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Master's Thesis

MORE COMPREHENSIVE DEMAND SIDE MANAGEMENT BY THE INTEGRATION OF THE POWERMATCHER AND TRIANA

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Abstract

To deal with challenges introduced by the adaption of Renewable Energy Sources, Demand Side Management (DSM) methodologies are being developed that focus on the availability and reliability of our electricity supply. In the Netherlands, two methodologies referred as The PowerMatcher and Triana have been developed. In this research the methodologies have been combined because the strengths of the individual approaches complement each other. In order to combine the approaches, a novel bidding strategy is developed. This strategy is unique in the sense that it incorporates a device specific planning when the bidding function is determined. By means of use case simulations, in which the objective is set to minimize peaks and improve the self-consumption of the cluster, the performances of the combined DSM approach are evaluated. The simulations point out that the combination is capable of following a planning, as is determined by Triana, while performing real-time balancing, which deals with prediction errors. It is shown that following a planning mitigates the effect exploiting flexibility on undesired periods. In the use case simulations, this results in a peak reduction of 25%.

Contents

Chapter 1

Introduction

Approximately 130 years ago modern societies, the US society in particular, faced a war on the electrification of the modern world. This "war of currents" was fought between advocates of Alternating Current (AC), of which George Westinghouse was the leading person, and Direct Current (DC) as advocated by Thomans Edinson. Back in the days, decisions were made that determined the design principles of the electricity grid as it is still in use today, based on the very same principles. Commercial interests, safety concerns, energy efficiency, and technical (im)possibilities, were the main concerns in this 'war' [1]. Interestingly, also the openness to devices played a minor role. Before the 'war' started, DC power was leading because it is suitable for small scale, densely populated situations. It was in 1887, when Nikola Tesla invented the induction motor, that AC power became more interesting to use. In addition, the advantage of AC to transform voltages is huge because it enables transporting electrical power over larger distances (typically, DC power could only be transported over a distance of 1-2 km).

Since the moment the 'war' ran to an end, the basic principles of electric power systems have not been changed. Instead, improvements have been made in terms of power generation efficiency and availability of service. Today, new developments are going on that lead to the need of redefining the principles of electrical power systems. Again, commercial interests, energy efficiency, technical challenges, and openness to devices play again important roles. Although speaking of a war like the war of the currents would be too much, the amount of scientific research in this field is huge. However, not only researcher are involved in the developments of this multidisciplinary, vitally, and complex problem. Policymakers, Distribution System Operator (DSO), Transmission System Operator (TSO), energy producers, ICT experts and in the end actually all citizens in the society are stakeholders. What is going on? And who knows where are we going? This introductory chapter sketches the bigger picture of the developments in the electrical power grid and positions the research presented in this master thesis.

1.1 Electricity in a broader perspective

In order to sketch the bigger picture of the developments related to the electrical power grid, this section will look at some concepts from several perspectives.

A physical perspective

The first perspective is a physical one and presents the two key elements of the topic. The most fundamental principle is the conservation of energy. Just like all kinds of energy, electrical energy cannot be generated out of nothing, it always has to be converted from another source of energy. Similarly, electric energy cannot suddenly disappear but only consumed, which is basically another conversion of energy. Hence, it can be stated that the electrical power system is a 'closed system' in which supply and demand should be in perfect balance (note that storing electricity is treated as demand and subtraction of energy from a storage system as supply). Next to the fundamental law of the conservation of energy, there is a practical challenge in play: the absence of a large scale storage mechanism for electricity. Numerous possibilities to buffer electrical energy, either in the form of electrical energy or by means of conversion to another type of energy, have been engineered. However, they are all relatively expensive and cannot be applied on a large scale. These two facts, the conservation of electrical energy and the lack of a proper way to buffer it, are the most important reasons for the challenges on the electricity grid from a physical point of view.

Another fundamental principle is based on the conducting properties of materials. Electricity is transported over a network of materials with good conducting properties, in practice copper and aluminium. However, the capacity of the cables and other components in the network, is limited by the physical properties of the materials. This makes that for the grid design estimations are performed to dimension cables and components. Grids reinforcements are typically very expensive and rely on 30-40 years of payback time. Considering the uncertainties of what could happen in future, it is very difficult to make a proper trade-off decision between capacity and costs.

A historical perspective

The next element, which shows an important trend, is presented from a historical point of view. In the past, the world consumption of electrical energy has more or less increased monotonically (see Figure 1.1). It is observed that energy consumption was linked to both GDP and population. This is expressed in 'energy intensity' and defined as, considering a certain geographical area, the amount of energy consumed per capita or as the amount of energy consumed relative to the GDP. These days, the global energy intensity of GDP is reducing with 1.1% per year [2]. In order to meet climate change mitigation goals, the International Energy Agency (IEA) recommends to aim at even higher reduction of energy intensity. However, looking at absolute numbers, the total energy consumption is not expected to diminish within the coming decades. Together with this increase in global energy consumption, also the dependability of societies on electricity has increased. Therefore, availability and stability of electricity have become one of the main challenges of the electricity supply.

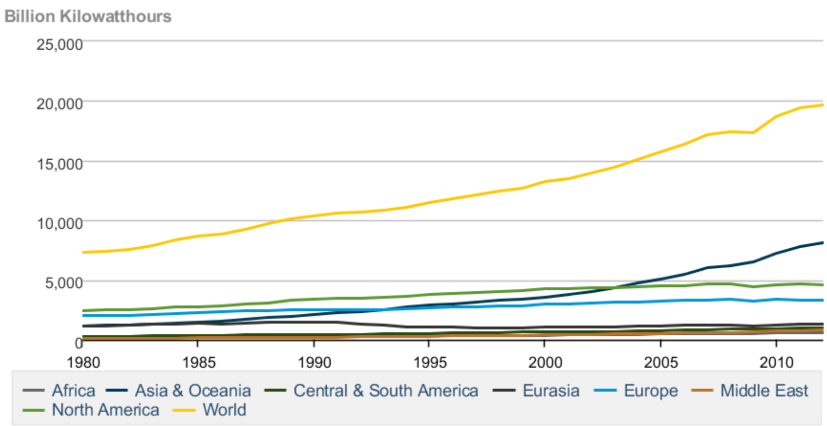


Figure 1.1: Total electricity consumption in the world [3]

An environmental perspective

Besides the already mentioned perspectives, there is also an environmental point of view. Amongst climate scientist there exists consensus on the process of global warming and that the emission of greenhouse gas is a significant contributor in this process [4]. Also, much earth-research points out that global warming is a threatening phenomenon for humanity, e.g. in terms of health, safety, and costs. Energy supply in the form of heat and electricity is, with 26% [5], the largest contributor to the world emission of greenhouse gas and it has even a larger share in the CO_2 emissions [2]. There do exist alternatives to generate electricity at way lower greenhouse gas emission rates, such as nuclear, hydro, wind and solar power. The world has adopted and is adopting these technologies more and more. However, the nature of renewable energy sources like wind and solar power differs from the traditional sources in two ways. In the first place, the electricity generation from renewable sources are way more intermittent. In the second place, renewable energy sources are also more distributed compared to traditional sources. These two differences have consequences for the way the electricity grid has to be organized.

There is another aspect which can be viewed from an environmental point of view. As shown in Figure 1.2, 13% of all greenhouse gas is emitted by the transport sector. In 2012 this sector was basically fully powered with engines which run on fossil fuels (95% according to [2]). However, considerable developments regarding the electrification of transportation are going on and this offers a large potential with respect to the reduction of greenhouse gas emissions of the transport sector. For example, McKinsey&Company writes in a report on the total world automotive industry that it is expected that 10% of all cars will be electricity powered by 2020 [6]. In The Netherlands, the government also anticipates on this trend, the target is to have 1 million Electrical Vehicles (EVs) on the road by 2025 [7], corresponding with 12.5% of all cars. With this substantial increase of electric loads, the electrification of transport will also be of great influence on the operation of the future electricity grid. The current network is simply not dimensioned to handle the envisioned increase in power which comes with the transition from fossil fuel powered engines to EVs [8].

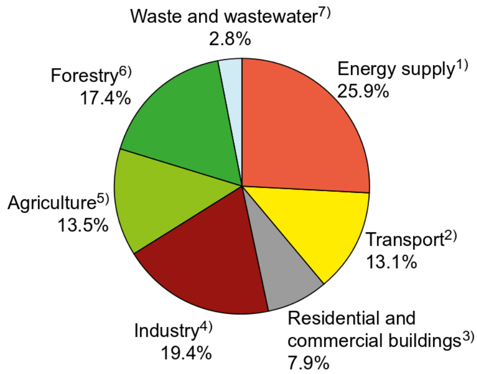


Figure 1.2: World greenhouse gas emission per sector in 2004 [5]

Another environmental aspect is related to the 8% of greenhouse gas emission due to residential and commercial buildings (Figure 1.2). This is mainly due to local burning of fossil fuels for heating and cooking purposes. New technological possibilities concerning the electrification of heating are investigated and introduced currently. One of the possibilities is to extract heat from soil by means of heat pumps, which run on electricity. The installed capacity of heat pumps in The Netherlands has increased by a factor 10 in the last ten years [9]. Although the adoption of these kinds of technology does not go as fast as the electrification of mobility, it shows that there are definitely alternatives which do result in greenhouse gas emission mitigation for the residential and commercial buildings sector.

Bringing the views from foregoing perspectives together
The foregoing considerations of facts, trends, and expectations lead to following conclusion: Given the physical facts, which form the fundamental framework of the electricity network, considering the trend that both the amount and importance of electricity for societies is not decreasing, and finally incorporating the intermittency introduced by the large scale deployment of renewable energy sources and the increase of power by the electrification of transportation and heating, it is concluded that the electricity grid faces challenges which shows resemblance to the period of the 'war of currents' and lead to a reconsideration on the organization of the electricity grid.

1.2 Two examples that indicate the challenge

As was sketched in the previous section, the main contributors to the challenges in the energy supply chain are the introduction of distributed generation resources and the electrification of mobility and heating. As a consequence, it is observed that the traditional approach of delivering electricity is not suitable anymore. We consider as an example the German situation because this country is a pioneer in terms of mass introduction of distributed generation, of which sun and wind power are the main contributors. The current situation is such that on a windy and/or sunny day, the German spot market prices drop below zero. For example, on March 16, 2014 both the day-ahead (€-55/MW) and the intraday (€-29.51/MW) spot prices were negative [10]. This also has implications for the grid stability. Rotating masses in conventional electricity generators (like coal fired or nuclear power plants) act as a fluctuation damping mechanism because energy unbalance will firstly be fed into or subtracted from the inertia of rotating masses. If there is a small electricity surplus, the masses will start rotating faster and this leads to an increase of grid frequency because the frequency is determined by the rotating speed of the generator's rotators. As a consequence, feeding a lot of electricity into grid by means of solar and wind power generators will not only result in increasing voltages in the grid but also to an increased frequency. This threatens the Power Quality (PQ) as specified in the European EN-50160 specification, which classifies PQ such as, but not limited to, under- and over-voltages, harmonic distortion and phase unbalance. There are already mechanisms applied to deal with this problem but it is not clear if they can solve the problems properly. For example, droop control, which is a mechanism to change the state of operation of a device based on the observed frequency or voltage, applied in Photovoltaic (PV) inverters can be really harmful. Since the frequency is the same in the whole grid, most current PV inverters will switch off if the frequency reaches its maximum allowed value. Imagine that all PV in Europe would suddenly be switched off by the frequency droop control mechanism. This leads to a massive increase of load in the European grid. The ramp-up time of backup capacity is most likely too large to prevent a blackout with huge impact. This problem with the ramp-up time of backup capacity does not only occur in such extreme scenarios. In general it can be stated that existing approaches to deal with unbalances might not be able to react quick enough, for example because of the ramp up time of a generator. Finally, with the integration of many renewable energy sources it is possible that they do not supply enough energy to meet the demand. In seldom times, this mismatch might even become quite large. Although this can be solved with reserve capacity, in the end it will not be very cost-effective to have a lot of reserve capacity since it will be rarely used. As the world continues the trend of adopting renewable energy resources, the challenges keep on growing.

The electrification of mobility will continue [7] [6] and also the electrification of heating is considered to play sooner or later a role in this principle as well. A field study in a Dutch town of Lochem [8] showed that a penetration of 12.5 % EVs already leads to network voltages approaching the PQ limits. In a follow-up experiment, which is not officially published but reported on [11], the grid load superseded the hosting capacity such that the protection system caused a blackout. A similar conclusion is drawn from simulations presented in [12], in which is argued that already at an EV penetration of 30% PQ rules and grid capacity of a typical residential grid are violated.

These two examples illustrate that the introduction of intermittent generation resources and the electrification of transportation give rise to challenges to which the traditional approaches do not have an adequate answer.

1.3 Definition of Smart Grid

In order to cope with the challenges as sketched above, a lot is expected from a concept that is called 'Smart Grid'. As argued in [13], there are many definitions of this concept but they all have in common that the electricity grid is extended with Information and Communication Technology (ICT) to achieve a certain goal. Unfortunately, some of the terms related to Smart Grids, including the definition of a smart grid itself, are not uniquely defined. Therefore, this chapter presents the definitions used in this work.

A first important term is Distributed Energy Resource (DER). Some research, for example [14] and [15] have a somewhat broader definition of DER than commonly applied. They include not only Distributed Generation (DG), which refers to all forms of electricity generation on a small level (typically smaller than 10 kW), but also Demand Response (DR) and energy efficiency into the definition of DER. Some people prefer to define DG as energy generation 'behind the meter', meaning that the generation is meant to serve primarily for the power supply of the owner and not for selling to the bulk power system [16]. DR is referred as electricity consuming devices that are capable to react on a certain incentive, in most cases a price signal, in order to shift the electric power demand over time. This work adopts the definition of DER that is used commonly: The collection of generation units that are capable of generating electrical power in small amounts. In this context, small is relative to traditional energy generation units which typically have a minimum capacity 100 kW. We do not include DR and energy efficiency in the definition of DER.

The definition for smart grid that is applied in this work is taken from the Smart Grid Dictionary [17]:

> *The Smart Grid is a bi-directional electric and communication network that improves the reliability, security, and efficiency of the electric system for small to large-scale generation, transmission, distribution, and storage. It includes software and hardware applications for dynamic, integrated, and interoperable optimization of electric system operations, maintenance, and planning; distributed generation interconnection and integration; and feedback and controls at the consumer level.*

In literature, various goals for smart grid operation are proposed and have been topic of research studies. For example, goals can be (a combination of):

- Improve Power Quality, e.g. by means of peak shaving.
- Enhance lifetime of system components.
- Organize a Virtual Power Plant (VPP) to sell electricity and/or flexibility on the markets.
- Use locally generated energy locally, e.g. store energy from a solar system on a residential roof in a battery and use the energy when needed inside the house.

Next to the different goals, a smart grid can be implemented and targeted at the benefit of various stakeholders. Examples of important stakeholders are:

- DSO: is responsible for the maintenance of the infrastructure and the PQ of the Low Voltage (LV) and Medium Voltage (MV) grid.
- Energy trader/retailer: buys and optionally produces energy in bulk quantities to sell it to many residential and commercial costumers.
- Aggregator: an electricity trading party with a portfolio that contains flexibility from prosumers and is active on the wholesale market.
- Prosumers: people who have DG in a residential or commercial setting.
- Balance responsibility party: a market party active on the balancing market which has the task to match supply and demand on short time interval (typical 15 or 30 minutes).

Note that the stakeholders operate in the same system but have different goals and therefore conflicts of interests will not be uncommon in smart grids. Depending on which stakeholders are involved and on what criteria the smart grid is operated, a smart grid provides significant advantages over the traditional operation of the grid. The main advantages that are frequently coined in relation with smart grids are: energy efficiency, integration of renewable energy sources, reliability, and cost effective operation of the grid [13, 18, 19].

1.4 Research questions

Up to here, a general introduction on smart grids is given. The following section is concerned with positioning the work of this master thesis in the bigger picture.

One of the solutions to achieve the goals of a smart grid is referred as Demand Side Management (DSM). A DSM methodology is an approach to balance energy supply and demand by steering/-managing the states of operation of devices. It mainly concerns managing consumption devices, such as washing machines, fridges, and EVs, but does not necessarily exclude generation units, for example micro-Combined Heat Power (CHP) generators. The DSM methodology should be designed on basis of fundamental requirements, for example: the system should be scalable, respect privacy and comfort of users, achieve an energy balancekate. A system that implements such a methodology is called an Energy Management System (EMS). In The Netherlands, the two main DSM methodologies in development are The PowerMatcher and Triana.

As will be pointed out further on in Chapter 3, both methodologies have their strengths and weaknesses. Also, in those chapters it is argued that the strengths and weaknesses seem to be each others complements, which raises the question: "How would a combination of the two methodologies perform?". Hence, this question is exactly what this thesis is about. Before listing the research questions, a short introduction of terms is given:

The DSM methodology PowerMatcher is an auction based control mechanism. What this means and how it works, is explained in Section 3.1 but for now it is just stated that an auction based control mechanism is suitable for real-time control[1]. However, as simulation studies show, auction based control has some disadvantages. On the one hand, undesirable behavior from an power engineering point of view can occur. On the other hand, when considering a larger time base, wrong decisions can be made, i.e. flexibility offered by controllable devices is exploited at incorrect moments.

Where The PowerMatcher is an auction based control mechanism, Triana controls devices by drawing predictions, determining a near-to optimal planning and executing the planning by online control. As will be argued in Chapter 3, it can be stated that Triana makes a proper planning but lacks a good controller, while The PowerMatcher is very good at momentary balancing supply and demand but is ignorant about anything which is presumably going to happen. This leads to the following research questions of:

> **Main question:** How can The PowerMatcher be extended with a planning from Triana and what is the performance, from a network point of view, of the combined energy management system in a residential microgrid setting?

> **Research Question 1:** On which level(s) in the PowerMatcher hierarchy should the planning of Triana be provided?

> **Research Question 2:** What strategy should be used in order to incorporate the planning of Triana in the PowerMatcher methodology?

[1]The term real-time control might be confusing because it is a different type of real-time than is known from real-time system theory. In order to avoid confusion, this text uses the term online control to refer to short time scale control in which devices communicate with each other or with global entities in the control structure.

Research Question 3: How does the combined DSM system perform compared to the PowerMatcher approach?

1.5 Research scope

Research question 1 and 2 are answered by means of theoretical considerations which leads to design choices. In order to answer research question 3, a scoping has to be defined in which the performance of the DSM approach is evaluated. This section describes the scope and evaluation criteria.

Many field trials and simulation studies pursue goals of maintaining PQ and enhancing system components lifetime, for example [8] [20]. This is because the DSOs are the main actors in the implementation of Smart Grids. They are responsible for PQ and grid maintenance and these are exactly threatened by the introduction of renewable energy sources and EVs. However, a fundamentally different goal is studied in [21] and [22], which focuses on the operation of an aggregator. An aggregator is the operator of a VPP that has a portfolio with controllable loads and hence can offer flexibility on the wholesale market. Other field tests with a wide variety of research questions, such as user acceptance, scalability, market integration, etc., are presented in [23].

A lot of research on the operation of smart grids is conducted and in many cases a microgrid situation is considered. A microgrid is a network that comprises DG, energy storage, and (controllable) loads and is capable to operate both in parallel to the grid or as an autonomous islanded grid [24]. In this work, a microgrid in grid-connected mode operation is considered as the setting for the research. Current field trials are of similar scales and the grid connection offers the possibility to cope with mismatches between local supply and demand. The focus will be on intra-day DSM, i.e. without considering energy supply and demand in periods later than 24 hours ahead. As a consequence, it is enough to evaluate only several days of different seasons. The following questions are evaluated:

- How does the combined DSM approach handle prediction errors?
- How does the combined DSM approach follow Triana's planning based on predictions, given an intermittent energy supply?

In order to evaluate these questions, a simplified case with the following DERs is considered: EVs, smart washing machines, smart dishwashers, batteries, and PV generation. The choice for using EVs is made because an EV offers a lot of flexibility in terms of time and power. The choice for solar power as DG is based on their (envisioned) large scale usage, intermittent power supply, and single domain operation (a CHP generator, for example, has dependencies with the heat domain). Appliances such as washing machines and dishwasher are becoming smarter and offer some flexibility, it is therefore interesting to take them into account in the use case as well. Nonetheless, the developed approach is generic and applicable to cases with other DR devices. A more detailed description of the scenario is given in Section 6.1.4.

Optimization criteria
In this study, the optimization criterion is to achieve a flat power profile and a well-balanced system which consumes electricity of local DG as much as possible within the microgrid. Another way of referring to local consumption of renewable energy is that the grid connection should only be used to supply in case of shortage or to dump a surplus of electricity. From a power engineering point of view, this is favorable because it will reduce stress on the MV/LV transformer, and thus enhance the transformer's life time and, as shown in [12], it will avoid the replacement of the transformer with a higher capacity one. It should be mentioned that it really depends on the methodology, and its implementation, what the improvement with respect to grid assets are. For example, in [25] it is shown how the original implementation of the DSM methodology Triana led to worse voltage profiles

compared to a situation without control. The paper also describes how incorporating a grid topology into the methodology leads to substantial improvements of voltage profiles with only a minor sacrifice in peak-shaving performance.

The study presented in [26] is written with major focus on network life-time and reliability. The authors claim that it is favorable to stay away from PQ limits as far as possible. Given the introduction of DG and EVs, this can best be achieved by flattening the power profile, which is also part of the optimization.

In this study, the optimization goal is to achieve a well-balanced system, which means that the PQ rules are respected. There are many PQ rules which cannot all be evaluated by means of simulations (mainly because of the too coarse time base of simulations and load profiles) and therefore only a number of rules is used to define a well balanced system. Although it is preferable that the PQ limits are not approached, strictly speaking a system is considered to be well balanced if:

- The voltages do not violate 230 V +/- 10% limits.
- The Voltage Unbalance Factor (VUF) does not violate 2% limits.
- The maximum allowed power of cables and components is not exceeded.

Chapter 2

Background & Related work

As argued in the introduction, the electricity system is changing drastically and this thesis contributes to the knowledge that is necessary to deal with the challenges. The focus will be on providing a solution to problems raised by the introduction of renewable energy sources such as wind power, solar power, and EVs. As mentioned in the introductory chapter, the futuristic scenario is more generic. Therefore, this chapter starts with some general information on the EMS context and requirements. Then, it contains a section with background information on the deregulated electricity system, which forms an important aspect of the context, and it ends with a related-work section.

