# On the three-step control methodology for Smart Grids

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# Abstract

Energy usage, dependability of energy supply and climate change are important topics in society. Today, a number of trends can be recognized in the electricity consumption and generation. On the one hand, the electricity consumption increases and becomes more fluctuating. This is caused by increasing economic activity and prosperity, but also by a shift towards more electricity supplied devices, for example electrical cars. On the other hand, the projected reduction in $CO_2$ emission requires the introduction of generation based on renewable sources. These renewable sources are based on uncontrollable and very fluctuating sun-, water- and wind power.

These trends introduce challenges to maintain a reliable and affordable electricity supply. Fluctuations in electricity demand decrease the efficiency of conventional power plants. Furthermore, peak demands determine the required generation and transportation capacity, higher peaks require more generation and transportation capacity. Moreover, renewable generation often does not match the demand profile and in addition to that inefficient peak power plants have to supply this fluctuating mismatch between generation and demand. Furthermore, since all produced electricity must be consumed, in the current electricity supply system the lowest demand results in an upper bound on the renewable generation. Therefore, only a limited amount of the demand can be supplied by renewable sources.

A solution to these problems may be to transform domestic customers from static consumers into active participants in the production process. Consumer participation can be achieved through the development of new (domestic) devices with controllable load, micro-generation and domestic energy storage of both heat and electricity. These devices have potential to shift electricity consumption in time without harming the comfort of the residents. Examples of devices with optimization potential are (smart) freezers and fridges which can adjust their cooling cycles to shift their electricity load and (electrical car) batteries that can temporarily store excess electricity. To exploit this optimization potential on a large scale, a global control methodology is required. In this thesis the above mentioned challenges and optimization potential are studied and a control methodology is derived. This control methodology aims 1) to achieve a more efficient use of the generated electricity of existing power plants, 2) to facilitate the large scale introduction of renewable sources and 3) to allow large scale introduction of new technologies for production, consumption and storage while at the same time maintaining grid stability and ensuring a reliable and affordable supply.

In this thesis, first a model of the energy infrastructure is derived. This model consists of multiple levels: the leaves are the devices within buildings, modelling a building as a collection of devices each with their own behavior and optimization potential. These devices can convert, buffer and consume energy and are connected to each other in such a way that energy can flow between these devices. Buildings can exchange energy with their outer world and multiple buildings can be combined into a grid. The electricity grid also consists of multiple levels, from the low voltage distribution level up to the high voltage lines connected to power plants. The different levels are connected by transformers, which are converting devices with their own characteristics (e.g. capacity). The low voltage distribution level can be split up in multiple segments, each with a number of buildings connected. These individual segments model a neighborhood, whereas multiple neighborhoods can be combined into a city, etc.

The core of the developed control methodology is a three-step control methodology introduced in this thesis. The goal of this control methodology is to tackle the above mentioned challenges by exploiting the domestic optimization potential of domestic customers. Domestic is in this case broader than only houses, it comprises all consumers at the distribution level: houses, schools, shops, factories, etc. The control methodology is based on a three-step approach to monitor and manage domestic energy demand as well as the generation and storage of the energy. In the first step, the energy usage or production for every individual building in the grid is predicted on a device level. In the second step, the predictions of the individual buildings are aggregated and a global planning is made in an iterative and hierarchical way. The result of this planning is an energy profile. In the last step, a local scheduler in every building schedules the devices in realtime, using steering signals determined by the global planning as an input. The base of all three steps of the control methodology is the mathematical analysis of the energy streams expressed in the energy infrastructure model in combination with mathematical optimization techniques. The main focus of this thesis is on the three-step control methodology and in particular on the last step of this control methodology.

The aim of the third step of the proposed control methodology is to decide which devices are to be switched on and when. The main task of the realtime controller of the third step is to guarantee the comfort level of the residents. Within the boundaries of this comfort level, it can exploit scheduling freedom to work towards certain objectives. The control methodology can use the steering signals from the global planning as input, but may optionally also incorperate realtime inputs. The overall control methodology can have two types of optimization objectives: 1) it can work towards a predefined consumption profile (e.g. lower peaks) or 2) it can react on realtime fluctuations (e.g. caused by renewable sources).

The planning determined by the second step of the control methodology is based on the predictions of the energy usage and behavior of customers, expressed in predictions of when and for how long devices are running (runtime). Based on these predictions and the objective of the optimization, a planning for the runtimes of devices can be derived. However, the actual behavior often deviates from the predictions (prediction errors). Due to these prediction errors, the actual situation often deviates from the predicted situation and it is not possible to stick to the planning. Furthermore, the steering signals do not always fit with the current situation anymore and can result in decisions that are very disadvantageous for later periods. The last step has to try to work around these prediction errors while keeping the closest possible to the planning. Therefore, the realtime controller is extended with Model Predictive Control (MPC). Within a Model Predictive Control approach the realtime controller not only takes the current situation into account, but also a certain period in the future. Short-term predictions of the behavior of the devices are made and based on the current situation, the short-term predictions and the steering signals, the best decision for the current situation is taken.

The decisions of the realtime controller are based on cost functions. The preferences and optimization potential for every device are expressed using cost functions. These cost functions express the desirability of possible choices. Furthermore, the steering signals of the global planner are also expressed as cost functions. Based on the cost functions and (technical and social) constraints the best decisions can be determined by the realtime controller. Cost functions are a very generic way of expressing preferences and optimization potential of devices and technologies. However, it is important to define the cost functions correctly, otherwise undesirable and unpredicted behavior can occur.

Based on the model of the energy infrastructure a simulator has been developed to simulate future energy infrastructure scenarios and control methodologies to tackle earlier mentioned challenges. The simulator is based on discrete simulations and the design is kept the closest possible to the energy infrastructure model. Individual buildings are specified on a device level and multiple buildings are combined into a (Smart) Grid. The simulator is fast, it can simulate a large group of buildings within reasonable time. Furthermore, it is generic in the sense that it allows to simulate a lot of different scenarios, technologies and control methodologies. The modular structure of the simulator eases the addition of models of new technologies and due to initiation through configuration files it is easy to define (large) scenarios. The extensive logging capabilities of all elements of the simulator enables the possibility to study the simulation results in detail. The possibility to use real world data for the simulations and the ability to use a broad range of stochastic variations helps to define a realistic scenario with only a limited amount of input data.

To study the effectiveness of the control methodology, to find the best parameters of the control methodology and to study the most economic use of the flexibility of devices, multiple scenarios have been simulated. The simulations show that the control methodology can optimize the energy flows and can control the operation of the domestic devices in an economic manner without discomfort for the residents. The prediction and planning step preceding the realtime control improves the results of the control methodology: much more optimization potential can be exploited and the results are more predictable and dependable. Furthermore, the addition of MPC strengthens the capabilities of the realtime controller to work around prediction errors.

Prototype experiments show that it is possible to incorporate the optimization algorithms in a real prototype and that the algorithms are able to manage the behavior of the devices within the comfort levels. Furthermore, experiments show that a microCHP device can act as a backup generator in case of a power cut: a disconnected grid situation was created using a microCHP device, a battery and multiple devices controlled by the optimization algorithm.

Based on the simulations and prototype experiments we conclude that the control methodology can monitor and adjust the consumption profiles and electricity streams. It can use the optimization potential of a large group of buildings to work towards global objectives. However, it requires a change of mind of customers to give the control of their devices to a global controller. The combination of prediction, planning and realtime control is a promising direction for control methodologies for Smart Grids: it is scalable, generic and reliable. The three-step approach can provide an important contribution to realize the European 20-20-20 ambition [22].

# Samenvatting

De laatste jaren zijn energieverbruik, betrouwbaarheid van de energievoorziening en klimaatveranderingen steeds belangrijkere onderwerpen van discussie geworden. Op dit moment kunnen een aantal tendensen onderscheiden worden op het gebeid van elektriciteitsconsumptie en -productie. De elektriciteitsconsumptie neemt toe en wordt steeds fluctuerender. Dit wordt enerzijds veroorzaakt door de toenemende welvaart, maar ook doordat steeds meer apparaten elektriciteit gebruiken als energiebron. Een voorbeeld hiervan is de elektrische auto. Daarnaast wordt een groeiend gedeelte van de elektriciteit gegenereerd op een duurzame manier: de beoogde reducties in $CO_2$ uitstoot kunnen alleen behaald worden wanneer meer elektriciteit wordt gegenereerd met behulp van duurzame bronnen. Deze duurzame generatie is vaak gebaseerd op onbestuurbare en zeer fluctuerende zon-, water- en windenergie.

Door deze veranderingen zowel aan de consumerende als aan de genererende kant wordt het betrouwbaar en betaalbaar houden van de elektriciteitsvoorziening steeds lastiger. Omdat alle elektriciteitvraag voorzien moet worden, bepaalt de hoogste piek in de elektriciteitsconsumptie de minimale capaciteit van de elektriciteitsgeneratie en van het elektriciteitsnet. Fluctuerendere vraag en daardoor hogere pieken vereisen dus een hogere generatie- en netwerkcapaciteit. Daarnaast veroorzaken de fluctuaties in de elektriciteitsvraag een afname van de efficiëntie van de conventionele elektriciteitscentrales. Verder is de generatie van duurzame bronnen in het algemeen niet bestuurbaar en vaak fluctuerend waardoor de hoeveelheid elektriciteit die gegenereerd wordt door duurzame bronnen vrijwel nooit gelijk is aan de elektriciteitsvraag. Het (fluctuerende) verschil moet bijvoorbeeld gegenereerd worden door inefficiënte (gasgestookte) piekcentrales. Bovendien moet alle elektriciteit die gegenereerd wordt ook geconsumeerd worden. Daarom mag in de huidige electriciteitsinfrastructuur de maximale productiecapaciteit van duurzame bronnen niet groter zijn dan de minimale elektriciteitsvraag. Het gevolg hiervan is dat slechts een beperkte hoeveelheid van de elektriciteitsvraag voorzien kan worden met behulp van duurzame bronnen.

Een mogelijke oplossing voor deze problemen is het veranderen van de eindgebruikers van statische consumenten in actieve deelnemers in de energieketen. De ontwikkeling van nieuwe apparaten met een verschuifbare elektriciteitsvraag, microgeneratie en opslag van elektriciteit en warmte in huis maken het mogelijk voor eindgebruikers om actieve deelnemers te worden. Met dit soort apparaten is het mogelijk om de elektriciteitsvraag (en lokale productie van microgeneratoren) te verschuiven in tijd zonder dat het comfort van de gebruikers wordt geschaad: het energieprofiel kan (gedeeltelijk) afgestemd worden op de generatie. Een voorbeeld van apparaten met de mogelijkheid om de elektriciteitsvraag te verschuiven in tijd zijn (slimme) vriezers en koelkasten. Deze apparaten kunnen hun koelcyclus aanpassen waardoor de elektriciteitsvraag verschuift. Een ander voorbeeld is het gebruik van batterijen (van elektrische auto's) die tijdelijk elektriciteit op kunnen slaan. Om het potentieel van deze apparaten maximaal te benutten is een besturingsmethode nodig die op grote schaal het potentieel van alle apparaten benut. In dit proefschrift zijn de bovenstaande veranderingen bestudeerd en wordt een besturingsmethode voor het gebruiken van het optimalisatiepotentieel van eindgebruikers besproken. Het doel van deze methode is om 1) de efficiëntie van bestaande elektriciteitscentrales te verhogen, 2) de introductie van generatie gebaseerd op duurzame bronnen op grote schaal te vergemakkelijken en 3) de introductie van nieuwe technologieën voor decentrale productie, consumptie en opslag van energie op grote schaal mogelijk te maken, waarbij het elektriciteitsnet stabiel blijft en de elektriciteitsvoorziening betrouwbaar en betaalbaar moet blijven.

In dit proefschrift wordt eerst een model van de energie infrastructuur afgeleid. Dit model is opgebouwd uit verschillende niveaus. Het laagste niveau wordt gevormd door de apparaten in gebouwen. Voor ieder apparaat zijn eigenschappen gedefinieerd: technische eigenschappen, de consumptie- en productiecapaciteit en de keuzevrijheid binnen het vereiste gedrag (optimalisatiepotentieel). De apparaten kunnen energie van vorm converteren (bijv. gas in warmte), opslaan en consumeren. Alle apparaten zijn zo met elkaar verbonden dat energie van het ene naar het andere apparaat kan stromen. Een gebouw is vervolgens gemodelleerd als een verzameling van apparaten. Gebouwen kunnen op hun beurt energie uitwisselen met hun omgeving en meerdere gebouwen samen vormen een wijk. Het elektriciteitsnet op zich bestaat ook uit verschillende niveaus: van het laagspanningsdistributienetwerk waarmee de gebouwen verbonden zijn tot het hoogspanningsnet waar de elektriciteitscentrales mee verbonden zijn. De verschillende spanningsniveaus zijn verbonden met transformatoren. Deze transformatoren kunnen gezien worden als converterende apparaten met hun eigen eigenschappen (bijvoorbeeld de capaciteit). Het laagspanningsdistributienetwerk kan onderverdeeld worden in meerdere segmenten, waarbij ieder segment met een aantal gebouwen is verbonden. Deze losse segmenten modelleren wijken, meerdere wijken kunen met behulp van een hoger spanningsniveau samengevoegd worden tot een stad, etc.

De kern van de besturingsmethode die we ontwikkeld hebben is een drie-staps besturingsmethode. Het doel van de methode is om de drie bovengenoemde doelen te halen door het optimalisatiepotentieel van de eindgebruikers te gebruiken. Met eindgebruikers worden in deze context alle gebruikers op het distributieniveau bedoeld: huizen, scholen, winkels, fabrieken, enz. De methode gebruikt drie stappen om de energieconsumptie en -productie van de eindgebruikers te monitoren en te reguleren. In de eerste stap wordt de energieconsumptie of -productie voor ieder individueel apparaat voorspeld. Daarna worden in de tweede stap deze voorspellingen verzameld en wordt op een iteratieve en hiërarchische manier een planning gemaakt. Deze planning wordt gemaakt voor de hele groep eindgebruikers die in het optimalisatieproces meegenomen worden. Het resultaat van deze planning is een energieprofiel voor de groep van eindgebruikers. In de laatste stap beslist een realtime regelaar, die geïnstalleerd wordt in ieder afzonderlijk gebouw, welke apparaten wanneer aan gaan en voor hoe lang, mede op basis van de stuursignalen die zijn afgeleid van de gemaakte planning. De basis van alle drie de stappen is een wiskundige analyse van de energiestromen in het model van de energieinfrastructuur gecombineerd met wiskundige optimalisatietechnieken. De focus van dit proefschrift ligt op deze drie-staps besturingsmethode en in het bijzonder op de laatste stap van de methode.

