*LP-ActPrice*) or knowledge of the expected prices (*LP-ExpPrices*). Finally, we test the two heuristic strategies proposed in Section 6.4, H_1 and H_2. All strategies that work on expected prices have the ability to calculate f_t^+ and f_t^- when given a price p_t (that is, they are equipped with a model of locations and behaviours of the households on the street).

The series of expected prices (which is used by the offline strategy *LP-ExpPrices* and the heuristic strategy H_2) is the average price series from all days of the month in which the current day lies. Furthermore, let ρ_a denote the average price per kWh, for any time of the day, of the month in which the current day lies. We assume the battery to be charged $\frac{B}{2}kWh$ before the day begins, for which we subtract $\rho_a * \frac{B}{2}$£ from its account. At the end of each day, we add to its account ρ_a times the number of kWh of electricity left in the battery. In each scenario, we vary ω, which denotes the weight with which we multiply overheating costs in the overall revenue function of the battery.

The mixed integer linear program that represents the offline strategies is calculated by the GNU Linear Programming kit[16]. Because of the long computation time and the high number of evaluated settings, we limited the running time of the linear programs to fifteen minutes[17]. We set the highest expected number of consecutive critical time steps (k) to ten.

6.5.B. RESULTS

General remarks Overall, all strategies decrease the costs on an LV cable that is overloaded by more than 50% at multiple times during the simulated day. An increase of ω leads to an increase in costs, which could of course be expected. However, ω does not have an influence on the ranking between strategies, which shows us that the outcomes of our model do not depend on how high overheating costs are in comparison to revenues made by the battery.

6

Comparison of strategies In both scenarios, *LP-ActPrice* performs best, as it has advance knowledge about actual prices and household behaviour. However, also our heuristics H_1 and H_2 can significantly reduce costs. Suppose that the distance (in costs) between the performance of *None* and *LP-ActPrice* denotes 100%, then H_2 reaches 83% of the approximated theoretical optimum in the pessimistic scenario and both H_1 and H_2 reach 66% of the approximated theoretical optimum in the optimistic scenario. H_2 performs better than H_1 in the pessimistic scenario, while the differences between the two are not significant in the optimistic scenario. The positive effect of planning ahead is visible in the pessimistic scenario, as the performance of H_1 (which does not plan ahead) falls behind both *LP-ExpPrice* and H_2.

Finally, the performance of H_1 is remarkably stable, with very low variance in outcomes. This is due to the non-speculative and robust nature of the algorithm. The performance of *LP-ExpPrice* varies the most by far. This is because the algorithm does not use online information and computes its schedule beforehand.

[16]http://www.gnu.org/software/glpk/

[17]We ran the mixed integer linear programs on selected settings for one hour and found that they achieve comparable performance.

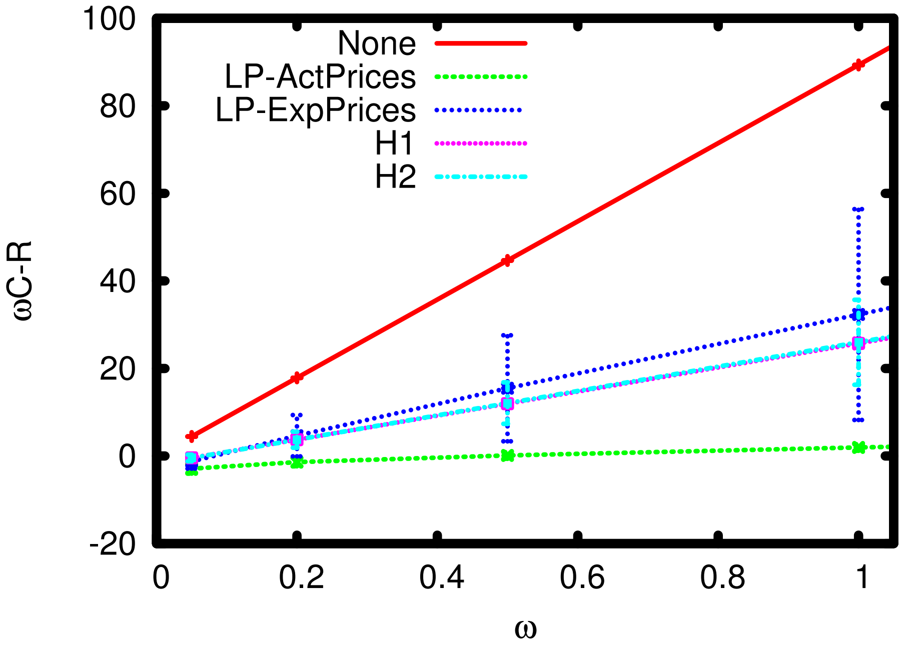

Figure 6.5: Simulation results for the optimistic case. ω denotes the weight of cost-consideration and $\omega C - R$ denotes total costs accumulated on a simulated day.

6.6. LABORATORY SIMULATIONS

In this section, we describe two laboratory experiments, which were performed in order to evaluate the H_2 strategy in a physical setting, where the actual effects on cable temperature could be studied. The experiments were conducted at the FlexPowerGrid Labratory[18] (FPG Lab) in Arnhem, The Netherlands. We begin by describing the experiment setup. Then, we discuss outcomes.

6.6.A. HARDWARE SETUP

We model the pessimistic layout scenario (see Section 6.5), where all loads and all generation are grouped together. The system voltage across all cables was a constant 230V (single phase) or 400V (three phases). For a schematic overview of the experiment setup, refer to Figure 6.7.

Cable We used 30 meters of YMvK mb cable made by Nexans B.V. (a 4x25mm2 copper cable, rated for approximately 45kW). The nominal ratings for this cable are given for voltage as 600Vac and for current as 127A. The maximum operating temperature

[18] A public-private partnership between DNV GL, the Dutch energy research institute ECN and the technical universities of Eindhoven and Delft, see http://www.flexpowergridlab.com/.

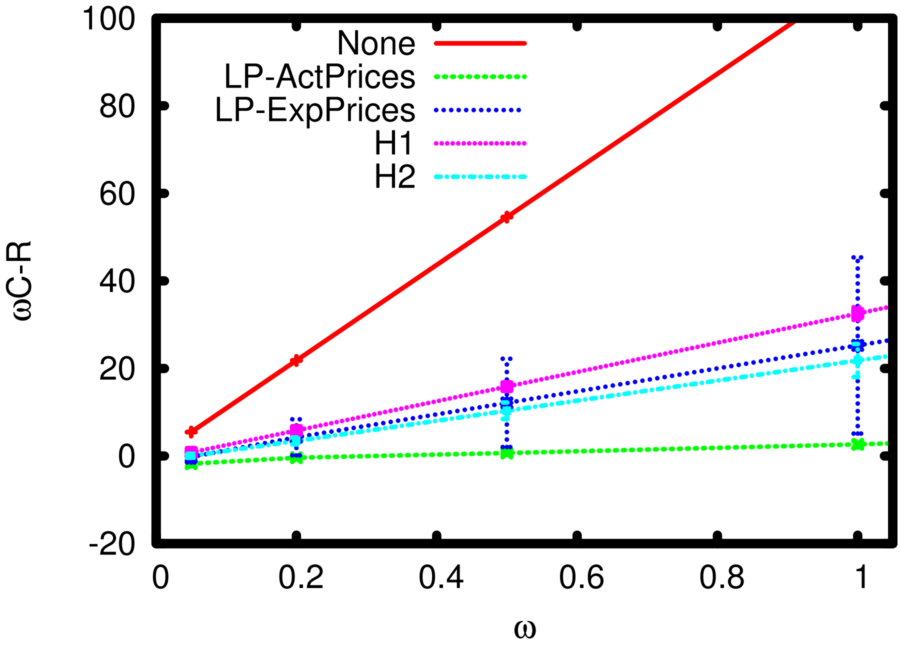

Figure 6.6: Simulation results for the pessimistic case. ω denotes the weight of cost-consideration and $\omega C - R$ denotes total costs accumulated on a simulated day.

is +95 degrees Celsius. We employed three cable segments, each being ten meters long. The beginning of the cable was connected to the MV grid. LV cables are underground in The Netherlands and thus the thermo-conductivity should resemble these difficult-to-observe settings, at least for average conditions. To achieve this, the measured segments were packed in insulation material commonly used for household CV pipes as thermal barrier, which is very similar to polystyrene.

The activity on the third segment simply represents the activity of the battery, therefore we only measured temperature in the first two cable segments. We measured the temperature of the segments at halfway length (5m) and on the outside of the cable (but within the isolation material). In addition, the ambient room temperature was measured to serve as a reference.