2.1 Context of a DSM methodology

The the setting in which a (technical) system should operate forms the context of the system. To identify this context is a prerequisite before one can come up with requirements. The complete context of a traditional electricity grid and its corresponding markets is already extremely complex. The system affects in principle all people and many stakeholders play a role in the operation of an electricity grid. A lot of educational books have been written to teach about the system. The challenges of today and the opportunities that a smart grid offers, add even more complexity to the system. In that sense, the following list of bullet points does not properly reflect the complexity and is only a very global description of the most important aspects that play of a major role in a DSM system.

- The physical law of conservation of energy requires supply and demand always to be in balance.
- Network components have a limited capacity and life-time is reduced in case of high stress on components.
- Energy supply varies over time and is only controllable to a certain extend.
- The coupling between different energy domains, mainly heat and electricity, is increasing because of techniques like heat pumps and microCHP units.
- Demand can partially be controlled.
- Flexibility is limited due to user and device constraints.
- User behavior is hard to predict on individual scale but the law of large numbers teaches that the predictability increases with an increasing number of participants in a region of interest.
- Electricity is traded on markets that operate on 24-hour and 15 (or 30) minutes intervals.
- Users are concerned about privacy.
- There are limits on the amount of computational power and communication resources available.

2.2 Requirements of a DSM methodology

The requirements of a system are the starting point to make implementation decisions. In case of our smart grid situation, most of the bullet points listed in the former section translate into requirements but firstly, the global goal of the system is described in very general terms:

> *The main task of an EMS is to control DERs and controllable loads in such a way that an optimization for a particular stakeholder, or multiple stakeholders, can be achieved.*

Within the context sketched above, many stakeholders do exist and different stakeholders may have different and conflicting interests. The optimization criterion is defined in favor of a certain stakeholder but the requirements of the EMS should be met in all cases. So it should not be of influence on the requirements how the system is exactly operated. In other words, an EMS should be generic and support various modes of operation.

2.3 Structure of the deregulated electricity system

In Europe, most countries have, or are in transition to, a deregulated (also called: liberal) electricity system. This is a complex system in which many parties, each with their own responsibilities, are involved. This section does not give an thorough description of all markets, parties, and responsibilities but only highlights some aspects which are closely related to smart grid operation. Refer to [15] Section 3.2, 10.1, and 10.2. for a more extensive description of the deregulated energy system.

An important aspect is the separation of energy flows and financial flows. For example, a retailer buys electricity from an electricity supplier and sells it to his customers without taking care about the physical system that is used to transport the electricity. The responsibility of transport of electricity is divided over two parties: the TSO, responsible for the High Voltage (HV) grid and its stability, and the DSO, which is responsible for the maintenance and stability of the MV and LV parts of the grid. Stability means that the TSO and DSO are responsible to make sure that the PQ rules are not violated.

Trading markets are the domain of the financial flows related to electricity transmission. On the so-called wholesale market, large power generation parties trade electricity with retailers (also called: energy traders) which typically represent a large number of residential and commercial clients. The trade takes place on different time scales, i.e. more than 1 year ahead, 1 year to a few days ahead, 1 day ahead, and a few hours ahead. Although, eventually all markets exist to match demand and supply, the former two are mainly focused on grid asset and portfolio planning, while the latter two, which are respectively referred to be day-ahead market and balancing market, focus on keeping the balance actively. As the name suggests, the day-ahead market operates on 24 hour time basis, requiring trading parties to make estimates of supply and demand 24 hours ahead. In order to cope with deviations of real production and consumption with respect to the estimates, the balancing market, typically operating at 15 minutes time basis, exists. If one of the parties does not meet the amount of energy that it did comply to buy or sell, the TSO will charge a penalty. This money is used by the TSO to buy or sell electricity on the balancing market in case of mismatch between supply and demand due to deviations from the estimations.

The operation of DERs can be integrated in the financial part of the electricity system. This can be done by means of a VPP. A VPP comprises of physically separated energy resources which are financially grouped and offer an aggregated amount of energy supply or demand. The party which offers this energy flexibility is called an aggregator and can be active on both the day-ahead and the balancing market. It is also possible that the aggregator sells flexibility to the DSO, which can use flexibility as an alternative to grid reinforcements.

The advantage of prediction and planning for market integration
An important advantage of using planning and prediction is that it gives a forecast of what is going to happen in the network. Whether the optimization aims at making profit on the wholesale market or aims at network reliability, in both cases it is important to be able to buy energy at the market in a sufficient amount and at the correct time. Using planning and prediction has a positive effect on this. It is important that a DSM methodology supports the market trading, not only in case of optimization for network reliability (and to be able to buy electricity) but also for operating in profit optimization mode. The DSM methodology Triana is based on these principles, it starts with predictions, subsequently a planning is made and finally, the planning is executed while dealing with prediction errors.

2.4 Related work

The amount of research related to the integration of renewable energy sources in our electricity grid is huge. In this section, some related work is presented.

2.4.1 Pro-active control: Triana

As argued in the section before, a control approach that uses predictions and a planning has advantages for operating on the wholesale market. In addition, these pro-active control approaches can optimize for distribution of energy over time. The DSM methodology Triana [27, 28] is such a control system. The methodology is generic, scalable, and supports energy management of complex systems with various types of energy carriers, such as electricity, heat and gas. The methodology is model based, i.e. the energy infrastructure with all its components can be modeled in a bottom-up fashion. At the lowest level in the model, devices are represented as energy producing, consuming, converting, or buffering units. The devices can be grouped to form houses and these houses can be grouped to constitute neighborhoods, cities, regions and the like. The electricity grid can also be modeled conform the situation in reality, i.e. by having LV, MV, and HV parts that are connected with each other by transformers.

The methodology consists of three steps: (1) local prediction of device behavior, (2) planning of individual controllable devices with a global optimization and (3) real-time control of the controllable devices. The three steps enable to focus on the implementation of these three steps separately and therefore offer possibilities to perform optimizations on both local and global level. Currently, the planning step is in particular well developed by means of fast and accurate algorithms. The profile steering algorithm, which is a heuristic, is used as a strategy to determine a planning and appears to be a great measure to achieve desired power profiles [29]. Further details of Triana and the profile steering approach will be explained further in Section 3.2.

2.4.2 Auction-based control: The PowerMatcher

In literature, many implementations of auction-based control methodologies are presented. Often they are referred as market-based or agent-based control methodologies. In [30], the results of field tests and simulations with the agent-based methodology The PowerMatcher are presented. The paper presents results that indicate that the DSM capabilities are promising in various scenarios. For example, the results of a successful real-life VPP experiment (called PowerMatching City) are presented and a simulation study shows that The PowerMatcher is capable of shifting loads to moments in time in which wind power generation peaks occur. Also, an EV charging case is presented and shows that the methodology flattens huge charging peaks that would arise in case of 100% penetration of EVs. A weakness of the presented EV simulation result is the very steep power curve decrease of approximately 120 kW in 1 time interval (apparently many cars are fully charged). This effect is very undesirable from a network stability point of view. Another weakness, also from a network point of view, is that not all flexibility is used resulting in a unnecessarily high stress on the network. Apparently, all the cars are fully charged around 2-3 a.m., leaving the hours between 2-3 a.m. and 6 a.m. unused. The PowerMatcher simulations in [30] assume a copper plate, so (local) grid limitations are not taken into account. Therefore, it is unknown what the effects of this approach are on voltage levels, neutral-point shifts and cable stress. Section 3.1 contains a more thorough explanation of The PowerMatcher and its strengths and weaknesses.

2.4.3 Auction-based control: The Intelligator

The basic structure of the PowerMatcher control methodology is also applied in the studies presented in [31, 32, 22], but the authors call the methodology Intelligator instead. Vandael et al. present in [32] a concept which is basically an extension of The PowerMatcher with a distributed prediction and planning approach. They introduce a three-step control methodology for charging of Plug-in Hybrid Electrical Vehicles (PHEVs). The most essential characteristic of the approach is that it distinguishes two responsibilities which are solved at separated levels in the hierarchy. At local level, device agents are responsible for meeting the user and charging power constraints of a particular PHEV. At global level, the 'PHEV fleet agent' optimizes for charging the fleet at lowest electricity prices possible. The PHEV fleet agent receives power and energy constraints from the device agents and calculates, by means of Dynamic Programming (DP), a *global* charging plan. Based on the global planning, incentives are communicated to device agents which individually determine the charging power for the PHEV. The result is a scalable, computationally light and close to optimal charging strategy. In a follow-up study [22], the methodology is further improved by the introduction of dual, event-based, coordination mechanism leading to 64% reduction of communication messages. Because the optimization is targeted at minimization of the electricity cost, the resulting power profile shows large peaks and also a kind of over-steering behavior. This over-steering behavior might be explained as follows: when a large group of cars become available for charging, many of them start charging at once because the system priority was still high (meaning that the system wants devices to consume energy). As a response to this charging peak, the priority goes low incenting many cars to decide not to charge anymore, which has again an increase in priority as result, which is again an incentive for many cars to start charging and so on. These oscillations are undesirable in case that other devices are involved as well: it will be really difficult to steer them properly. In addition, from a network point of view, drops of 2 MW in a very short time is really unwanted. In contrast to the paper on the event-driven dual coordination mechanism, the power profile of the study in [26] is desirable from a network point of view. It is based on a straightforward implementation of the PowerMatcher methodology with a peak shaving objective, so it does not incorporate any predictions and planning. However, this has a drawback because a system based on a planning could perform better in terms of peak shaving [33]. This is due the fact that a planning can incorporate external factors like wind and solar peaks and adjusts the loads based on that information.

2.4.4 Agent-based control by mathematical optimization

Another implementation of an multi-agent based, but not auction-based, control methodology is presented in [34, 35] by Logenthiran et al. The authors have looked at many mathematical techniques, mainly heuristic methods, that could be used to solve a scheduling problem, e.g. Priority Lists, Dynamic Programming, and Lagrangian Relaxation but they have also looked at meta-heuristic methods such as a Genetic Algorithm and Evolutionary Programming. They report that their methods find feasible, close to optimal schedules but do not report anything about computation time. Usually, this could be, but is not necessarily, a potential drawback of mathematical scheduling. In [35], the same authors stress extensively the advantages of Multi-Agent Systems (MASs). A MAS is a collection of physically separated agents that can make autonomous decisions. The behavior of agents can be categorized in the following abstract characteristics: they are reactive, proactive and have social abilities. This enables agents to make autonomous decisions, taking local and global information into account. In smart grid terms, but also in general multi-agent terms, it is usually advocated that MASs are an effective way to create a scalable system. Logenthiran et al. focus in [35] on the control of generating units by means of a Lagrangian Relaxation of the scheduling problem and by using a Genetic Algorithm. The same authors state that a lot of research focuses on scheduling of DERs in microgrids on 24 hours basis and that there is a lack of real-time control algorithms which are unambiguously necessary for reliable system operation [21]. Therefore, they propose a more comprehensive MAS methodology that consists of two steps in which both generation scheduling and DSM are involved. The first step is concerned with scheduling DERs on a 24 hour basis, by means of day-ahead market prices and the second step, operating on 5 minutes intervals, provides a real-time balancing schedule. Basically, the second step tries to solve power unbalance by means of a 650 kWh battery and if this appears to be impossible, it applies load curtailment. Both a grid-connected and islanded mode of operation are considered and the effectiveness of the approach is demonstrated by simulations of a use-case. In a follow up study, the problem is treated from a power engineering perspective [36]. Apparently there was need for control on an even finer time scale because the two step approach is extended with droop control. Also, agents for power, voltage and current monitoring are added to the simulation and the measurement data is incorporated in the real-time scheduling. The results show that the control system is capable of handling an abrupt change of the microgrid from the grid connected mode to an islanded mode. Although the complete system proposed by Logenthiran et al. (a proper overview can be found in Logenthiran's PhD thesis [37]) definitely shows its scheduling and real-time control capabilities, there remain some uncertainties, e.g. about computation times (nowhere is mentioned what the computational power is required by the control methodology), privacy protection of end-users (DSM agents seem to communicate user constraints freely through the system), and deploying the method in a real-life situation (in the PhD thesis (2012) it is mentioned as part of future research but there are no follow-up reports).

2.4.5 Comparing auction-based control with mathematical optimizations

In [33] a comparison between different types of DSM approaches is presented. The authors compare a mathematical control approach (namely an Integer Linear Programming (ILP)), which was used as implementation of the real-time control step in Triana, with an auction-based control approach. The results point out that the auction-based approach performs better in terms of achieving a flat power profile at the transformer. Also, the auction-based approach has a way lower computation time. Another result is that the power profile of a case in which planning and prediction is applied is better than pure auction-based control. From [25] it is learned that incorporating the grid topology is of crucial importance for the Triana methodology to improve the PQ. The paper shows that without considering the underlying network, the voltage profiles may even become worse when Triana controls loads compared to the results of the very same use case without control.

Chapter 3

Theory behind The PowerMatcher and Triana

The former two chapters have described the problems and system characteristics of our electricity supply in general terms and presented related work concerning DSM solutions. Chapter 3 tarts focusing by paving the way for the contribution of this thesis to smart grid research. In order to do so, the chapter provides the theoretical basis of the DSM methodologies, The PowerMatcher and Triana, and theoretical considerations related to the combination of the methodologies.

3.1 The PowerMatcher

The PowerMatcher is a well developed implementation of an agent-based control methodology, underpinned by the specifically developed multi-agent theory and has proven its value in field experiments, for example reported in [30, 39]. The field experiments have shown that The PowerMatcher is capable of balancing supply and demand in a fast and very scalable fashion, while incorporating user and grid constraints. The field experiments are diverse in terms of optimization objectives, scales, and types of commodities and devices. The balancing mechanism of The PowerMatcher is based on an auction of electrical power, which is schematically presented in Figure 3.1. The inwards directed arrows indicate that device agents emit bidding functions in which they communicate for what price they want to consume a certain amount of power (power production is considered as negative power). So a bidding function is a power vs. price function (an example is given in 3.2). Concentrators aggregate the bidding functions to create a scalable hierarchy and a system in which privacy is assured. Finally, all aggregated bids end up at the auctioneer which determines the Market Clearing Price (MCP). The MCP is sent back to all agents, as indicated by the outwards directed arrows in Figure 3.1). The MCP is essentially the steering signal that tells the devices what they should consume. Typically, the prices are artificial prices, meaning that they are only used to balance supply and demand and do not explicitly represent economic value. When device agents receive the MCP, they steer their devices such that they consume/produce the exact amount of energy that corresponds to this MCP

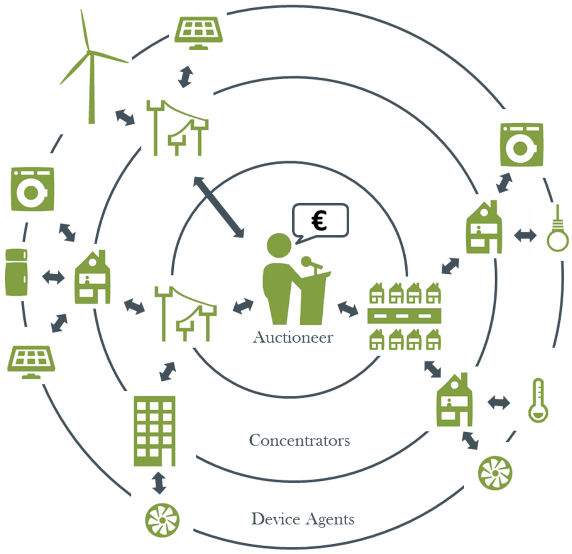


Figure 3.1: Schematic illustration of PowerMatcher's principle [38]

in their bidding function. As the bids are purely momentary, that they do not take any possible future events into account, and thus the load curve flattening capabilities are limited. Although it is proven in [15] that the auction leads to a Pareto optimal distribution of energy, this is still a momentary optimum. If one wants to optimizes for the power distribution over time, no guarantees on the optimality are given. This points to the major shortcoming of The PowerMatcher and will be further explained in following parts of this section. A complete in-depth description of The PowerMatcher can be found in [15].

3.1.1 Microeconomics and Pareto-optimality

The terms 'bids' and 'MCP' originate from the field of microeconomics, which is a branch of economics that studies how individual agents decide to allocate a limited amount of resources. To understand what microeconomics is about, consider a market place in which certain goods and services are sold and bought. In microeconomics, this market place is mathematically formalized which makes it possible to formulate hypotheses and proof the validity of certain principles.

One of the key principles is the concept of Pareto-optimality, which is referred as the situation that there is no other resource allocation in which a consumer is better off without making another consumer worse off. It is proven that a market outcome is necessarily Pareto-optimal in case that all prices are publicly known and that all consumers act as price takers. A consumer acts as price takers if he does not have the power to influence market prices with his bidding behavior. A market in which all consumers act as price takers is called competitive. The auction that is organized in this way, which has as characteristic that it matches supply and demand perfectly, is referred as a Walrasian auction.

3.1.2 Multi-agent theory

During the development of the PowerMatcher DSM methodology a theory, referred as 'multi-agent theory', has been derived. The theory is generic and therefore also applicable in other systems than a DSM system. It is a combination of classical control theory and microeconomics. The domain of control theory is to steer a system to a particular state by means of a steering signal $r(t)$ - in PowerMatcher terms, this steering is the responsibility of an individual device agent. A very popular form of classical control is PID control, which is a linear system that uses a feedback with a proportional, integral and or differential term to steer a device's state to the setpoint. The theory of microeconomics provides a theoretical basis for the optimality of the allocation of a shared resource to many consumers in a competitive market situation - in PowerMatcher terms, this is the responsibility of the DSM system as a whole. Hence, the multi-agent theory is the theoretical basis for any system that is based on the combined use of linear control of devices and a supply and demand balancing mechanism in a situation with a shared and limited/constrained resource, e.g. electricity. The theory is presented in Chapter 5 of [15] but here the most important result of the theory is quoted:

> *For resource-shared large-scale PID control, we have shown how to construct a Pareto-optimal agent-based market solution. (page 101 of [15])*

The referred 'how to' is given by a definition of a utility function $u_\alpha = f_\alpha(r_\alpha)$, with r_α being the resource variable, which is typically power in a DSM setting, α is the device indicator, and the total number of devices is N, hence $\alpha \in 1, ..., N$. The utility function has to meet the following constraints:

1. $f(r_\alpha)$ is a strictly concave function of r_α.
2. $f(r_\alpha)$ is twice continuously differentiable on a suitable interval $[-R^{unc}, R^{unc}]$, where R^{unc} is the total, and unconstrained amount of resource to be allocated to all devices.
3. $f(r_\alpha)$ has its maximum at the local resource value r_α as given by the linear control equation, e.g. a PID controller.

4. The total available resource is scarce: $0 \leq \sum_{\alpha=1}^{N} r_{\alpha} = R^{max} \leq R^{unc}$
5. Finally, all agents are self-interested utility maximisers and they are price takers.

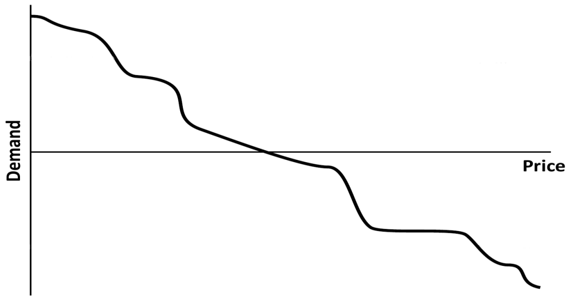


Figure 3.2: Example of a demand function which complies to the requirements of the multi-agent theory, adapted from [15]

It is important to note that the theory is defined for *utility functions*. A utility function is a measure of relative happiness or satisfaction, a way to rank different goods in accordance with the preferences of an individual. In practice, The PowerMatcher works with *demand functions* which gives the amount of a certain commodity an agent wishes to consume (or produce) given the price of the commodity. Demand functions are sometimes referred as *Walrasian demand functions* because they form the basis under Walras's general equilibrium theory. The relation between a utility function and a demand function is that a demand function can be obtained from a utility function by differentiation of the utility function. Therefore, criteria (1), (2), and (3) lead to demand function that is a continuous, strictly descending function of the form as shown in Figure 3.2.

3.1.3 Considering physical network constraints in multi-agent theory

A flow commodity is a physical stream which is infinitely divisible, e.g. electricity, gas, or liquid. The Walrasian auction, and its corresponding Pareto-optimal resource allocation, as described in the previous section does not take the physical flow of a commodity in the network into account. To phrase it in electrical engineering terms, a Walrasian auction is referred as a situation that assumes a copper plate, i.e. all required energy is available instantly and the transport occurs without losses. In reality however, the flow commodity does deal with a physical network which introduces, depending on the actual physical quantity, flow resource capacity limits, inherent storage and network losses. This means that a Pareto-optimal solutions as found by the Walrasian auction may be not feasible in a situation with a physical network, this is referred as a network unfeasible solution. To incorporate the characteristics of physical networks, a concept from HV power networks, called Locational Marginal Pricing (LMP), is added to multi-agent theory. Basically, LMP algorithms adapt bidding functions and apply price transformations such that they incorporate capacity limits, network inherent storage and network losses. More on this topic can be found in [15], Chapter 6.

3.1.4 From multi-agent theory to The PowerMatcher

The multi-agent theory applies to all forms of control in which individual devices are PID controlled and in which the devices share a scarce resource. In the application of The PowerMatcher, the PID controller is in fact only a proportional (P) controller because the device agents are not really controlling a physical plant but are rather connected to a device that simply wants to consume a particular amount of electricity, which is the set point in PID control terms. Since the devices are connected to a grid, which practically can be considered to be infinitely strong, the controller has the electrical power that is requested to meet this set point available instantly. This leaves no need for an integral or differential term in the controller. Another note is that in practice PowerMatcher's demand functions do not meet the criterion of being strictly monotonically decreasing and continuously differentiability. The example of a freezer's demand function given in Section 8.2.1 of [15] is monotonically decreasing, but not strictly monotonically decreasing and also not continuous and therefore not continuously differentiable. Apparently, for a real-life operation of The PowerMatcher it is sufficient to work with demand functions that do not meet all requirements of the generic multi-agent theory. It still is important that the demand function is monotonically decreasing. If this would not be the case, the MCP may not be uniquely determined.