Het doel van de derde stap van de voorgestelde methode is het beslissen wanneer welke apparaten aan of uit gaan. Een belangrijke randvoorwaarde hierbij is om het comfort van de eindgebruikers te garanderen. Binnen de grenzen van dit comfort kan het regelalgoritme de keuzevrijheid gebruiken om bepaalde doelen te bereiken. Hierbij kunnen de stuursignalen van de planning gebruikt worden, maar ook realtime stuursignalen. De gehele drie-staps besturingsmethode kan twee verschillende typen van doelen hebben: 1) het bereiken van een vooraf gedefinieerd energieprofiel (bijvoorbeeld het verlagen van pieken) en 2) het realtime reageren op fluctuaties (bijvoorbeeld veroorzaakt door windmolens).

De planning die is bepaald in de tweede stap is gebaseerd op het voorspelde gedrag van apparaten en daarmee het voorspelde gedrag van eindgebruikers, uitgedrukt in wanneer en voor hoe lang apparaten aangezet gaan worden. Op basis van deze voorspellingen en het doel van de optimalisatie wordt vervolgens een planning bepaald wanneer welk apparaat aan of uit gaat. Echter, het daadwerkelijke gedrag wijkt vaak af van het voorspelde gedrag (voorspellingsfouten). Als gevolg van deze voorspellingsfouten wijkt de daadwerkelijke situatie vaak af van de voorspelde situatie waardoor de planning niet altijd gehaald kan worden. Daarnaast passen de stuursignalen, gebaseerd op de voorspelde situatie, dan niet meer bij de daadwerkelijke situatie met als gevolg dat er mogelijk beslissingen genomen worden die negatieve gevolgen hebben voor latere tijdstippen. De laatste stap van de methode moet proberen om, ondanks deze voorspellingsfouten, zo dicht mogelijk bij de planning te blijven. Om dit te bereiken is de ontwikkelde regelaar uitgebreid met Model Predictive Control (MPC). Bij MPC kijkt de regelaar bij het nemen van beslissingen niet alleen naar het huidige tijdstip, maar ook naar latere tijdstippen. Er worden korte-termijn voorspellingen gemaakt van de apparaten en op basis van de huidige situatie, de korte-termijn voorspellingen en de stuursignalen worden de beste beslissingen voor het huidige tijdstip bepaald.

De beslissingen die de realtime regelaar neemt zijn gebaseerd op kostenfuncties. De voorkeuren en de keuzevrijheid van ieder apparaat worden uitgedrukt met behulp van kostenfuncties. Deze kostenfuncties kennen aan alle mogelijke opties van het apparaat bepaalde kosten toe op basis van de wenselijkheid van iedere optie. Daarnaast zijn de stuursignalen die afgeleid zijn van de planning ook gebaseerd op kostenfuncties. Op basis van alle kostenfuncties en de (technische en niet-technische) restricties kunnen de beste keuzes uit de mogelijke opties worden gemaakt. Kostenfuncties zijn een zeer generieke manier om voorkeuren en keuzevrijheid van apparaten uit te drukken. Echter, het is wel belangrijk dat de kostenfuncties correct zijn, anders kan er onwenselijk en onvoorspelbaar gedrag optreden.

Op basis van het afgeleide model is een simulator ontwikkeld voor het simuleren van toekomstige energie infrastructuren en optimalisatie algoritmen. De simulator is gebaseerd op discrete simulaties en sluit zo dicht mogelijk aan bij het model. De gebouwen zijn gespecificeerd op apparaat niveau en meerdere gebouwen zijn gecombineerd in een (slim) netwerk (Smart Grid). De simulator is snel en kan grote groepen gebouwen simuleren binnen afzienbare tijd. Daarnaast is de simulator generiek, deze kan veel verschillende scenario's, technologieën en optimalisatie algoritmen simuleren. De modulaire opbouw van de simulator maakt het gemakkelijk om modellen van nieuwe technologieën toe te voegen. Door het gebruik van initialisatiebestanden is het gemakkelijk om (grootschalige) scenario's te definiëren. Het uitgebreide loggen van data van alle elementen van de simulator maakt het mogelijk om de simulatieresultaten in detail te bestuderen. Doordat meetgegevens van echte apparaten gebruikt kunnen worden en door de mogelijkheid om hier stochastische variaties op toe te passen is het mogelijk om realistische scenario's te definiëren met een beperkte hoeveelheid gegevens.

Er zijn meerdere scenario's gesimuleerd om de effectiviteit van de methode aan te tonen, om de beste parameters van de methode te vinden en op de meest economische manier de keuzevrijheid van de apparaten te gebruiken. De simulaties hebben aangetoond dat de besturingsmethode goed werkt en in staat is om het gedrag van apparaten van eindgebruikers te regelen op een economische manier zonder verlies van comfort. De voorspellingen en planning voorafgaande aan de realtime regelaar verbeteren de resultaten van de methode aanzienlijk: er kan veel meer keuzevrijheid nuttig gebruikt worden en de resultaten van de methode zijn voorspelbaarder en betrouwbaarder. De toevoeging van MPC aan de realtime regelaar verbetert het omgaan met voorspellingsfouten.

Experimenten met een prototype hebben aangetoond dat het mogelijk is de besturingsmethode ook toe te passen op echte apparaten en dat de algoritmen in staat zijn om het gedrag van de apparaten te beïnvloeden binnen de grenzen van het comfort. Daarnaast hebben experimenten aangetoond dat een HRe-ketel gebruikt kan worden als backupgenerator: er is een situatie gecreëerd waarin het systeem was afgekoppeld van het elektriciteitsnet en waarin een HRe-ketel en een accu zorgen voor de elektriciteitsvoorziening van meerdere apparaten, waarbij alle apparaten aangestuurd werden door de optimalisatie algoritmen.

Op basis van de simulaties en de tests met het prototype concluderen we dat de besturingsmethode in staat is om de energiestromen te monitoren en de energiestromen en -profielen te reguleren. Het kan het optimalisatiepotentieel van een grote groep huizen gebruiken om bepaalde optimalisatiedoelen te behalen. Echter, om dit daadwerkelijk toe te passen moet de instelling van de eindgebruikers veranderen zodat ze de controle over hun apparaten aan de besturingsmethode geven. De combinatie van voorspelling, planning en realtime regeling is een veelbelovende aanpak voor besturingsmethoden voor Smart Grids: het is schaalbaar, generiek en voorspelbaar. De drie-staps besturingsmethode kan een belangrijke bijdrage leveren aan het behalen van de Europese 20-20-20 doelstellingen [22].

# Dankwoord

Na bijna vier jaar is het einde van mijn tijd als promovendus op de UT bijna in zicht. Het resultaat van deze vier jaar is het proefschrift dat nu voor je ligt. Graag zou ik hier nog van de gelegenheid gebruik maken om de mensen te bedanken die, direct of indirect, hebben bijgedragen aan de totstandkoming van mijn proefschrift en de leuke periode als promovendus aan de UT.

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Albert Molderink
Enschede, mei 2011

# Contents

# CHAPTER 1

# Introduction

Energy efficiency, electricity supply and sustainability are important research topics in society [21]. The provisioning of energy is subject to increasing resource usage, scarcity and environmental concerns. Next to a slightly increasing energy usage in the Western world, developing countries like China and India show growth figures up to 25%. Since the production capacity of fossil energy sources, especially crude oil, cannot keep up with this growth, the oil reserves are diminishing and energy is becoming scarce and expensive. Furthermore, a lot of fossil energy sources are obtained from politically less stable regions. This, in combination with the growing awareness of the greenhouse effect drives the search to renewable energy sources.

A more sustainable energy supply is required for all sectors: residential, transportation, industry, agriculture, etc. At present, more and more fossil fuel energy sources are replaced by electricity, for example through the introduction of electrical vehicles. This transition to a more electricity based society is initiated by a shift towards using more renewable sources for generating electricity. An advantage of using electricity is that conventional fossil fuel based generation can be replaced by renewable sources step-by-step without major changes on the consuming side of the supply chain. However, this increasing electricity demand leads to more stress on the electricity grid. Furthermore, renewable sources are less controllable and dynamic than conventional sources, so a shift towards renewable sources requires a more intelligent grid and flexibility of consumers.

The goal of the research presented in this thesis is to determine and exploit the flexibility of consumers and to study ICT systems and algorithms to control a large group of these consumers.

The remainder of this chapter is built up as follows: first the current trends in energy generation, demand and supply are discussed. The usage and the influence of ICT on energy usage is studied, followed by the challenges, domestic technologies and the potential of these technologies. Next, the problem statement of this thesis is given: the objectives and our research focus. Section 1.3 discusses the approach and

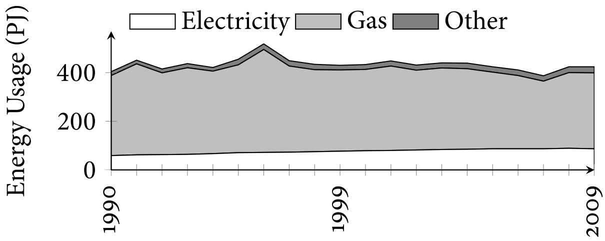


Figure 1.1: Energy usage per household for Dutch households (CBS)

the contribution of the research presented in this thesis. In Section 1.4 the outline of this thesis is given.

## 1.1 Trends in electricity generation, demand and supply

In this section the current and expected trends in the *electricity supply chain* are investigated, together with its associated challenges and opportunities. The electricity supply chain consists of electricity generation, transportation, distribution and consumption. In this supply chain a lot of changes are ongoing or expected, driven by increasing (fossil) energy prices and awareness of the greenhouse gas effects. These changes are discussed more detailed in Section 2.2 in the following chapter, the supply chain is sketched in Figure 2.1. Within these changes four trends can be identified:

**electrification of energy distribution:** a growing part of the consumed energy is transported and consumed as electricity,

**increase in energy consumption:** the energy consumption, and the electricity consumption in particular, increases,

**more dynamic electrical loads:** electricity consumption not only increases, it also becomes more fluctuating and sometimes even controllable,

**more distributed electricity generation:** where in the past all electricity was generated in a few large power plants and was transported via the grid to the consumers, nowadays more and more electricity is generated lower in the grid.

The most important change in the electricity supply chain is a shift from centrally produced electricity flowing downwards the grid to the consumers towards a distributed electricity generation on different levels in the grid. These trends and changes result in challenges to maintain a reliable and stable supply, but it also opens opportunities when this distributed generation and other (domestic) technologies are monitored and managed using wide-spread ICT. In the remainder of this section these challenges and opportunities are discussed more detailed.

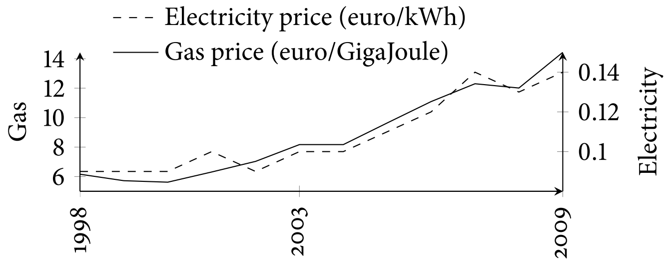


Figure 1.2: European gas and electricity prices for residential usage (Eurostat)

### 1.1.1 ENERGY USAGE AND ICT

From 1990 up to now, the overall energy usage in Western Europe increased only slightly, but the electricity demand increased significantly. This is illustrated with the energy usage of households in the Netherlands in Figure 1.1. The electricity usage of individual houses increased from 2800 to 3400 kWh in the period from 1990 to 2006, i.e. an increase of 20 %. This endorses partly the transition towards a more electricity based society; less natural gas is used due to better insulation (gas is mainly used for heating) whereas more electricity is used. At the same moment, devices became more energy efficient so the number of electricity consuming devices increased even more than the 20 % increase of usage. During the same period, the electricity prices increased by 66 % and gas prices even doubled (see Figure 1.2).

Recently, ICT contributes for a significant part to the electricity consumption, in the Netherlands in 2006 7.3 % of the 115 TWh produced electricity was consumed by ICT [23]. This usage can be divided in residential (67 %), office (13 %) and infrastructure (20 %) usage (data communication and data-centers). At the moment, ICT consumes approximately 840 kWh in an average house, or 25 % of the total domestic demand, resulting in 6 TWh for all Dutch households. The expectation is that this will increase up to 11.7 TWh in 2020. In office surroundings the expectation is that the usage caused by ICT will stay constant till 2020, on a 27 kWh/m$^2$/year or 1.2 TWh in total. For the ICT infrastructure itself (e.g. internet) the expectation is that the usage will increase by 8 % per year, from 1.5 TWh in 2006 to 3.4 TWh in 2020. These expected growth figures already incorporated the increase in energy efficiency ICT reached in the last years and will reach the coming years. Up to 2005, the main drive of innovation in ICT was getting more performance, but the last five years the focus shifted more and more to energy efficiency.