Loads We connected one load after the first segment, which represents the aggregated load of several households. We modelled loads with resistances. The FPG lab has available resistances of 24 Ohm and 12 Ohm. We modelled four switches with different resistances each. All possible combinations of switches thus equalled $2^4 = 16$ distinct settings for the load. In Section 6.5, the aggregated consumption load varies between 0 kW and 50 kW, thus we made the following choices for the settings of the four switches: 6 Ohms (2x12 Ohms in parallel), 12 Ohms (1x12 Ohms), 24 Ohms (1x24

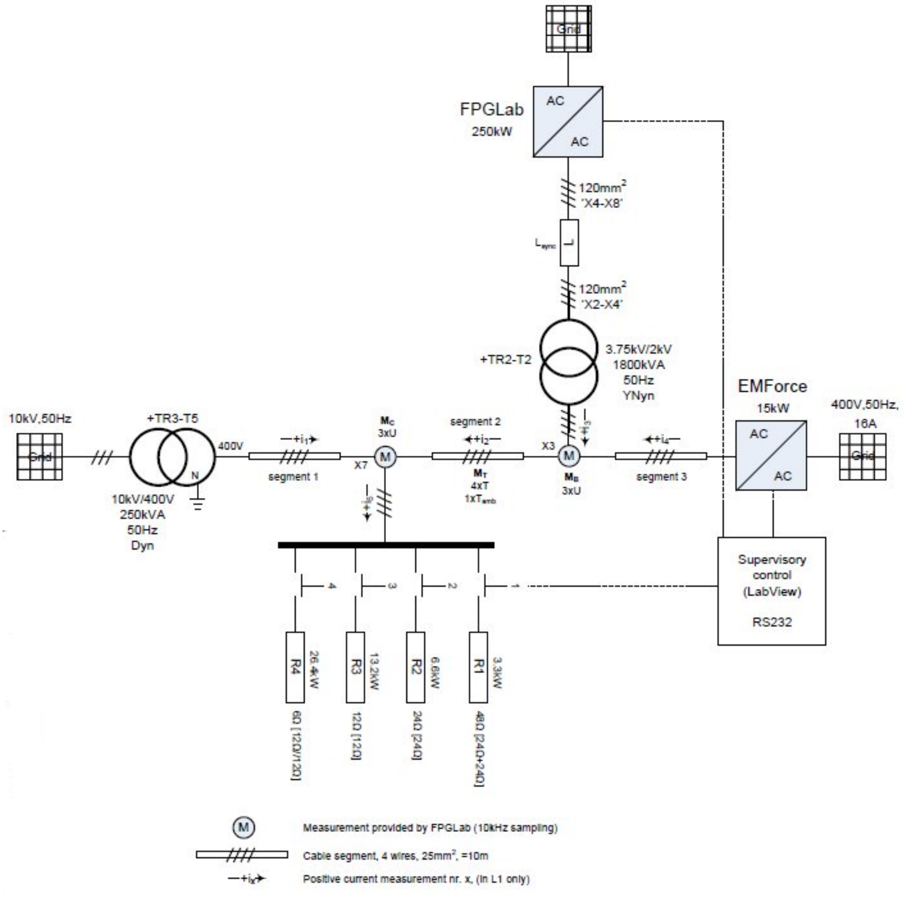

Figure 6.7: Experiment setup in the FPG lab

Ohms) and 48 Ohms (1x24 Ohms+1x24 Ohms in series). If the resistances of all the switches were on, up to 49.6 kW of demand were simulated.

Generation In the simulations from Section 6.5, all generation (10 solar panels[19] with 5kW output each) was either on or off, which made representing it in the lab straightforward (as opposed to the representation of loads we describe above). We connected a diesel generator after the second segment, which represents high currents from an aggregated number of generators, e.g. assuming a high penetration of solar panels. The simulation traces specify either 0kW or 50kW.

Battery At the end of the cable, we placed a battery emulator provided by EMForce[20]. It emulated a 15kW, bi-directional battery and could simulate battery operation for any continuous value between -5kW and +5kW. In Section 6.5, a larger example of a battery used in electric vehicles was assumed (with a capacity of 31kWh). In this experiment, we use a size of 24kWh which is found in mass-produced electric vehicles (e.g. the Nissan Leaf[21]) and we also adjust for the assumed advanced lifetime of the battery - we assume the battery is in its so-called "second life", not being suitable any more to operate an electric vehicle. Thus, we subtract 50% capacity and use 12kWh. Batteries are assumed not suitable for EVs if the capacity drops below 70% but we assume an even lower capacity to be on the safe side, as capacity also degrades during the second life of the battery.

6.6.B. EXPERIMENT TRACES

Before we explain the two experiments and report on the results in Section 6.6.c, we now explain how we generated the experiment traces which we used in the second experiment (the second experiment involved the H_2 algorithm). These traces are shown in Table 6.2. Just as in Section 6.5, all activity by consumers (and, consequently, by the battery) is based on APX wholesale market traces from 2012. Because we conducted experiments in real time, we had to choose one price series from the 2012 set. We chose May 21st, 9am to 5pm (see Figure 6.4, May 21st is shown in dotted black). Due to the laboratory setup for the load (see Section 6.6.a), we discretised the resulting load profile to the values we could emulate. The activity of solar panels was fixed to be active (full production) from noon to 4pm. During each half hour time step, all activity is kept at constant kW levels. The activity of the battery is determined by the heuristic algorithm H_2. Table 6.2 shows the resulting experiment used as input to simulate May 21st, 2012, 9am to 5pm.

[19] For an example of such panels, see https://web.archive.org/web/20150228223707/http://www.eurosolar.com.au/5-kw-solar-system/
[20] http://www.emforce.nl/
[21] https://web.archive.org/web/20140712025737/http://www.nissanusa.com/electric-cars/leaf/charging-range/battery/

Minutes	Aggr. Load	Aggr. Gen.	Seg. 1 (no battery activity)	Seg. 2 (no battery activity)	H_2 action	Seg. 1 (with battery activity)	Seg. 2 (with battery activity)
0	26.45	0.0	26.45	0.0	0.0	26.45	0.0
30	26.45	0.0	26.45	0.0	-1.99	24.46	-1.99
60	42.98	0.0	42.98	0.0	-5.0	37.98	-5.0
90	42.98	0.0	42.98	0.0	-5.0	37.98	-5.0
120	49.6	0.0	49.6	0.0	-4.6	45.0	-4.6
150	46.29	0.0	46.29	0.0	-1.29	45.0	-1.29
180	46.29	-50.0	-3.71	50.0	5.0	1.29	-45.0
210	42.98	-50.0	-7.02	50.0	5.0	-2.02	-45.0
240	36.37	-50.0	-13.63	50.0	5.0	-8.63	-45.0
270	33.06	-50.0	-16.94	50.0	5.0	-11.94	-45.0
300	23.15	-50.0	-26.85	50.0	1.87	-24.98	-48.13
330	23.15	-50.0	-26.85	50.0	0.39	-26.46	-49.61
360	19.84	-50.0	-30.16	50.0	0.09	-30.07	-49.91
390	19.84	-50.0	-30.16	50.0	0.03	-30.13	-49.97
420	19.84	0.0	19.84	0.0	1.02	20.86	1.02
450	19.84	0.0	19.84	0.0	0.22	20.06	0.22

Table 6.2: Aggregated consumption and generation traces to simulate May 21st 2012, 9am to 5pm and the resulting power on segments S1 and S2 without and with battery activity. All values (besides first column) in kW. Values for loads are positive and values for generation are negative (imagine a meter at a house, it runs backward when net generating).

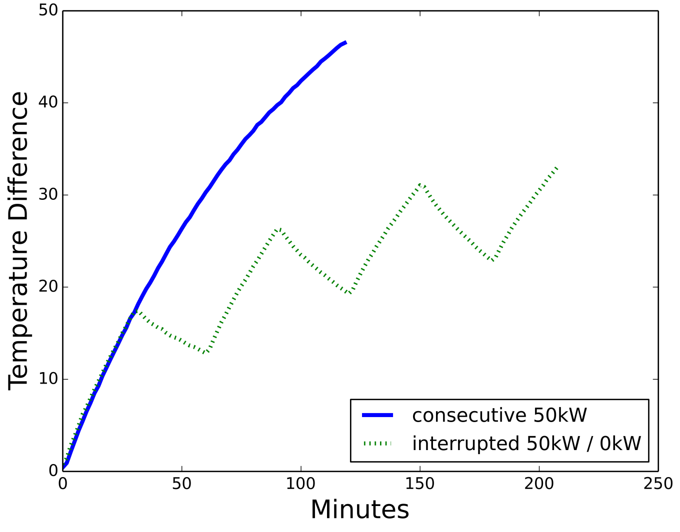

Figure 6.8: Results of Experiment 1, temperature on segment 2.