3.1.5 A special agent: the objective agent

Until now, three types of PowerMatcher agents have been introduced: (1) device agents, (2) concentrator agents, and (3) auctioneer agents (of which there is only one in a cluster). However, the implementation of The PowerMatcher has another agent, referred as the objective agent. The objective agent also actively emits bidding functions, however, not with the intention to buy or sell electricity, like the device agents, but to steer the cluster into a certain direction. The direction depends on the chosen objective. Within a scenario in which the PowerMatcher cluster is operated as a VPP, an example of an objective is to make sure that the cluster's demand matches the amount of power that was promised to be consumed. The objective agent will also be part of the auction to make sure that the cluster follows the profile that the aggregator complied to achieve. In this way, it minimizes the costs imposed by penalties due to power mismatches.

3.1.6 How The PowerMatcher deals with physical constraints

As stated in Section 3.1.3, the multi-agent theory is extended with the concept of LMP to achieve network feasible solutions. The LMP theory is presented from a computer science point of view and applicable to all types flow commodity resource variables. It is capable to incorporate (1) network losses, (2) component constraints, and (3) internal storage. Because The PowerMatcher focuses on electricity networks, which do not have network inherent storage, the current implementation only applies LMP to component constraints. In addition, LV power networks are typically radial networks, which allows a simplification of the LMP algorithms. The LMP algorithms are implemented in PowerMatcher's concentrator agents that correspond to congestion management points, which are nodes in the power network that could potentially be overloaded.

Basically, the congestion management concentrator agent applies a transformation on the demand function to guarantee that no more power flows through the congestion point than is allowed by capacity constraints. This is achieved by flattening the aggregated demand function, which represents the functions of all devices beyond the congestion point in a radial network, at the maximal allowed power value. Figure 3.3 shows an aggregated demand function for a point in the network were congestion management is applied. The agent that is virtually present at this point, flattens the bidding function for power values larger than the grid constraint $Z_{i,max}$. When the auctioneer determines a MCP that is within the flattened region of the bidding function of the congestion management agent (e.g. region B in Figure 3.3), the agent performs a price transformation $p_j \rightarrow p_k$. In this way, the devices will consume no more energy than can be transported through the congestion point in the physical network. The consequence of this approach is that not all devices receive the same price. As long as the cluster uses artificial prices, this is not a problem. However, in the end, someone, most likely the DSO, should be paying for the flexibility offered by end users that was used for congestion management.

In field tests, the part of the LMP algorithm that accounts for network losses is not implemented.

3.1.7 The problem with limited knowledge and limited flexibility

The PowerMatcher concept is validated in many field experiments. One of the fundamental principles on which The PowerMatcher is built, is that the 'market will work'. The market will always choose an option which is a Pareto optimal solution for the resource allocation problem. However, a momentary Pareto optimal resource allocation is not always the only desired result. Consider a case with a wind park and an EV fleet which is grouped in a PowerMatcher cluster to flatten the wind peaks. In

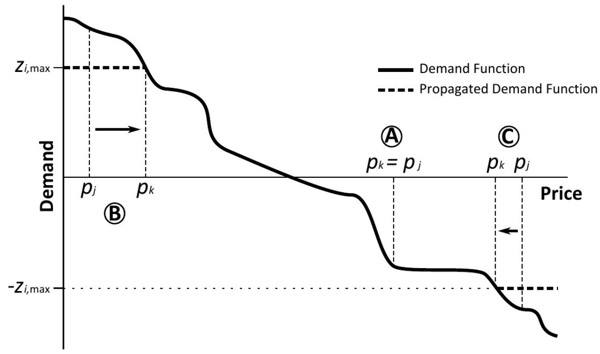


Figure 3.3: PowerMatcher's implementation principle for congestion management [15]

a thought experiment, two large wind peaks occur. The PowerMatcher may use all flexibility of the EV fleet to balance out the first wind peak completely. During this peak the methodology will continuously find Pareto optimal solutions. However, it does not have knowledge about the second wind peak. Even though the resource distribution will still be Pareto optimal during the second peak, there is no flexibility available to balance the power generation, resulting in severe PQ problems. Although the solutions in all time intervals are Pareto optimal solutions of the resource allocation problem, the whole set of these solution is not the best option to deals with the two wind peaks. Theoretically, there are two options to solve the problem. The first one is to enlarge the PowerMatcher cluster such that there is practically an infinite amount of flexibility available. The capacity needed to achieve this may be very expensive and the flexibility gained not cost-effective, so this is not a realistic option. Another option is to give The PowerMatcher information from predictions and use this information to influence the auction. Influencing the auction can be done in several ways, e.g. by using an objective agent or by using a global controller which sends, in addition to the MCP, steering signals to device agents. The most important requisite for this solution is that the objective agent - or the controller - has to have knowledge about the amount of flexibility of the devices. Otherwise, no statements can be done about the optimality of the solution over a longer time horizon other than that it is unlikely that the methodology chooses an optimal solution.

A comparison between DSM approaches [33] also shows that Triana's approach results in a flatter power profile than an auction based approach, for a particular use case. So, the sub-optimality of PowerMatcher resource allocation over time does not only occur in a thought experiment, but also follows from a comparison study with a use case (the use-case description is given in [40]).

A similar suggestion is reported in [31] were the authors use a divergence from The PowerMatcher, called The Intelligator, and implement it with the addition of some techniques that make it more reliable and useful in a real-world setting. In the future work section, the authors state literally:

> "(...) one shortcoming of the market based control system lies in the instantaneous matching of demand and supply. It would be more efficient to incorporate information on future events (e.g. wind prediction or estimated vehicles arrivals) as this would remedy situations in which all the flexibility of the device agents is depleted and demand effectively becomes uncontrollable."

In Section 2.4, the papers [32, 22] have been discussed. Those papers present a system that implements an approach with a global controller that receives information from devices about their flexibility, calculates an optimal charging plan, and sends steering signals to devices to realize the plan. This approach has a disadvantage, namely that the charging plan does not take the real physical network into account. In [25] it is shown that not incorporating the physical network in the the Triana

DSM methodology resulted to very poor PQ performances. When the methodology of [32] uses LMP in order to guarantee that grid constraints are not violated and the plan is not network feasible, the final allocation of resources will be different with respect to the planning. The approach in [32] iteratively computes a new charging plan in order to cope with prediction errors, being computational demanding. To generate network feasible solutions would require even more computational power. Another disadvantage, which is inherently related to the integration of a planning, is that a planning limits the flexibility of the cluster. EVs receive a steering signal which makes them willing to consume electricity at the point the planning prescribes. This flexibility can, for example, not be offered to an aggregator. The authors are aware of these important drawbacks since they write in the future work section:

> "(...) Another aspect herein is the integration of grid constraints (e.g., power constraints of transformers and cables, limitation of voltage levels). Besides scalability of computations, communication scalability will also be a topic of future research."

3.1.8 PowerMatcher bidding strategies

In Chapter 4 a novel bidding strategy will be introduced. In order to compare that bidding strategy with a 'normal' PowerMatcher strategy that does not incorporate a device planning, a bidding strategy for the PowerMatcher has been implemented. The bidding function complies to a relaxed version of the requirements given in Section 3.1.2. Note that the relaxation is applied in other PowerMatcher implementations, which are used in field trials, as well. The formal definition of a bidding function, to which all bidding functions in this work do comply, is given Section 4.1.2, Definition 1. Basically, the functions are constituted on basis of a small number of points and the lines connecting the points indicate that all power values between the points can be selected too. Figure 3.4a shows an example of such a function, which belongs to an EV that has a minimum and maximum charging power, P_{min} and P_{max}, respectively. The price on which is the minimum power options is positioned depends on the time till deadline. In Section 6.2.1, simulation results are presented that show what happens if all EVs in the cluster would put the minimum power option on the same price. The experiments reveal that the aggregated bidding function will contain a large discontinuity at this price, which is a thread for the diversity in the function. In order to stimulate the diversity, the time till deadline, which will not be exactly the same for different EVs, is taken as input for determining the maximum price at which the device will not charge.

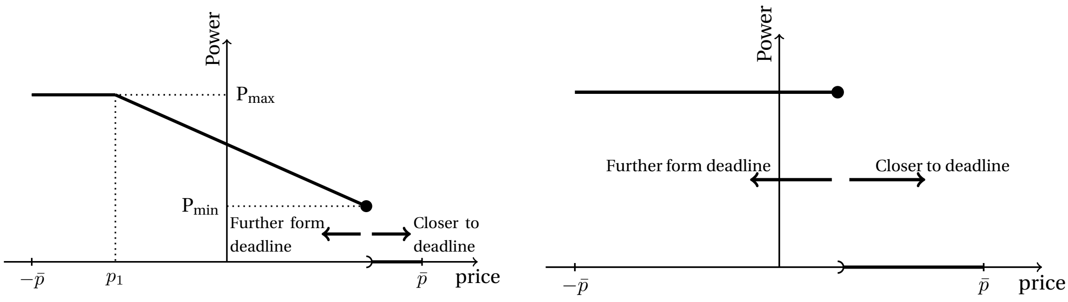
The two flat parts of the bidding function in Figure 3.4a are introduced to exploit flexibility with a lower priority. In a bidding function, three parts can be identified:

1. Curtailment region: is meant to curtail energy production, for example by switching off PV inverters. This region is positioned in the lowest part of the price range: the price should be really low (below p_1 in Figure 3.4a) before PV is going to be switched off.
2. Normal operation region: a region in the middle of the price range where devices such as EVs, batteries, and smart appliances differentiate their power consumption as function of price.
3. Shedding region: load shedding can actively be applied in this region. It is placed in the region of the price spectrum where the prices are the highest.

For example, on an extremely sunny day with relatively little demand, one wants to make sure that all flexible load is switched on before curtailing PV; the decisions for curtailment can be put the price region between $-\bar{p}$ and p_1. The opposite principle, i.e. load shedding, applies to region with high prices. The final aspect of the bidding strategy for EVs is that, when an EV reaches the point that charging at maximum power should be done to meet the deadline, it will only offer that option in its bidding function.

Smart dishwashers and smart washing machines are somewhat different since they have a fixed power profile. Flexibility can be offered in the sense that the start time can be postponed. The closer a smart dishwasher or washing machine gets to its deadline, the higher the price, according to a linear relationship, will be for not starting the device, see Figure 3.4b.

Batteries have a bidding strategy that expresses a lower priority with respect the EVs. This is implemented by assigning power values of 0 to a pretty large part of the price range, symmetrical around 0. For negative prices, the bidding function contains a slope from P_{max} to 0 and for positive prices it contains a line from 0 to P_{min}.



(a) The bidding function of an EV

(b) Bidding function of a timeshiftable device

Figure 3.4: Two examples that show the basic shape of bidding functions.

3.2 Triana

Where The PowerMatcher is an agent-based methodology focusing on momentary balancing of demand and supply, Triana is a three-step approach based on bottom-up modeling and mathematical optimizations [28]. This section presents the fundamental basis of Triana.

3.2.1 Bottom-up multi-domain modeling

Triana is build on the principles that (1) a network should be modeled bottom-up supporting all types of energy and all types of possible configurations, and (2) clever decisions should be made between what should be treated local and what global. Bottom-up modeling requires models to be available at device level, which enables to constitute models of houses. In this way, all types of houses can be modeled, typically based on stochastic variations. These houses can be added together to constitute neighborhoods, and finally even cities and countries. Since all devices are present in the model, the approach enables to make decisions and calculations locally. The first step of Triana, which is realized on this local level, is concerned with making predictions for the individual appliances. A possible implementation to achieve this, is by means of neural network theory. The second step in Triana's approach is to make locally, based on the prediction outcome, a device specific planning that satisfies local constraints and optimizes for a global objective. Using a global objective is advantageous because in this way devices can be scheduled such that they contribute to achieve a global optimization. A global optimization offers better optimization possibilities than local optimization, both in economic and network operational terms. The third step is concerned with real-time control, i.e. steering the devices into a particular state while coping with deviations from the planning.

An elegant aspect of Triana is the domain-independent modeling because it uses energy streams (referred as energy carriers) as its basic quantity. The model elements are generic and therefore applicable to all energy domains, e.g. heat, gas and electricity. The complete model is described in [41] but we will give an example in Figure 3.5 of a typical household situation and its corresponding Triana

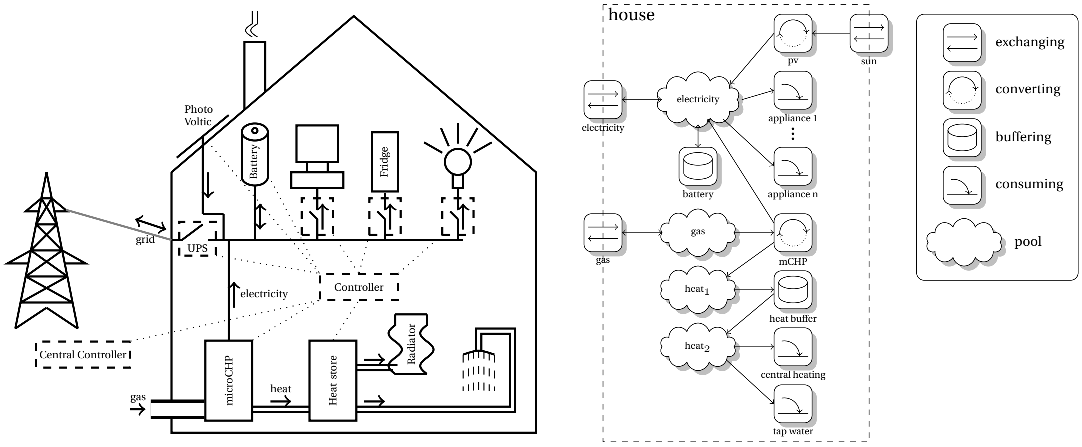


Figure 3.5: Left: drawing of a typical household. Right: its corresponding Triana model

model. The basic model elements are:

- **Energy carriers**: a generic term for all kinds physical quantities that can carry energy, e.g. heat, electricity, sunlight and gas.
- **Energy streams**: defined for a specific energy carrier to connect devices with each other.
- **Devices**: devices can act on energy carriers by either consuming, converting, buffering, or exchanging energy. For each type of device, a number of states is defined. Controllable devices can offer flexibility as long as their constraints allow so.
- **Pools**: an abstract modeling element to which energy streams are connected in order to connect multiple devices with each other. Pools are only present for modeling purposes, they cannot buffer energy, i.e. input and output flows must be equal at all time, and per pool only one type of energy streams can be connected.

Another key aspect of Triana is the tree structure for controllers - every device can have a controller so that it can be incorporated in the planning optimizations - , which result in a scalable architecture for the optimization algorithms. This is not only desirable from a computational point of view but also regarding communication intensity [42].

3.2.2 The problem of determining a planning

Planning approaches in the Smart Grid context are in general related with scheduling problems. In general terms the problem is as follows: when and at what power levels should devices, being subject to its constraints, be switched on to achieve an optimal distribution of energy. As noted in earlier sections, different stakeholders have different interests and therefore various optimization criteria can be adopted in a smart grid. Next to the optimization objective, the scheduling algorithm has to deal with user and device constraints. For example, an EV should be charged till the user setpoint at the deadline and a micro-CHP unit has a minimal run time and minimal off time. The requirement of scalability, and the presence of user and device constraints, make that the problem of finding an optimal planning is in general very difficult. As proven in [43], the optimal scheduling of a VPP that consists of microCHPs, and being subject to an global objective, is already NP-complete in the strong sense. As result, planning algorithms in DSM methodologies are highly based on heuristics to solve the problems.

The section which treats related work (Section 2.4) already touched methods like Dynamic Programming, Priority Lists, Genetic Algorithms, and Evolutionary Programming to find solutions for the scheduling problem. In one of the papers that introduces Triana [28], it is described that Iterative

Distributed Dynamic Programming was used to solve the scheduling problem by means of cost functions. The approach uses time intervals as a basis for the planning. One part of the Iterative Distributed Dynamic Programming algorithm is that locally a plan is constituted, based on electricity prices on the markets. The second part is that the devices send their (local) plans to a global planner which sends back a steering prices in order to change local plannings such that they contribute to a global optimized plan. Although the algorithm in [28] was distributed, enabling to maximally utilize computation power in the network, it was still quite computationally intensive, mainly caused by a large state space. Therefore, new heuristic algorithms have been developed and implemented which significantly reduce the computation time but are still based on the concept that a local controller determines a planning, given a steering signal from a global optimization controller. One of these contributions is presented in [44], the scheduling of an EV fleet. The scheduling problem is treated as a convex optimization, by defining a minimization function of the weighted sum of the consumption cost implied by the prices and the squared deviation from the target profile. This convex function could in principle be solved by using a quadratic programming solver (for example as used in [32]) but the authors show their algorithms is several order of magnitude faster. This fast EV scheduling algorithm is a good example of the planning algorithms in the second step of the Triana methodology.

3.2.3 Profile steering

A lot of research regarding algorithms to make a planning for DSM purposes is performed. Most research is based on the concept of dynamic pricing, i.e. prices change over time as an incentive to steer loads to a desired state. One of the possibilities is to use uniform prices, which means that all consumers/houses receive the same price, this referred as Time of Use (TOU) pricing. All research on this principle points at the same result: power peaks are not flattened but only shifted in time, for example [45, 29]. In order to circumvent the problem of all houses reacting simultaneously and more or less similarly to uniform prices, the concept of differentiated dynamic pricing has been topic of research (see for example [28]). In differentiated dynamic pricing, houses receive different prices at a certain time interval. As a result, the power profile at the transformer is flattened but the method leads to local peaks which may cause phase unbalances and cable overloading. Another disadvantage is that the approach of differentiated dynamic pricing can be unfair because some people are asked to contribute to the balancing the system more than others.

The underlying problem of all dynamic pricing based methods is that they encourage extreme behavior. Prices are used to obtain a desired power profile but the relation between power and price is not one-to-one and dependent on external factors. Therefore, it appears that severe problems arise when dynamic pricing is used to steer loads aiming at achieving a particular power profile. Based on this reasoning, an iterative planning approach, which uses incentives based on power profiles rather than prices, is proposed in [29]. The method, coined "profile steering", is applied in Triana's planning step. During the planning step, devices are iteratively asked to contribute to a global planning in order to make the global planning match the desired load profile as closely as possible. In the planning step, two time periods are considered. The first one is called the *planning horizon* and refers to the number of intervals used to look into future. Typically, the planning horizon is twice the *planning interval*, which is the time elapsed upon determining a new planning. The planning horizon should be larger than the planning interval because it enables devices to have a deadline in the next planning interval after the current planning interval, in which the device was started/arrived. In this way, a device can really be planned in the time available, i.e. the time until the deadline, instead of only considering the time left in the current planning interval. An objective function, which is e.g. the Euclidean distance between the desired profile and the profile in a particular iteration, is applied to iteratively steers the planning to achieve the desired global power profile. Note that the desired profile can have any arbitrary shape and is not necessarily a flat power profile; it can also be constituted with a cost optimization objective which will definitely result in another load profile.

3.2.4 Local real-time control and implications

By design, Triana has a very strong focus on local optimization and control. The vision is to apply real-time control[1] on local level because computational power is distributed as much as possible. Another advantage is related to reliability because the controller can still operate when it is disconnected from the global controller [41]. On the other hand, there appear to be two problems when real-time control is implemented locally as an ILP model. In the first place, the study in [33] indicated that auction based control is better capable of achieving a desired power profile than the ILP approach. In the second place, ILP is computational intensive which makes it, in particular for simulation purposes, unfavorable. The reason for the differences between auction based control and ILP control is that ILP operates locally to work around prediction errors. For example, a prediction error occurs due to an EV arriving later than expected at house A. A local solution would be to turn on a heat pump or charge a battery, while this is not strictly necessary, to cope with the prediction error. In contrast, the auction based control does not have to solve the problem locally but can decide to start charging another EV, which arrived earlier with respect to the planning and is present outside the scope of the local controller of house A. Although there are good reasons for using local real-time control, the contextual characteristic that user behavior on individual level is badly predictable, makes that local real-time control leads in practice often to undesired behavior.

3.3 Where The PowerMatcher and Triana meet

Up to this point, the chapter was concerned with the theory of existing DSM methodologies. The following section is concerned with considerations of the combination of the two methodologies. The combination can be viewed as: Triana is used to constitute a device specific planning and the PowerMatcher methodology is applied as a online control mechanism to realize this planning and to cope with prediction errors.

3.3.1 Combining the methodologies: requirements

Firstly, we look at the requirements that both systems have listed in the theses [15, 41] where they were introduced. The requirements that match with each other are:

- Scalability.
- Openness for DERs. Coined 'flexible and generic' in Triana's requirements.

Furthermore, the following requirements are only mentioned for one of the two methodologies.

The PowerMatcher:

- Respect privacy of users.
- Trade and supply functionality, the system should be integrated in the wholesale markets.
- Contribute to active management of distribution networks.
- Raise the electric power system ceiling in order for more integration of renewable energy sources.

Triana:

- Local and global control and optimizations.
- Respect comfort of residents.
- Support damage control.
- Limited requirements on communication links.
- Local controller must be able to work independently.

[1] In this section, the term real-time control is used rather than online control because it is term originally applied as Triana's third step. Since real-time control was meant to be performed locally, we cannot speak of online control.

Only the very last requirement of Triana is a problem when the two methodologies are combined. All others were implicitly used as a requirement of the other system and/or do not lead to conflicts. Since the system context (Section 2.1) conflicts with the idea of applying real-time control locally, this idea is dropped in the combination of the two methodologies. Hence, the requirements of the combined approach is just a combination of the requirements of the individual approaches with exception of Triana's last requirement.

3.3.2 Considerations regarding the combination

When the prediction and planning of Triana is to be combined with the online control of The PowerMatcher, there are still some important question left open. Basically, these questions are the first and second research questions (see Section 1.4):

- On which level(s) in the PowerMatcher hierarchy should Triana's planning be provided?
- What strategy should be used in order to incorporate Triana's planning in the PowerMatcher methodology?