However, next to increasing the electricity consumption in the coming years, ICT also has a potential to play a key role in making the electricity supply more efficient, sustainable and affordable. ICT is already used in many areas to monitor, manage and optimize processes. An example of ICT playing a crucial role in the total process is the automotive industry; the efficiency and safety of cars increased significantly by incorporating ICT in the control loops. But also in the electricity supply chain ICT found its way. Power plants are controlled by ICT-based control

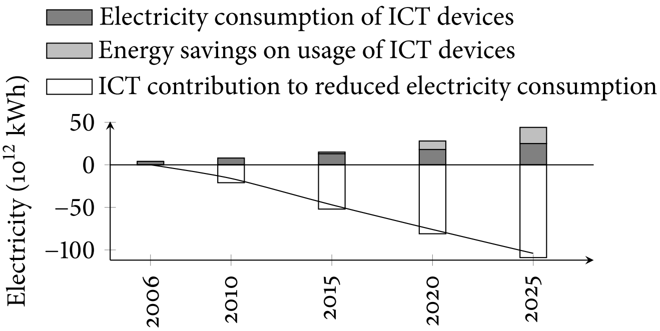


Figure 1.3: Energy consumption and saving of ICT (Source: Simon Mingay of Gartner UK and Ministry of Economy, Trade & Industry, Japan)

processes. Furthermore, electricity transport via the grid is monitored and managed using ICT. These principles might also be useful in the residential areas. In most buildings there is a certain amount of *scheduling freedom*, i.e. the ability of shifting electricity consumption in time without discomfort for the residents. This scheduling freedom is quite useful to increase the energy efficiency and to incorporate more renewable sources in the current mix of generation sources. However, individual persons probably cannot exploit this scheduling freedom themselves, so an ICT based solution to automatically exploit this potential on a large scale is required. This is illustrated in a graph developed by Simon Mingay of Gartner using data from the Ministry of Economy, Trade & Industry in Japan, Figure 1.3. The figure shows that the increase in energy consumption of ICT is superseded by the impact of smart ICT for energy management.

### 1.1.2 CHALLENGES INTRODUCED BY CURRENT TRENDS

In the last decades, more and more stress is put on the electricity supply and infrastructure. On the one hand, the electricity usage increased significantly and became very fluctuating. Fluctuations in demand are caused by the stochastic nature of demand; people switch on the dishwasher or washing machine whenever they like. The electricity supply chain is designed decades ago and is completely demand driven; consumers just switch on devices when they want to and the generation side has to deal with this fluctuating and hard to predict demand. Therefore, demand peaks result in peaks in generation and transmission, which define the requirements in the supply chain. Thus, due to the fluctuating demand, grid requirements have increased. When electricity demand rises and becomes more fluctuating, for example with a large scale introduction of electrical cars without charge time optimization, the efficiency of conventional power plants drops [26] and large investments in grid capacity are required to be able to transport all electricity (peaks) from the power plants to the consumers [4].

On the other hand, the reduction in the $CO_2$ emissions and the introduction of generation based on renewable sources become important topics today. The current rate of natural resource consumption will lead to depletion of these resources, urging for alternative methods to provide the required energy. However, renewable resources are mainly 'fueled' by very fluctuating and uncontrollable sun-, water- and wind power. The generation patterns resulting from these renewable sources may have some similarities with the electricity demand patterns, but they are in general far from being equal. To maintain grid stability, all generated electricity must be consumed. Therefore, the peaks in renewable generation should be lower than the electricity consumption. For this reason, supplemental peak generation capacity is required to keep the demand and supply in balance, resulting in an even more fluctuating generation pattern for the conventional power plants. Another consequence is that within the current demand-supply philosophy only a limited percentage of the conventional generation can be replaced with renewable generation.

While a lot of research is ongoing to enable the possibility to supply our energy needs with renewable sources, still a lot of improvements can be achieved on the efficiency of current systems as long as not all energy needs can be supplied sustainably. For example, most residential used electricity is generated at central power plants consuming environmentally unfriendly and scarce natural resources like coal or natural gas with an efficiency of 30 up to 50%. The low efficiency is mainly caused by wasting the heat produced as byproduct and by high fluctuations in demand [26].

Therefore, the challenges we face are 1) to increase the efficiency of current power plants, 2) to reduce the stress on the grid resulting from higher demand peaks and prevent investments in grid capacity and 3) to facilitate a large percentage of renewable sources for electricity generation in the grid while maintaining a stable grid and a reliable supply.

### 1.1.3 DOMESTIC TECHNOLOGIES

Due to increasing energy prices and a growing awareness of the greenhouse effect, new domestic technologies to save money and energy are being developed. Unfortunately, some of these technologies may introduce even more fluctuations on the electricity grid.

One example of these technologies are *micro-generators*. Micro-generators generate electricity at kilowatt level in or nearby houses resulting in less transport losses and better optimization potential for matching demand and supply. Often micro-generators are more energy efficient than conventional power plants and some are based on renewable energy sources [26, 61]. Examples of micro-generators are Photovoltaics (PV), micro wind-turbines and microCHP devices. MicroCHPs are replacements for conventional high efficiency boilers producing both heat and electricity using natural gas. The expectation is that the coming years microCHP devices will replace the conventional gas-fired high-efficiency boilers [61]. The advantage of this type of micro-generator is that the produced heat is used for central heating and hot-water taps and the electricity is used within the building or exported to the grid. This results in an efficiency of up to 95 %, although it still consumes conventional fuel. The device is heat driven, i.e. in the microCHP concept electricity is seen as a byproduct (electricity can be imported and exported, while heat cannot). Just replacing a conventional boiler with a microCHP device already results in a significant reduction of energy usage [52]. However, a microCHP device is heat-driven: it only produces electricity when there is a heat demand. If next to a microCHP device also a heat buffer is installed, the heat and electricity production are decoupled, since heat can be produced before it is used. Therefore, electricity production can be shifted in time.

Micro-generators based on renewable sources like sun and wind have a very fluctuating production pattern and even for a large scale introduction of controllable microCHPs a fit-and-forget strategy is not applicable [59]. Furthermore, the grid is designed and built for an electricity stream from power plants to consumers. The transformers cannot manage large electricity flows from the low voltage to the high voltage parts of the grid. Therefore, ideally the locally produced electricity should be used locally, i.e. within the neighborhood without passing a transformer.

Other new technologies are energy buffers and smart devices. Energy buffers can (temporarily) store energy. Heat buffers are already common in current houses, but more and more electricity buffers are introduced. An example of an electricity buffer for domestic usage is the combination of a local battery and the PowerRouter developed by Nedap[1]. These energy buffers make it possible to shift electricity consumption in time, e.g. shift consumption to earlier times by filling the buffer and supply the demand with the stored energy.

In our context, smart devices are defined as devices with the ability to temporarily switch off (parts of) the device or devices that can shift the demand in time. A smart washing machine is an example of a device that can be switched on within a certain time frame, i.e. the optimal runtime within a certain time frame can be determined. A smart fridge is an example of a device that can shift load in time; the temperature should stay in between certain bounds, within these bounds there is freedom to start cooling earlier. This is sketched in Figure 1.4.

### 1.1.4 DOMESTIC OPTIMIZATION POTENTIAL

A lot of challenges concerning the future electricity supply are mentioned in the previous two subsections. Some of these challenges are caused by a fit-and-forget introduction of the new domestic technologies mentioned. However, the new technologies also introduce opportunities. A solution for these challenges may be to transform customers from static consumer into active participants in the production/consumption process. Consumers can exploit the potential of the new technologies, by shifting load and/or generation to the most beneficial times, where "beneficial" depends on the optimization objective. More can be reached when a large group of consumers together works towards objectives, but this requires a central coordination and consumers lose (a part of) the control over their devices. Domestic

[1]http://www.nedap-atrium.nl

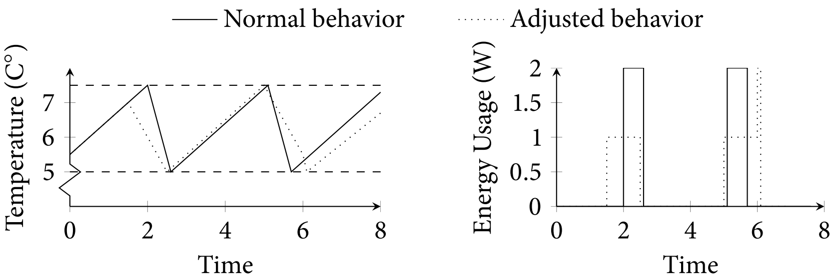


Figure 1.4: Shift the load of a fridge in time

electricity demand accounts for 21 % of the total Dutch electricity consumption [23], so controlling this load comprises a significant part of the electricity load. In this way, the decrease in flexibility at the generation of the electricity supply chain is compensated by an increase of flexibility on the consumer side. However, this transformation of consumers into active participants requires a change in the state of mind of people, i.e. consumers for whom the availability of energy was always evident should cooperate in keeping the quality and reliability of supply at a high level. A start of this transformation is awareness of the energy they consume. Just this awareness leads to a decrease of electricity usage of up to 20 % [25]. Furthermore, it requires co-operation from politics and policy makers. In the current legislation and the division of utilities in generation, transportation and distribution it is difficult to introduce such a control methodology and it is hard to find a business case for the stakeholders.

*Optimize domestic electricity import/export patterns*

To overcome the challenges mentioned in the previous subsection, the consumption side of the supply chain should cooperate with and/or react on the generation side. Consumers can adjust their electricity consumption to reduce the streams through the grid and match the required generation patterns. In other words, the import/export profile of the electricity of buildings[2] is fine-tuned. Since electricity is heavily intertwined with other types of energy, the complete energy infrastructure is incorporated in the control methodologies.

Some technologies itself may lead to a decreased domestic energy usage (electricity and heat). However, the goal of this control methodology is not primarily to decrease energy usage but to optimize the usage to increase efficiency and sustainability of the overall energy supply chain. Next to improving efficiency, optimizing the usage of the domestic technologies can (and has to) enhance the reliability of supply [33, 59]. The objective of such a control methodology is to optimize the

[2]building: house, office, school, shop, etc.

electricity import and export profile of (a group of) buildings. The optimization objective can differ, depending on the optimization criteria of the stakeholder. Such a stakeholder could be an electricity supply company, a consortium of house owners, etc.





### 1.1.5 ISLANDED HOUSE PROJECT

The research was initiated by a research question of E.ON UK which supplied the funding to start a research project. This project is called *IFI Islanded House* and focuses on using a microCHP device as backup generator in case of a power outage. During the research concerning islanded houses it became clear that the local control methodology required for the islanded house project could be extended to a large scale control methodology working towards global objectives. This section gives an introduction to the research question. Within this thesis we will first refer to the islanded house as use case and later we will prove that this is a special case of the global control methodology.

Starting point for the project was a marketing driven factor: for an easier market introduction, producers of microCHPs and electricity suppliers are looking for additional benefits for microCHPs. One possible additional functionality is using the microCHP as a backup generator in case of a power outage. A power outage does not only lead to discomfort caused by not working devices, for example lights, but can also lead to safety and security issues. Safety systems and security systems require electricity for their proper functioning. Most of these systems have their own backup supply (mostly a battery), but these batteries can only be used for a limited time. In case of a longer outage, these systems require an external supply. Another effect of power outage is a non-functioning central heating, even when natural gas is available, since the water pump that pumps the water through the radiators requires electricity.

A microCHP could, with some modifications and additions, be capable of producing energy when the main supply fails. In case of a power outage the house is decoupled from the grid and the microCHP produces electricity for the most important devices. This is called islanding: the house acts as an electrically independent island. When the microCHP is used as a backup generator, it could supply at least the safety and security systems and the natural gas fired central heating.

The security/safety devices, heating, lights and the water heater have the highest priority. Next, it is investigated whether more devices can be supplied to decrease discomfort for the residents. The research includes both the software and the hardware challenges since the expected outcome was a working prototype.

## 1.2 Problem statement

The goal of this research is to investigate how ICT based control mechanisms are able to overcome the challenges of a transition towards a sustainable electricity based society. Our research focusses on control methodologies to exploit the flexibility of (new) domestic technologies. This section discusses the objectives used for the proposed control mechanism and introduces the research focus and research questions.



*Optimization of energy streams*

Control methodologies can work towards objectives on different levels. On a high level, a large group of buildings is combined to improve efficiency of power plants by reducing fluctuations in demand or the flexibility is used to compensate for fluctuating renewable generation to allow a higher penetration rate of renewable energy. On a medium level the electricity streams through the grid are managed to optimally use the available grid capacity. On a low level the locally generated electricity is kept within the neighborhood and peaks in consumption are lowered (*peak shaving*). Summarizing, this thesis is focussed on three different objectives:

1. improve the efficiency of existing power plants,
2. facilitate the large scale introduction of renewable generation,
3. allow large scale introduction of new domestic technologies, both producing and consuming, using the current grid capacity,

while at the same time maintaining grid stability and reliability of supply.

*Research focus*

The focus of our research is to reach the global objectives mentioned above, using the local flexibility. So, the algorithms optimize on a domestic (in-building) level managing the runtime of individual devices. However, the control methodology can also incorporate other consumers: schools, shops, factories, etc. This is schematically shown in Figure 1.5. Thus, the term domestic in this thesis refers to the low voltage, consumer side of the supply chain.

The optimizations are performed at the end of the supply chain, at the consumer side, located in the low voltage distribution network. A network of nodes spread over the grid can cooperate to work towards global and large scale optimizations. By managing the consumer side, the electricity streams within the end points (e.g. houses, shops or schools) and in the low voltage distribution network can be managed, but also the electricity streams through the medium and high voltage network. By managing the individual devices on the consumer side of the electricity supply chain, the goal is to work towards objectives in the low, medium and high voltage network. As described above, the work is closely related to research on Smart Grids.

The research focus can be summarized in four research questions:

- What is the optimization potential of domestic technologies?
- Can this potential be used for the objectives mentioned?
- Is it possible to create a control methodology to exploit this potential?

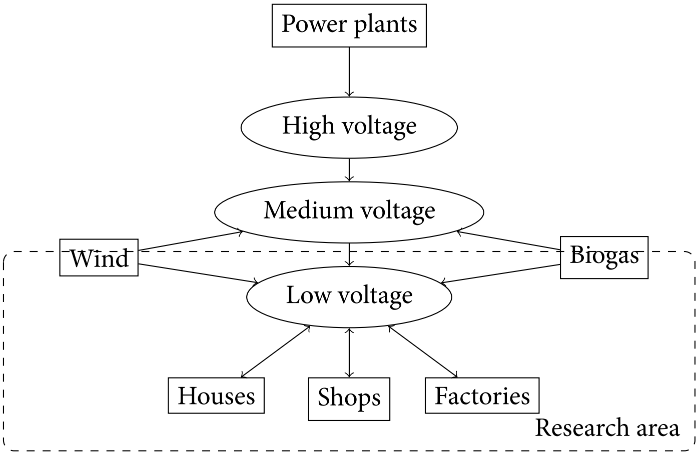


Figure 1.5: Schematic of the electricity grid and our research area

- What is the best structure for such a control methodology and which algorithms should be used?