6

6.6.C. RESULTS

REGULAR INTERRUPTIONS OF POWER FLOW

The first experiment tests how beneficial it is (for the reduction of temperature) to regularly interrupt a continuous power flow, i.e. to prevent a build-up of temperature by consecutive high currents. During this experiment, we only used the generator, so no consumption or battery activity took place. In one condition, we generated 50kW consecutively for four half-hour steps. In a second condition, in order to simulate interruptions to high power flow, we introduced a half-hour time step with no generation after each of the four time steps with generation activity of 50kW. Again, we report on the temperature of segment 2. Of course, a temperature build-up is to be expected in both conditions, but were interested in the percentage of the difference between the conditions. The results in Figure 6.8 show that in the second condition, the peak temperature difference built up to only 60% of what the first condition exhibited.

REALISTIC LOAD PATTERNS AND SMART BATTERY OPERATION

For the second experiment, we run an eight-hour experiment with realistic load patterns (see Section 6.6.b) and the H_2 algorithm. In the tested scenario, both the load and the generation are (during some time steps) overloading the rated capacity of the cable (on segment 1 and segment 2, respectively).

Before the actual experiment started, we brought the cable into a thermal state which approximated the conditions which would exist due to previous activity before 9am. To this end, the load and generation levels of the first 30-minute time step of the traces (see minute 0 to 30 in Table 6.2) were performed for 90 straight minutes, as preparation. We report the temperature of both segments, for the case with no battery activity and for the case with smart battery operation present.

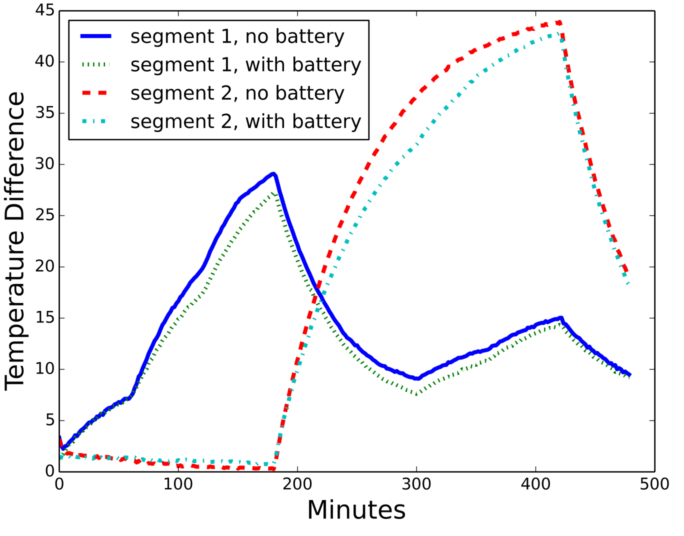

Figure 6.9: Results of Experiment 2.

The results in Figure 6.9 show that even a battery with a small energy capacity can make a valuable contribution to avoiding overheating: With a battery present, the temperature of the cable was lowered up to 13 percent compared to when the same scenario was tested without a battery present. Between minutes 30 and 180, the battery was discharging. This is both a preparation for the later part of the day, when high excess generation from solar panels is expected (and thus charging becomes necessary for cable protection), but between minutes 120 and 180, cable overloading (due to high local consumption) was avoided by this battery activity. The effect on cable temperature was several degrees Celsius. After minute 180, cable temperature rose to the highest values in our experiment. Between minutes 180 and 300, the battery was charging at its highest possible rate of 5kW and achieving valuable reductions in cable temperature (5 degrees). Due to its low capacity, it could not sustain this reduction for longer, but a positive effect on the cable temperature remained clearly visible even for two more hours of overloading the cable. This can already reduce damage to the cable significantly.

6.7. Conclusions

Storage technology (like batteries which we used here as a concrete example) can play an important role in future energy systems. It combines well with novel technology on both the generation and consumption side, which are likely to lead to peaks. The overarching benefit of storage technology is that it can help to avoid those peaks. However, a closer look reveals that there are multiple advantages of operating storage technology in modern distribution grids, especially when they are placed next to other assets. Making use of several of these advantages leads to a combined objective function. The optimisation of this objective function by intelligent battery control strategies thus is a multi-objective problem.

The first advantages which we are specifically interested in within this chapter is the ability to protect assets in the local network. This can relieve a major investment challenge faced by distribution system operators during the next two decades. The second advantage is that storage technology can, due to its flexibility of operation, profit from price fluctuations in the market by implementing revenue management into its strategy.

In this chapter, we have modelled a neighbourhood (with low voltage cables, used car batteries and a transformer) and a dynamic pricing market. We then use this model to design a mixed integer linear program to solve the multi-objective problem mentioned above, where we assume that advance knowledge of household activity is given. The solution represents an optimal schedule for the battery, with an amount to charge or discharge in each time step. However, the expectations of future household activity, weather conditions and market prices are uncertain. We thus propose two heuristic strategies to dynamically construct a schedule over time, based on available information in each time step. The strategy H_1 uses information about the current time step and attempts to bring back the battery to half its capacity if possible. The strategy H_2 uses expectations about future time steps in addition to current information, in order to prepare the battery successfully for expected future states (e.g. for peaks or changes in market prices).

We perform stochastic computational simulations, where we simulate 20 different days of operation for several settings. We can show that the strategy H_2 performs within 83% of a theoretical upper bound (achieved by the mixed integer linear program with complete information). The obtained results indicate that (used) batteries placed in low voltage neighbourhoods can perform important protection and the proposed strategies are promising candidates for control algorithms being used in this technology.

Next to performing stochastic computational simulations, it is also important to study, in real-world circumstances, the precise thermal reaction of low voltage cables to novel usage spikes and to proposed protection mechanisms. We emulated the low voltage cable of a Dutch neighbourhood in the FPG laboratory in Arnhem, The Netherlands, and conducted several overheating experiments for multiple hours. We could show positive effects on reducing cable temperature by operating even a small battery (a used battery from an electric vehicle).

Future development of the H_2 strategy could improve the protection during longer overheated intervals, by interrupting the interval repeatedly (rather than reducing peak temperatures consistently until the battery has no more capacity to do so). This would probably have positive effects, given that we assume a cost function which is exponential with respect to multiple consecutively overloaded time steps. However, this idea was left out of this work as it involves another loop in the algorithm over future steps and thus adds to the complexity of the necessary analysis.

7

CONCLUSIONS

In future electricity systems, settings are expected to be more dynamic and uncertain. This is due to ongoing technological and economic developments on both the supply and the demand side. These developments promise to be highly useful, for example in order to lower CO_2 emissions, to increase energy efficiency or to enable more freedom of choice in the marketplace. However, they also introduce new challenges, which is why we need to reconsider how electricity is distributed and paid for in real time.

The most significant developments in this regard are of technological nature. On the generation side, renewable generators with intermittent supply patterns are being introduced. For example, solar and wind power generators depend on the weather, which is inherently hard to predict (at a local level). Likewise, on the consumption side, massive use of new powerful devices with novel usage patterns is on the horizon. For example, electric vehicles need to be charged in advance of journeys and heat pumps need electricity to keep the room temperature within a given temperature range. Furthermore, ongoing developments in the IT world make it feasible to collect and distribute real-time information on the electricity grid and in homes, as well as to implement local decision-making in smart devices. These capabilities can be of use in dynamic systems, where the novel generation and consumption patterns discussed above can be dealt with better than today.

As a response to these technological developments, the smart grid vision has been formulated recently. In this vision, the availability of real-time sensor data and local computing power enables much more fine-grained decision making and thus the participation of smaller actors in dynamic mechanisms. This can lead to significantly more efficient outcomes within the daily operation of the energy system.

Next to technological developments, there are also economic developments, due to the ongoing liberalisation of electricity markets in many countries. Here, the most remarkable trends are the unbundling of the roles of wholesale producer and retailer and the involvement of domestic consumers into dynamic pricing. These and other related economic trends enable new business cases within the smart grid vision. For instance, real-time prices can inform and motivate the decisions made by software which guides the charging of an electric vehicle. This software can attempt to save charging costs by charging when the price is low and by waiting otherwise (in expectations of prices decreasing again before the time of departure). Another example for a new business case is a retailer (an actor who buys electricity on the wholesale market and then sells it to multiple consumers) who uses dynamic pricing strategies. If he can vary prices for his consumers to a certain degree in real time, he can limit his exposure to high prices during consumption peaks, which may exist due to intermittent generation and unexpected consumption peaks.

In order to keep the security of supply high and prices within acceptable ranges in these novel circumstances, it is crucial to find suitable methods with which to allocate electricity among both generators and consumers. In addition, these methods need to set a price for each actor, which he can earn or needs to pay. Market mechanisms are very useful procedures for such allocations. Today, there are usually one or two markets in place per country, being operated by the nationwide grid operator. In future energy systems, operators of lower grid levels can also operate markets. Furthermore, market mechanisms can be used in other use cases, e.g. to manage generation and consumption in microgrids, office buildings or virtual power plants.

For a market mechanism to be effective in these settings, it needs to assess the flexibility of participants or of their devices to deviate from their natural course of action. An example of useful flexibility is the ability to shift actions across time (we have mentioned electric vehicle batteries as a possible use case above). Finally, a market mechanism will need to operate with multiple objectives, for instance to allocate electricity to those who want it the most, to protect expensive network assets, and to provide some level of fairness.