Since Triana and The PowerMatcher have both formulated the requirements of scalability, more or less the same decisions are made when it comes to the hierarchy of the system, i.e. the system is implemented as in a tree structure. In order to meet the requirements of scalability and privacy protection, the decision to use this structure is straightforward. This is convenient when the approaches are to be combined. In the PowerMatcher hierarchy, there are three types of agents, all present on different levels in the hierarchy. In principle, the planning of Triana can be provided on either one of the three levels (device agent, concentrator, auctioneer) or on multiple levels.

3.3.3 Alternatives for the combination

There are globally two possibilities to combine The PowerMatcher and Triana. In the first place, the bidding functions of The PowerMatcher can be adapted such that a local device planning is incorporated when the bidding function is determined. In this strategy, a global planning is also used at the auctioneer to clear the market on a planned power value. The second possibility is to use regular bidding strategies and incorporate only the global planning at the auctioneer to clear the market at power values that occur in the global planning.

The most fundamental advantage of the first option is that the devices only know how much flexibility they have available, i.e a device can decide how much flexibility it will provide to the system. Based on its local planning, a device can choose to 'save flexibility' for later. Recall the thought experiment in Section 3.1.7, in which there were two wind peaks during night and all EVs were charged during the first peak, resulting in severe PQ problems during the second peak. Now, consider that the wind peaks are predicted and planned, then a device could choose to only offer options to charge at a little higher (and lower) power than the planning prescribes such that not all flexibility is exploited in the first peak. Of course, the bidding strategy still should provide enough flexibility to cope with prediction errors. These two effects should be balanced well; it's a matter of trade-off.

On the other hand, one may reason that typical use cases do not include scenarios as presented in the thought experiment. In contrast, consider the energy supply to be 'more stable' and DSM boiling down to matching the demand with this 'more stable' supply. For example, when some EVs arrive later than expected but others arrive earlier than expected, it might be sufficient to use regular bidding strategies, which simply provide all flexibility possible and follow the planning on global level to stimulate the cluster to follow a profile based on predictions.

In this work, those two options are considered. Of course, other possibilities with a planning on different levels and combinations could be possible but first these two extreme options in the design space will be evaluated. It is not expected that other combinations options will provide extra performance over the effort it cost to implement it.

3.3.4 Device models

Both in Triana and The PowerMatcher, abstractions for devices have been introduced because some devices can be treated similarly. It would we cumbersome to write drivers and also optimization strategies for devices that operate in essence similarly. Within the framework called EF-Pi, similar abstraction have been made. EF-Pi provides an abstract interface between real devices and an EMS to stimulate interoperability. Within this approach the following classes have been formulated:

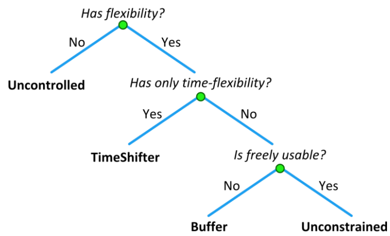


Figure 3.6: EF-Pi abstract device class overview [46]

- **Uncontrollable devices:** such as PV and dumb loads.
- **Timeshifter devices:** for example dishwashers and washing machines.
- **Buffers:** for example batteries or EVs.
- **Unconstrained devices:** one can think of a fuel cell or a gas generator.

In Triana, a similar abstraction of real devices is done:

- **Uncontrollable devices:** idem as in EF-Pi.
- **Timeshiftable devices:**Timeshiftable devices, idem as in EF-Pi.
- **Buffers:** storage elements without user deadlines.
- **Buffer-timeshiftable devices:** storage elements with user deadlines, for example EVs.
- **Buffer-converter devices:** explicitly used for generators, which convert one type of energy to another type of energy and have storage of energy. For example, a heat pump-heat buffer combination.

The device classes for buffers in Triana are somewhat more specific than the ones of EF-Pi. However it is good to know that there is mostly overlap in device classes because it make integration of the two methodologies easier. From this point on, the terms proposed in Triana will be used. The remainder of the section is devoted to listing device parameters.

Uncontrollables
Uncontrollable devices only have a fixed power profile. In Triana, there are two power profiles, the one is the predicted profile for the simulation interval and the other is the real profile containing power values that the device is going to consume or produce.

Timeshiftables
Timeshiftable devices have a predicted and real power profile as well. In addition, they also have predicted and real start time and end time.

Buffers
Buffers have a capacity, initial state of charge, and maximum charging power.

Buffer-timeshiftables
Buffer-timeshiftable devices have the same parameters as buffers but in addition also the following parameters, of which both a predicted and real version should be provided: start times, end times,

energy loss (or energy consumed) between the particular end and the following start time, and a minimum charging power. The minimum charging power is added to the model because the EVs currently on the market cannot charge with powers lower than approximately 1300 W.

3.3.5 Market integration of the combined strategy

In order to be active on the wholesale electricity market, it can be, on the one hand, really useful to determine a planning and try to follow it as good as possible. The reason is that electricity trade on the market always is about matching electricity consumption in future. The better a trader complies to the amount of electricity he traded, the better it is. Deviating from the traded amount leads to a penalty given by the TSO. So there is economic value in drawing proper predictions and making these predictions, on global level, come true. On the other hand, it also introduces some rigidness in the cluster. Users typically look ahead for 24 hours, so this is a reasonable time period to plan ahead. For the day-ahead market, this really suits well. In contrast, DSM also offers possibilities to operate on the balancing market, which typically is concerned with time intervals of 15 minutes. This is a too fine time period to determine a planning for. Although realizing a power profile as determined by the planning algorithm is desirable in terms of achieving the optimization criterion, it is not strictly necessary for a system to operate properly. Therefore, the combined DSM approach should offer the possibility to deviate from the planning such that in principle a Balancing Respsonsible Party (BRP) can be incorporated in the system as well.

Chapter 4

Contribution - A novel bidding strategy

The basic theory of The PowerMatcher and Triana has been described in the previous chapter. On basis of the theory, this chapter builds a novel bidding strategy. The bidding strategy uses a device specific planning to determine a bidding function. In order to be able to describe the bidding strategy, first some definitions, formalizations and introduction of terms are given. Subsequently, a characterization of prediction errors is described and the final part of the chapter gives a detailed description of the bidding strategy variations.

4.1 Fundamentals of the combined DSM approach

Basically, the combined DSM approach works as follows: the prediction and planning of Triana is applied as an input for the real-time control, which is done on basis of the PowerMatcher methodology. Although the online control step heavily builds on PowerMatcher concepts, the way it is operated differs substantially from the regular PowerMatcher operation (as described in [15]). The PowerMatcher is based on the principle that devices bid according to some local consideration, e.g. the device state, user constraints and device constraints. They do not take information about the future into account. Depending on the available supply and demand, the MCP is determined. Typically, the MCP is an artificial price, only used as a price steering signal to tell devices how much they should consume or produce.

4.1.1 Basic idea

The proposed combined system of this research works differently. In the system, devices have a planning and therefore do have 'knowledge' about the future. Moreover, the planning 'prescribes' what a device should consume/produce, because the planning was constituted based on a certain optimization criterion. In the combined DSM approach, devices bid according to this plan *and* provide options to the auction to cope with prediction errors (see Figure 4.1 for an example of a bidding function of the combined DSM approach). This principle differs from the PowerMatcher bidding behavior and is applied in the combined DSM approach. Therefore, the auction cannot be viewed the same way as the PowerMatcher auction. As a consequence, another term for the MCP is introduced, namely the Online Steering Price (OSP). Although the OSP is, just as in The PowerMatcher, the out-

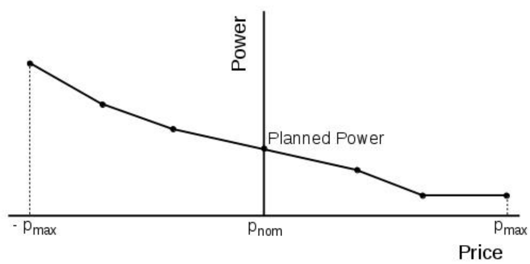


Figure 4.1: Basic illustration of a bidding function in the combined DSM approach

come of the auction and used to communicate to devices what they have to consume, the bidding strategies of devices are fundamentally different and therefore the name of the steering price as well.

4.1.2 Definition of a bidding function

In this section the properties of a bidding function for the combined DSM approach are formalized.

DEFINITION 1. A bidding function $b(p)$ is a monotonically decreasing function that relates a price $p \in [-\bar{p}, \bar{p}]$ to a power $PW \in \mathbb{R}$:

$$b(p) : p \to PW,$$

(i.e. $p_1 > p_2$, then $b(p_1) \leq b(p_2)$). Hereby, $\bar{p} > 0$ is a given input. Furthermore, the demand function is restricted in the sense that $b(p)$ gets characterized by the values for a finite subset $\mathcal{P} = \{p'_1, .., p'_N\} \subset [-\bar{p}, \bar{p}]$, with $p'_i < p'_{i+1}$, for $i = 1, .., N-1$, $p'_1 = -\bar{p}$ and $p'_N = \bar{p}$. □

The basic approach is to use the given values and interpolate between them. More precisely, for $p \in \mathcal{P}$, the value $b(p)$ is a given input value $\bar{b}(p)$ and for other prices $b(p)$ is calculated by interpolation between the two neighbored point, i.e.:

$$b(p) = b(p_i) + (p - p_i)\frac{b(p_{i+1}) - b(p_i)}{p_{i+1} - p_i} \text{ if } p \in [p_i, p_{i+1}[\tag{4.1}$$

Note that if the bidding function would not be *monotonically* decreasing, local minima and maxima would occur with the result that there are possibly multiple outcomes of the auction. Obviously, this leads to undefined and undesired behavior of the auction.

The choice of defining the bidding function using interpolation is the result of a design decision. In Section 5.2.1, the reasons for the choice is given. Basically, the interpolation is added to represent bidding functions in an easy and compact way. In addition, because some devices can only operate on some discrete number of power values, which inherently introduce discontinuities in the bidding function, the function should support discontinuities as well. As will be discussed in the following section, the compact representation of bidding functions, can easily be used to offer this support.

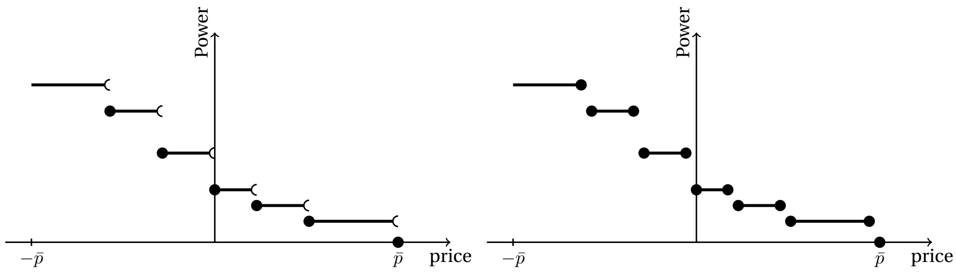
Discrete bidding functions

Some devices only allow to consume or produce electricity at some discrete power values. For such devices the bidding function cannot contain interpolated regions between two different power values. Therefore, the following property for a discrete bidding function has to hold, in addition to the properties of Definition 1:

DEFINITION 2. A discrete bidding function $d(p)$ is a bidding function, as defined in Definition 1, that also fulfills the following: For $\epsilon \to 0$, $d(p'_i) = d(p'_{i+1}) - \epsilon$. □

In Figure 4.2a, a bidding function that complies to this definition is given. Note that in reality, it is not possible to work with a concept of $\epsilon \to 0$, but a concrete choice for ϵ has to be made. In principle, it is chosen to use $\epsilon = 1$, implying that prices in $]p'_i - 1, p'_i[$ have no corresponding power value. If a large interval of all possible prices is used, these intervals $]p'_i - 1, p'_i[$ are only a small portion of the overall interval.

A better approach is to combine the above concept with the earlier mentioned interpolations. More precisely, we extend $\mathcal{P}$ to the set $\mathcal{P} = p'_1, p'_2 - 1, p'_2, ..., p'_{N-1}, p'_N - 1, p'_N$, define $d(p) = d(p_{i+1} - 1)$ and use interpolation. This leads to horizontal lines between p'_i and $p'_{i+1} - 1$ and discontinuities between



(a) Illustration of a discrete bidding function, $\epsilon \to 0$.

(b) Illustration of a discrete bidding function, $\epsilon = 1$.

Figure 4.2: Discrete bidding function.

$p'_{i+1} - 1$ and p'_{i+1} (see Figure 4.2b). The only problem now occurs if the clearing price is in an interval $]p'_i - 1, p'_i[$, as this interval leads to a power value which is not supported by the device. However, since $\epsilon = 1$, this interval can be omitted by restricting to integer clearing prices.

The nominal price: expresses a device's preferred power consumption
The planned power value is a device's preferred power consumption. In order to express this preference in the bidding function, the function should be normalized. This is achieved by the convention that all devices position their planned power value at the nominal price, i.e. $b(p_{nom}) = P_{plan}$. The nominal price is a system wide parameter and typically placed in the middle of the price range, i.e. $p_{nom} = 0$. Intuitively one can reason that if no prediction errors occur, the market will always clear at the nominal price.

The addition of two bidding functions
A key aspect of an auction based control mechanism is the addition of bidding functions. Obviously, the same applies for the combined DSM approach and therefore a mathematical description of the bidding function is given in previous section. Adding two valid bidding functions b_1 and b_2 leads to a valid function $b_3 = b_1 + b_2$ as well. As by Definition 1, both b_1 and b_2 are monotonically decreasing, it follows from simple calculus that the addition of two such functions results in a monotonically decreasing function. Furthermore, if a price p is in $\mathcal{P}_1$ and is also in $\mathcal{P}_2$, the power values are known directly from $b(p_1)$ and $p(b_2)$. If p is in $\mathcal{P}_1$ but not in $\mathcal{P}_2$, or visa versa, the missing power value is obtained by interpolation. Therefore, $\mathcal{P}_3 = \mathcal{P}_1 \cup \mathcal{P}_2$ and hence, b_3 is a valid bidding function.

4.1.3 Two types of predictions errors

Until this far, the basis of bidding strategies for a combined DSM approach is presented. Before going deeper into the combined DSM approach, some background on prediction errors and the relation between the nature of prediction errors and the way they should be dealt with is given.

Typically, a Triana planning is determined for 24 hours in advance but this interval is configurable. Not all information about events and conditions in the planning horizon is available at the moment the planning is determined so predictions have to be made. Obviously, those predictions will not perfectly match the reality which results in prediction errors. Prediction errors are defined as the differences between the predicted data and the real data as it is during run-time. Two types of prediction errors can be distinguished. The first type is referred as "event-based prediction errors" which are prediction errors that arise during run-time when information becomes available that provides sufficient information to determine the planning completely, i.e. an event happens. Examples are EV arrival times and deadlines, EV State of Charge (SoC), washing machine start times and deadlines, etc. These errors can be viewed as being merely internal, i.e. all information about the errors is provided by the device itself. The second type of errors is related to external phenomena which can occur during the complete planning horizon, they are referred as "external prediction errors". These errors can be caused by differences between expected and real weather conditions which influence, for example, solar or wind power generation or heat demand. It is important to distinguish between these two types of errors because they should deal with differently in the combined DSM approach.

4.1.4 Introduction to planning adaptation

In the combined DSM approach, the planning is used as an input for defining the bidding function. A bidding function should not offer an unrealistic amount of flexibility so it is necessary that the planning corresponds to the state of a device as accurate as possible, i.e. when the planning would be executed perfectly, all device and user constraints should be met. In this way, the planning - and therefore the bidding functions - represents the device's desires and possibilities to cope with prediction errors as accurate as possible. To make this possible, the combined DSM approach uses planning adaptation. In the process of planning adaptation the device specific planning is adapted locally such that it complies to the information about the device that is available at that moment. Therefore, a device does not only have a 'normal' planning, which is the result of the Triana's planning phase, but also an "adapted planning". The adapted planning will be updated during run-time when both event-based prediction errors and external predictions errors are encountered.

The main advantage of the combined DSM approach is that more device specific information is taken into account compared to the approach in which the bidding strategy does not incorporate a device planning. For example, the bidding strategy that is presented in Section 3.1.8 only considers device and user constraints. As a consequence, it typically offers all the time all the flexibility it has available.

In the combined DSM approach, the bidding function reflects how much a certain option leads to deviating from the planning. It can be decide to save flexibility by not offering some options that deviate too much from the device planning. In this way, the system will only choose the options that causes the least deviations and it mitigates the problem of exploiting flexibility on the wrong moments.

4.1.5 The basis of the combined DSM approach

In order to make the system capable of coping with prediction errors, devices have to constitute bidding functions that contain, in addition to the planned power value at the nominal price, extra options. This enables the auction to pick an option in which supply and demand are matched, even when devices cannot follow their planning. This is where the main question of this thesis can be introduced: "How is a bidding function determined?" There are three main components related to this question:

1. The bidding function has to take the device planning into account.
2. The bidding function has to support event-based prediction errors.
3. The bidding function has to provide, if possible, extra options to ensure that the system can deal with external prediction errors and event-based prediction errors of *other* devices.

Because the basic idea of the combined DSM approach is to place the planned power at the nominal price, component 1 is easily achievable. In case of no prediction errors, this will yield an OSP which is exactly the nominal price. This can be understood by considering that all devices put - by definition - their planned power value at the nominal price and the aggregated planning at the auctioneer is used to determine the steering price.

The realization of component 2 requires an adaptation the planning such that the adapted planning is based on run-time information rather than on predictions. There are various ways to accomplish this. In fact, an important part of the remainder of the text is devoted to this question. Here, only the most basic idea is formulated: the original planning, which is the result of Triana's profile steering algorithm, is adapted such that the adapted planning meets the device demands based on run-time information. Mathematically, this is represented as by a function f which is used to adapt the original planning $O_\alpha = \{o_1, o_2, ..., o_N\}$ of device α at an event when run-time information becomes available (N is the planning horizon). The result of the function is the event-based adapted planning E_α:

$$f(O_\alpha) = E_\alpha \tag{4.2}$$

Given that devices are allowed to change their planning independently from other elements in the system, a new problem is introduced. The planning at the auctioneer, which is used to determine the steering price, now deviates from the sum of the device plannings. It might be that the individual deviations cancel out each other but it might also be that they add up. To enable the auction to still find a power balance, devices have to add extra options to their bidding functions for coping with prediction errors of *other* devices. This is where component 3 comes into play. More or less the same holds for external prediction errors. If a device's bidding behavior deviates from the prediction, and therefore from the planning at the auctioneer, *other* devices should add extra options to their bidding function to enable the auctioneer to find a power balance. How such bidding functions are determined, is expressed by a function g. This function takes an event-based adapted planning E_α and an auction-based adapted planning A_α as input and provides a bidding function $b_t(p)$ at time interval t:

$$b_t(p) = g(E_\alpha, A_\alpha) \tag{4.3}$$

The exact strategy followed to determine a bidding curve $b_t(p)$ at time interval t, which is the implementation of f and g, will be part of considerations in the remainder of this text.

4.1.6 A new interpretation of the MCP

A result of this approach is that the interpretation of the MCP price is different. In the original operation of The PowerMatcher it holds for consuming devices that the lower the price, the better. Similarly, for producing devices, the higher the price, the better. In the combined system, there is a preferred price - which is the nominal price - because at this price the planning is followed. If a device has a symmetric bidding function around the nominal price (p_{nom}), then it does not make a difference whether the online steering price (p_{OSP}) becomes $p_{OSP} = p_{nom} + p_{diff}$ or $p_{OSP} = p_{nom} - p_{diff}$. Another interesting interpretation of the OSP is that it does reflect the system state. A price lower than the nominal price means the system faces a surplus of energy with respect to the planning. A price higher than the nominal price indicates that the systems has a shortage of electric power with respect to the planning. This is important because it provides a measure for the system to know in general how well the planning is followed. In other words, in our combined DSM approach, the steering price has the same function as the frequency has in the electric domain when it comes to expressing the amount of balance in a power network with a significant amount of rotating mass. The information expressed by the steering price can be used by global controllers to adapt their planning or by device controllers to incorporate this information in the bidding strategy. In the bidding strategies presented in this work, this principle is not applied but it is considered to have promising advantages.

4.2 Coping with prediction errors

It differs per type of device how much it is able to deal with prediction errors. Timeshiftable devices are typically less suitable than buffering devices because timeshiftable devices have a fixed power profile and only the start time can be influenced. Although it could be an option to start the device at a moment where the amount of power that differs with respect to the planning is needed, but this will introduce a similar problem at the moment that the device was originally planned. In order words, this solution may indeed solve the problem of a prediction error but also introduces the exact same problem at another time. It would be better to solve the problem either with a device that can spread out the difference in power consumption over the remainder of the device's planning period or by a number of devices that all diverge only a little from their plan (for example, both options could be offered by an EV).

Dealing with event-based prediction errors: Re-planning vs. planning adaptation
During run-time, new information becomes available step by step, i.e. at events. The following question arises: How should be dealt with the difference between predictions and run-time information? Basically, there are two possibilities. The first one is to make a new planning each time new information becomes available. The second option is to adapt the original local planning such that the adapted planning complies to the demands corresponding to the run-time information.

Option 1: Re-planning (a part of) the cluster
The advantage of performing re-planning is that the achieved solution will be near-to-optimal. Triana's profile steering algorithm uses a global optimization objective but produces only a near-to-optimal schedule because it is based on a heuristic algorithm. The disadvantage of performing a re-planning every time a difference between the prediction and the run-time information occurs, is that it is computationally and communicationally intensive. Another disadvantage is that is not clear to the end user when a smart devices - let's say device A - will be finished at the moment the user starts the device because events triggering a re-planning are likely to occur and therefore, the planning of device A may change many times.

Option 2: Adapt the local planning locally
This option is based on the idea that predictions and run-time information are not too far off and that the differences can be dealt with by locally adapting the planning at the moment run-time information becomes available. The option requires an algorithm which determines the adaptation of the planning. The objective of this algorithm is to adapt the planning such that the difference with the original planning is as small as possible. Later on, starting from Section 4.3.1, a more thorough description of the algorithm will be given.