## 1.3 Approach and contribution

In this research a bottom up approach is used. The research started with an investigation of the current energy streams, electricity infrastructure and supply chain from a domestic level up to the central electricity generation. Based on this information, the challenges to maintain a reliable electricity supply while evolving to a sustainable supply and electrification of the energy supply can be determined. Next, possible solutions for these challenges can be derived. The last step in the problem identification is to reason whether and how domestic consumers can contribute to overcome the challenges.

The above bottom up approach is based on mathematical modeling and optimization techniques. In other words, a theoretical approach is chosen to tackle the research questions. However, as proof-of-concept and to verify assumptions a prototype has been built in a lab environment and several field tests have been performed.

*Contribution*

Based on the research questions and using the above described approach, this research resulted in five contributions:

- a mathematical model of (domestic) energy streams,

- a generic simulator able to simulate multiple scenarios, technologies and control methodologies,
- a control methodology to exploit the domestic potential on a large scale,
- an overview of the domestic optimization potential by simulations,
- a lab prototype and field tests to proof the concept and to verify assumptions.



In the remainder of this section these contributions are explained more detailed.

To study the optimization potentials and to determine a control methodology for using the domestic optimization potential, first the current electricity streams within the building and through the grid must be investigated. The different energy streams within the building are heavily intertwined, e.g. heat is sometimes produced using electricity (microCHP device), hot fill washing machines consume heat and electricity at the same time. Therefore, not only the electricity streams within the building are topic of study, but the complete energy infrastructure within the building is taken into account.

To be able to analyze current energy streams and to study the effects of technologies and control methodologies, first a model of the energy streams has been derived. This model incorporates all energy streams within the building on a device level and combines multiple buildings in a grid, respecting the hierarchical voltage levels of the grid and the number of buildings behind one transformer (neighborhood). Based on this model, a simulator has been developed to be able to simulate large scale scenarios, the impact of different new technologies and the effects of control methodologies. This simulator allows usage of realistic, measured data and can, based on this data, create scenarios with a large number of buildings using different levels of stochastic variations. Furthermore, it is rather easy to incorporate new (future) devices and control methodologies. Simulations can be initiated, parameters can be set and results are clearly presented in a Graphical User Interface (GUI).

At the University of Twente, a control methodology has been developed to exploit the domestic optimization potential. The control methodology is based on a three-step approach to control domestic energy demand, as well as the generation and storage of the energy. First, the energy usage and therefore the optimization potential for every individual building in the grid is predicted. Next, the predictions of the individual buildings are aggregated and a global planning is made. In the last step, a local realtime controller in every building schedules the devices realtime, using the global planning as an input. The main focus of this thesis is on the the three-step control methodology and in particular on the last step of this control methodology. The base of all three steps of the control methodology is a mathematical analysis of the energy streams expressed in the model in combination with mathematical optimization techniques. The problem is approached from a theoretical view. However, a prototype has been built in one of the university labs and assumptions have been verified by converting the algorithms to this prototype.

The basic goal of this control methodology is to supply all domestic energy demands without loss of comfort while optimizing the overall energy efficiency. The combination of prediction, local controllers and global controllers can be extended to a Smart Grid [59] solution, controlling central power plants, non-domestic distributed generation, non-domestic buffers and domestic imports/exports. Because of the continuous development of technologies mentioned above and different combinations of them in buildings, the developed control methodology has to be generic.

The proposed control methodology is divided into three steps and there is a local (within a building) and a global (combining multiple buildings) part. The three steps of the control methodology are:

1. **Local offline prediction** In the first step, a system located at the consumers' predicts the production and consumption pattern for all devices for the upcoming day. In Chapter 2 we will explain why we need a prediction for the upcoming day. For example, in a normal household multiple devices like a TV, washing machine and central heating are present. For each device, based on the historical usage pattern of the residents and external factors like the weather, a predicted energy profile is generated. These energy profiles are aggregated by the local controller and sent to the global controller. The global controller is structured as a hierarchical tree for scalability and to reduce communication. In each node of the tree the profiles received are aggregated and sent upwards in the tree towards the root node.

2. **Global offline planning** In the second step, these profiles can be used by a central planner to exploit the potential to reach a global objective. The root node determines steering signals based on the information received and the objective. These steering signals are distributed via the tree structure, whereby each node may adjust the steering signals. Adjusted profiles are determined by a controller in the buildings, based on the (new) steering signals and the predictions. These new profiles are again sent upwards. In this iterative way a near-optimal solution can be found with a reasonable computation time. Example objectives are peak shaving or compensating the fluctuation of the production of renewable sources like wind-parks. The result of the second step is a planning for each household for the upcoming day and an overall production/consumption profile.

3. **Local Realtime control** In the final step, which is the focus of this thesis, a realtime control algorithm decides when devices are switched on/off, when and how much energy flows from or to the buffers and when and which generators are switched on. This realtime control algorithm uses the steering signals from the global planning as input, but preserves the comfort of the residents in conflict situations. The local controller can also run independently, for example when the connection with the global controller is lost.

Using the simulator, multiple use case have been simulated with the control methodology incorporated. With these case studies, the optimization potential and ability of our control methodology to exploit this potential has been investigated. Furthermore, the best parameters for the control methodology have been determined.

Finally, a prototype has been built and several field tests are performed to study controllability of the devices in the real world and to verify assumptions. The control algorithms are converted to these prototypes and a subset of the use cases have been verified.

Another important factor when domestic potential is used is the co-operation of residents. However, we approached this optimization potential from a purely technical view, the social and acceptance issues are left out of scope. This is left for future work in the Route 14 Energy track of the University of Twente.

## 1.4 Outline of the thesis

In this chapter we have given an introduction in the foreseen challenges regarding the changing electricity supply chain. The remainder of this thesis will give more detailed information about the current and foreseen electricity infrastructure in Chapter 2 and answers to the afore mentioned challenges. Based on this information, in Chapter 3 a model of the current electricity infrastructure is derived. This model describes buildings on a device level. Multiple buildings in combination with generation and grid infrastructure are combined into a grid. The next chapter, Chapter 4, describes the developed control methodology with a focus on the third step of the control methodology. Using the model a simulator has been developed, this simulator is described in Chapter 5. This simulator can be used to study the impact of (future) scenarios and to analyze the impact of control methodologies on these scenarios. In Chapter 6 the results of simulated use cases and experiments are given. Chapter 7 ends up with conclusions and future work.

CHAPTER 2

# Background and related work

Abstract – *This chapter describes the current situation and the foreseen changes in the electricity supply chain. Nowadays, the electricity supply chain is designed with a demand driven philosophy. However, rising energy prices and awareness of the greenhouse effect initiate changes in the energy supply chain philosophy. These factors lead to an electrification of the energy supply: a growing part of the energy is supplied as electricity. At the same time, a growing share of the consumed electricity is produced by (uncontrollable) sustainable generation. These two trends result in more distributed generation, less controllable generation and higher (peaks in) electricity supply and demand. To facilitate the distributed sustainable generation and the increasing demand, the grid must become a Smart Grid. This is often extended with an European or European/African super grid to transport sustainable generated electricity. One of the main challenges is to change passive consumers into cooperative players in the electricity supply chain. The main goal of a Smart Grid is to maintain grid stability and reliability of supply by monitoring, managing and cooperation of all elements in the grid. To reach this, technical, economical and political challenges have to be tackled and it requires cooperation of the consumers. ICT will play an essential role within this Smart Grid to control the whole system. A widespread control mechanism is required for monitoring the complete electricity supply chain, from central generation in power plants and large scale renewable generation via transportation to technologies in buildings on a device level.*

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In this chapter the current energy infrastructure is described, with a focus on the electricity generation and supply. In most European countries the energy supply is split up into generation, transportation and distribution leading to a complicated energy market. These energy markets are shortly described. Furthermore, the foreseen changes in the transition towards a Smart Grid are discussed: the driving factors, challenges and control methodology. Finally, the emergence of the transition towards a Smart Grid is discussed using a short overview of the Smart Grid programs, related projects and operational test sites.

Although the focus is on electricity, all energy streams within a building are taken into account since different types of energy can be coupled by the energy transformations and consumption. Furthermore, incorporating the optimization of import and export of other types of energy in future algorithms is simplified. Since the goal is to optimize electricity production, consumption and transportation, the remains of this section focusses on electricity.

Enabled by smart metering, electronic control technologies, modern communications means and the increased awareness of customers, local electricity supply management will play a key part in establishing new services that will create value for the parties involved. ICT will play an important role in realtime management.

The rest of this chapter is built up as follows: first, the current domestic energy infrastructure is discussed and the current electricity supply infrastructure and electricity markets are introduced. Next, in Section 2.2 the driving factors, definitions, challenges and control of Smart Grids are discussed. In Section 2.3 the emergence of Smart Grids is emphasized by introducing programs and alliances, related projects and operational test sites. The last section ends up with conclusions.

## 2.1 Current domestic energy infrastructure

In the modern world people are used to the availability of energy in their buildings. This availability of energy has increased the comfort level significantly and it is nowadays hard to live without it. Heating and cooling the building is just a push on a button, the laundry is rinsed in a washing machine and the TV lights up when it is switched on. To enable this, multiple types of energy are used, for example electricity for the TV, gas for cooking, heat (hot water) for heating, etc. These types of energy are called *energy-carriers* [35].

Within the building multiple streams of energy-carriers can be found (gas pipes, electricity wires, etc.). Furthermore, energy-carriers can be *converted* into other energy-carriers. A well known example is producing heat using gas or electricity. Sometimes multiple types of energy are used as input or output, for example a hot-fill washing machine is filled with hot water and consumes electricity. But heat, coldness (cold water or air for cooling the building) and electricity can also be produced using sun, wind or heat and cold from the earth. One can see this as importing sun energy or wind energy into the building where it is converted into heat or electricity.

Energy can be temporarily *stored*. For hot water this is already common (hot water tank), but also storing electricity becomes possible and is more used. Eventually, the energy is *consumed* by consuming devices: e.g. the TV and fridge consume electricity, the central heating consumes hot water. Some devices may consume two types of energy, for example a hot-fill washing machine consumes electricity and hot water.

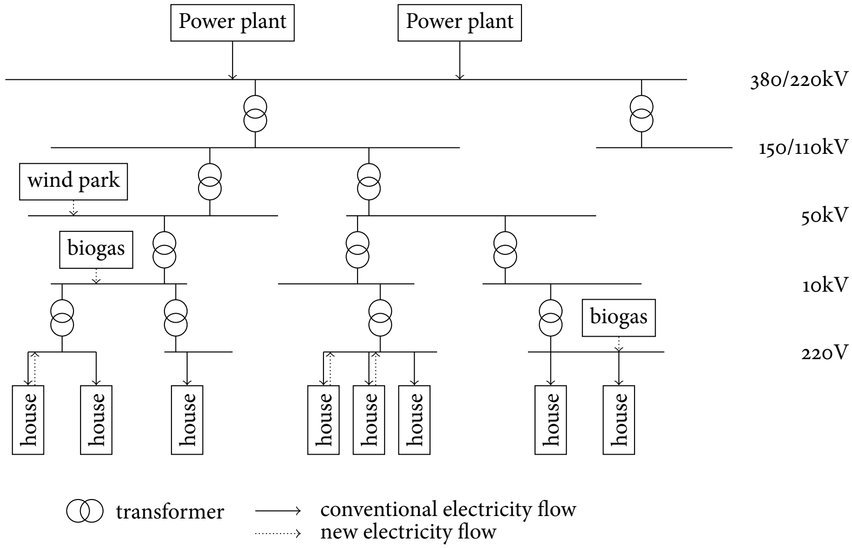



Figure 2.1: Sketch of the (changes in) Dutch electricity grid structure

Nowadays, depending on the availability in certain areas, three energy-carriers can be delivered to a building by utilities: electricity, gas and hot water. Each energy-carrier has its own characteristics. For example, gas and hot water can be stored easily and efficiently while gas and electricity can be transported quite efficiently. Since gas and hot water can be stored easily, fluctuations in demand do not influence the production significantly. However, dealing with fluctuations in electricity demand is much harder and does influence the production.

### 2.1.1 CURRENT ELECTRICITY PRODUCTION AND SUPPLY

Traditionally, the electricity is produced in power plants and transported via the electricity grid to the consumers. I.e., the *supply chain* consists of central generation sites from which the electricity is transported via a (leveled) electricity grid to the consumers, which only consume electricity. This electricity grid is divided into different voltage levels. A higher voltage has lower transportation costs (losses) but requires more insulation and induces more safety issues. The electricity produced by power plants flows into the network on the highest voltage levels and is also transported on the high voltage levels. Closer to the customers the voltage is lowered step-wise using transformers. A schematic of the electricity grid is shown in Figure 2.1, the Dutch electricity infrastructure is shown in Appendix A. On the intermediate and low voltage levels electricity can be fed into the network by (unmanageable) renewable sources like wind turbines, on the low voltage levels

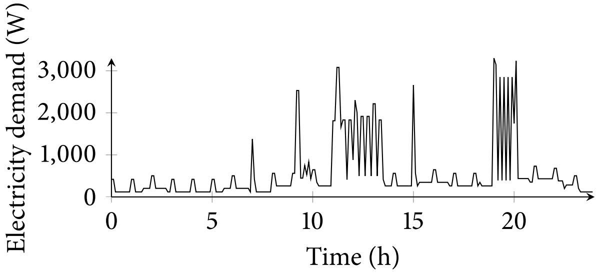



Figure 2.2: Example of a daily electricity demand profile of a typical household

electricity is drawn by consumers. The difference between the consumption and this renewable production needs to be produced by power plants, flowing into the network on the high voltage levels. The maximum difference that can be supplied is limited by the generation capacity of the power plants and the transportation capacity of the grid (lines and transformers).

When a consumer switches on an appliance, e.g. the TV, he expects it starts right away. Furthermore, to maintain grid stability the electricity production and consumption needs to be in balance. In other words, the electricity should be delivered right away, the production is completely demand driven without feedback. This results in a fluctuating demand pattern. An example of the daily electricity demand is shown in Figure 2.2. As can be seen in the picture, there is always a minimum demand level (in this case 120 W). This is called the *base-load*. The highest peak in demand is called the *peak-load* (in this case 3300 W), the quotient of the peak-load and base-load is called the *load-factor* (in this case 0.04).