In this thesis, we have proposed several novel algorithms and allocation mechanisms which can be useful for participants in future electricity systems. We have outlined the problem motivation and the reasons for our technical methods in Chapters 1 and 2. Furthermore, each contribution chapter (Chapters 3 through 6) summarises the problem it tackles and the contributions it makes (in their introduction section), as well as the possible future work for its specific approach (in their conclusion section). In order to conclude this thesis in addition to these chapter summaries, we will in this chapter discuss the methodological approach taken in this thesis. We also revisit the research questions which were outlined in Section 1.3 and evaluate to what extent this thesis has been able to answer them.

7.1. METHODOLOGY DISCUSSION

In this thesis, we have addressed the novel problem settings in future electricity systems which we outlined above with methods from computer science. In particular, we have focused on relevant markets for electricity (i.e. markets suitable for smart grid settings, where small actors are involved and decisions should be made fast) as a method to find well-working solutions for given problems in these settings. The contributions in this thesis have been made in the form of novel market mechanisms and strategies which participants can use.

Our methodological approach has been as follows: We have developed an agent-based model of each chosen problem setting and proposed a novel solution. We have then evaluated our proposed solution using stochastic computational simulations in parameterised scenarios. In this section, we review this methodological approach from three angles. We consider our choices for stakeholder perspectives in problem models, the evaluation of outcomes and the use of optimisation techniques.

In markets for electricity, a range of different stakeholders with distinct objectives take part. As a consequence, novel solutions should consider several different relevant points of views. Agent-based modelling is a useful approach in this regard. In this thesis, we have taken the point of view of small market participants, namely producers who sell electricity (Chapters 3), consumers who buy electricity (Chapters 3, 4 and 5), and also prosumers who do both (Chapters 3 and 6). In particular, we have proposed a mechanism which can make it easier for these small participants to decide how to successfully engage in novel markets for electricity (Chapter 3). We have also proposed ways to measure whether a market is too complex to be comprehensible for small participants, given their local knowledge (Chapter 4). Finally, we have provided pricing strategies for sellers in settings in which a maximal price limit shields small consumers from too much price variation (Chapter 5). In addition to small market participants, we have also taken the point of view of market operators. We have proposed methods to combine the trade of binding commitments with the trade of reserve capacity, in order to reduce the inherent complexity of running two markets at the same time (Chapter 3). Finally, we have tackled a problem specific to distribution system operators and proposed algorithms to operate a battery in a low voltage neighbourhood, in order to avoid costs which can exist if the network cable is overloaded (Chapter 6).

The chosen method of evaluation should ensure that solutions are robust against many different what-if scenarios. This is particularly important for the problem settings addressed in this thesis, for three reasons. First, the settings we address model economic problems with a high level of complexity. In our models (as is the case in reality), agents have a wide variety of possible actions (e.g. how much to buy) for a number of time steps, where the consequences of the decisions in each time step affect other time steps, as well. Second, it is currently not known precisely which scenarios will exist in future energy systems. The main concerns in this regard are the economic affordability of novel technologies in the mass markets, the acceptance among end customers and the adaptations which will be made to existing regulations. Finally, future dynamics are more variable than today due to novel developments. The influx of renewable energy makes it more difficult to predict supply levels (or prices, for that matter), as intermittent factors like the weather have a large influence. Novel consumption devices like electric vehicles or heat pumps can be controlled in a more reactive fashion and thus strategic economic behaviour will lead to novel consumption dynamics. As a consequence, we have, in each of Chapters 3 through 6, modelled several possible what-if scenarios in the computational simulations, e.g. different market conditions or different setups of devices that take part. Furthermore, we have sampled multiple instances for each scenario, by choosing randomised parameter settings (this technique is commonly referred to as “Monte-Carlo Sampling"). This approach has enabled us to record a variety of outcomes from which we drew our conclusions. For example, two scenarios of interest can be compared or averages and standard deviations can be investigated across a range of different parameter settings.

We have made use of optimisation techniques to either find good solution parameters, to facilitate the stochastic evaluation or to implement agent behaviour. Using markets and multi-agent systems as an approach to modelling in this thesis has allowed us to keep an open attitude towards optimisation techniques and we have taken care to use a fitting approach to each problem. We have used simplex optimisation (in Chapter 3) and greedy algorithms (in Chapter 4) to model economic decision making in agents. Furthermore, we have used linear programming (in Chapter 6) and brute force methods (in Chapter 5) to compute problem benchmarks. Finally, we have used evolutionary algorithms to optimise parameterised strategies (in Chapter 5).

7.2. REVISITING THE RESEARCH QUESTIONS

In this section, we revisit the research questions which were outlined in Section 1.3. We first state each question and then evaluate to what extent this thesis has been able to answer them.

Future energy systems will exhibit more intermittent supply and more heterogeneous demand, while storage technology will still be expensive. Consequently, we will require flexible participants and devices to adapt their activities on short notice, in order to balance supply and demand and to protect assets. Existing dynamic pricing mechanisms for smart grid settings are able to achieve balancing of supply and demand by providing monetary benefits for such behaviour. However, in these mechanisms the ability of both flexible and inflexible participants to plan ahead is usually greatly reduced. *Can we design pricing mechanisms that enable adaptations by flexible participants on short notice, but still maintain the ability of participants to plan ahead?*

This research question addresses settings with high uncertainty about the near future and decentralised decision-making. In particular, it asks for mechanisms in which flexible participants (who can react to price changes on short notice) are incentivised to make use of their flexibility in order to facilitate balancing of supply and demand, but at the same time both flexible as well as inflexible participants can plan ahead sufficiently. The ability to plan ahead is important for the efficient operation of all participants and thus makes a mechanism more attractive to use, but it can also increase the effectiveness of flexible participants with respect to system goals, such as the reduction of consumption peaks. We have proposed contributions in this regard in Chapters 3 and 5.

The market mechanism we have proposed in Chapter 3 explicitly addresses the uncertainty about the near future by adding a market for reserve capacity. All participants can plan ahead explicitly by bidding on binding commitments as well as reserve capacity, which flexible participants would sell and inflexible participants would buy in case of unforeseen peaks in demand or supply. Price-finding in the market is facilitated by the ability of the bid format to represent both binding commitments and optional reserve capacity. In our proposed mechanism, flexible consumers are incentivised to offer reserve capacity ahead of time, which we prove for the case of perfect competition and show in simulations for the case of imperfect competition. To ensure that our mechanism does not trade in these advantages for any major disadvantages, we compared outcomes to a benchmark mechanism and were able to show that our proposed mechanism has no economic drawbacks for participants.

Chapter 5, on the other hand, proposes pricing strategies for a seller who can adjust unit prices dynamically (and can thus incentivise flexible consumers not to consume during consumption peaks). The ability for participants (i.e. consumers) to plan ahead is introduced by two means. First, the seller is bound by his promise to the consumers to keep prices below a maximal limit. Defining price limits will be crucial for retailers (to attract consumers as customers) as well as regulators (to protect consumers). However, when designing dynamic pricing strategies, peak reduction and keeping prices within limits can be conflicting goals. Second, the pricing strategies are optimised offline for a given setting and are applied consistently for an extended time period, during which participants can form reasonable expectations of prices and thus their ability to plan ahead improves. We have proposed two parametrisable strategies for setting prices dynamically, based on limited information about current demand for electricity. Among other results, we were able to show that employing the proposed dynamic pricing strategies reduces consumption peaks, although their parameters are being optimised for the maximisation of retailer profits.

Today, participants in dynamic economic allocation mechanisms for electricity are professional energy traders, who make use of elaborated financial portfolio management techniques and powerful computation facilities to find the best strategies. If many more actors are exposed to dynamic prices, then the level of required sophistication that is needed to take part in pricing mechanisms should be lowered. ***Can we design pricing mechanisms that require little sophistication from the participants, are able to find allocations fast (suitable for smart grids) and are able to limit the exposure of small participants to risk?***

7

This research question addresses the fact that many small players with limited computational facilities take part in future smart grid settings, who also need to have a lower exposure to risk than the more professional participant in today's wholesale settings. We have made several contributions in this regard, in Chapters 3, 4 and 5.

The market mechanism which we have proposed in Chapter 3 (see our answer to the first research question above) reduces the necessary level of sophistication to take part in a smart grid market which has modern features for planning ahead in electricity markets (the ahead market supports both binding ahead-commitments and reserve capacities in bids). The construction of bids is then straightforward and fast.

In Chapter 4, we have modelled the perspective of participants in dynamic pricing settings, which receives very little attention in contemporary research. We were interested in both flexible as well as inflexible consumers, where we especially focus on non-sophisticated ones (our modelling can apply to both human or automated decision-making in this regard). The insights from this chapter can be a valuable contribution to the discussion of complexity in future electricity markets. Furthermore, the indicators we have proposed might prove useful to tweak pricing strategies for settings with non-sophisticated decision-makers.