The advantage compared to option 1 is that this option is computationally and communicationally less intensive and it is more clearly to the end user when the device will run. On the other hand, the planning of devices will be changed independently from each other and, therefore, we loose track of how far the locally adapted plan diverges from the the near-to-optimal solution as provided by the profile steering algorithm. A possibility to tackle this problems is to communicate the differences between original planning and adapted planning to a global controller every now and then. If it appears to be that the differences of some houses cancel out each other, which is likely to happen in case of proper predictions, no re-planning is needed. On the other hand, when the difference sum up instead, a global decision to do a re-planning could be made. The open question of this option is: At what level in the control hierarchy should the decision of a re-planning be made? The answer to this question involves a trade-off between a higher level, which is more favorable because differences may cancel out better, and a lower level, which is better because it is able to track down local problems better (e.g. phase unbalances and local voltages).

Dealing with external prediction errors: Planning adaptation

In the former section, two possibilities to deal with event-based prediction errors have been described. In contrast, the only option to deal with conditions-based prediction errors is to perform planning adaptation. Doing a re-planning every time the solar production differs a little from the prediction, which is likely to occur many times, is simply not an option. Also, it would completely conflict with the concept of online control.

4.3 Planning adaptation

The following section describes the heart of the novel bidding strategy. It is concerned with the adaptation of the device planning, which can either be caused by event-based prediction errors or by external predictions errors.

There are two domains related to the problem of planning adaptation, namely power and time. All types of devices, whether they are consumption, production, or buffering devices, operate in the power and time domain. As a result, predictions for devices leads to a planning which is a power versus time plot. During the online control it gets clear how proper the predictions are and what efforts in time and power have to be taken to cope with prediction errors. Prediction errors can occur in one of the domains or in a combination of the two. For example, the power production of a solar panel during a particular time interval can differ from the prediction. In this case, there are only prediction errors in the power domain. However, an EV which does not arrive at the predicted time, and does not arrive with the predicted SoC causes prediction errors in both domains. A washing machine, which is programmed by the end user to execute the predicted program but with another deadline as predicted, is an example of a prediction error in the time domain.

Of course, a time domain prediction error could theoretically also be viewed as a power domain prediction error but for clarity the two are distinguished. A time domain prediction error is a deviation from the planning in the sense that the original planning only will be shifted in time. As pointed out earlier, this typically is only an event-based planning adaptation.

There can be two reasons to adapt the planning. The first one is when a device becomes available, i.e. an event happens, and it appears that the predictions were incorrect. Planning adaptation of this kind is referred as 'event-based planning adaptation' and typically occurs only a few times a day. On the other hand, a difference with respect to the planning can occur as a result of the auction outcome. This can happen if a device offers flexibility to the auction such that prediction errors of other devices can be dealt with. In this way, the adaptation originates from the auction and therefore this is referred as 'auction-based planning adaption'.

Mathematical description of planning adaptation

The principle of the combined DSM approach is to stick to the planning as close as possible. In order to achieve this, event-based planning adaptation should yield a device planning that (1) deviates minimally from the original planning and (2) takes into account run-time information that reflects the real user preferences and device states. The same applies to auction-based adaptation. Planning adaptation options offered to the auction should be positioned at prices that reflect how much is deviated from the planning when the option would be chosen. Deviating more, should result in relative higher costs. A suitable criterion to evaluate a certain planning adaptation option for a device α is the squared euclidean distance with respect to the original planning. An extra term to account for time domain planning adaptation is added, as is explained later on.

The first and most important term of the criterion is the squared euclidean distance between the original and the proposed planning, which would be the result of choosing a proposed option. Assume

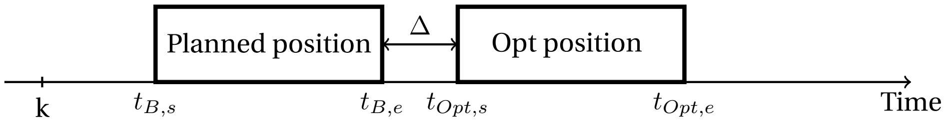


Figure 4.3: Schematic overview of time-shift compensation.

that at time interval k, the following information is available:

- $B_{\alpha,k} = \{b_1, .., b_i, .., b_N\}$, is the base planning of device α at the beginning of time interval k to which the option is evaluated, with b_i being the planned power at interval i and N the planning horizon.
- $A_{\alpha,k} = \{a_1, .., a_i, .., a_N\}$ is adapted planning of device α at time the beginning of time interval k that is the result of options chosen in time intervals before k

Furthermore, assume that the adaptation option $Opt_{\alpha,k} = \{o_1, .., o_i, .., o_N\}$, which may be applied at the beginning of time interval k, contains the power deviations of the option with respect to $A_{\alpha,k}$ per time interval. Then the base definition of the costs of applying option $Opt_{\alpha,k}$ is given by:

$$dev_{\alpha,base}(Opt_{\alpha,k}) = \sum_{i=k}^{N-1} (b_i - (a_i + o_i))^2$$

For time domain planning adaptation, another cost term that quantifies the deviation should be added to the function. The origin of this term comes from the fact that if power profiles are shifted in time, at a certain point the profiles do not overlap anymore. Still the criterion should account for the time shift in the sense that the larger the time shift, the larger the cost for the shift should be. Figure 4.3 visually presents the time shift and the parameters involved. The parameters are:

- $t_{B,s}$: the start time of the device according to the base planning.
- $t_{Opt,s}$: the start time of the device if the planning adaptation option would be chosen.
- $t_{B,e}$: the end time of the device according to the base planning.
- $t_{Opt,e}$: the end time of the option.
- k: the current interval in which the planning adaptation options are calculated.
- N: the current planning horizon.

As long as the two power profiles have some overlap, the term to incorporate the time shift is not needed because the squared euclidean distance term provides a sufficient evaluation criterion. Therefore, the time-shift term, which is proportionally dependent on the time between the planned end time and start time of the option - or visa versa for the case in which the option is earlier in time than the planned profile -, only will be added if there's no overlap, i.e.:

$$dev_{\alpha,ts} = C \cdot max(0, t_{Opt,s} - t_{B,e}, t_{B,s} - t_{Opt,e}),$$

where C is a multiplication factor that depends on power profile of the device. The value of C is given by the squared sum of the power deviation values of the option in case of no overlap:

$$C = \max_{i=1}^{N}(o_i^2)$$

Combining both terms results into the following optimization criterion:

$$dev_{\alpha}(k) = \sum_{i=k}^{N-1} (b_i - (a_i + o_i))^2 + C \cdot max(0, t_{Opt,s} - t_{B,e}, t_{B,s} - t_{Opt,e}), \tag{4.4}$$

The task of the strategy is to find an option $Opt_{\alpha}(k)$ such that the deviation $dev_{\alpha,k}$ is minimal.

Four types of planning adaptation
The basic idea an mathematical description of planning adaptation is given in the foregoing section. The following sections describe how the planning adaption can be realized. The planning adaptation strategies can be categorized in four categories, which all are described in different sections, that are the combination of two times two possibilities:

- Event-based planning adaptation in the power domain.
- Event-based planning adaptation in the time domain.
- Auction-based planning adaptation in the power domain.
- Auction-based planning adaptation in the time domain.

4.3.1 Event-based planning adaptation

Event-based prediction errors should be solved with a so-called event-based planning adaptation strategy. When an event occurs, all information to make a planning which complies to the user demands and device constraints is available. Equation 4.4 should be used to evaluate an event-based planning adaptation option. In event-based planning adaptation, the adapted planning $A_{\alpha,k}$ is the same as the base planning $B_{\alpha,k}$ because no auction-based planning adaptation has been applied; after all, the device just becomes available at the occurrence of an event. So, with $B_{\alpha} = A_{\alpha}$, the optimization criterion boils down to:

$$dev_{\alpha}(k) = \sum_{i=k}^{N-1} Opt_i^2 + C \cdot max(0, t_{Opt,s} - t_{B,e}, t_{B,s} - t_{Opt,e}), \tag{4.5}$$

Event-based planning adaptation can be done in the time domain and/or in the power domain. When a device encounters a time domain planning error, the solution could be to shift the planning of this device completely and in accordance with the time that the device is off the planning. This is called time domain planning adaptation. In case of some devices, like a washing machine or a heat pump without buffer, this is the only option. On the other hand, when a device is not an on/off device, it might be better to apply power domain planning adaptation. The strategies described in this section are divided over the domains in which the adaptation can be applied.

Event-based planning adaptation: time domain
The amount of flexibility offered by timeshiftable devices, like washing machines and dishwashers, is relatively small. This is mainly because there is only flexibility in the time domain and preemption is not allowed for these type of devices. However, there is some flexibility available and the following strategy enables the utilization of this flexibility. The evaluation criterion for time domain planning adaptation is the very same as given in (4.5).

Strategy ET1: stay close to original plan, plan unpredicted devices randomly
There are three possibilities in which the planning of a timeshiftable device should be adapted in case of an event, the strategy handles the possibilities in the following ways:

- The device becomes available after the planned start time. In oder to minimize $dev_\alpha(k)$, the best option is to schedule the device at the moment of arrival.
- The device has its deadline before the planned finish time. Again, the options which introduces the least possible deviation from the planning is to start the device as late as possible or, phrased differently, as close as possible to the planned schedule.
- The device was not scheduled at all. All solutions now have the same cost for deviating from the original planning. A solution would be to position the start time randomly, which has the advantage of stimulating diversity in the cluster. On the other hand, this solution could position the start time at a moment that is undesirable because there might be running many other devices as well.

Applying this way of event-based planning adaptation does not mean that the device necessarily has to run at that time interval. It will be scheduled there but the auction is still offered the option to start the device earlier or defer its start time.

Strategy ET2: stay close to original plan, unpredicted devices at local valley
This strategy is a variant on ET1. It still minimizes for (4.5) so it applies the first two bullet points of ET1 as well but deals with unpredicted devices differently.The devices are scheduled at a moment in which the local planning does not contain much demand, i.e. apply local valley filling. A drawback is that it may occur that many unscheduled devices all are positioned in this region because the local valley is there for an external reason.

Event based planning adaptation: power domain
Similarly as time domain planning adaptation, the planning can also be adapted by the adjusting power values such that the new planning meets the real user and device constraints. Again, the mathematical basis for determining the optimal planning adaptation is given in (4.4) but in this case without the timeshift-compensation term:

$$dev_\alpha(k) = \sum_{i=k}^{N-1} Opt_i^2 \tag{4.6}$$

Because of device constraints, the optimization is subject to the minimum and maximum charging powers, P_{min} and P_{max}. So Opt_α may not contain values larger than P_{max} or smaller than P_{min}, that is not 0.

Strategy EP1: spread deviations out over time till deadline
A straightforward algorithm to find a solution for this problem, which can be applied to buffer-time-shiftable devices, is described in this section. The strategy basically calculates the total difference in energy due to prediction errors and aims to spread it out over the available time till deadline. The algorithm is schematically shown in Figure 4.4.

The algorithm compensates for the following amounts of energy, which is the complete set of possible compensations:

- If the device arrives after the predicted start time, compensate for the amount of energy that should have been charged between the predicted start time and the arrival time.
- If the deadline is before the predicted end time, compensate for the amount of energy that should have been charged between predicted deadline and end time.
- If the SoC differs from the prediction, compensate for this amount of energy.

In words, the algorithm works as follows:

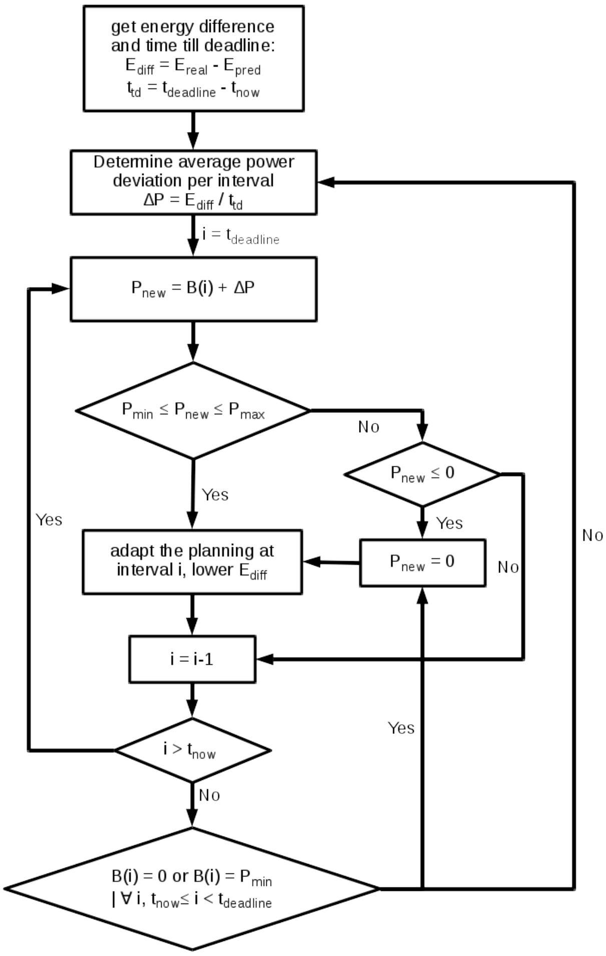


Figure 4.4: Flowchart of algorithm EP1: the deviations with respect to the planning are spread out over all time intervals till the deadline

- Calculate the difference between the predicted and real amount of requested energy.
- Calculate the time till deadline.
- Determine, based on the former results, the average power deviation to compensate for the prediction error per time interval.
- Start at the deadline looking for intervals to adapt the planning. It is chosen to start looking at the deadline because positioning a compensation over there gives most time to deal with prediction errors of other devices, i.e. during auction-based prediction errors.
- If the inferred deviation results in a valid charging power, then adapt the planning and lower the amount of energy required to compensate and continue to the previous time interval.
- If the deviation does not result in a valid charging power, continue to the previous time interval.
- After having iterated over the planning without having found intervals to adapt, compensate by setting the charging power interval 0.

4.3.2 Auction-based planning adaptation

For auction-based planning adaptation, again the principle of sticking to the plan as close as possible is leading. For example, if an EV planning prescribes that the EV should charge with 1000 W and the auction determines, due to lack of consumption, that the EV has to charge with 1500 W, then the planning should also be adapted to compensate for the deviation. In this way, the planned power values are always up-to-date and calculations for other planning adaptation options, which might be done in future, can evaluate the costs of deviations more accurately. In terms of the symbols occurring in equation 4.4, the event-based adapted planning is used as the base planning ($B(i)$) and a new, dynamically adapted planning is used as adapted planning ($A(i)$). For auction-based planning adaptation, the deviation will be transformed to a price such that the options can be offered to the auction by means of a bidding function. The larger the deviation with respect to the planning, the larger the difference between the nominal price and price for this option. More on this in the section about auction-based planning adaptation in the power domain (Section 4.3.2).

Auction-based planning adaptation: time domain
Again, flexibility in the time domain is mainly provided by timeshiftable devices. In general, it can be stated that power domain planning adaptation provides more flexibility and hence is preferable to apply if possible. However, for timeshiftable devices time domain planning adaptation is the only possibility.

Once a time-shiftable has been scheduled, it could be switched on at another moment than the planning prescribes. The flexibility should be expressed by a price which indicates how much will be deviated from the planning.

Strategy AT1: time from scheduled start time linearly determines the price
A straightforward strategy to do so is using the time from the scheduled start time as linear input for determining the maximum price of the 'switch-device-on' option. This strategy is more or less similar to the one presented in Section 3.1.8, i.e. there are only two options: switch on and stay off. However, the maximum price for which the device will be switched on is not depended on the deadline but on the scheduled start time instead. From experiences it appears that shifting timeshiftable devices too much usually results in device synchronization, i.e. many devices are all switched on just before their (common) deadline. Therefore, this strategy only allows a small time deviation with respect to the planned start time for starting a timeshiftable device. Outside this time interval, the device is not allowed to run at all. How small this time deviation is, is obviously a system parameters but one hour is typically a proper value.

Strategy AT2: calculate the price of an option by means of equation 4.4

It is more accurate to obtain the price for the 'switch-device-on' option on basis of the evaluation criterion in 4.4 instead using the linear relation of AT1. For this specific type of planning adaption, 4.4 does not reduce because it uses all terms. Apart from the advantage of a more accurate price, the disadvantage is that it slightly takes more calculations. On a system scale, it is not expected that the influence of the slightly more accurate price will be significant.

Auction-based planning adaptation: power domain
There are several strategies that could be followed to adapt the planning in the power domain to deal with a prediction error. Again, the strategy tries to find a minimum value for the optimization criterion, which boils to equation 4.7 for this type of planning adaptation.

$$dev_\alpha(k) = \sum_{i=k}^{N-1} \left(B_\alpha(i) - (A_\alpha(i) + Opt_\alpha(i))\right)^2 \tag{4.7}$$

Strategy AP1: Compensate on a single interval for a deviation in the current interval
The basic idea of the strategy is to compensate for a power deviation in the current time interval - which is an option offered to the auction and, based on the steering price, chosen - by a deviation on a *single* time interval in future. This strategy starts looking for compensation options at the deadline

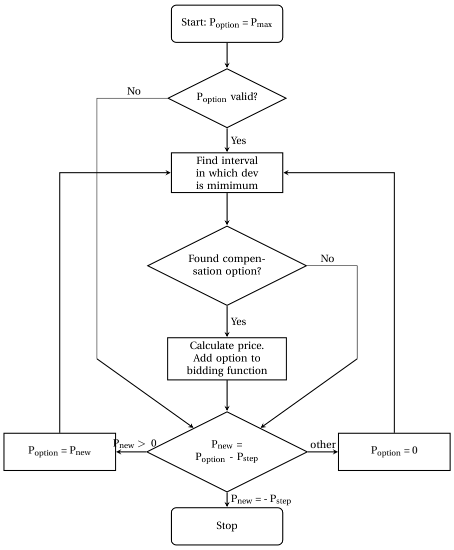


Figure 4.5: Flowchart of algorithm AP1: compose a bidding functions with options that lead to minimum deviation from the original planning

and goes back to the current moment in time. The reason to start at the end of the charging period is that compensating later in time results in extra time to cope with (other) prediction errors, which might undo the compensation.

Compensating on a single interval will definitely result in a solution that is further from the optimal solution than an algorithm which spreads out the deviation over multiple intervals. After all, the optimization criterion is a quadratic term so the solution that spreads out the deviation over the complete time till deadline, will result in lower quadratic deviation than the option that uses only one interval to compensate. For reasons of implementation simplicity, this strategy only compensates at one time interval and hence, equation 4.7 reduces to:

$$dev_{\alpha}(k) = (B(k) - (A(k) + \Delta P))^2 + (B(j) - (A(j) - \Delta P))^2 \tag{4.8}$$

With j is the time interval on which the compensation is positioned and ΔP is the difference between the originally planned power and the power of the planning adaptation option for time interval k. The algorithm of this strategy starts searching for the time interval of the earliest following deadline and goes all the way back to time interval k. The time interval j that yields the smallest $dev(k)$ is the time interval in which the compensation will be placed. The algorithm is schematically depicted in Figure 4.5.

The price is determined as follows: from equation 4.8, it follows $max(dev) = 2 * \Delta P^2_{max}$. With this maximum deviation, it is possible to scale dev to a price in the range: $p_{dev} \in [p_{nom}, .., \bar{p}]$.

$$p = \begin{cases} p_{nom} - \frac{dev \cdot \beta \cdot \bar{p}}{max(dev)} & \Delta P > 0 \\ p_{nom} + \frac{dev \cdot \beta \cdot \bar{p}}{max(dev)} & \Delta P \leq 0 \end{cases} \tag{4.9}$$

Note that for $\beta > 1$ the price obtained by (4.9) can be outside the price interval. In that case, the price should be set to the minimum or maximum value, depending on whether $\Delta P > 0$ or not.

Strategy AP2: Start looking for compensation halfway the charging interval
The disadvantage of strategy AP1 is that the compensation may be shifted too much to the future. As a result, the sum of all adapted plannings may have a peak at the end of the charging period. The compensations of deviations during the charging interval of many devices will all be positioned at the end of the charging interval. So basically, it boils down to: all devices have separately, the same compensation strategies. On system level, this may lead to an undesired peak. In order to prevent this phenomenon, and stimulate diversity, it could be better to start looking for compensation options halfway the charging interval.

Strategy AP3: Find a price based on a dedicated algorithm
The algorithms described above are all pretty simple and straightforward solvers for the problem of finding a proper planning adaptation option but are restricted by only considering compensations at one specific interval. A solver which searches for compensation on multiple intervals will inherently be able to find a better solution, i.e. $dev_{\alpha}(i)$ will be smaller. In [44] an algorithm is presented which solves the problem. The algorithm should be provided a target profile, which is the original planning and the energy difference which would be introduced when the planning adaptation option would be chosen by the auction. Basically, the objective in [44] is the same as the evaluation criterion in 4.7 when the charging cost in the objective are not taken into account.

4.3.3 Auction-based planning adaptation: dependencies of the price

Now, many planning adaptation strategies have been introduced, it is good to list the dependencies of the price for a particular planning adaption option. The price in this section refers to the price that belongs to a certain power option in the bidding function.

1. The price of a planning adaptation option depends on the planned power value. This is obvious, if the planned power is 1500 W, the option to charge with 2000 W is cheaper than if the planned power is 1000 W.
2. The price also depends on the options that have been chosen previously because they result in the plan being adapted. For example, we refer to *experiment 2* which shows the following. An EV which can charge at the following power values [500, 600, , 2000] and its planning is for the first 3 hours 1400 W and the rest of the planning 1800 W. Power domain planning adaptation - which will be explained later on - is applied, so the option to charge at time interval 1 with 2000 W will result in a difference of 1400-2000 = -600 W. If this option is chosen, the adapted plan will have a time interval which differs with -600 W with respect to the original planning. Which time interval exactly depends on the strategy, in this case it is adapted at the final charging time interval. So the adapted planning contains 1800-600 = 1200 W at this time interval. Then, at time interval 2, the option to charge with 600 W, which corresponds with a difference of 1400-600 = 800 W, is cheaper than the very same option at time interval 1. One could say that this option 'restores' the adapted planning back to original planning.

Chapter 5

Implementation - Work on the Triana Simulator

Now all theoretical considerations have been presented in the previous chapters, it is time to describe what effort has been taken to integrate the combined DSM approach in the Triana simulator. In this chapter, design consideration and decisions are described. For more detailed information about the contribution to the software, see Appendix A

5.1 A technical introduction to the Triana Simulator

This section gives a look under the hood of the Triana simulator. The concepts presented in this section should be understood before the contributions of this work to the simulator can be understood.