To supply the fluctuating demand, multiple types of power plants are used, each with different efficiencies, start up times and flexibility in production. The base-load is supplied by large gas-fired, coal-fired or nuclear power plants with a start up time of days, relative high efficiencies and a low flexibility. The peak-load on the other hand is supplied by so called peak-plants with a short start up time, relative low efficiency and high flexibility. However, even these plants take at least several minutes to startup, so they can only cope with the slow fluctuations. These plants are used for the high, predictable fluctuations (e.g. to supply the evening peak). The real short-term fluctuations (e.g. switching on a light) are dealt with by so called spinning reserves, in case these fluctuations are not already leveled out by the large number of buildings. All conventional power plants (coal, gas, nuclear) use in the end a steam driven turbine. The rotor is quite heavy, when the demand rises a bit (e.g. by switching on a load) the rotor slows down only a bit. Since it is only a small decrease in rotation speed, the electricity is supplied, the voltage stays at the correct level and only the AC-frequency decreases a bit. As long as the frequency drop stays within the limits this is no problem. The control algorithm of the power plant can increase the steam production to steer the frequency within the correct range.

So, important for the grid stability is the generation capacity of the power plants, the ability to cope with fluctuations in demand and the grid capacity in comparison to the (fluctuations in) demand. The overall efficiency is defined as the amount of primary, fossil fuel (coal, gas, nuclear, etc.) used in comparison with the amount of electricity consumed by the customers. This incorporates the efficiency of power plants and transportation losses.

*Electricity markets*

Due to European regulations, the utilities in Europe are split up into independent production, transportation and distribution companies. The production companies produce the electricity, i.e. they own power plants, and the distribution companies sell the electricity to customers. There are multiple production companies that have to compete with each other, just like distribution companies. Transportation companies own, maintain and exploit (a part of the high-voltage) electricity grid without competitors. Distribution companies have to predict the amount of electricity their customers will consume and they buy this amount of electricity from production companies. Trading electricity is done on different markets. On the *long term market* (months up front), electricity prices are low but predictions hard and less accurate. On the *short term market* prices are higher but predictions more accurate (e.g. an important soccer match has a lot of influence on consumption). Electricity on the short term market is traded up to 24 hours before consumption/production. Most distribution companies buy about 80% of the electricity on the long term market since this part of the consumption is season related, the other 20% is bought on a short term market since this part is related to fluctuating circumstances like daily weather, soccer matches, etc. [60].

The distribution companies give the predicted consumption patterns to the grid operator and the production companies provide their planned production patterns (which should be in balance) to the grid operator. Furthermore, production companies can offer so called balancing power: when there is a difference between production and consumption (imbalance) they can decrease or increase their planned production to maintain stability, of course for a certain (high) price. The grid operator has to maintain the balance and stability on the grid. When a production or distribution company deviates from the given pattern it causes imbalance. This imbalance is neutralized using the offered balancing power, the grid operator decides which offered balancing power is used. The (distribution or production) company that caused the imbalance has to pay a penalty and the costs of the balancing power.

The distribution companies try to predict the electricity consumption very accurately, buy as much electricity as possible on the long term and prevent imbalance penalties. Customers pay a fixed price for electricity, all electricity bought for a lower price is profit for the distribution company. The production companies on the other hand make profit by selling electricity to the distribution companies on beforehand, but especially by supplying imbalance power. However, they have to make sure they can get rid of all produced electricity, it is not possible to just switch off a large coal-fired plant. The network companies have no competitors and are therefore strictly regulated by the government. They have to facilitate the transportation of electricity from power plants to customers, required investments can be recharged towards the customers. Therefore, there are no incentives to optimize grid usage for these companies.

## 2.2 Transition towards a Smart Grid

The electricity grid as we know it today (as described above) has been designed 50-100 years ago and still works via the same principles. 50 years ago, fossil fuels were cheap and abundant, electricity was produced at central places and transported one-way downwards to the customers [10, 56]. Nowadays, the circumstances are changing: fossil fuels are expensive and produced by politically less stable countries as discussed in the previous chapter and concerns about the greenhouse gas effect and climate change influence the public opinion. Therefore, groups of countries (e.g. G8) made thorough agreements about $CO_2$ emission reduction [10, 56], for example in the Kyoto agreement. These changes in the way people think about electricity supply and the need for other, sustainable energy sources drive a transition towards an electricity grid that is monitored and managed.

In this section the foreseen transition towards a more monitored and managed grid, a so-called *Smart Grid*, is studied in more detail. First, the driving factors are listed, followed by a definition of Smart Grids and the technical challenges. The last part of this section focuses on the required control for a Smart Grid.

### 2.2.1 Driving factors

A stable and reliable electricity supply is obvious for most people. However, to maintain a stable and reliable electricity supply that is sustainable and also affordable, the complete supply chain has to change. In all three parts of the supply chain, generation, transport and distribution/consumption, driving factors exist for the transition towards a Smart Grid. The European Technology Platform Smart Grids display these driving factors in a triangle by dividing these driving factors in three groups (Figure 2.3). The grid needs to be updated to keep up with changes in demand and supply. This is the right moment since the lifetime of a lot of grid elements comes to an end and need to be replaced [28].

In this subsection the driving factors for the three parts of the supply chain and the driving factor due to liberalization are discussed.

#### *Generation*

Today, coal is the main source of electricity generation. A future without electricity generation using coal is almost unthinkable since coal is cheap, is still almost abundant and can be digged up in more stable countries [56]. However, coal is one of the most polluting fossil fuels concerning the amount of $CO_2$ emission. One of the solutions is to capture and store the $CO_2$, so called Carbon Capture and Storage

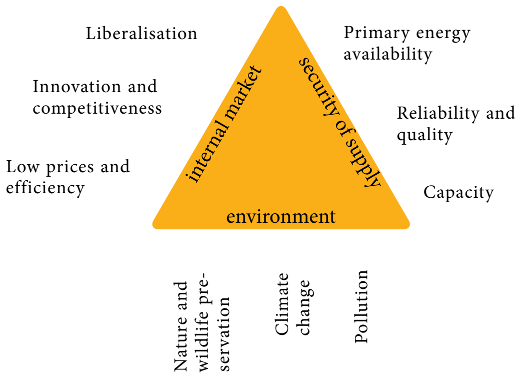



Figure 2.3: Schematic of the driving factors for a Smart Grid [56]

(CCS). At the moment, a couple of CCS installations are in use (for example [19]). However, it is not (yet) a broad applicable option and still based on fossil fuels. Another, better option is sustainable electricity generation using renewable sources (sun, wind, tides, etc.). However, this requires thorough changes and improvements of the electricity grid.

First, large scale sustainable electricity generation is often only possible on remote places with a low density of population and therefore a low electricity demand (e.g. large offshore wind power farms or solar panels in the desert). Therefore, electricity needs to be transported to the customers, requiring a large transmission capacity. It is expected that the renewable potential in Europe is large enough to supply all electricity [10]. Mainly in the southern parts of Europe there is a large (solar energy) potential, when the Northern part of Africa is taken into account the potential is huge. In the Desertec project [32] a concept is proposed for making use of sustainable energy worldwide. In Figure 2.4 the proposed solution is shown. The dark squares in the desert depict the area required to generate enough electricity using sun collector plants for the world, Europe, the Middle East and Northern Africa (MENA) and the proposed combination of Europe and MENA.

Second, large scale sustainable electricity generation has large differences with conventional power plants, both in generation capacity and controllability. It is, in general, agreed that it is both desirable and necessary to manage this new type of generation and adapt the rest of the grid infrastructure to facilitate the sustainable, unmanageable generation. Also on a domestic level more and more electricity is generated using micro-generators. Lower capacity generation on various sites, i.e. generation with lower capacity than conventional large power plants (e.g. sustainable and domestic generation), is called *Distributed Generation (DG)*. In [59] it is stated that a fit-and-forget introduction of domestic DG will cause stability problems, amongst others by large flows from lower to higher voltage levels. A study of the International Energy Agency concludes that, although DG has higher capital

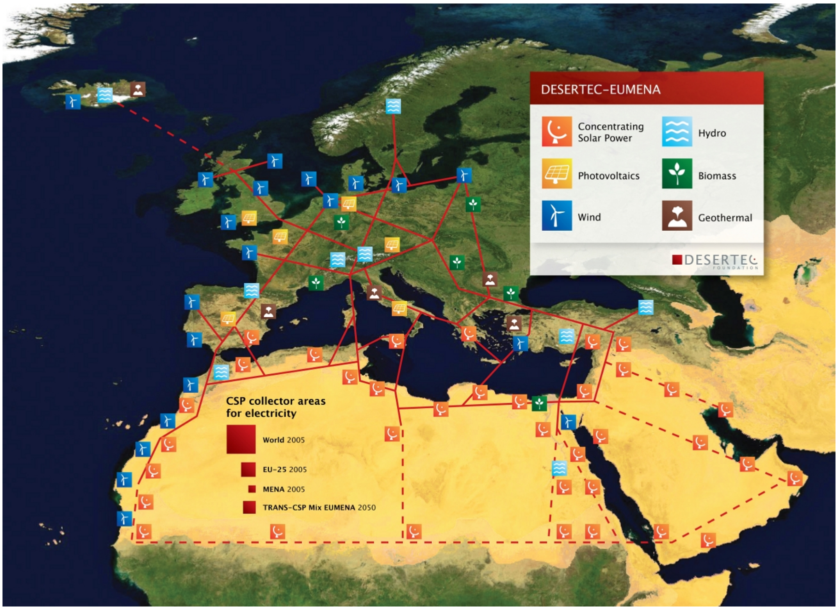



Figure 2.4: Sketch of possible infrastructure for a sustainable supply of power to Europe, the Middle East and North Africa (EU-MENA) (Euro-Super grid with a EU-MENA-Connection proposed by TREC) [32].

costs than power plants, it has a huge potential and that it is possible with DG to supply all demand with the same reliability, but with lower capacity margins [33]. The study foresees that the supply can change to decentralized generation in three steps: 1) accommodation in the current grid, 2) introduction of a decentralized system cooperating with the central system and 3) supplying most demand by DG.

So, next to high capacity lines for long-distance transportation of electricity, a sustainable electricity supply also requires more and better monitoring and control capabilities of all types of generation on different levels of the grid.

*Consumers*

Next to a changing supply of electricity, also the demand of electricity changes, especially when the trend towards a mainly electricity based energy supply continues. The overall electricity demand increases every year and is expected to keep increasing in the coming years. Furthermore, when more electricity consuming technologies are developed (e.g. electrical cars) the demand will increase and become more fluctuating. A fit-and-forget introduction will have a severe impact on the grid and generation [29]. In [4] the effects of a shift from conventional cars to PEVs is analyzed in an actual situation (city of Gothenburg), this study shows that this introduction will cause overloaded lines and transformers in worst-case scenarios. More capacity and flexibility is required to ensure the expected reliability and stability of supply. A naive introduction will lead to large investments and decreased generation and transportation efficiency.

New domestic technologies also introduce freedom in the electricity consumption patterns. These devices can be monitored and managed to change their consumption profile.

So, monitoring and control on the lowest level, on a device level, is desired. With monitoring the expected consumption and production of domestic devices can be predicted, control enables the possibility to exploit scheduling freedom of domestic devices to work towards (global) objectives.

*Transport*

For a transition towards a sustainable electricity supply as energy-carrier of the future, both renewable generation and an electricity based energy supply are required. To merge these two tendencies, generation and consumption need to be matched. To make this possible, significant improvements in the grid infrastructure and more intelligence in the grid are required.

The foreseen changes in production and consumption as described in the previous paragraphs will increase the stress on the grid while at the same time stability, reliability and self-healance of the grid become more important due to the increasing importance of electricity for society. Therefore, the streams through the grid should be monitored and managed.

In [35] an alternative transport medium is proposed by combining multiple energy-carriers in one "cable". This leads to a more flexible supply of combinations of energy-carriers and to a synergy of energy-carriers. For example, natural gas can cool the electricity transportation cables resulting in less transport losses, at the same time the transport losses (heat) of the electricity transport are absorbed by the natural gas.

Another issue is the large distance between areas with high potential for generating renewable electricity and areas where the electricity is consumed. To transport the sustainable electricity from the generation site towards the customers, an European wide interconnected high capacity electricity grid is required, in combination with a European wide electricity market. One of the technologies for the high capacity backbone for this European network is High Voltage DC (HVDC). This technology is already used for transport of electricity from offshore wind parks to the coast. In [10] a super Smart Grid is proposed: a combination of a European wide HVDC backbone (super grid) to transport the unevenly distributed renewable potential through Europe, partly from the African continent. This is combined with clusters of Smart Grids, using decentralized generation and demand side management in combination with electricity supplied by the super grid to supply all demand.

The earlier called Desertec project also proposes a super grid, not only covering Europe but also Northern Africa and parts of the Middle East (see Figure 2.4). They propose a 17,000 km$^2$ solar power system in the Sahara desert producing the main part of the electricity consumption in Northern Africa and 15% of the electricity needs of Europe.

*Liberalization*

A third driving factor for improving grid capabilities, next to environment and changes in demand/supply, is the liberalization of the electricity market. Due to competition between (distribution) companies they aim for an affordable electricity supply and a stable and reliable grid. Furthermore, an "innovative and green image" is important for companies.

### 2.2.2 SMART GRID

The improved version of the grid is often called a Smart Grid. It is hard to give a definition of a Smart Grid, different parties have their own definition, ranging from a grid capable of charging electrical cars up to a completely controlled grid, including producers, transmission and consumption. In [46] is stated that the Smart Grid is not a "thing" but rather a "vision": "*The Smart Grid vision generally describes a power system that is more intelligent, more decentralized and resilient, more controllable, and better protected than today's grid*". The definition given in [59] is rather common, so we choose for this definition:

"*A Smart Grid generates and distributes electricity more effectively, economically, securely, and sustainably. It integrates innovative tools and technologies, products and services, from generation, transmission and distribution all the way to customer devices and equipment using advanced sensing, communication, and control technologies. It enables a two-way exchange with customers, providing greater information and choice, power export capability, demand participation and enhanced energy efficiency.*"

To develop a Smart Grid, it is important to incorporate the complete grid including supply and demand [45]. Within the grid itself monitoring and switching possibilities are added, generation and consuming devices are (partially) extended with a monitoring and managing interface [56]. Optionally this can be extended with (electricity) storage. A (central) monitoring and control system matches generation and consumption in the most efficient way (the definition of efficiency can differ depending on the stakeholder: reduced $CO_2$ emission, less fossil fuel usage, more profit, etc.). In [45] is stated that the U.S. electrical infrastructure will evolve as a highly automated and interconnected network much in the fashion of the Internet; one where information and knowledge will flow through intelligent systems to serve the entire grid community; one where a dynamic network of smart devices enables the realtime balance of generation and delivery of electricity with the highest reliability and lowest cost.