The pricing strategies for a retailer which we have proposed in Chapter 5 (see our answer to the first research question above) includes the promise of an upper price bound, which is an important ingredient to reduce risks for consumers in dynamic pricing settings. These promises are commonly made either because the retailer needs to attract consumers or due to regulation (consumer protection). Furthermore, the strategies have been designed to compute prices fast in real time (they are fine-tuned by finding the most promising parameters for a given setting offline).

Automated grid protection is a crucial innovation step for network operators. Smart devices can be programmed to perform protective actions, but they can react to dynamic prices as well. ***Is it possible for such devices to combine the objective of protection with market participation, such that the devices can earn back parts of their own costs and at the same time add flexibility to the markets?***

This research question addresses the need for novel control strategies which can be used by smart devices in dynamic market settings. Each device has a primary objective, e.g. the primary objective of a deep freezer is to keep temperatures within a given range. We can assume that in future energy systems, a smart device is buying or selling electricity in a market with a dynamic price. It therefore becomes crucial that the device can limit its cost of operation by taking these price dynamic into account, or even make a profit during times where its primary objective is not relevant. In Chapter 6, we have developed algorithms for the application of such an approach to small storage devices. In the setting we modelled, the primary objective for the storage device is the protection of network assets. The algorithms we proposed compute an action for the current time step (to charge or discharge the battery), where the protection of the cable takes precedence over profitable market participation.

We have modelled a domestic neighbourhood with powerful new generation and consumption devices present. In such possible settings, overloading of the low voltage cable is expected to happen frequently, which can reduce the cable lifetime significantly. Due to the introduction of electric vehicles to mass markets, so-called second life batteries will become affordable in a few years, and we therefore proposed to use such a battery for cable protection, controlled by our algorithms. The motivation is that this solution can be a much more cost-efficient alternative than simply reacting to such settings (with frequent overloading) by replacing the cable right away. We were able to show in computational simulations that our proposed strategies perform well when compared to an approximated theoretical optimum (which was computed with clairvoyant knowledge of future prices). We also studied the thermal reaction of real-world cable hardware in laboratory experiments, where we could show positive effects on reducing cable temperature by operating a small battery with one of our proposed strategies.

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Writing a PhD dissertation is in some ways a job like many other (it can be described as being employed as a junior scientist for a few years), but in other ways it is a unique experience. It is by definition a document of one person's attempt to tackle a difficult problem. By experience, we can see that it is a project with larger-than-zero probabilities of taking longer than anticipated and also of not being completed at all. I therefore feel gratitude towards the people who have helped me to complete this project.

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Curriculum Vitae

Nicolas Höning was born in Hannover (Germany) on June 2nd, 1980. He received a Bachelor of Science in the field of Cognitive Sciences from University Of Osnabrück (Germany) in 2007. He received a Master of Science in the field of Computational Intelligence & Self-Organisation from Vrije Universiteit Amsterdam (the Netherlands) in 2009. He started his doctoral research at the Centrum Wiskunde & Informatica (CWI, the Netherlands) in 2009. Since 2014, Nicolas has been employed as lead software engineer at Softwear BV (the Netherlands).

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36 Marco Kalz (OUN) *Placement Support for Learners in Learning Networks*
37 Hendrik Drachsler (OUN) *Navigation Support for Learners in Informal Learning Networks*
38 Riina Vuorikari (OU) *Tags and self-organisation: a metadata ecology for learning resources in a multilingual context*
39 Christian Stahl (TUE, Humboldt-Universitaet zu Berlin) *Service Substitution: A Behavioral Approach Based on Petri Nets*
40 Stephan Raaijmakers (UvT) *Multinomial Language Learning: Investigations into the Geometry of Language*
41 Igor Berezhnyy (UvT) *Digital Analysis of Paintings*
42 Toine Bogers (UvT) *Recommender Systems for Social Bookmarking*
43 Virginia Nunes Leal Franqueira (UT) *Finding Multi-step Attacks in Computer Networks using Heuristic Search and Mobile Ambients*
44 Roberto Santana Tapia (UT) *Assessing Business-IT Alignment in Networked Organizations*
45 Jilles Vreeken (UU) *Making Pattern Mining Useful*
46 Loredana Afanasiev (UvA) *Querying XML: Benchmarks and Recursion*

2010

1 Matthijs van Leeuwen (UU) *Patterns that Matter*
2 Ingo Wassink (UT) *Work flows in Life Science*
3 Joost Geurts (CWI) *A Document Engineering Model and Processing Framework for Multimedia documents*
4 Olga Kulyk (UT) *Do You Know What I Know? Situational Awareness of Co-located Teams in Multidisplay Environments*
5 Claudia Hauff (UT) *Predicting the Effectiveness of Queries and Retrieval Systems*
6 Sander Bakkes (UvT) *Rapid Adaptation of Video Game AI*
7 Wim Fikkert (UT) *Gesture interaction at a Distance*
8 Krzysztof Siewicz (UL) *Towards an Improved Regulatory Framework of Free Software. Protecting user freedoms in a world of software communities and eGovernments*
9 Hugo Kielman (UL) *A Politiele gegevensverwerking en Privacy, Naar een effectieve waarborging*
10 Rebecca Ong (UL) *Mobile Communication and Protection of Children*
11 Adriaan Ter Mors (TUD) *The world according to MARP: Multi-Agent Route Planning*
12 Susan van den Braak (UU) *Sensemaking software for crime analysis*
13 Gianluigi Folino (RUN) *High Performance Data Mining using Bio-inspired techniques*
14 Sander van Splunter (VUA) *Automated Web Service Reconfiguration*
15 Lianne Bodenstaff (UT) *Managing Dependency Relations in Inter-Organizational Models*
16 Sicco Verwer (TUD) *Efficient Identification of Timed Automata, theory and practice*
17 Spyros Kotoulas (VUA) *Scalable Discovery of Networked Resources: Algorithms, Infrastructure, Applications*
18 Charlotte Gerritsen (VUA) *Caught in the Act: Investigating Crime by Agent-Based Simulation*
19 Henriette Cramer (UvA) *People's Responses to Autonomous and Adaptive Systems*
20 Ivo Swartjes (UT) *Whose Story Is It Anyway? How Improv Informs Agency and Authorship of Emergent Narrative*
21 Harold van Heerde (UT) *Privacy-aware data management by means of data degradation*
22 Michiel Hildebrand (CWI) *End-user Support for Access to*
Heterogeneous Linked Data
23 Bas Steunebrink (UU) *The Logical Structure of Emotions*
24 Zulfiqar Ali Memon (VUA) *Modelling Human-Awareness for Ambient Agents: A Human Mindreading Perspective*
25 Ying Zhang (CWI) *XRPC: Efficient Distributed Query Processing on Heterogeneous XQuery Engines*
26 Marten Voulon (UL) *Automatisch contracteren*
27 Arne Koopman (UU) *Characteristic Relational Patterns*
28 Stratos Idreos (CWI) *Database Cracking: Towards Auto-tuning Database Kernels*

29 Marieke van Erp (UvT) *Accessing Natural History: Discoveries in data cleaning, structuring, and retrieval*
30 Victor de Boer (UvA) *Ontology Enrichment from Heterogeneous Sources on the Web*
31 Marcel Hiel (UvT) *An Adaptive Service Oriented Architecture: Automatically solving Interoperability Problems*
32 Robin Aly (UT) *Modeling Representation Uncertainty in Concept-Based Multimedia Retrieval*
33 Teduh Dirgahayu (UT) *Interaction Design in Service Compositions*
34 Dolf Trieschnigg (UT) *Proof of Concept: Concept-based Biomedical Information Retrieval*
35 Jose Janssen (OU) *Paving the Way for Lifelong Learning: Facilitating competence development through a learning path specification*
36 Niels Lohmann (TUe) *Correctness of services and their composition*
37 Dirk Fahland (TUe) *From Scenarios to components*
38 Ghazanfar Farooq Siddiqui (VUA) *Integrative modeling of emotions in virtual agents*
39 Mark van Assem (VUA) *Converting and Integrating Vocabularies for the Semantic Web*
40 Guillaume Chaslot (UM) *Monte-Carlo Tree Search*
41 Sybren de Kinderen (VUA) *Needs-driven service bundling in a multi-supplier setting: the computational e3-service approach*
42 Peter van Kranenburg (UU) *A Computational Approach to Content-Based Retrieval of Folk Song Melodies*
43 Pieter Bellekens (TUe) *An Approach towards Context-sensitive and User-adapted Access to Heterogeneous Data Sources, Illustrated in the Television Domain*
44 Vasilios Andrikopoulos (UvT) *A theory and model for the evolution of software services*
45 Vincent Pijpers (VUA) *e3alignment: Exploring Inter-Organizational Business-ICT Alignment*
46 Chen Li (UT) *Mining Process Model Variants: Challenges, Techniques, Examples*
47 Jahn-Takeshi Saito (UM) *Solving difficult game positions*
48 Bouke Huurnink (UvA) *Search in Audiovisual Broadcast Archives*
49 Alia Khairia Amin (CWI) *Understanding and supporting information seeking tasks in multiple sources*
50 Peter-Paul van Maanen (VUA) *Adaptive Support for Human-Computer Teams: Exploring the Use of Cognitive Models of Trust and Attention*
51 Edgar Meij (UvA) *Combining Concepts and Language Models for Information Access*