A hierarchical control structure
The device classes (see Section 3.3.4) are all implemented as an entity in the simulator. Similarly, a controller is an entity that can be connected to a device of the device class it corresponds with. Device controller can be grouped by connecting one or multiple device controllers to a group controller. Group controller can, again, be grouped by group controllers such that a tree structure is formed. Typically, there is one master controller under which all other controller are grouped. The master controller initiates the planning algorithms and the online control as well.

The iteration of a simulation interval
Every simulation interval, the simulator executes the following steps:

- Calculate and update predictions. Note that this step is not implemented yet.
- If the current simulation interval requires a re-planning, perform the profile steering planning algorithm.
- Perform online control by an auction, i.e. devices come up with a bidding function and the auction is cleared subsequently, after which the device states are updated.
- Finally, the load-flow calculations will run to determine PQ values.

The concept of a job
In the simulator, a job is a concept that is used to organize the operation of devices that have interaction with the user, i.e. a user can apply constraints to the device. For example, when an EV arrives, the controller is provided with a deadline and a requested state of charge. By means of a job all these parameters can be indexed, and easily related with each other in code.

5.2 Bidding functions

5.2.1 Implementation consideration for bidding functions

A bidding function is represented in software by a bidding function object. The price power points of the function itself are stored in a QMap, which is a container class in Qt, of an integer and a double - the first one representing a price and the second its corresponding power. In practice, it turns out that there are three types of devices: (1) devices can only operate on discrete power values, (2) devices can operate on a continuous range of power values, and (3) devices can have both a region with continuous power values and a discrete part. A possible implementation of a bidding function in software, which supports all three types of devices, could be to add a power-price point for the complete price range. A device controller is responsible for determining a valid bidding function for its device. However, consider a device cluster containing hundreds of thousands devices, then it is of importance to represent bidding function with as little data as possible. Therefore, an it is better to only add price-power points that define a straight line. A horizontal line can be used for discrete power values and a continuous range of power values can be represented by a descending line. For the discrete power values, two adjacent price points that do not have the same power value will occur, i.e. a discontinuity in the bidding function. In order to guarantee that a values in between the discrete points will not be chosen, the MCP and OSP have to be integers. This is an implementation of formal definition as given in Section 4.1.2.

Integer clearing prices

The implementation of obtaining clearing prices can either be done by a floor, a ceil, or a round function. With the current prediction algorithms, it turns out that overall too little energy is predicted. Therefore, it is decided to floor the clearing price after is has been determined by the auctioneer. In this way, slightly more energy compared to the clearing of the auctioneer will be consumed.

5.2.2 How to construct a bidding function?

A bidding function should always be valid, i.e. comply to the definition in Section 4.1.2. Bidding function are determined step by step, i.e. points or lines will be added to a bidding function one by one. Globally, there are two implementation possibilities when it comes to adding a point (or line) to and existing bidding function.

In the first place, one can decide that the point which is to be added will be added anyway and that other points will be removed in case that the new point causes the bidding function to become invalid. The disadvantage is that one has no idea what will happen with the function when one single point is to be added. The second possibility is to add a new point only if it does not cause the bidding function to become invalid. In this way, a bidding function can be constructed more gradually because a bidding function will not be changed too much when one tries to add an invalid point. For the combined DSM approach this is more desired than guaranteeing that the last added point will always be present in the bidding function.

Discrete bidding functions

In addition to the base definition of a bidding function (see Section 4.1.2), there is a stricter requirement for discrete bidding functions. For a proper operation of the combined DSM approach a class 'BidFunctionDiscrete' was added. A function, contained in the QMap<int,double> of the class, complies to the definition of a discrete bidding function. A class method, called 'continuousToDiscrete', which transforms a continuous function into a discrete function, is written.

There are two possibilities for discretization. The horizontal lines of the discrete function can either be drawn above the continuous function or below it. For the application of an EV, it would be best to choose the second option because a quantization error is introduced during the process of discretization. If the horizontal lines are put below the continuous line, in reality the EV will charge slightly higher than the option in the planning, also implying that the compensation option will be slightly higher than necessary. From experience it appears that typically too little energy is predicted, and therefore it is favorable to charge slightly less at the end of the charging interval compared to charing a little more.

5.3 Finding a relation between real and predicted jobs

One of the encountered problems that had to be overcome is related to the way predictions are loaded into the Triana simulator. Unfortunately, the predicted jobs do not have a direct relation with the real jobs. Therefore, code is written in order to relate predictions to real jobs. All information, both predictions and real data, is provided by separated csv files. Each parameter has its own file with the values for the simulation run of that particular parameter. In code, the information is organized in a similar way. All parameters are stored in separated lists. In this way, it is not clear to which real job a predicted job belongs. This section describes how it is figured out to which predicted job a particular job belongs.

There are many ways in which predicted jobs and real jobs could relate to each other. For example, there can be overlap between the jobs or no overlap at all, in the latter case, a device may be delayed significantly. Also, it is possible that one large predicted job occurs as two jobs in reality or the other way around. Because there does not exist a direct relation between real jobs and predicted jobs, a straightforward implementation decision is made. The predicted jobs that has most overlap in time with the real job is the one assumed to belong to the job. The planning horizon is taken as time to look into future for finding the relation.

There are three important implications of the decisions. (1) A heavily delayed or unpredicted job will not be related to the predicted job it may have belonged to, (2) A predicted job can be found to belong to multiple real jobs, (3) A large real job may overlap with multiple, short predicted jobs. It should be better to take into account all short jobs that overlap with the real job.

Note that these implications only occur in case of very bad predictions. It is not quantified how many times the approach encounters the implications but a manual inspection of the predictions supports the claim that the predictions are proper enough to not suffer significantly from this problem. By the way, the event-based planning adaptation strategy will update the planning anyway. However, when it can use information from the prediction for this procedure it can do it more accurately.

An alternative would be to check for energy overlap instead of time overlap. This may not be accurate because the average charging power when the energy would be spread out evenly over the job may differ hugely from the power that is used when the device is really charged.

Chapter 6

Simulation

6.1 Simulation setup

In order to evaluate and compare the DSM approaches, a realistic use case is taken as scenario for simulations. When simulating a use case, one needs load profiles for households, a network topology and, obviously, a simulator. Before presenting the simulation results, this section provides a background on those three components.

6.1.1 Load profiles and flexibility information

Load profiles and flexibility information are required to run DSM simulations. Load profiles contain the power consumption/production per interval for a particular device or group of devices. Flexibility information, e.g. device start times and deadlines, or the requested state-of-charge for EVs, is needed for steering smart devices. In real life, flexibility information originates from a user and for simulation purposes, there are several options to get this information. An option is use questionnaires and interviews, but the drawback is that it requires a lot of work. Another option is to obtain the information from smart meters and smart appliances. However, apart from the fact that the infrastructure is currently not available to obtain the data on device level, this approach has privacy concerns. Actually, we are not looking for real data but for realistic profiles and flexibility information. Therefore, user behavior can be modeled and, by means of stochastic variables, realistic load profiles can be achieved. This approach is taken in [47]. Hoogsteen et al. present an artificial load profile generator which generates both load profiles and flexibility information. The approach has been validated by modeling a real street in Lochem, The Netherlands and comparing the simulated transformer profile with a measured profile at the transformer. As part of the validation, profiles of individual houses have been compared as well.

An important feature of the profile generator is that it generates profiles and flexibility information on device specific level. However, in contrast to comparable approaches, the model does not have to be defined for each and every device individually, this would be really cumbersome. Instead, classes exist which can be used to define a neighborhood, household, house, person, or device. The profile generator has some predefined configurations for those classes but custom configuration can be added as well. Stochastic variables are used to ensure diversity in user behavior by translating high level parameters into device specific ones. In order to generate realistic profiles, the approach uses generated user occupancy profiles as input for deciding whether a device will change its state.

6.1.2 The Triana Simulator

All simulations have been carried out by the Triana Simulator. The simulator is written at the University of Twente and supports many useful features for DSM simulations. It is build on the principles of the Triana methodology, i.e. prediction, planning and online control are executed in different steps. User input can either be provided via the GUI or by means of a python script. For the configuration of the scenario, a python script is used that defines all devices in the cluster by setting its configuration parameters (see Appendix B for more details). The values for consumption profiles and flexibility information is referenced by the python script. In addition, the network topology has been defined in the script as well.

Note that the version of the Triana Simulator used for this thesis did not have the prediction algorithms included in the simulator; they were obtained from an external python script. The predictions algorithms works as follows: predictions are made on basis of load profiles as generated by the load profile generator. For a particular time interval, the algorithm looks four weeks back and takes a weighted sum of the intervals in the preceding weeks. Mathematically, let $x(k)$ be the predicted power consumption for an interval k, Δt the interval length in seconds, and T the number of weeks in the past that the prediction takes into account, then:

$$x(k) = \begin{cases} 0 & : k < \frac{168}{3600}\Delta t \cdot T \\ \sum_{i=0}^{T}(T-i)\cdot x(k-(i+1)\frac{168}{3600}\Delta t) & : \text{otherwise} \end{cases} \tag{6.1}$$

The first intervals ($k < \frac{168}{3600}\Delta t \cdot T$) should be used for the predictions. The output is written to csv files and by means of the network configuration python script provided to the simulator.

The simulator supports physical grid modeling and load flow calculations such that PQ can be evaluated easily. The load flow calculations have been validated and provide comparable results as commercially available suites such as Phase2Phase's Gaia or the open-source grid modeling tool OpenDSS.

6.1.3 Diversity of a bidding function

To study the behavior of auction-based DSM, the diversity is an important measure to get insight in the auction operation. However, they are hard to define formally and therefore hard to quantify. The diversity in a bidding function is related to the amount of options that can be chosen by the auction, but also, for discrete power devices, the amount of power between two consecutive price values. During simulations, the latter plays an important role and therefore, the following definition of diversity is applied. The diversity d of a bidding function $b(p)$ is expressed by the following summation:

$$d = \sum_{p=-\bar{p}}^{\bar{p}-1} (b(p) - b(p+1))^2 \tag{6.2}$$

The interpretation is that the lower d, the less is the amount of discrete steps and the the less is the power difference of the steps, which is considered as good. Note that the definition does account for the difference between the minimum and maximum power value in the bidding function. This is a shortcoming of the definition because it means that a bidding function with a huge difference between the maximum and minimum power value but with only very small discrete steps (if they are there at all), still can have a higher value for d than a bidding function in which a large discrete step is the only power difference. The quadratic term will counteract this only partially but since the corner cases are not expected to occur in the simulations, the definition for diversity is considered proper.

6.1.4 Topology and DER penetration of the use case

The network topology used is based on a real street in the Dutch town of Lochem (see Figure 6.1). The street contains 81 houses, of which 22 are apartments, and are all connected to one feeder. In order to simulate a futuristic scenario with envisioned flexibility, the following devices have been added.

- 32 Electric Vehicles
- 18 houses with PV
- 8 houses with a battery (1x 2 kWh, 3x 12 kWh, 4x 5 kWh)
- All houses have a smart washing machine
- 1 out of 2 houses has a smart dishwasher

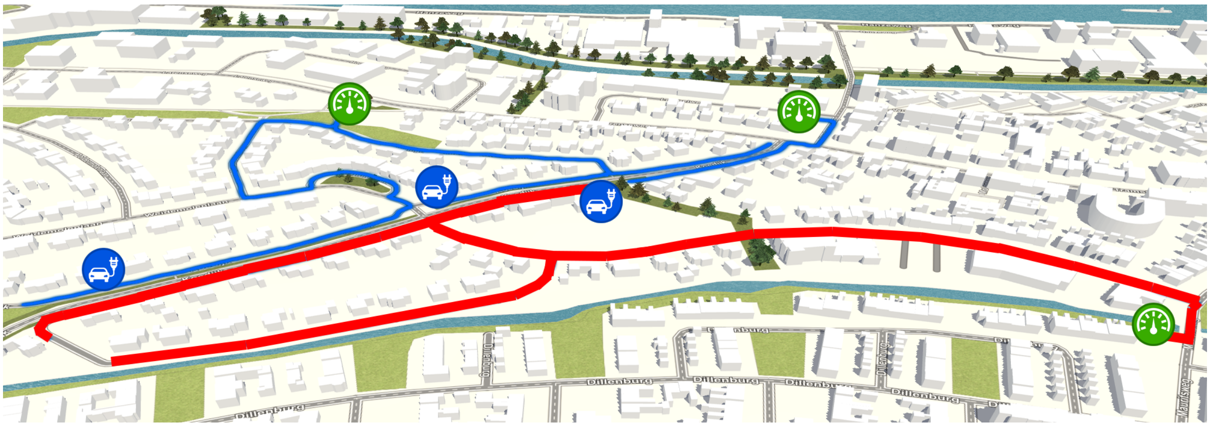


Figure 6.1: OpenStreetMap picture of scenario. The red line represents the feeder that is simulated.

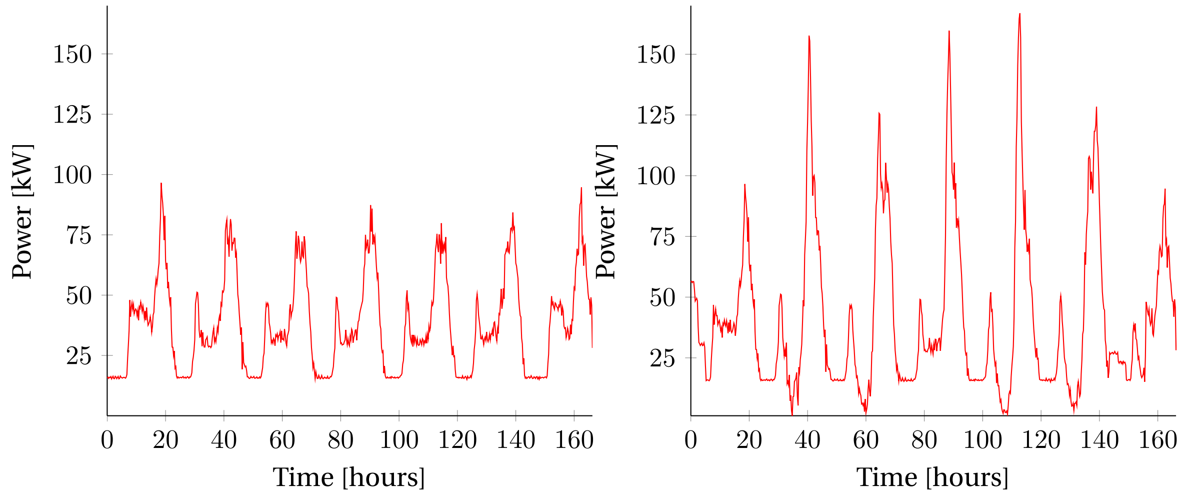
6.1.5 General simulation notes

Finally, the following notes apply to all simulations:

- The simulation interval is 9 days, of which only day 3 through 6 are presented in the plots, because startup and fade-out phenomena lead to unfair presentation of results. The four days presented correspond to the days Wednesday through Saturday of a winter week in the end of January/beginning of February.
- The interval length for the planning and online control is 15 minutes. In principle, Triana supports different intervals for different devices and steps of the methodology but 15 minutes intervals is a good starting point the balancing markets work on this interval as well.
- A planning is made every 24 hours, i.e. the planning interval is 96 time intervals (see Section 3.2.3 for background on the planning algorithm).
- A planning is determined for 48 hours, i.e. the planning horizon is 192 time intervals.
- The MCP and OSP are integers numbers.

6.1.6 Base load of the use case

Figure 6.2a shows the base transformer power profile of the use case. This corresponds with the situation as it is right now, so without EV, PV, batteries and smart appliances (dishwashers and washing machines simply start when they become available). As reference, a simulation has been run with the use case that includes above mentioned EV and PV but does not apply any DSM. The corresponding results in 6.2b show a enormous increase of peak demand, particularly in the evening. Also, during day-time, the generation due to PV shows already in winter that the cluster is on the limit of energy import. The loadflow calculations showed that many fuses in houses were overloaded and the transformer capacity was exceeded many times.



(a) Transformer power levels in the present situation. No EV, PV, batteries and control.

(b) Transformer power levels of the base load, including EV and PV but without control.

Figure 6.2: Base load of the use case as a reference.

6.2 Results from experiments

In this section, simulation results of several DSM approaches are given by the presentation of experiments. The experiments aim to give more insight in the separated approaches. In the section that follows the current one, the best results of the different approaches are presented by comparing three DSM approaches.

In the experiments, many references to the 'device-off point' are made. The device-off point is the minimum price in the bidding function for which the device is switched off. As will become clear from the experiments, the simulation outcomes are significantly influenced by the position of this price in the price range.

The following experiments have been executed:

- **Experiment 1**: Experiment 1 is concerned with the combined DSM approach that uses a planning on auctioneer level only, this approach is referred as PM-GP. In this experiment the power values in the planning are used to clear the market, i.e. to determine the price. The main goal of the experiment is to present the influence of a basic decision for the bidding function. This concerns the position of the device-off point in the bidding function.
- **Experiment 2**: The idea of Experiment 2 is similar as for Experiment 1, but now the DSM approach that uses a global planning for clearing the market and a bidding strategy for devices that incorporates the device planning is studied.
- **Experiment 3**: In Experiment 3, results of simulations that allow a continuous clearing price rather than a discrete price, which is used in Experiment 1 and 2, are presented. The experiment is performed because it shows how predicting too little energy leads the problems in following the planning.
- **Experiment 4:** Finally, Experiment 4 is performed to confirm the interpretation of Experiment 3 by adding a static amount of power to all planned power values such that a compensation for the energy prediction error is done.

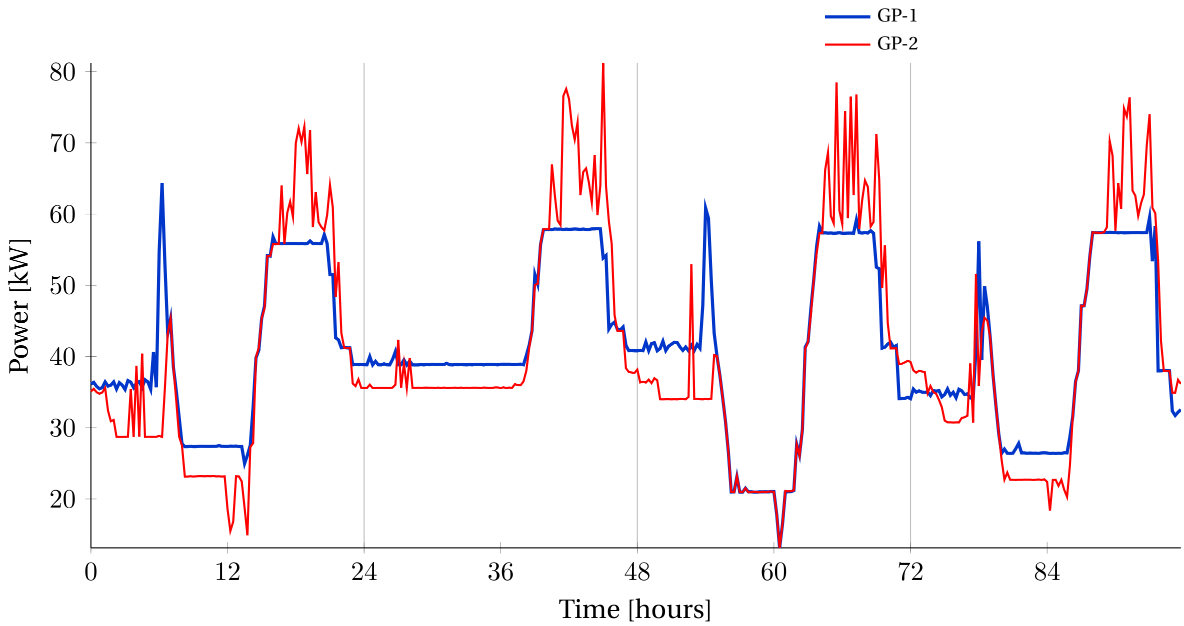


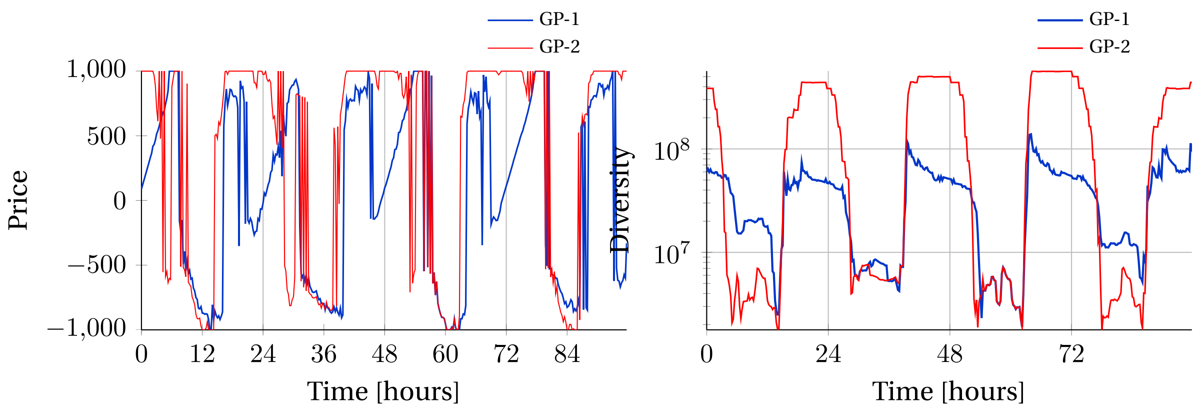
Figure 6.3: Ex1 - Transformer power profile to compare strategies with different prices for the device-off option

6.2.1 Experiment 1: On the bidding strategy with a global planning (PM-GP)

In this experiment, it is shown that the position of the device-off point significantly influences the power profile results. Based on insights gained during simulations, the bidding strategy described in Section 3.1.8 has evolved. Figure 6.3 and 6.4 show the results of an experiment with two different buffer-timeshiftable bidding strategies that finally led to the bidding strategy of Section 3.1.8. The blue curve (GP-1) corresponds to the strategy in which the minimum price to switch/keep the EV off depends on the time till deadline, and the red curve (GP-2) shows the results of the strategy in which this price is put at the maximum price.