The Smart Grid should be accessible to distributed generation and renewable energy sources, comply with different forms of generation, enable local energy demand management (optionally through smart metering systems) and facilitate dynamic control techniques [56]. Furthermore, it should facilitate high levels of power security, quality, reliability and availability with minimum negative side-effects on the environment and the society [56]. In [46] the required functionality is summarized in seven important characteristics of a Smart Grid:



1. enable active participation by consumers,
2. accommodate all generation and storage options,
3. enable innovation, new products and services by market forces,
4. provide high quality power,
5. optimize asset utilization and operate efficiently,
6. anticipate and respond to system disturbances (self-healing),
7. operates resiliently against attacks and natural disasters.

An important issue is the large number of stakeholders involved in the transition towards a Smart Grid: governments, regulators, consumers, generators, traders, power exchanges, transmission companies, distribution companies, power equipment manufacturers and ICT providers [56]. These stakeholders need an incentive to cooperate while in first instance it seems to be unattractive for companies. However, distribution companies can decrease operating and maintenance costs and reduce capital costs. Production companies can introduce new types of generation and increase generation by relatively cheap base-load plants [28]. The consumers can reduce their costs and increase power quality and finally society will benefit from a stimulated economy and improved environmental conditions [28].

Both [59] and [33] indicate that commercial attainability and legislation are important issues for the success of the introduction of DG. The opinions on the investments and profits differ strongly. On the one hand, the European Climate Forum states that large investments are required while it is unknown what the actual benefits and profits are [10]. On the other hand, the U.S. Department of Energy states that the transition towards a Smart Grid already started and that profits are higher than the investments [28]. They even claim that due to all benefits (e.g. improve safety and efficiency, better use of existing assets) the transition towards a Smart Grid will be market driven.

### 2.2.3 TECHNICAL CHALLENGES

For a successful introduction of a Smart Grid we face a number of technical challenges. There is a lot of research ongoing on different fields for a more efficient and sustainable electricity supply. New power plants themselves are much more efficient, CCS is developed to decrease emissions, transmission mediums with lower losses are developed and domestic devices become more efficient and controllable. In [45] five key technologies required for the Smart Grid are identified:

1. sensing and measurement,
2. integrated communications,
3. advanced components,
4. improved interfaces and decision support,
5. advanced control.

Since you can only manage what you measure, sensing and measuring are an important part of the Smart Grid. The health parameters of the transmission lines and substations should be monitored to prevent the grid from outages. Monitoring and forecasting of the weather can be used for forecasting load and potential output of renewable sources. This can subsequently be correlated with transmission line capacity. Next to the grid, also the generation, storage and consumption sites and devices need to be monitored to be capable of balancing generation and usage and respecting transmission limitations. An advanced metering infrastructure (AMI) is not only used for billing, but also for monitoring domestic usage, voltage and power quality. Furthermore, the Smart Meter can be used as a gateway to the domestic devices and to determine the optimization potential.

To transport all information, a high speed communication infrastructure is required. This integrated communications (IC) infrastructure moves the information between sensing and measurements devices towards the operators and management information back to the actuators. Creating a homogeneous infrastructure requires standards respected by all stakeholders, from home networks and all devices connected to it via the smart meters and the distribution companies to the overall network operators. The National Institute for Standardization and Technology (NIST) addressed this problem and is working together with IEEE to create Smart Grid standards [53]. The IC infrastructure should be designed with future in mind, the capacity, security and performance should be sufficient to facilitate also future applications. A fast, reliable and well designed IC infrastructure glues all the parts of the Smart Grid together.

A Smart Grid is built up from a network of advanced components. The grid itself should consist of efficient transmission elements connected by advanced flow control devices, e.g. HVDC lines and solid state transformers. On domestic level a lot of technologies are in development. These technologies range from PV panels on roofs and micro Combined Heat and Power (microCHP) [61] up to controllable devices [36]. The technologies can be subdivided in three groups:

- *Distributed Generation (DG)* In contrast to electricity generation in a few large power plants a growing share of the electricity is generated in smaller, geographically distributed generators. This DG ranges from wind turbine parks with a capacity on a MW level up to domestic DG with a kW level capacity.

- *Distributed Storage (DS)* Especially with a growing amount of renewable sources in the electricity supply chain there is a growing demand for electricity storage [34]. Sometimes electricity can be produced more efficiently (e.g. at daytime) or at certain times when it is not needed (e.g. wind, sun) and thus needs to be stored [56].

  Storage can take many forms, can be spread across a large geographic area and can connected to any voltage level [56]. Especially with the large scale introduction of electrical cars huge distributed controllable storage capacity becomes available. Furthermore, in multiple projects hardware is developed to manage domestic electricity streams and store electricity within buildings, e.g. within the PowerRouter project[1]. On the other hand, also larger scale electricity storage is developed, for example in the Smart Substation project of a Dutch consortium [42], which can be seen as a large version of the PowerRouter. Important research area for storage is the development of batteries meeting high requirements concerning capacity, charge/discharge currents and lifespan of many charge/discharge cycles.

- *Demand Side (Load) Management (DSM)* DSM can modify the consumption pattern of consumers. About 50% of the load in houses is dedicated to controllable devices such as refrigerators, freezers, heaters, washing machines and dryers [14]. These devices can be managed with only a little discomfort for the residents in contradiction to lights and a television, which cannot be switched off or shifted without discomfort. Field tests in the USA have shown that optimizations with these manageable devices already can lead to significant peak reductions [36]. Furthermore, when residents choose for a certain level of discomfort, e.g. a deviation of 0.5°C from the settled room temperature, even more scheduling freedom is gained. Of course there has to be an incentive for the residents to accept the reduction in comfort.

The grid operators' job became much more challenging in the last years, from respond times of minutes some years ago they have to react in seconds nowadays. New tools are required to assist the grid operators. To have enough information to take decisions, data mining is very important. Data is produced by measurement devices, transported via the IC infrastructure and gathered and presented by advanced visualization tools. This improved interface is required to visualize the large amount of data on such a way it can be understood at a glance. Furthermore, decision support tools help taking decision, for example fast simulations to forecast consequences of decisions.

To make use of all control capabilities and to exploit all optimization potential, advanced control systems need to be developed. Advanced protection systems can adjust relay settings in time for better protection of the grid and even increased power flows in some cases [45]. Controlling flows can for example increase stability, increase damping of oscillations, operate transmission networks as efficiently as

[1] http://nedap-energysystem.com

possible and assure maximum utilization of transmission assets. The growing share of technologies on a lower voltage level that can influence real and reactive flow, can enhance operators' ability to influence grid conditions significantly. Furthermore, coordination of (renewable) generation, storage and consumption is fundamental to reach all targets of a Smart Grid.

### 2.2.4 SMART GRID CONTROL

To create a successful Smart Grid solution and exploit all optimization potential the introduced technologies need to be monitored and synchronized to each other. On the production side of the electricity chain already a lot of control is available. Controllable production sites, e.g. central power plants, adjust their production to the demand, i.e. a feedback loop adjusts the settings based on the grid frequency to react on small variations. This monitoring and controlling system is a so called Supervisory Control And Data Acquisition (SCADA) control system. Next to adjusting the amount of production in a production site, grid operators can decide to start or stop a complete (peak) production site based on the demand forecasts and the current power plant states and energy demand. Production sites that are not controllable need to be monitored and their production need to be forecasted.

At the moment, the electricity flows within the grid are mainly monitored. Managing electricity flows by adjusting transformer settings is used on a smaller scale. By adjusting transformer settings the direction of the flow and the amount of energy can be managed. In a Smart Grid these streams also need to be managed to maintain stability and prevent blackouts caused by overburdening.

However, production and transportation control are important issues, the biggest challenge is managing the technologies connected to the medium and lowest voltage levels of the grid, the medium sized DG and domestic technologies. By managing the electricity production, storage and consumption of these technologies a lot of electricity flows in the net can already be managed. The combined flexibility of these technologies is high, but to exploit this potential a lot of devices need to be monitored and managed. Therefore, scalability, communication and uniformity issues need to be solved.

To overcome the scalability and communication issues the structure of the control system is important. A hierarchical structure with data aggregation on the different levels is an often proposed scheme. Such a structure is scalable while the amount of communication can be limited. However, when data is aggregated, information gets lost, so it is a trade-off between precision and the amount of communication.

The goal of a low voltage control system is to manage the cooperation between the domestic technologies to use the maximum optimization potential. The primary functionality of the system is to control the domestic generation and buffering technologies in such a way that they are used properly and efficiently. Furthermore, the required heat and electricity supply and the comfort for the residents should be guaranteed. Some devices have scheduling freedom in how to meet these requirements. This scheduling freedom of the domestic devices is limited by the comfort and technical constraints and can be used for optimizations.

In Section 4.2 different structures and control methodologies proposed in literature are discussed.

The optimization objective can differ, depending on the stakeholder of the control systems, the system state and the rest of the electricity infrastructure. The objective for residents or utilities can be earning/saving money and therefore the goal is to generate electricity when prices are high and consume electricity when prices are low. For network operators the goal can be to maintain grid stability and decrease the required capacity while an environmental goal can be to improve the efficiency of power plants. Therefore, a control methodology should be able to work towards different objectives.

Next to different objectives, control methodologies can have different scopes for optimization: a local scope (within the building), a scope of a group of buildings e.g. a neighborhood (micro-grid) or a global scope (Virtual Power Plant). Every scope again might result in different optimization objectives.

*Local scope*

On a local scope the import from and export into the grid can be optimized, without cooperation with other buildings. Possible optimization objectives are shifting electricity demand to more beneficial periods (e.g. nights) and peak shaving. The ultimate goal can be to create an independent building. This can be done in two forms: *energy neutral* or *islanded*. Energy neutral implies that there is no net import from or net export into the grid. A building that is physically isolated from the grid is called an islanded building.

The advantage of a local scope is that it is relatively easy to realize; there is no communication with others (less privacy intrusion) and there is no external entity deciding which devices are switched on or off (better social acceptance). The disadvantage is that it might result in high investment costs, e.g. in storage capacity and micro-generation.

*Micro-grid*

In a micro-grid a group of buildings together optimize their combined import from and export into the grid, optionally combined with larger scale DG (e.g. wind turbines). The objectives of a micro-grid can be shifting loads and shaving peaks such that demand and supply can be matched better internally. The ultimate goal can be perfect matching within the micro-grid, resulting in a neutral or islanded micro-grid. The advantage of a group of buildings is that their joint optimization potential is higher than that of individual buildings since the load profile is less dynamic (e.g. startup peaks of devices disappear in the combined load). Furthermore, multiple micro-generators working together can match more demand than individual micro-generators since better distribution in time of the production is possible [1]. Finally, within a micro-grid the locally produced electricity can be used locally, saving transmission costs and preventing streams from lower to higher voltage levels. However, for a micro-grid a more complex control methodology is required.





*Virtual Power Plant (VPP)*

The original VPP concept is to manage a large group of micro-generators with a total capacity comparable to a conventional power plant. Such a VPP can replace a power plant while having a higher efficiency, and moreover, it is much more flexible than a normal power plant [29]. Especially this last point is interesting since it expresses the usability to react on fluctuations. This original idea of a VPP can of course be extended to other domestic technologies [29]. Again, for a VPP a complex control methodology is required. Furthermore, communication with every individual building is required and privacy and acceptance issues may occur.

## 2.3 Emergence

The emergence of energy-efficient electrification of the society and a sustainable supply is illustrated by the large amount of initiatives from academia, business and authorities. A lot of projects are started, conferences are organized and test sites are built up. In this section a short survey of a number of programs, alliances and projects is given.

### 2.3.1 programs and alliances

On different levels programs and support initiatives are started. The IEEE, the world's largest professional association for the advancement of technology, organizes many conferences covering all aspects of the Smart Grid with a focus on both academia and industry. The IEEE Power & Energy Society (IEEE PES) moves its focus more and more towards Smart Grid technologies and IEEE even started a web portal focussed on Smart Grids[2]. Furthermore, a new journal is initiated focussed on Smart Grids, IEEE Transactions on Smart Grids.

A lot of governments provide extra funds to research focusing on Smart Grids and energy departments more and more focus on Smart Grid technologies. For example, the USA invests nearly $ 100 million[3], the UK[4] and the Netherlands[5] have similar programs.

Also in the European Union the emergence of Smart Grids is realized. They state that for a successful transition to a future sustainable energy system all the relevant stakeholders must become involved and coordination at regional, national and European levels is essential. Therefore, the Smart Grids Technology Platform [56] has been designed to facilitate this process. The International Energy Agency

[2] http://smartgrid.ieee.org/

[3] http://www.energy.gov/news/8842.htm

[4] http://www.decc.gov.uk/en/content/cms/what_we_do/uk_supply/network/smart_grid/smart_grid.aspx

[5] http://www.twanetwerk.nl/default.ashx?DocumentId=13256

published a road map, stating that demonstrations of Smart Grid technology are urgently needed [2].

Probably the largest industrial initiative is the Gridwise Alliance [36], a collaboration of companies to realize a Smart Grid, with as mission *to transform the electric grid to achieve a sustainable energy future*. But also on a smaller scale there are a lot of industrial initiatives, for example Renqi [41], a collaboration of three Dutch research facilities, and the Smart Energy Collective[6].

Furthermore, a lot of projects concerning Smart Grid are ongoing, both on the technical side as well as on the control side. A lot of projects in Europe are funded by the European programs FP5-FP7 [20]. Next to these European fundings, also on a national levels a lot of research programs are started to fund this research. Example are the earlier mentioned $ 100 million of the US and natural gas profits in the Netherlands used for Smart Grid research[7].