2011

1 Botond Cseke (RUN) *Variational Algorithms for Bayesian Inference in Latent Gaussian Models*
2 Nick Tinnemeier (UU) *Organizing Agent Organizations. Syntax and Operational Semantics of an Organization-Oriented Programming Language*
3 Jan Martijn van der Werf (TUe) *Compositional Design and Verification of Component-Based Information Systems*
4 Hado van Hasselt (UU) *Insights in Reinforcement Learning: Formal analysis and empirical evaluation of temporal-difference*
5 Base van der Raadt (VUA) *Enterprise Architecture Coming of Age: Increasing the Performance of an Emerging Discipline*
6 Yiwen Wang (TUe) *Semantically-Enhanced Recommendations in Cultural Heritage*
7 Yujia Cao (UT) *Multimodal Information Presentation for High Load Human Computer Interaction*
8 Nieske Vergunst (UU) *BDI-based Generation of Robust Task-Oriented Dialogues*
9 Tim de Jong (OU) *Contextualised Mobile Media for Learning*
10 Bart Bogaert (UvT) *Cloud Content Contention*
11 Dhaval Vyas (UT) *Designing for Awareness: An Experience-focused HCI Perspective*
12 Carmen Bratosin (TUe) *Grid Architecture for Distributed Process Mining*
13 Xiaoyu Mao (UvT) *Airport under Control. Multiagent Scheduling for Airport Ground Handling*
14 Milan Lovric (EUR) *Behavioral Finance and Agent-Based Artificial Markets*
15 Marijn Koolen (UvA) *The Meaning of Structure: the Value of Link Evidence for Information Retrieval*
16 Maarten Schadd (UM) *Selective Search in Games of Different Complexity*
17 Jiyin He (UvA) *Exploring Topic Structure: Coherence, Diversity and Relatedness*
18 Mark Ponsen (UM) *Strategic Decision-Making in complex games*
19 Ellen Rusman (OU) *The Mind ' s Eye on Personal Profiles*
20 Qing Gu (VUA) *Guiding service-oriented software engineering: A view-based approach*
21 Linda Terlouw (TUD) *Modularization and Specification of Service-Oriented Systems*
22 Junte Zhang (UvA) *System Evaluation of Archival Description and Access*
23 Wouter Weerkamp (UvA) *Finding People and their Utterances in Social Media*
24 Herwin van Welbergen (UT) *Behavior Generation for Interpersonal Coordination with Virtual Humans On Specifying, Scheduling and Realizing Multimodal Virtual Human Behavior*

25 Syed Waqar ul Qounain Jaffry (VUA) *Analysis and Validation of Models for Trust Dynamics*
26 Matthijs Aart Pontier (VUA) *Virtual Agents for Human Communication: Emotion Regulation and Involvement-Distance Trade-Offs in Embodied Conversational Agents and Robots*
27 Aniel Bhulai (VUA) *Dynamic website optimization through autonomous management of design patterns*
28 Rianne Kaptein (UvA) *Effective Focused Retrieval by Exploiting Query Context and Document Structure*
29 Faisal Kamiran (TUe) *Discrimination-aware Classification*
30 Egon van den Broek (UT) *Affective Signal Processing (ASP): Unraveling the mystery of emotions*
31 Ludo Waltman (EUR) *Computational and Game-Theoretic Approaches for Modeling Bounded Rationality*
32 Nees-Jan van Eck (EUR) *Methodological Advances in Bibliometric Mapping of Science*
33 Tom van der Weide (UU) *Arguing to Motivate Decisions*
34 Paolo Turrini (UU) *Strategic Reasoning in Interdependence: Logical and Game-theoretical Investigations*
35 Maaike Harbers (UU) *Explaining Agent Behavior in Virtual Training*
36 Erik van der Spek (UU) *Experiments in serious game design: a cognitive approach*
37 Adriana Burlutiu (RUN) *Machine Learning for Pairwise Data, Applications for Preference Learning and Supervised Network Inference*
38 Nyree Lemmens (UM) *Bee-inspired Distributed Optimization*
39 Joost Westra (UU) *Organizing Adaptation using Agents in Serious Games*
40 Viktor Clerc (VUA) *Architectural Knowledge Management in Global Software Development*
41 Luan Ibraimi (UT) *Cryptographically Enforced Distributed Data Access Control*
42 Michal Sindlar (UU) *Explaining Behavior through Mental State Attribution*
43 Henk van der Schuur (UU) *Process Improvement through Software Operation Knowledge*
44 Boris Reuderink (UT) *Robust Brain-Computer Interfaces*
45 Herman Stehouwer (UvT) *Statistical Language Models for Alternative Sequence Selection*
46 Beibei Hu (TUD) *Towards Contextualized Information Delivery: A Rule-based Architecture for the Domain of Mobile Police Work*
47 Azizi Bin Ab Aziz (VUA) *Exploring Computational Models for Intelligent Support of Persons with Depression*
48 Mark Ter Maat (UT) *Response Selection and Turn-taking for a Sensitive Artificial Listening Agent*
49 Andreea Niculescu (UT) *Conversational interfaces for task-oriented spoken dialogues: design aspects influencing interaction quality*

2012

1 Terry Kakeeto (UvT) *Relationship Marketing for SMEs in Uganda*
2 Muhammad Umair (VUA) *Adaptivity, emotion, and Rationality in Human and Ambient Agent Models*
3 Adam Vanya (VUA) *Supporting Architecture Evolution by Mining Software Repositories*
4 Jurriaan Souer (UU) *Development of Content Management System-based Web Applications*
5 Marijn Plomp (UU) *Maturing Interorganisational Information Systems*
6 Wolfgang Reinhardt (OU) *Awareness Support for Knowledge Workers in Research Networks*
7 Rianne van Lambalgen (VUA) *When the Going Gets Tough: Exploring Agent-based Models of Human Performance under Demanding Conditions*
8 Gerben de Vries (UvA) *Kernel Methods for Vessel Trajectories*
9 Ricardo Neisse (UT) *Trust and Privacy Management Support for Context-Aware Service Platforms*
10 David Smits (TUe) *Towards a Generic Distributed Adaptive Hypermedia Environment*
11 J. C. B. Rantham Prabhakara (TUe) *Process Mining in the Large: Preprocessing, Discovery, and Diagnostics*
12 Kees van der Sluijs (TUe) *Model Driven Design and Data Integration in Semantic Web Information Systems*
13 Suleman Shahid (UvT) *Fun and Face: Exploring non-verbal expressions of emotion during playful interactions*
14 Evgeny Knutov (TUe) *Generic Adaptation Framework for Unifying Adaptive Web-based Systems*
15 Natalie van der Wal (VUA) *Social Agents. Agent-Based Modelling of Integrated Internal and Social Dynamics of Cognitive and Affective Processes*
16 Fiemke Both (VUA) *Helping people by understanding them: Ambient Agents supporting task execution and depression treatment*
17 Amal Elgammal (UvT) *Towards a Comprehensive Framework for Business Process Compliance*
18 Eltjo Poort (VUA) *Improving Solution Architecting Practices*

19 Helen Schonenberg (TUe) *What's Next? Operational Support for Business Process Execution*

20 Ali Bahramisharif (RUN) *Covert Visual Spatial Attention, a Robust Paradigm for Brain-Computer Interfacing*

21 Roberto Cornacchia (TUD) *Querying Sparse Matrices for Information Retrieval*

22 Thijs Vis (UvT) *Intelligence, politie en veiligheidsdienst: verenigbare grootheden?*

23 Christian Muehl (UT) *Toward Affective Brain-Computer Interfaces: Exploring the Neurophysiology of Affect during Human Media Interaction*

24 Laurens van der Werff (UT) *Evaluation of Noisy Transcripts for Spoken Document Retrieval*

25 Silja Eckartz (UT) *Managing the Business Case Development in Inter-Organizational IT Projects: A Methodology and its Application*

26 Emile de Maat (UvA) *Making Sense of Legal Text*

27 Hayrettin Gurkok (UT) *Mind the Sheep! User Experience Evaluation & Brain-Computer Interface Games*

28 Nancy Pascall (UvT) *Engendering Technology Empowering Women*

29 Almer Tigelaar (UT) *Peer-to-Peer Information Retrieval*

30 Alina Pommeranz (TUD) *Designing Human-Centered Systems for Reflective Decision Making*

31 Emily Bagarukayo (RUN) *A Learning by Construction Approach for Higher Order Cognitive Skills Improvement, Building Capacity and Infrastructure*