Interpretation of the results

The diversity plot shown in Figure 6.4b, points at an important point: the diversity plot of the aggregated bidding function acquired in simulation GP-1 is much lower (which means that the diversity is higher) than the diversity plot of simulation GP-2. So putting the discrete step, caused by the device-



(a) Price plot

(b) Diversity plot

Figure 6.4: Ex1 - Price and diversity plots to compare strategies with different prices for the device-off option.

off point, for all devices on the same price (GP-2) leads to significantly less diversity in the aggregated bidding function compared to the situation in which the device-off point depends on the deadline.

Another observations is that the market clearing price curves (Figure 6.4a) are very different. The prices during night (when the EVs are being charged) of GP-2 fluctuate because of timeshiftable device's peak consumption but in general the MCP of simulation GP-2 is very high during night. This means that the market is cleared around the discontinuity in the bidding function. Because of the high price during night, undesired device behavior is observed, such as batteries being discharged at other times than planned or timeshiftable devices being shifted to the deadline. This results in peaks observed in the morning.

Another observation is that the transformer power of GP-2 in Figure 6.3 is substantially above the planning during the evening. The reason is the discretization of the MCP. In this experiment, the discontinuity must have been large because the difference between the power the auction thinks it clears, which is before the discretization, and the realized power is large. The effect is also that the EVs charge more between 6 pm and midnight such that the planning, which is determined at midnight, is lower with respect to the planning of GP-1 between 12.00 am and 8 am.

In general, it can be stated that the strategy of GP-1 is able to follow the planning better, so the strategy is considered to give the best results. However, the peaks in Figure 6.3 occuring in the morning are still pretty large. The reason of the peaks to occur is that the price just before the morning peak is high, after all, the EVs are close to the deadline. As a result, the batteries start discharging just before the morning peak and are empty during the morning peak. Hence, the morning peaks arise in the transformer power profile.

The most important interpretation of Experiment 1 is: the strategy in which the minimum price for switching an EV off depends on the time till deadline has a positive effect on enhancing the diversity of the aggregated bidding function and thus is capable of following the planning better.

6.2.2 Experiment 2: On the bidding strategy with device planning (PM-GDP)

In this experiment, the results of the bidding strategy that uses a global planning to clear the market and a bidding strategy for EVs that incorporates the device planning are presented and discussed. The strategy is referred as PM-GDP. Only the results obtained with the buffer-timeshiftable strategy (EP1), which is used for EVs, are presented by looking at the influence of some parameter values. Other devices use regular bidding strategies, see Section 3.1.8.

Buffer-timeshiftable bidding strategy

The result in Figure 6.5 and Figure 6.6 compare three simulation runs in which only the bidding strategy of the buffer-timeshiftable devices was changed. In these simulations, the influence of the position of the device-off point in the bidding function and the influence of two simulation parameters is studied. The two simulation parameters are related to bidding strategy that incorporates the device planning. In Section 4.3.1 the bidding strategy EP1 is introduced. In this bidding strategy, P_{step} is the parameter that defines the power difference between two planning adaptation options. The price is determined by (4.9), in which β is a price scaling factor.

The result of the following simulations are presented.

- **GDP-1:** The device-off point, is placed next to the minimum charging power. In addition, the price values of the power options are scaled by a factor 250, i.e. $\beta = 250$ and the step size between two power options, i.e. P_{step} is set to 20 W. The parameter value are chosen because they result in a flattened bidding function in comparison with the bidding function used in GDP-2 and GDP-3.

- **GDP-2:** The device-off point is placed at the maximum price. Furthermore, $\beta = 5$ and P_{step} = 50.
- **GDP-3:** The device-off point is placed on the price next the price of the minimum charging power that is present in the bidding function. Furthermore, $\beta = 5$ and P_{step} = 50.

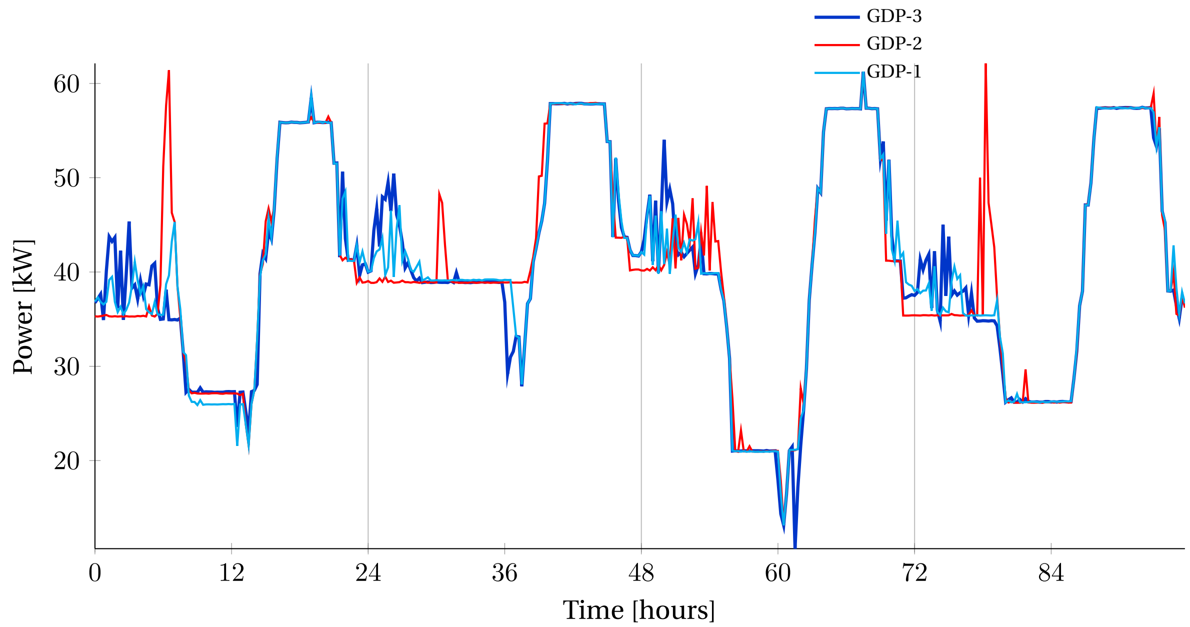


Figure 6.5: Ex2 - Transformer power profile of the bidding strategies with the device-off option on different prices.

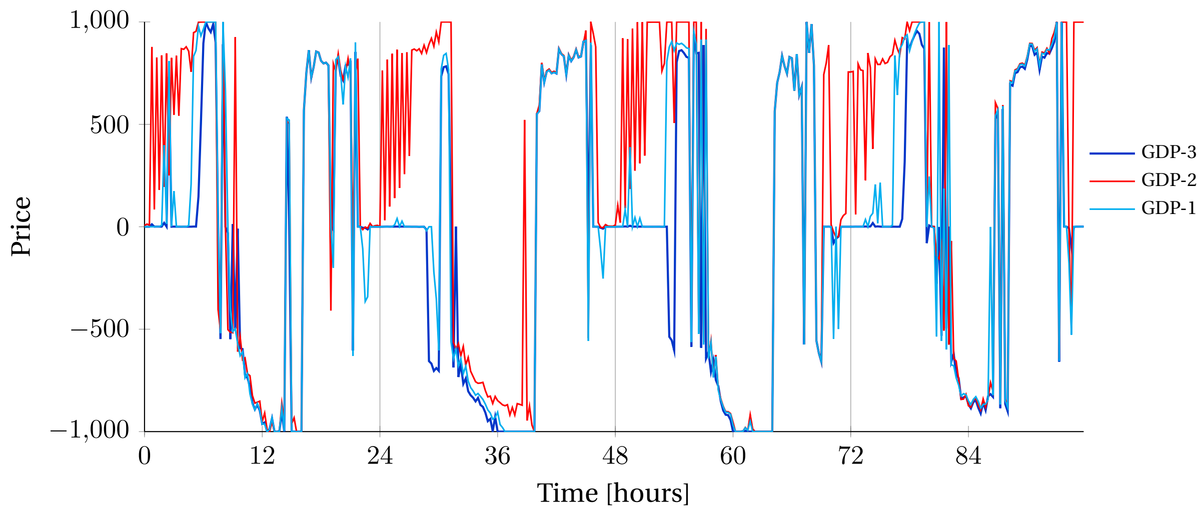


Figure 6.6: Ex2 - OSP curves of the bidding strategies with the device-off option on different prices.

Interpretation of the results

Just as in the observations of Experiment 1, the results of this experiment show that positioning the device-off point at the maximum price (GPD-2) leads to higher values in the diversity plot (Figure 6.7), i.e. less diversity in the aggregated bidding function. Again, the large discontinuity at the maximum in the aggregated bidding function is the cause of this.

Observations of the OSP graph of GDP-1 (Figure 6.6), shows that the price is very close to 0 during night. This means that, given the aggregated bidding function, the auction can easily follow the plan-

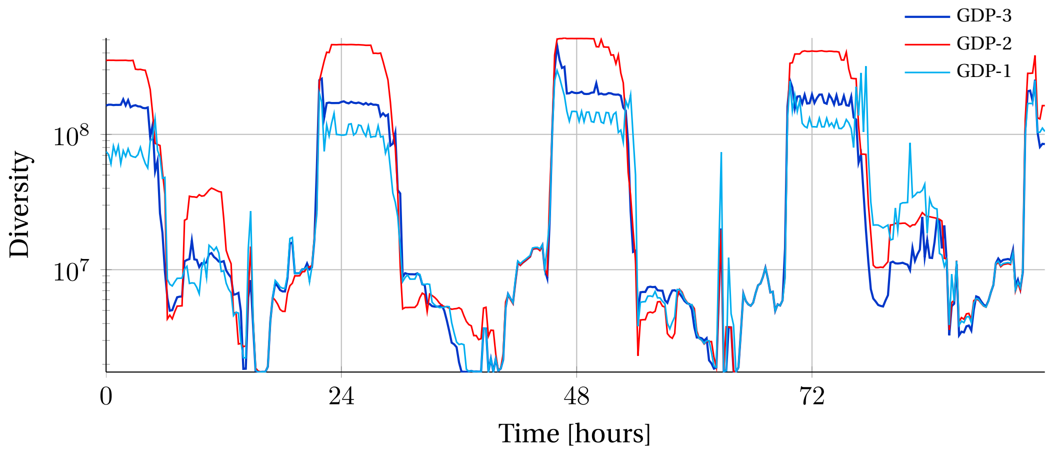


Figure 6.7: Ex2 - Diversity plot to compare the effect of the shape of the buffer-timeshiftable bidding function.

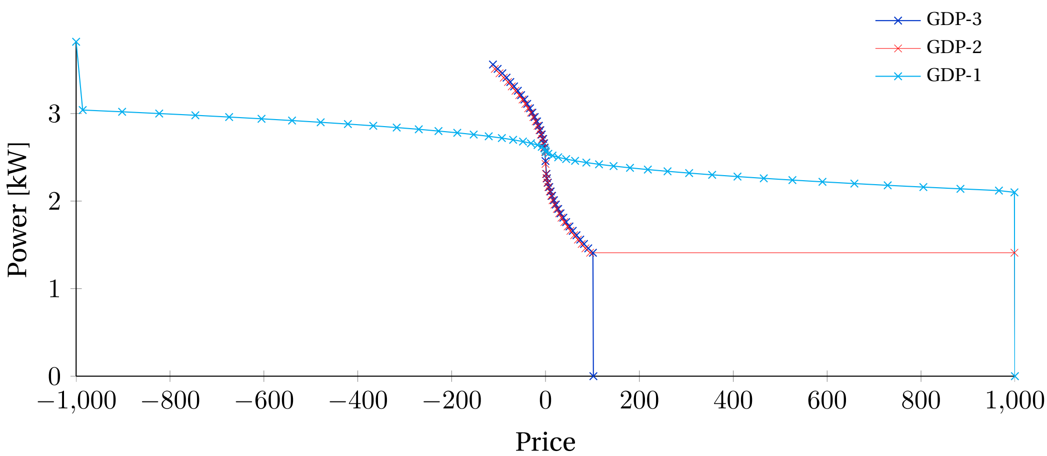


Figure 6.8: Ex2 - Comparing bidding functions of one EV on interval 192 (start of day 3).

ning. Although the price is close to 0, which indicates that the planning can be followed well, Figure 6.5 shows that power consumption during night is actually higher than the planned power. This is explained by the discretization of the OSP. The market is cleared at a non-rounded OSP and the power value of the integer price on the left-hand side is significantly higher. In other words, the auction 'thinks' that it clears at a value in between the two prices, i.e. the exact planned power value, but in reality a lower price, due to the floor function, - and thus a higher power value - is used by the devices to determine their consumption.

The former paragraph leads to an important interpretation: prediction errors in energy, i.e. unpredicted jobs, are solved by the discretization of the clearing price. In case that no floor function was applied on the OSP the similar behavior as observed in GDP-2 would occur, i.e. the price goes high to cope with unpredicted energy and as a result, the buffers start contributing to solve the unbalance and finally the morning peak would arise again because flexibility of the buffers is exploited during incorrect periods.

When comparing GDP-1 and GDP-2, Figure 6.5 shows that flattening the bidding function (GDP-1, the cyan curve) has a positive effect on the transformer power profile, i.e. the peaks occurring with GDP-1 are lower than the ones in the results of GDP-3. The explanation is as follows: the auction can determine the OSP more accurately in case of a flattened bidding curve. Again, the discretization of the OSP is the reason for this. However, the power value of the next integer price on the left-hand side of the non-rounded OSP is closer to the planned power in GDP-1 than it is in GDP-3.

During many intervals in the night, the price of GP-2 is above 700, which has as consequence that the batteries are discharging, while they were not scheduled to discharge in that period. As consequence, the batteries cannot provide the energy they were supposed to deliver during the morning peaks, which is observed in the peaks of GP-2 in Figure 6.5.

6.2.3 Experiment 3: Using a continuous clearing prices

In the interpretations of Experiment 1 and 2, it is argued that the discretization of the clearing price, which is implemented by a floor function, has as side effect that the problem of predicting too little energy is more or less solved. Experiment 3 will further underpin this interpretation. The results presented in Figure 6.9 have been obtained by using the very same settings as the simulations of GDP-3, so with non-flattened bidding function and the device-off point positioned next the minimum charging power. In the results, it is observed that the planning is followed for longer periods than in Experiment 1. However, the peaks occurring in the morning are significantly larger. This also appears in the numerical off-the-plan results: 9.43E+09 in this experiment vs. 5.70E+09 in Experiment 1. Observations of the batteries show that they are discharging during night, while they are not planned to be used in that period. A final observation is that many timeshiftable devices are, as result of the relative high price, shifted to their deadlines.

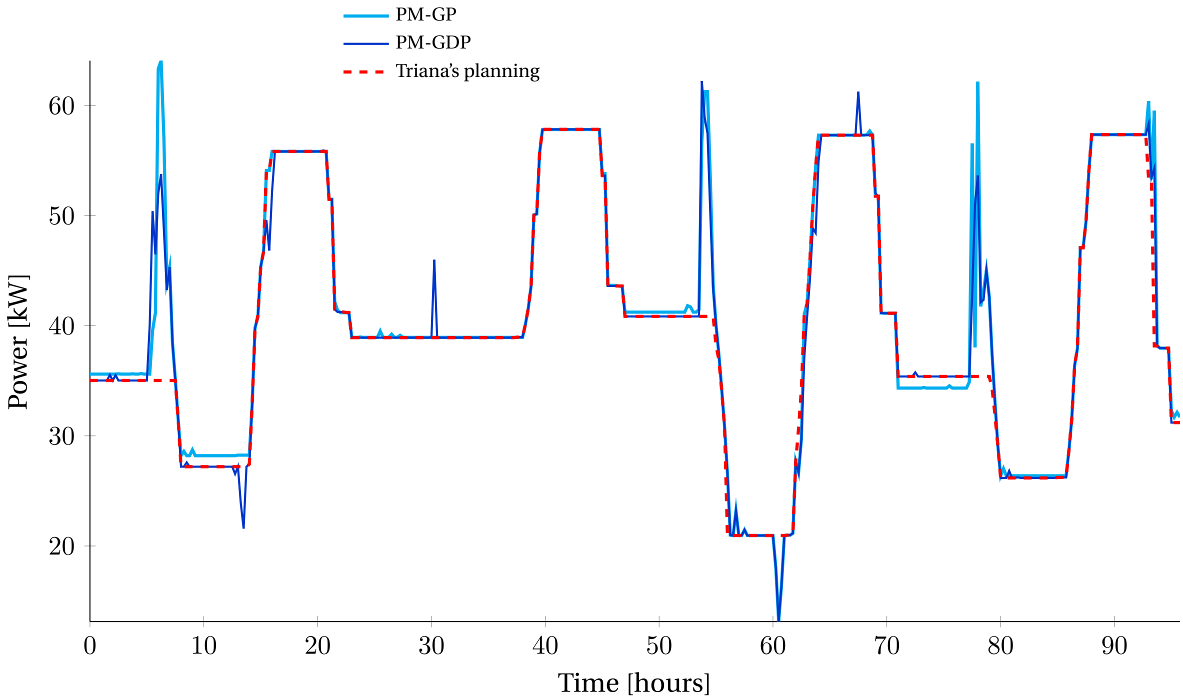


Figure 6.9: Ex3 - Transformer power profile of two bidding strategies, using a continuous MCP/OSP

Interpretation of the results

The large peaks in the morning point at the following problems: flexibility of batteries is exploited during incorrect periods, and when all flexibility of batteries is exploited and there is still too little energy, timeshiftable devices will be shifted to their deadlines. The underlying problem of these effects is that too little energy was predicted. Some of the jobs of timeshiftable or buffer-timeshiftable devices are simply not taken into account when the planning was determined. If the auctioneer tries to follow the planning by all means, larger peaks arise.

6.2.4 Experiment 4: Using a continuous clearing prices, with energy compensation

The most important interpretation of the results in Experiment 3 was that too little energy was predicted. As consequence, flexibility is used to deal with the prediction errors, leading to larger peaks in the morning. In Experiment 4, the behavior of a cluster in which enough energy is predicted is studied. This is achieved by adding an artificial compensation for the energy prediction error to the planned power values. This is done by subtracting the predicted amount of energy from the realized amount of energy in the simulation, which are both obtained from a previous run. The energy difference is spread out over the complete simulation interval by adding an average power deviation of 3400 W per interval to the planned power. Obviously, this solution is not suitable for real-life applications but the simulations are used to understand the operation of the cluster better. The result is shown in Figure 6.10.

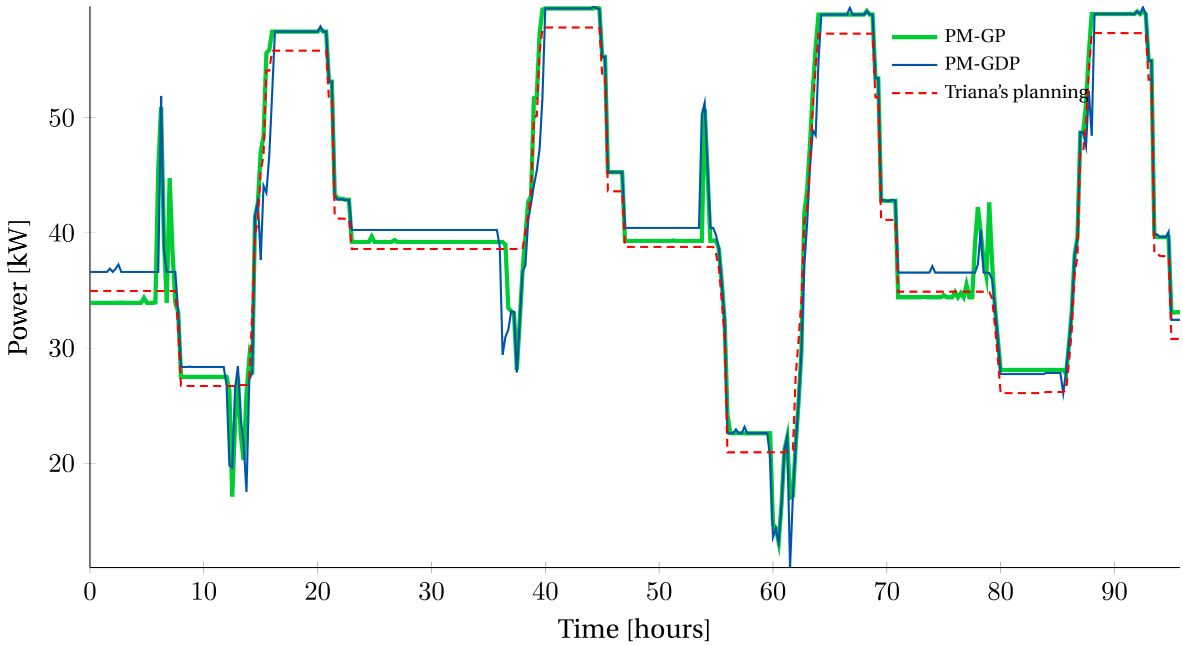


Figure 6.10: Ex5 - Transformer power profiles of the experiment with a continuous clearing price and energy compensation at the auctioneer.

The following observations can be done:

- The morning peaks that occurred in experiment 3 are both for PM-GP and PM-GDP significantly lower. Also, observations of the utilization of the battery show that flexibility provided by the battery is not exploited during night but that the energy from batteries is used in the morning, as it is supposed to be according to the planning.
- On the other hand, valley in Figure 6.10 that go below the planned power values are now introduced. This is caused by PV generation in the afternoon. The flexibility offered by the batteries is the root cause of the difference. Since the market is cleared at a higher power value, the batteries are full too early. As a result, energy from PV cannot be stored therefore less energy from the grid is needed.

Interpretation of the observations

Statically adding an amount of power to compensate for prediction errors is not a favorable approach because it needs external information, i.e. the amount of energy that was not predicted, and it only allows to compensate for power deviations in one direction. The latter drawback became clear from the observation that the batteries were charged too quickly because the clearing price was artificially lower. However, Experiment 4 is a conformation that the problems of experiment 3 indeed were caused by predicting to little energy.