### 2.3.2 TEST SITES

As mentioned in the road map of the IEA, demonstration projects are very important to demonstrate developed technologies. Examples of such demonstration projects are Boulder Colorado, Mannheim-Wallstadt, Meltemi and Powermatching City. In Boulder Colorado a Smart Grid City [30] is implemented with as goal to incorporate 1000 households in the Smart Grid project. The Smart House project [65] is an FP7 funded research project with as goal to demonstrate how ICT can help to achieve maximum energy efficiency. In the project 100 houses in Mannheim, Germany are connected to each other with as main goal to supply washing machines with electricity produced by PV panels. Within the same project on the Greece camping site Meltemi PV panels and a diesel generator are installed to reach islanded operation of the camping site. The Powermatching City project [13] in Groningen, the Netherlands, is a testbed for the PowerMatcher [38], an optimization algorithm developed by the Energy Centrum Nederland (ECN). In this project houses are equipped with smart devices and a local controller to test the optimization abilities of the PowerMatcher algorithm (see Chapter 5).

## 2.4 Conclusion

Changing circumstances ask for a renewed electricity grid to maintain an affordable and reliable supply, to shift towards more sustainable generation and to keep up with the electrification of the energy supply. Since the lifetime of a lot of elements in the electricity grid comes to an end, this is the time to implement a smarter grid. This renewed electricity grid should support distributed (sustainable) generation and should be able to supply the growing demand. To reach this, consumers should change from passive consumers to active prosumers, cooperating with each other and plant/grid operators to maintain grid stability and reliability under the

[6] http://www.smartenergycollective.com
[7] http://nlenergieenklimaat.nl

changing circumstances. However, to reach this, a number of technical, economical (e.g. who has to pay), political (e.g. is it allowed) and ethical (e.g. privacy issues) challenges have to be tackled. To tackle the technical challenges, ICT is one of the key technologies. Essential in a Smart Grid is a monitoring and management system that monitors and manages all parts of the grid, from central generation and large scale renewable generation, via transportation up to consumption/generation at the consumers on device level, in a cooperative way. The emergence of smartening the grid and updating the electricity supply chain is emphasized by the numerous initiatives worldwide from the European Union, from governments, from industry as well as from the academic world.

CHAPTER 3

# Modelling the energy infrastructure and streams

Abstract – *This chapter describes and explains the model of the energy infrastructure, used for the developed simulator, to derive optimization algorithms and to verify these algorithms. The goal of the algorithms is to optimize the electricity streams through the grid by influencing individual domestic devices. Therefore, the model consists of multiple levels: the leaves are the devices within buildings, a collection of devices each with their own behavior and optimization potential. These devices can convert, buffer and consume energy and are connected to each other in such a way that energy can flow between these devices. Buildings can exchange energy with their outer world and multiple buildings can be combined into a grid. For electricity, the grid itself also has a leveled structure, it consists of multiple voltage levels. On the lowest voltage level, multiple buildings form a neighborhood behind one transformer. Multiple neighborhoods can be combined into cities with higher voltage levels, etc. Furthermore, on different voltage levels electricity is fed in by different types of generators.*

In this chapter, a model of the energy streams within the building and through the grid is derived. To develop algorithms to optimize the electricity streams within the grid and to simulate the effectiveness of these algorithms, also a model of the energy infrastructure is needed. Furthermore, the different energy streams within a building are related, so all energy streams within the building have to be modelled. In the grid these energy streams are only modelled up the a certain level. Summarizing, a model is required that models individual devices within the

Parts of this chapter have been presented at [AM:14] and [AM:4].

building, energy streams within the building and by combining multiple buildings it should result in a model of energy streams through the grid, where the focus is on electricity streams.



The model is derived using a bottom up approach. We start with modelling the behavior of individual devices in the buildings, each with their own energy consumption, production or buffering. Next, connections between these devices are modelled, resulting in an expression for the energy streams within the building. Connections have to specify their type of energy (e.g. heat streams cannot be connected to electricity streams) and the way devices are connected has to be defined. For example, heat flows often from the boiler to the heat store and from there to the heating. The set of devices, how they are connected and the connections with their outer world together form a building.

Multiple buildings are combined into a grid, all connections of the buildings with the outer world are connected to the right type of energy supply. Most types of energy supply can be modelled straightforwardly. The natural gas and district heat supply are hardly influenced by fluctuation in demand since gas and heat can be stored easily. Next to connections with external energy suppliers, some buildings have their own energy stock (e.g. oil fuel). Also, these energy sources can be modelled rather easily.

However, the electricity grid is more complicated and has a leveled structure itself. Since it is hard to store electricity, power plants have to deal with fluctuations immediately. Furthermore, to decrease transport losses there are multiple voltage levels and transformers between the voltage levels to transform the voltages. These voltage levels, the capacity of the transformers and the capacity of the grid should be incorporated in the model. Buildings are connected to the lowest voltage level. They are connected in groups behind one transformer. Power plants and renewable sources are connected to different voltage levels. The model should keep track of locality of the electricity; electricity exported by a building might be imported by a buildings behind the same transformer. Furthermore, the model should keep track of production patterns of power plants and the electricity streams through the grid.

Summarizing, the model should take into account the complete infrastructure from the behavior of individual domestic devices up to the grid infrastructure with multiple voltage levels, transformers and generation sites. Furthermore, the model should be generic to be able to also incorporate future technologies and devices.

The model described in this chapter represents the status of the buildings and network at a certain moment in time. Especially the status of the devices, e.g. energy demand of devices and levels of buffers, change over time. Therefore, the observed horizon is divided in time intervals, the model describes the status of the buildings and network during a certain time interval, or to be more precisely, at the beginning of the time interval. Based on the choices made and energy streams during a time interval, the status of devices and therefore the parameters of the model for the next time interval can be derived.

In this chapter the complete model is described. The next section starts with a derivation of a model for the building, starting with the underlying idea of the model. In Section 3.2 it is described in a compact way how multiple buildings can be combined into a grid and the last section ends up with conclusions.

## 3.1 Building model



The model of a building should model all energy streams within the building and the exchange of energy with its environment. The energy streams need to be modelled up to a device level since optimization algorithms may influence the behavior of individual devices. In this section we first develop an intuitive notion of the energy streams. In subsequent subsections the notion will be formalized.

In most (European) buildings electricity and gas are imported and heat is produced inside buildings. However, it should also be possible to model a district heating system. Furthermore, for stability and reliability analysis it is required to model phase shifting in the electricity network (both real and reactive power). Finally, the amount of sun and wind imported and the conversion efficiency should be incorporated in the model. Therefore, a generic model of the considered types of energy, the available devices and the energy exchanged with the direct environment is required. A sketch of a possible house is given in Figure 3.1.

In the remainder of this section the complete model for the building is derived, from a device level via the connections between devices up to energy import and export. The next subsection describes the underlying idea of the model and in Subsection 3.1.2 the model of a building is derived, based on the presented idea. Finally, in Subsection 3.1.3 concrete models in the devices used for this thesis are determined.

### 3.1.1 Idea

The model of a building is built on the notion of energy-carriers and devices. All devices in the building consume, convert or buffer one or more types of energy-carriers. For example, a fridge consumes electricity, a boiler converts gas into heat and a hot water tank stores heat. Devices are interconnected via streams that transport energy-carriers. However, some devices are connected to multiple other devices, for example all electrical devices consuming electricity from the same source (e.g. imported electricity). Therefore, devices are interconnected via pools, i.e. every stream of a certain type of each device is connected to a pool. Since pools are abstract elements only introduced for modelling purposes, it cannot contain any energy and the sum of energy streaming in and out of a pool has to be zero at every moment in time. The model corresponding to the house sketched in Figure 3.1 is given in Figure 3.2. In the following paragraphs the four elements, energy-carriers, devices, energy streams and pools, are explained more detailed.

*Energy carriers*

The developed model is based on a set of *energy-carriers*. An energy-carrier is defined as an elementary manifestation of energy, i.e. a medium or substance

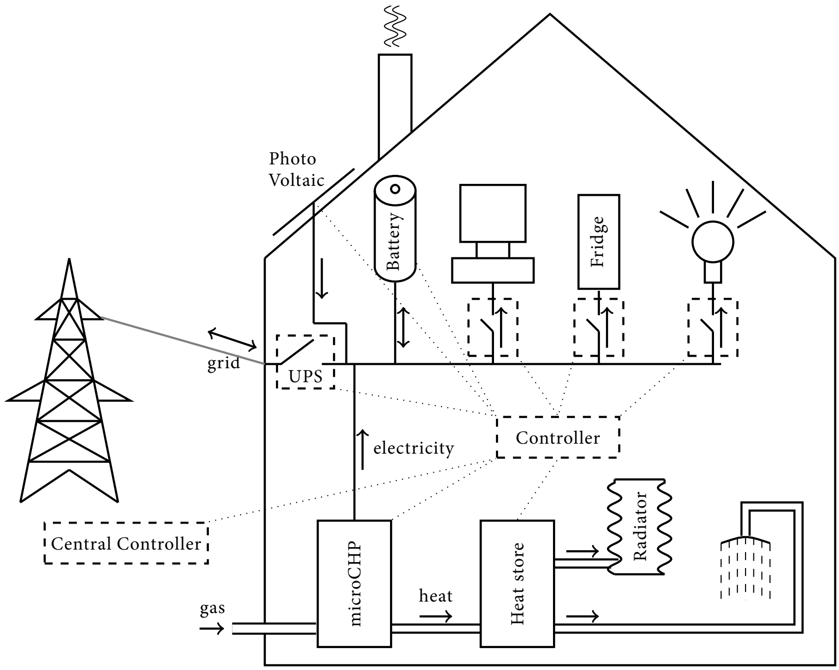



Figure 3.1: Schematic of the foreseen house

that contains energy. Most used energy-carriers in buildings are electricity, heat and natural gas. But also sunlight and wind can be seen as energy-carriers. All energy streams within a building and the energy sources used from outside are seen as streams of these energy-carriers: streams of heat, electricity and gas, but also sunlight, wind, etc. Electricity streams can be split up into a real and a reactive stream to observe the phase shift. Each stream consists of a flow of a single energy-carrier.

Within a building energy is exchanged with its environment, converted (change of energy-carrier type), (temporarily) stored and consumed by devices. In this context, e.g. a hot water tap is assumed to be a heat consuming device just as a TV set is an electricity consuming device. The model distinguishes four different types of devices within the building: 1) exchanging devices, 2) converting devices, 3) buffering devices and 4) consuming devices.

*Devices*

The basis of the model are devices and energy streams between these devices: energy of a specific type flows from device to device. A device does something with the

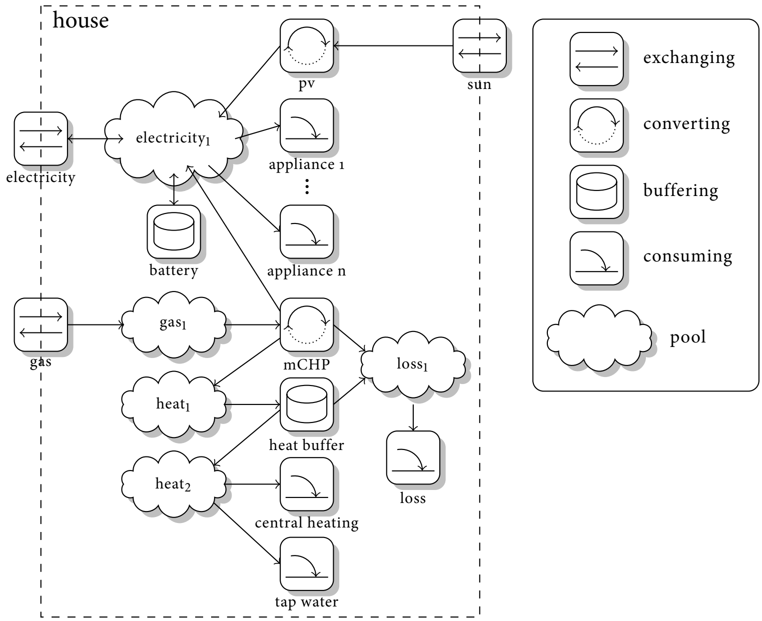



Figure 3.2: Modelled house

energy-carriers (exchange, convert, buffer, consume). So, a device is an entity where energy flows in and/or out and where the type of these energy flows is specified.

All devices within the building are modelled separately. We chose for this granularity, since the optimization algorithms to be tested with the model influence the behavior of individual devices. Such behavior can for instance be the decision when to run a converting device or when to temporarily buffer electricity, e.g. in order to shave peaks. Similarly, by decoupling the heat production and consumption using a heat buffer, shifting the runtime of a microCHP may become possible. Furthermore, demand side load management of consuming devices builds on managing individual devices. However, also not manageable devices can be used. Since these devices have no optimization potential and just consume the energy they need, they can be modelled as one or a few big devices, i.e. these devices can be aggregated into one device. Furthermore, import and export of energy is also modelled by a device, an exchanging device. By introducing an exchanging device the number of different elements stays limited and the model stays simple, generic and extendable.

In the following paragraphs, the specific characteristics of the four different types of devices are discussed.

*Exchanging devices* exchange energy with the environment. From a building point of view, a building exchanges energy with its environment. For most conventional buildings this is only electricity that can be imported and exported and gas that can be imported, but some buildings also may import heat from district heating. Furthermore, in recent years also sunlight and wind play a role and these are modelled as energy imports connected to exchanging devices. We model exchanging devices such that they exchange only one energy-carrier with the environment.

*Converting devices* convert one or more energy-carriers into one or more other energy-carriers. In our model, we assume that the amount of energy streaming into these devices is equal to the amount of energy streaming out of these devices. However, energy conversions (often) have a certain amount of loss during conversion. This is modelled as a separate energy stream out of the device (loss streams). So, a microCHP for example has a gas stream in (100%) and a heat stream (80%), an electricity stream (15%) and loss stream (5%) out.

*Buffering devices* can temporarily store an energy-carrier. These devices have an energy-carrier stream in and the same energy-carrier stream out. This separation of the stream in and out is necessary since these streams are not always shared, e.g. most currently installed heat stores have separate in and out flow circulations. When the in and out stream are shared, this can be enforced by the characteristics of the device. Next to the in and out stream, a separate energy-carrier stream out can be used for modeling loss.

*Consuming devices* consume one or more energy-carriers in a certain ratio. For most devices, the amount of energy consumed in a certain time interval (the consumption profile) is a characteristic of the device and is therefore defined on beforehand. A special type of a consuming device is a *loss device*. For this device it is not defined how much energy it consumes, it simply consumes all loss based on the loss streams connected to this device.