32 Wietske Visser (TUD) *Qualitative multi-criteria preference representation and reasoning*

33 Rory Sie (OUN) *Coalitions in Cooperation Networks (COCOON)*

34 Pavol Jancura (RUN) *Evolutionary analysis in PPI networks and applications*

35 Evert Haasdijk (VUA) *Never Too Old To Learn: On-line Evolution of Controllers in Swarm- and Modular Robotics*

36 Denis Ssebugwawo (RUN) *Analysis and Evaluation of Collaborative Modeling Processes*

37 Agnes Nakakawa (RUN) *A Collaboration Process for Enterprise Architecture Creation*

38 Selmar Smit (VUA) *Parameter Tuning and Scientific Testing in Evolutionary Algorithms*

39 Hassan Fatemi (UT) *Risk-aware design of value and coordination networks*

40 Agus Gunawan (UvT) *Information Access for SMEs in Indonesia*

41 Sebastian Kelle (OU) *Game Design Patterns for Learning*

42 Dominique Verpoorten (OU) *Reflection Amplifiers in self-regulated Learning*

43 Anna Tordai (VUA) *On Combining Alignment Techniques*

44 Benedikt Kratz (UvT) *A Model and Language for Business-aware Transactions*

45 Simon Carter (UvA) *Exploration and Exploitation of Multilingual Data for Statistical Machine Translation*

46 Manos Tsagkias (UvA) *Mining Social Media: Tracking Content and Predicting Behavior*

47 Jorn Bakker (TUe) *Handling Abrupt Changes in Evolving Time-series Data*

48 Michael Kaisers (UM) *Learning against Learning: Evolutionary dynamics of reinforcement learning algorithms in strategic interactions*

49 Steven van Kervel (TUD) *Ontologogy driven Enterprise Information Systems Engineering*

50 Jeroen de Jong (TUD) *Heuristics in Dynamic Sceduling: a practical framework with a case study in elevator dispatching*

2013

1 Viorel Milea (EUR) *News Analytics for Financial Decision Support*

2 Erietta Liarou (CWI) *MonetDB/DataCell: Leveraging the Column-store Database Technology for Efficient and Scalable Stream Processing*

3 Szymon Klarman (VUA) *Reasoning with Contexts in Description Logics*

4 Chetan Yadati (TUD) *Coordinating autonomous planning and scheduling*

5 Dulce Pumareja (UT) *Groupware Requirements Evolutions Patterns*

6 Romulo Goncalves (CWI) *The Data Cyclotron: Juggling Data and Queries for a Data Warehouse Audience*

7 Giel van Lankveld (UvT) *Quantifying Individual Player Differences*

8 Robbert-Jan Merk (VUA) *Making enemies: cognitive modeling for opponent agents in fighter pilot simulators*

9 Fabio Gori (RUN) *Metagenomic Data Analysis: Computational Methods and Applications*

10 Jeewanie Jayasinghe Arachchige (UvT) *A Unified Modeling Framework for Service Design*

11 Evangelos Pournaras (TUD) *Multi-level Reconfigurable Self-organization in Overlay Services*

12 Marian Razavian (VUA) *Knowledge-driven Migration to Services*

13 Mohammad Safiri (UT) *Service Tailoring: User-centric creation of integrated IT-based homecare services to support independent living of elderly*

14 Jafar Tanha (UvA) *Ensemble Approaches to Semi-Supervised Learning Learning*

15 Daniel Hennes (UM) *Multiagent Learning: Dynamic Games and Applications*

16 Eric Kok (UU) *Exploring the practical benefits of argumentation in multi-agent deliberation*

17 Koen Kok (VUA) *The PowerMatcher: Smart Coordination for the Smart Electricity Grid*

18 Jeroen Janssens (UvT) *Outlier Selection and One-Class Classification*

19 Renze Steenhuizen (TUD) *Coordinated Multi-Agent Planning and Scheduling*

20 Katja Hofmann (UvA) *Fast and Reliable Online Learning to Rank for Information Retrieval*

21 Sander Wubben (UvT) *Text-to-text generation by monolingual machine translation*

22 Tom Claassen (RUN) *Causal Discovery and Logic*

23 Patricio de Alencar Silva (UvT) *Value Activity Monitoring*

24 Haitham Bou Ammar (UM) *Automated Transfer in Reinforcement Learning*

25 Agnieszka Anna Latoszek-Berendsen (UM) *Intention-based Decision Support. A new way of representing and implementing clinical guidelines in a Decision Support System*

26 Alireza Zarghami (UT) *Architectural Support for Dynamic Homecare Service Provisioning*

27 Mohammad Huq (UT) *Inference-based Framework Managing Data Provenance*

28 Frans van der Sluis (UT) *When Complexity becomes Interesting: An Inquiry into the Information eXperience*

29 Iwan de Kok (UT) *Listening Heads*

30 Joyce Nakatumba (TUe) *Resource-Aware Business Process Management: Analysis and Support*

31 Dinh Khoa Nguyen (UvT) *Blueprint Model and Language for Engineering Cloud Applications*

32 Kamakshi Rajagopal (OUN) *Networking For Learning: The role of Networking in a Lifelong Learner's Professional Development*

33 Qi Gao (TUD) *User Modeling and Personalization in the Microblogging Sphere*

34 Kien Tjin-Kam-Jet (UT) *Distributed Deep Web Search*

35 Abdallah El Ali (UvA) *Minimal Mobile Human Computer Interaction*

36 Than Lam Hoang (TUe) *Pattern Mining in Data Streams*

37 Dirk Börner (OUN) *Ambient Learning Displays*

38 Eelco den Heijer (VUA) *Autonomous Evolutionary Art*

39 Joop de Jong (TUD) *A Method for Enterprise Ontology based Design of Enterprise Information Systems*

40 Pim Nijssen (UM) *Monte-Carlo Tree Search for Multi-Player Games*

41 Jochem Liem (UvA) *Supporting the Conceptual Modelling of Dynamic Systems: A Knowledge Engineering Perspective on Qualitative Reasoning*

42 Léon Planken (TUD) *Algorithms for Simple Temporal Reasoning*

43 Marc Bron (UvA) *Exploration and Contextualization through Interaction and Concepts*

2014

1 Nicola Barile (UU) *Studies in Learning Monotone Models from Data*

2 Fiona Tuliyano (RUN) *Combining System Dynamics with a Domain Modeling Method*

3 Sergio Raul Duarte Torres (UT) *Information Retrieval for Children: Search Behavior and Solutions*

4 Hanna Jochmann-Mannak (UT) *Websites for children: search strategies and interface design - Three studies on children's search performance and evaluation*

5 Jurriaan van Reijsen (UU) *Knowledge Perspectives on Advancing Dynamic Capability*

6 Damian Tamburri (VUA) *Supporting Networked Software Development*

7 Arya Adriansyah (TUe) *Aligning Observed and Modeled Behavior*

8 Samur Araujo (TUD) *Data Integration over Distributed and Heterogeneous Data Endpoints*

9 Philip Jackson (UvT) *Toward Human-Level Artificial Intelligence: Representation and Computation of Meaning in Natural Language*

10 Ivan Salvador Razo Zapata (VUA) *Service Value Networks*

11 Janneke van der Zwaan (TUD) *An Empathic Virtual Buddy for Social Support*

12 Willem van Willigen (VUA) *Look Ma, No Hands: Aspects of Autonomous Vehicle Control*

13 Arlette van Wissen (VUA) *Agent-Based Support for Behavior Change: Models and Applications in Health and Safety Domains*

14 Yangyang Shi (TUD) *Language Models With Meta-information*

15 Natalya Mogles (VUA) *Agent-Based Analysis and Support of Human Functioning in Complex Socio-Technical Systems: Applications in Safety and Healthcare*

16 Krystyna Milian (VUA) *Supporting trial recruitment and design by automatically interpreting eligibility criteria*

17 Kathrin Dentler (VUA) *Computing healthcare quality indicators automatically: Secondary Use of Patient Data and Semantic Interoperability*