6.3 Results of the comparison simulations

In this section, the best simulation results of the foregoing experiments, i.e. GP-1[1]and GDP-1[1], and the results of The PowerMatcher without a planning (PM) are compared with the each other. The approach referred as GDP is the one developed in this thesis and described in Chapter 4. Figure 6.11 shows the power profiles at the transformer, Figure 6.12 the MCP/OSP, and Figure 6.13 the load duration curve at the transformer.

- **PowerMatcher only (PM):** A simulation run in which the PowerMatcher without planning is used to clear the market at an average power level of 39.95 kW for this scenario. This value is obtained from a previous simulation run and is the average power value per time interval, i.e. if it would be possible to clear the market every interval at this value, all devices would have received/produced the requested energy.
- **PowerMatcher with global planning (PM-GP):** A simulation run which uses only a global planning from Triana to clear the market at power values that are the result of predictions and planning optimizations.
- **PowerMatcher with global and device planning (PM-GDP):** In this simulation, the bidding strategy developed in this thesis, which incorporates a device planning to determine the bidding function, is used.

Numerical simulation results are all tabulated in table 6.1. In this table, the values for 'off the plan' and 'off the average' are determined as follows. For every interval, apart from the ones in day 1 and 9, the difference between the planned power value and real power consumption is squared and summed to get one number for the whole simulation run. The deviation is squared because deviating more should be penalized more and it assures that negative deviations do not cancel out positive deviations. The same calculations have been done for 'off the average' but this was done after the simulation run, such that the average power value could be calculated. The values for 'peak deviation from average' are the difference between the maximum occurring power value at the transformer and the average power, so the maximum positive difference. Similarly, the 'valley deviation from average' gives the minimum negative difference between the power at the transformer and average power.

Table 6.1: Quantitative simulation results. 7 days of simulation.

	PM-GDP	PM-GP	PM
Off the plan:	3.47E+09	3.44+09	
Off the average:	8.79E+10	8.90E+10	4.75E+10
Energy consumed (MWh)	6.66	6.69	6.96
Peak deviation from avg (kW)	31.9	28.9	42.4
Valley deviation from avg (kW)	26.5	26.7	40.3
Max peak power (kW)	71.6	78.7	83.8
Min valley power (kW)	13.1	13.1	1.2

In Figure 6.11, The PowerMatcher without planning results show the largest peak deviations, the largest peak deviation from the average is reduced with 25 % when the GDP strategy is used compared to the PowerMatcher simulation. As shown in Table 6.1, the maximum peak values of the The PowerMatcher are reduced with 15 % in the GDP simulation. Note that the peak of GDP occurred in a interval that is not shown in Figure 6.11 because the figures only show four days while actu-

[1] In this section, the index -1, which refers to a simulation configuration in Experiment 1 or 2, is omitted

ally seven days of simulation are considered to provide valid results. The squared euclidean distance between the average and the power curve as shown in Table 6.1 is smaller for The PowerMatcher than for the other approaches. The high peak values are mainly caused by the synchronization of timeshiftable devices. Because of the high clearing prices for periods with a lot of demand, the start time of timeshiftable devices will be deferred until many devices run into their deadline, then they all run at more or less the same time, i.e. the devices are synchronized. Also, observations of the batteries show that they are not utilized on the 'desired' moments, i.e. they are not used to mitigate high demand peaks. Another important observation is that the prices are really extreme for large parts of the simulation interval. Finally, the load-flow calculations report that two fuses experience a higher current than they are rated for.

The peaks of PM-GP occur during the morning peaks. This is explained in interpretations of Experiment 1: the buffers are discharged too early with respect the planning and, consequently, the buffers do not contain enough energy to lower the morning peak.

The results of the strategy that uses the global planning and incorporates a device planning in the bidding function shows the smallest peaks. Instead, over a larger time during night, the deviations are spread out.

Above mentioned observations are also clearly visible in the load duration curve which is depicted in Figure 6.13

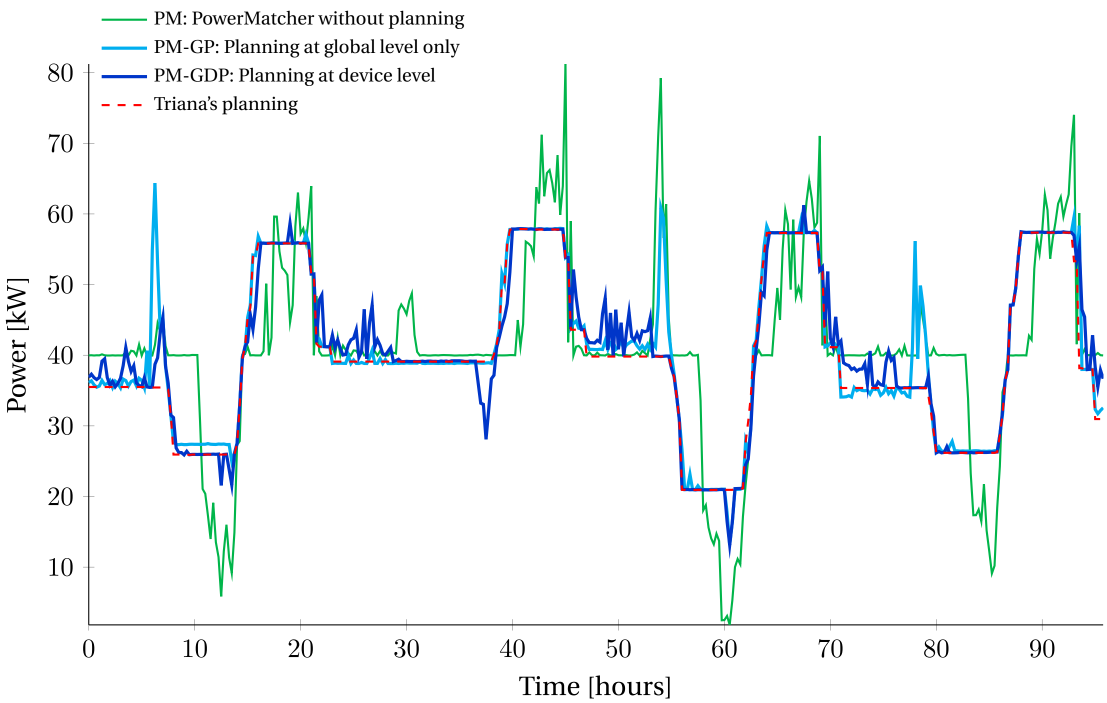


Figure 6.11: Transformer power profile of the three best simulation results from Experiment 1 and Experiment 2, together with The PowerMatcher results.

6.4 Discussion

The simulation result of the use case confirm the idea that a combination of The PowerMatcher and Triana leads to a DSM approach that builds on the strengths of both methodologies. Prediction errors in time can be dealt with very well. However, predictions errors in energy are more difficult because clearing the market on a value that presumes less energy than in reality is to be consumed, still leads

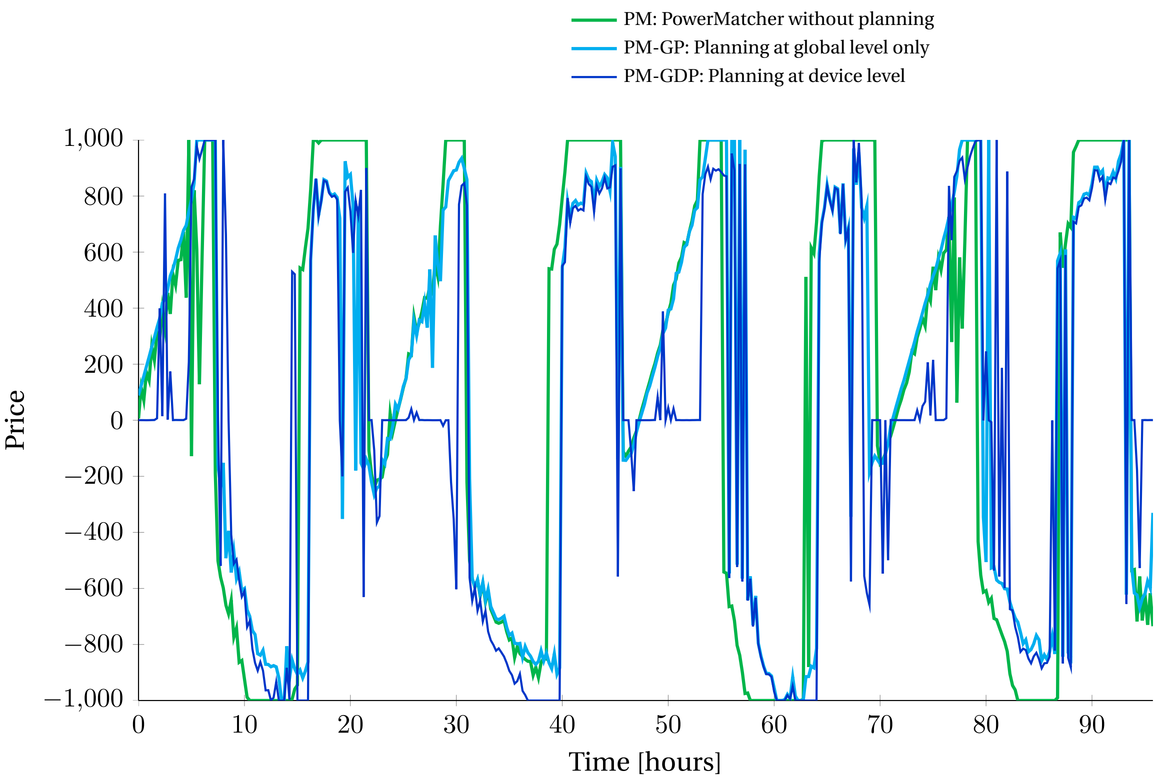


Figure 6.12: MCP/OSP of the three best simulation results from Experiment 1 and Experiment 2, together with The PowerMatcher results.

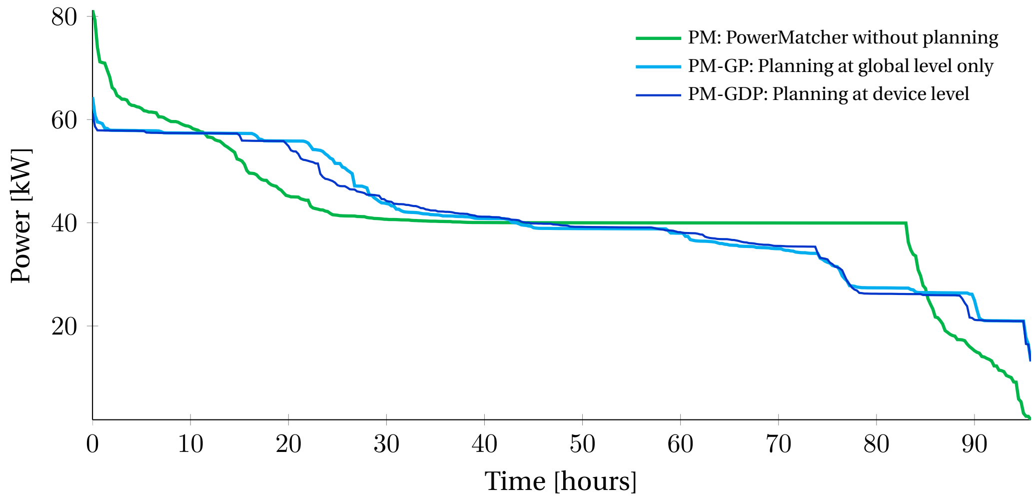


Figure 6.13: Load duration curve the of transformer power profile.

to the problem of exploiting flexibility on the wrong periods.

The combined DSM approach that uses a device planning provides a way to deal with predicting too little energy. The approach is based on the idea that flexibility can be 'saved' by only offering options that only deviate a little from the planning. In that case, the OSP is expected to take extreme values because the auction wants to use all flexibility provided to stay on the planned power value, which is too low. The extreme price values provide a very good indication that a too little energy is predicted and can for example be used by the auctioneer to compensate for the error. In the presented simulations, the extreme values for the OSP were not observed because the discretization of the clearing price already solved the problem of the prediction errors in the energy domain. However, this should not be considered as a general solution for predicting too little energy.

It should be understood that the bidding strategy in which a device planning is incorporated, provides an advantage over regular bidding strategies if not all options are provided to the auctioneer. Although the strategy already may lead to slightly better results if all options are provided - because of the quadratic term for evaluation planning adaptation options - the simulation results of the use case show that this advantage may not be significant. Note that if it is decided to 'save' flexibility, this will be a trade-off between, on the one hand following the planning and, on the other hand, offering options to the auctioneer for dealing with prediction errors.

An alternative solution to deal with predicting too little energy is to use the regular bidding strategies and let the auctioneer observe what the prediction errors are by inquiring when peaks occur. A challenge with this approach is that the occurrence of peaks does not give an explicit indication about the solution. For example, the typical morning peaks that were observed in the simulations of the use case, could best be solved by using a little more energy during night without extracting this energy from the buffers. However, the auctioneer has no information about the buffer levels and whether they are discharging or not. Therefore, theoretically, is better to take the device planning into account when the device determines its bidding function.

In the simulations, not all devices used a bidding strategy that incorporate the device planning. This may be an explanation that the results of the strategy provide only minor improvements with respect results of the strategy in which the device planning is not used. Also, the effect of the discretization of the clearing price has a significant influence on the overall power profile. Therefore, more simulation and improvements should be done in order to study the strategies better and provide more thoroughly argued conclusions.

Chapter 7

Conclusion

The combination of the DSM methodologies The PowerMatcher and Triana leads to a DSM approach that is more comprehensive than the individual methodologies themselves. The planning from Triana, which is based on predictions, can be provided to a PowerMatcher implementation, resulting in an approach that follows the planning while dealing with prediction errors. This is an improvement with respect to The PowerMatcher because it provides a powerful way to achieve not only a momentary balancing of energy, which is a strength of The PowerMatcher, but also a solution that is optimized taking a larger time span into account. This mitigates the effect of exploiting flexibility on moments that leads to balancing problems later on. The simulation results of the comparison study (Section 6.3) shows that the largest peak deviation from the average is 33 % higher for The PowerMatcher compared to approach that uses a device planning for determining the bidding function.

Comparing the combined DSM approach with Triana, it is concluded that applying an auction-based approach is very suitable as implementation of Triana's real-time control step. The combined approach provides a fast way of balancing and it is shown that following the planning from Triana is possible.

Former two paragraphs answers the main research question in very general terms. In Chapter 1, the main question was presented and it is quoted below, after which a more detailed answer is provided:

> **Main question:** How can The PowerMatcher be extended with a planning from Triana and what is the performance, from a network point of view, of the combined energy management system in a residential microgrid setting?

To provide an answer to the research question, two options for incorporating the planning of Triana in The PowerMatcher have been compared. In the first place, the option of only using the planning at auctioneer level to clear the market at a global planned power value is evaluated. This option is the most extreme possibility of the combination with respect to the level at which the planning is provided in the PowerMatcher hierarchy, i.e. at the very top of the hierarchy. In the second place, the possibility of incorporating a device specific planning in the bidding strategy of a device has been studied; this is the other extreme of providing a planning to The PowerMatcher, i.e. at the bottom of the hierarchy. In Chapter 4 a novel bidding strategy for device agents to incorporate a device planning in the bidding strategy is presented.

The effect of taking a device specific planning for EVs into account has been evaluated by simulations of a use case. The simulations did not point at significant advantages over the option of only using a global planning. Instead, more basic decisions for determining the bidding function, such as the minimum price for which the device is switched off, have more impact. It is important to consider that not all devices in the simulations used a device-planning based bidding strategy, which partly explains that no significant advantages were observed.

Furthermore, it is concluded that the problem of predicting too little energy in the cluster was not solved by either one of the strategies. In principle, the bidding strategy that incorporates a device specific planning is capable of solving this problem better because it is based on the idea that not all flexibility is provided to the auction. However, this could not be observed in the simulation results obtained from the use case.

Although the combined DSM approach still can be improved, it already can be stated that the combination of The PowerMatcher and Triana provides a very powerful way to achieve short term balancing on the one hand, and optimizations for longer time spans on the other hand.

Future work

Several improvements with respect to the combination of The PowerMatcher and Triana can be made. For the bidding strategy that incorporates a device planning, it is recommended to finish the bidding strategy for timeshiftable devices and develop a strategy for buffers. When that is accomplished, all devices use a planning as input while determining the bidding function. It is expected that this mitigates the effect of exploiting flexibility on unplanned periods even further.

It is recommended to run extra simulations for comparing the two possible combinations. For example, a simulation with tighter deadlines for EVs would be interesting because the planning of many EVs in the simulations in this thesis were similar, which means that the influence of using the device planning in the bidding strategy on the power profile at the transformer decreases.

With respect to the problem of predicting too little energy in the cluster, and therefore, clearing the market on a too low power value, the following improvement is suggested: a learning algorithm, which estimates how large the error of the energy prediction is, can be added to the auctioneer. The auctioneer can use the estimations for clearing the market at a value that is compensated for the prediction error. The estimation can be calculated by considering time intervals in the past, i.e. observing the difference between the planned power value and the realized power value in the past intervals. In order to implement this, using the bidding strategy developed in this thesis is advantageous over using the normal strategies. The reason is that bidding functions that incorporate the device planning provide information to the auctioneer about the realized total amount of energy in the cluster because devices update their planning individually.

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Appendix A

Software contributions

The most important additions are the implementation of the bidding strategies which is described in Chapter 4. Mainly, the focus has been on the strategy for buffer-timeshiftables (strategies EP1 and AP1, see Section 4.3.1 and 4.3.2, have been implemented). An important addition is the 'adaptedPlanning', which is just as a normal planning a QVector<double>, to the controller basis. The adapted planning is used by both the event-based planning adaptation and auction-based planning adaptation algorithm to keep the planning comply to the information known as accurately as possible. The device specific classes have functions to adapt the planning. In the first place, in the class 'TrianaBufferTimeShiftableController', the functions that follow in this section have been added. The pointers that are passed as argument to the functions are (1) a pointer to a TrianaBufferTimeShiftable object, this is the buffer-timeshiftable which is linked to this controller and (2) a pointer to a SimulationControl object, which contains some useful simulation variables such as the current time interval.

BidFunction setupBidFunction(TrianaBufferTimeShiftable *, SimulationControl *)
The function *setupBidFunction()* is used to see whether some corner case is reached. For example, if an EV is that close to its deadline that it should charge at maximum power, the bidding functions only contains that option. If no corner cases are reached, the planned power for the device is put at the nominal price.

void extendBidFunction(TrianaBufferTimeShiftable *, SimulationControl *)
In the function *extendBidFunction()*, the actual algorithm of Section 4.3.2 is implemented. For several power options, the consequences for the planning are evaluated and expressed as a price. The price-power option is added to the bidding function and the option is stored such that the planning can be really adapted (this is done by the function *adaptActivePowerPlanning()*) when the option will be chosen by the auction.

void eventPlanAdaptation(TrianaBufferTimeShiftable *, SimulationControl *)
The function *eventPlanAdaptation()* contains the algorithm described in Section 4.3.1. It is called at the moment the EV becomes available and updates the adaptedPlanning vector such that it complies to the run-time information.

void adaptActivePowerPlanning(int) override
The function *adaptActivePowerPlanning()* is called when the OSP is received. It performs a discretization of the bidding function such that a power look-up can be done for the OSP. Based on the power that results from the look-up, the corresponding planning adaptation option is applied to the adaptedPlanning vector, after which the discrete function is obsolete.

Also, the implementation for timeshiftables (strategies ET1 and AT1) is added to the class 'Triana-TimeShiftableController' by the following methods:

void eventPlanAdaptation(TrianaTimeShiftable *e, SimulationControl *simCtrl)
Again, the functions for timeshiftable devices are the implementation of the algorithms described in corresponding section of Chapter 4. The function *eventPlanAdaptation()* contains the implementation of the strategy ET1, see 4.3.1. If the device is scheduled, it searches in the planning for the start time and stores the start time. If the device is not scheduled, it takes a random start time between the current time interval and the deadline minus run time, and stores the start time.

BidFunction determineBidFunction(TrianaTimeShiftable *e, SimulationControl *simCtrl)
Based on the start time, which is set in *eventPlanAdaptation()*, and the deadline, the function *determineBidFunction()* will constitute a bidding function that aims to make the device run from the planned start time but also gives some slack to run earlier or later. The window of the slack is a parameter.

Appendix B

Simulation configurations

The simulation have been run with a python script that contains all the configuration parameters. This script can be found in the repositories under the name: "models/lochem_realtimebench/more ComprehensiveDSM-model.py". The commmit that references to the code used for the simulation is: 012d6c15b7240696ca3aec7196964571a8e6e0e4, "More Comprehensive DSM simulations".

The experiments have been run with the following parameters:

Default parameter values

intervalLength = 15*60
timeIntervals = 4*24*9
startInterval = 42474

control = True
planning = True
initialPlan = True
RtControl = True
usePlanningInRT = False
useDiscretebids = True
ExtendedBid_ev = True
ExtendedBid_ts = False
optionsDeltaP = 50
optionPriceScaling = 5
ev_discrete_charging = False
energyCompensation = 0

In the file 'TrianaBufferTimeShiftableController.cpp', either the line 704 or 705 (is default) is commented out. This means that default the simulation have been run with the following active code:
newBid.addDeviceOffPoint(newBid.getFunction().lastKey()+1);

Experiment 1

GDP-1:
optionsDeltaP = 20
optionPriceScaling = 250

GDP-2:
newBid.addDeviceOffPoint();

GDP-3:
newBid.addDeviceOffPoint(newBid.getFunction().lastKey()+1);

Experiment 2

GP-1:
ExtendedBid_ev = False

GP-2:
ExtendedBid_ev = False
Default parameters and the line 293 in 'TrianaBufferTimeShiftableController.cpp' being active such that device-off point is positioned at the maximum price.

Experiment 3

GDP:
useDiscretebids = False

GP:
useDiscretebids = False
ExtendedBid_ev = False

Experiment 4

GDP:
useDiscretebids = False
energyCompensation = 1656

GP:
useDiscretebids = False
ExtendedBid_ev = False
energyCompensation = 1656

PowerMatcher without planning

planning = False initialPlan = False ExtendedBid_ev = False

Cleared at: 39952.4 W (added on line 617 in 'TrianaGroupController.cpp')