18 Mattijs Ghijsen (UvA) *Methods and Models for the Design and Study of Dynamic Agent Organizations*

19 Vinicius Ramos (TUe) *Adaptive Hypermedia Courses: Qualitative and Quantitative Evaluation and Tool Support*

20 Mena Habib (UT) *Named Entity Extraction and Disambiguation for Informal Text: The Missing Link*
21 Kassidy Clark (TUD) *Negotiation and Monitoring in Open Environments*
22 Marieke Peeters (UU) *Personalized Educational Games: Developing agent-supported scenario-based training*
23 Eleftherios Sidirourgos (UvA/CWI) *Space Efficient Indexes for the Big Data Era*
24 Davide Ceolin (VUA) *Trusting Semi-structured Web Data*
25 Martijn Lappenschaar (RUN) *New network models for the analysis of disease interaction*
26 Tim Baarslag (TUD) *What to Bid and When to Stop*
27 Rui Jorge Almeida (EUR) *Conditional Density Models Integrating Fuzzy and Probabilistic Representations of Uncertainty*
28 Anna Chmielowiec (VUA) *Decentralized k-Clique Matching*
29 Jaap Kabbedijk (UU) *Variability in Multi-Tenant Enterprise Software*
30 Peter de Cock (UvT) *Anticipating Criminal Behaviour*
31 Leo van Moergestel (UU) *Agent Technology in Agile Multiparallel Manufacturing and Product Support*
32 Naser Ayat (UvA) *On Entity Resolution in Probabilistic Data*
33 Tesfa Tegegne (RUN) *Service Discovery in eHealth*
34 Christina Manteli (VUA) *The Effect of Governance in Global Software Development: Analyzing Transactive Memory Systems*
35 Joost van Ooijen (UU) *Cognitive Agents in Virtual Worlds: A Middleware Design Approach*
36 Joos Buijs (TUe) *Flexible Evolutionary Algorithms for Mining Structured Process Models*
37 Maral Dadvar (UT) *Experts and Machines United Against Cyberbullying*
38 Danny Plass-Oude Bos (UT) *Making brain-computer interfaces better: improving usability through post-processing*
39 Jasmina Maric (UvT) *Web Communities, Immigration, and Social Capital*
40 Walter Omona (RUN) *A Framework for Knowledge Management Using ICT in Higher Education*
41 Frederic Hogenboom (EUR) *Automated Detection of Financial Events in News Text*
42 Carsten Eijckhof (CWI/TUD) *Contextual Multidimensional Relevance Models*
43 Kevin Vlaanderen (UU) *Supporting Process Improvement using Method Increments*
44 Paulien Meesters (UvT) *Intelligent Blauw: Intelligence-gestuurde politiezorg in gebiedsgebonden eenheden*
45 Birgit Schmitz (OUN) *Mobile Games for Learning: A Pattern-Based Approach*
46 Ke Tao (TUD) *Social Web Data Analytics: Relevance, Redundancy, Diversity*
47 Shangsong Liang (UvA) *Fusion and Diversification in Information Retrieval*

2015

1 Niels Netten (UvA) *Machine Learning for Relevance of Information in Crisis Response*
2 Faiza Bukhsh (UvT) *Smart auditing: Innovative Compliance Checking in Customs Controls*
3 Twan van Laarhoven (RUN) *Machine learning for network data*
4 Howard Spoelstra (OUN) *Collaborations in Open Learning Environments*
5 Christoph Bösch (UT) *Cryptographically Enforced Search Pattern Hiding*
6 Farideh Heidari (TUD) *Business Process Quality Computation: Computing Non-Functional Requirements to Improve Business Processes*
7 Maria-Hendrike Peetz (UvA) *Time-Aware Online Reputation Analysis*
8 Jie Jiang (TUD) *Organizational Compliance: An agent-based model for designing and evaluating organizational interactions*
9 Randy Klaassen (UT) *HCI Perspectives on Behavior Change Support Systems*
10 Henry Hermans (OUN) *OpenU: design of an integrated system to support lifelong learning*
11 Yongming Luo (TUe) *Designing algorithms for big graph datasets: A study of computing bisimulation and joins*
12 Julie M. Birkholz (VUA) *Modi Operandi of Social Network Dynamics: The Effect of Context on Scientific Collaboration Networks*
13 Giuseppe Procaccianti (VUA) *Energy-Efficient Software*
14 Bart van Straalen (UT) *A cognitive approach to modeling bad news conversations*
15 Klaas Andries de Graaf (VUA) *Ontology-based Software Architecture Documentation*
16 Changyun Wei (UT) *Cognitive Coordination for Cooperative Multi-Robot Teamwork*
17 André van Cleeff (UT) *Physical and Digital Security Mechanisms: Properties, Combinations and Trade-offs*
18 Holger Pirk (CWI) *Waste Not, Want Not!: Managing Relational Data in Asymmetric Memories*
19 Bernardo Tabuenca (OUN) *Ubiquitous Technology for Lifelong Learners*
20 Loïs Vanhée (UU) *Using Culture and Values to Support Flexible Coordination*

21 Sibren Fetter (OUN) *Using Peer-Support to Expand and Stabilize Online Learning*
22 Zhemin Zhu (UT) *Co-occurrence Rate Networks*
23 Luit Gazendam (VUA) *Cataloguer Support in Cultural Heritage*
24 Richard Berendsen (UvA) *Finding People, Papers, and Posts: Vertical Search Algorithms and Evaluation*
25 Steven Woudenberg (UU) *Bayesian Tools for Early Disease Detection*
26 Alexander Hogenboom (EUR) *Sentiment Analysis of Text Guided by Semantics and Structure*
27 Sándor Héman (CWI) *Updating compressed column-stores*
28 Janet Bagorogoza (TiU) *Knowledge Management and High Performance: The Uganda Financial Institutions Model for HPO*
29 Hendrik Baier (UM) *Monte-Carlo Tree Search Enhancements for One-Player and Two-Player Domains*
30 Kiavash Bahreini (OUN) *Real-time Multimodal Emotion Recognition in E-Learning*
31 Yakup Koç (TUD) *On Robustness of Power Grids*
32 Jerome Gard (UL) *Corporate Venture Management in SMEs*
33 Frederik Schadd (UM) *Ontology Mapping with Auxiliary Resources*
34 Victor de Graaff (UT) *Geosocial Recommender Systems*
35 Junchao Xu (TUD) *Affective Body Language of Humanoid Robots: Perception and Effects in Human Robot Interaction*

2016

1 Syed Saiden Abbas (RUN) *Recognition of Shapes by Humans and Machines*
2 Michiel Christiaan Meulendijk (UU) *Optimizing medication reviews through decision support: prescribing a better pill to swallow*
3 Maya Sappelli (RUN) *Knowledge Work in Context: User Centered Knowledge Worker Support*
4 Laurens Rietveld (VUA) *Publishing and Consuming Linked Data*
5 Evgeny Sherkhonov (UvA) *Expanded Acyclic Queries: Containment and an Application in Explaining Missing Answers*
6 Michel Wilson (TUD) *Robust scheduling in an uncertain environment*
7 Jeroen de Man (VUA) *Measuring and modeling negative emotions for virtual training*
8 Matje van de Camp (TiU) *A Link to the Past: Constructing Historical Social Networks from Unstructured Data*
9 Archana Nottamkandath (VUA) *Trusting Crowdsourced Information on Cultural Artefacts*
10 George Karafotias (VUA) *Parameter Control for Evolutionary Algorithms*
11 Anne Schuth (UvA) *Search Engines that Learn from Their Users*
12 Max Knobbout (UU) *Logics for Modelling and Verifying Normative Multi-Agent Systems*
13 Nana Baah Gyan (VU) *The Web, Speech Technologies and Rural Development in West Africa: An ICT4D Approach*
14 Ravi Khadka (UU) *Revisiting Legacy Software System Modernization*
15 Steffen Michels (RUN) *Hybrid Probabilistic Logics: Theoretical Aspects, Algorithms and Experiments*
16 Guangliang Li (UvA) *Socially Intelligent Autonomous Agents that Learn from Human Reward*
17 Berend Weel (VUA) *Towards Embodied Evolution of Robot Organisms*
18 Albert Meroño Peñuela (VUA) *Refining Statistical Data on the Web*
19 Julia Efremova (TUe) *Mining Social Structures from Genealogical Data*
20 Daan Odijk (UvA) *Context & Semantics in News & Web Search*
21 Alejandro Moreno Célleri (UT) *From Traditional to Interactive Playspaces: Automatic Analysis of Player Behavior in the Interactive Tag Playground*
22 Grace Lewis (VU) *Software Architecture Strategies for Cyber-Foraging Systems*
23 Fei Cai (UVA) *Query Auto Completion in Information Retrieval*
24 Brend Wanders (UT) *Repurposing and Probabilistic Integration of Data; An Iterative and data model independent approach*
25 Julia Kiseleva (TUe) *Using Contextual Information to Understand Searching and Browsing Behavior*
26 Dilhan Thilakarathne (VU) *In or Out of Control: Exploring Computational Models to Study the Role of Human Awareness and Control in Behavioural Choices, with Applications in Aviation and Energy Management Domains*
27 Wen Li (TUD) *Understanding Geo-spatial Information on Social Media*
28 Mingxin Zhang (TUD) *Large-scale Agent-based Social Simulation - A study on epidemic prediction and control*
29 Nicolas Höning (CWI/TUD) *Peak reduction in decentralised electricity systems - Markets and prices for flexible planning*