### *Streams between devices*

As mentioned before, the basis of the model are devices and energy streams between these devices. Every device has certain energy-carrier streams in and/or certain energy-carrier streams out. Input streams for one device are coupled to output streams of other devices, so energy-carriers can flow from one device to another. For example, in most buildings all electricity producing and consuming devices are connected to one grid in the building. Electricity can flow from every electricity output stream to every electricity input stream. On the other hand, hot water flows from the boiler via a pipe to the hot-water buffer and via another pipe to the consuming devices.

### *Pools*

To manage these flows in a proper way, all devices are interconnected through *pools*. A pool can only transport one energy-carrier and has no loss. This means that a pool has to be balanced: the amount of energy flowing in has to be equal to the amount of energy flowing out at every period of time. Every stream of every device is coupled to one pool and all streams connected to a pool must have the same energy-carrier. Finally, the amount of energy flowing from and to a pool can be limited due to limits in the transportation medium. In the house depicted in Figure 3.2 there are e.g. two "hot water pools" present.

Summarizing, within every pool one energy-carrier is transported and every stream is connected to one pool. This introduces a lot of expressive power. For example, we can model the situation that (a part of) the building is protected with an Uninteruptable Power Supply (UPS) system.



*Limitations and flexibility*

Every device has certain physical limitations, e.g. the amount of energy it can import, the amount of energy it can convert, etc. Furthermore, within the limitations of the device, often some kind of flexibility or operation modes are possible. Examples for such flexibility in options are the timestamp a microCHP is switched on to fill a heat buffer or the decision whether to store energy in a battery and how much. The amount of every energy-carrier flowing in and out, as well as the limits, are defined in Watt (W). Every device $d$ has a set of possible options $Opt^d$ to act (microCHP on/off, buffer charge or discharge and how much, etc.). Based on the state $state$ of the device (e.g. State of Charge of the buffer) a subset $Opt^d_{state}$ of the set of options are valid options. A control algorithm needs to decide which option to choose.

### 3.1.2 FORMAL MODEL OF A BUILDING

We now have sufficient background information to develop a formal model of the energy streams in the building. To model a building, all energy carriers, devices, energy streams, pools and the way they are connected need to be defined. For every device the input and output streams are defined together with the set of options, the possible states and which options are valid for each state ($Opt_{state}$). The model represents the situation in a building at a certain moment in time since the valid options depend on the state, which changes over time. In this subsection every part of the model is described in more detail, a complete overview of the model can be found in Appendix B.

For each instance of the model a set of energy-carriers $EC$ is defined. For every energy-carrier, at least one pool is present. Therefore, a set of pools $P$ is introduced containing for every energy-carrier $ec \in EC$ a set of disjoint pools $P_{ec} \subseteq P$:

$$P = \cup P_{ec},$$

where $P_{ec} = \{p_{ec_1}, ..., p_{ec_{N_{ec}}}\}$. For example, the sets for the house in Figure 3.2 are given by:

$$EC = \{electricity, gas, heat\}$$

$$P = P_{electricity} \cup P_{gas} \cup P_{heat},$$

where $P_{electricity} = \{p_{electricity_1}\}$, $P_{gas} = \{p_{gas_1}\}$ and $P_{heat} = \{p_{heat_1}, p_{heat_2}\}$. Furthermore, the house contains a set $Dev$ of devices. There are four types of devices: exchanging devices, converting devices, buffering devices and consuming devices. This leads to the following sets:



$$Dev = Dev_{ex} \cup Dev_{conv} \cup Dev_{buf} \cup Dev_{cons},$$



where $Dev_{ex} = \{d_{ex_1}, ..., d_{ex_{N_{ex}}}\}$, $Dev_{conv} = \{d_{conv_1}, ..., d_{conv_{N_{conv}}}\}$, $Dev_{buf} = \{d_{buf_1}, ..., d_{buf_{N_{buf}}}\}$ and $Dev_{cons} = \{d_{cons_1}, ..., d_{cons_{N_{cons}}}\}$.

*Streams of energy-carriers*

Streams of energy-carriers flowing from or to devices are connected to pools. To model this, let $Str^p$ ($Str^d$) be the set of all streams from pools to devices (devices to pools). Note that a stream can only transport a single type of energy-carrier. Each energy-carrier stream from $Str^p$ ($Str^d$) thus, is given by a tuple $str = (p, d)$ ($str = (d, p)$) with $p \in P$ and $d \in Dev$. Furthermore, let $Str = Str^p \cup Str^d$. The amount of energy flowing through a stream $str \in Str$ is modelled with variable $x_{str}$. Since as much energy must flow into a pool as flowing out, we must have for each time interval:

$$\sum_{(p,d)\in Str^p} x_{(p,d)} = \sum_{(d,p)\in Str^d} x_{(d,p)} \qquad \forall p \in P.$$

*Devices*

Multiple streams can flow in and out a device. There always has to be a certain fixed ratio between the streams, possibly depending on the amount of energy flowing to or from the device. Therefore, a variable $x_d$ is introduced to represent the total energy flowing through the device $d \in Dev$. Next, for every energy carrier stream $str \in Str$ connected to a device $d$ a multiplication factor $M_{str} \in [0, 1]$ is defined. The actual amount of energy flowing through a stream $(p, d) \in Str^p$ or $(d, p) \in Str^d$ has to fulfill:

$$x_{(p,d)} = x_d \times M_{(p,d)} \tag{3.1}$$

$$x_{(d,p)} = x_d \times M_{(d,p)} \tag{3.2}$$

Since not an arbitrary amount of energy can flow through a device, the possible values for $x_d$ are restricted. The possible values depend on the *state* of the device. In every time interval, the device has a certain state. Depending on the state $state$ of the device $d$, only a subset $Opt^d_{state}$ of all options $Opt^d$ can be chosen. In the next time interval, the new state can be derived based on the chosen option. So, the decision in this time interval influences the state in the next time interval and therefore the possible options in the next time interval.

Each option $opt \in Opt^d$ specifies an interval $[Min_{opt}, Max_{opt}]$ for $x_d$ for which the option is valid. In this way, a number of disjoint intervals is defined for every device. For $x_d$, only values of one of these intervals may be chosen. To capture this, decision variables $c_{opt} \in \{0,1\}$ are introduced. Only one of these decision variables is allowed to be nonzero, representing the chosen interval:

$$\sum_{opt \in Opt^d_{state}} c_{opt} = 1 \tag{3.3}$$

$$c_{opt} = 0, \qquad \forall opt \in Opt^d \setminus Opt^d_{state},$$

where $state$ is the current state.
To combine the flow variable $x_d$ of a device to the different options $opt \in Opt^d$, we introduce a flow variable $x_{opt}$ for each $opt \in Opt^d$ and define

$$x_d = \sum_{opt \in Opt^d} x_{opt}. \tag{3.4}$$

To make sure that only the flow variable of the chosen option $opt \in Opt^d$ is non-zero, we add the following constraint:

$$c_{opt} \times Min_{opt} \leq x_{opt} \leq c_{opt} \times Max_{opt}.$$

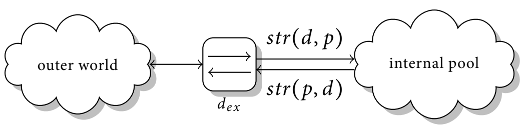
Multiplication factors $M_{(d,p)}$ and $M_{(p,d)}$ may depend on the chosen $opt \in Opt^d$. So for every device $d \in Dev$ and every energy carrier stream $(p,d) \in Str^p$ and $(d,p) \in Str^d$ multiplication factors $M^{opt}_{(p,d)}$ and $M^{opt}_{(d,p)}$ have to be given. The equation 3.1 and 3.2 now have to be replaced by

$$x_{(p,d)} = \sum_{opt \in Opt^d} M^{opt}_{(p,d)} x_{opt}$$

and

$$x_{(d,p)} = \sum_{opt \in Opt^d} M^{opt}_{(d,p)} x_{opt}.$$

*Exchanging devices* An exchanging device $d \in Dev_{ex}$ exchanges one type of energy-carrier and has one stream flowing out of the device (import into the building from the outer world) and optional one flow in (export). Only one of the streams can be non-zero. This can be enforced using the set of options $Opt^d$. We define



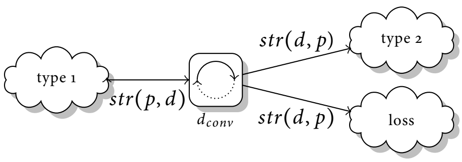

two options $imp$ and $exp$ (i.e. $Opt^d = \{imp, exp\}$), where the bounds $Min$ and $Max$ of the options specify the limitations for the import and export and where $M^{imp}_{(d,p)} = M^{exp}_{(p,d)} = 1$ and $M^{imp}_{(p,d)} = M^{exp}_{(d,p)} = 0$ for the energy carrier stream connections with its pools. In other words, there can be a flow from this device to the pool ($M^{imp}_{(p,d)} = 0$ and $M^{imp}_{(d,p)} = 1$) or there can be a flow from the pool to this device ($M^{exp}_{(p,d)} = 1$ and $M^{exp}_{(d,p)} = 0$).

*Converting devices* A converting device $d \in Dev_{conv}$ converts one or more energy-carriers into one or more other energy-carriers. Thus, this device can have multiple streams in and multiple streams out. The amount of energy flowing in must be equal to the amount flowing out (including the optional loss-stream), so:

$$\sum_{(p,d) \in Str^p} x_{(p,d)} = \sum_{(d,p) \in Str^d} x_{(d,p)} \qquad \forall d \in D_{conv}.$$

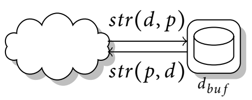
Since the amount of energy flowing through a stream is defined by $x_d$ times the multiplication factor, the sum of the multiplication factors of all stream in must be equal to the sum of the multiplication factors of all streams out, so:

$$\sum_{(p,d) \in Str^p} M^{opt}_{(p,d)} = \sum_{(d,p) \in Str^d} M^{opt}_{(d,p)}, \qquad opt \in Opt^d.$$

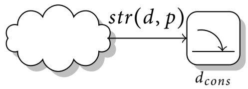



*Buffering devices* A buffering device $d \in Dev_{buf}$ buffers one type of energy-carrier and has one stream in and one or two streams out (the optional one is the loss). Furthermore, the buffering device has a current state, namely the State Of Charge $SoC_d$, specifying the amount of stored energy. The possible options to use the buffer are charging (energy flowing in), discharging (energy flowing out) or not using the buffer (loss energy may flow out). The amount of energy flowing in, flowing out and the increase of the SoC ($\Delta SoC_d$) must be in balance:

$$\sum_{(p,d) \in Str^p} x_{(p,d)} - \sum_{(d,p) \in Str^d} x_{(d,p)} = \Delta SoC_d.$$




*Consuming devices* A consuming device $d \in Dev_{cons}$ consumes one or more types of energy-carriers and has only streams flowing into the device. The values for $x_d$ determine the demand of the device. In case of a smart appliance or demand side load management, multiple values for $x_d$ might be valid: the device can be switched off or the consumption can be lowered temporarily.




*Control*

Within the building, the pools need to be in balance and the constraints of the devices need to be respected. The constraints for the streams, pools and devices have been discussed above.

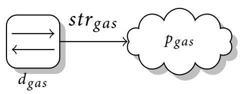
In general, within the specified constraints a lot of combinations of options are possible, e.g., electricity can be supplied by the installed battery or imported from the grid. Therefore, a best combination of options $opt \in Opt^d$, for all $d \in Dev$ need to be found. Since the devices themselves only allow valid options, the constraints of the devices are met automatically. Thus, a control methodology only has to deal with the balance per pool when picking options and values for $x_d$. When there are multiple valid combinations, a best combination should be picked based on a certain objective. An algorithm to pick the best values for $opt \in Opt$ and $x_d$ is discussed in Chapter 4.

### 3.1.3 MODELLING OF SPECIFIC DEVICES

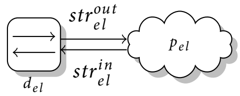
In this subsection we give the modelling of a number of actual devices, using the given model. These devices are used for the analyzis of the developed algorithms and are described in detail in this subsection.

*Exchanging devices*

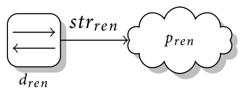
Exchanging devices are used for the import and export of energy. Two conventional energy sources are modelled with an exchanging device, gas and electricity. The exchanging device for gas $d_{gas}$ has only one option specified by a maximum amount of import $MAXIMPORT_{gas}$ which is delivered to the pool $p_{gas}$. As a consequence only one energy carrier stream is connected to $d_{gas}$, namely the stream $str_{gas} = (d_{gas}, p_{gas})$ and for this stream $M^{d_{gas}}_{str_{gas}} = 1$. Furthermore, for the only option the interval $[Min, Max]$ is given by $[0, MAXIMPORT_{gas}]$. The device is stateless, so $Opt^{d_{gas}}_{state} = Opt^{d_{gas}}$.




The electricity exchanging device $d_{el}$ used for this thesis has two different options: *import* and *export*. Therefore, it has two energy streams connecting it to the electricity pool $p_{el}$: $str_{el}^{in} = (d_{el}, p_{el})$ and $str_{el}^{out} = (p_{el}, d_{el})$. Both streams have an upper bound $MAXIMPORT_{el}$ and $MAXEXPORT_{el}$ respectively. The two multiplication factors are $(1,0)$ and $(0,1)$ for the two options $import$ and $export$. This device is also stateless: $Opt_{state}^{d_{el}} = Opt^{d_{el}}$. However, more sophisticated scenarios can be modelled (e.g. higher currents lead to higher losses).




Renewable sources like sun and wind are also imported into the building with exchanging devices. For renewable sources, the amount of import is a measure for the amount of energy. For example, the amount of wind import is a measure for the wind speed, the amount of sun import a measure for the sunlight intensity. Therefore, a device $d_{ren} \in Dev_{ex}$ importing a renewable source has only one option $opt \in Opt_{state}^{d}$ for every state, specifying the (encoded) amount of renewable energy imported. This energy is delivered in pool $p_{ren}$, thus there is only one energy carrier stream from the device to the pool $str_{ren} = (d_{ren}, p_{ren})$, with as multiplication factor 1.



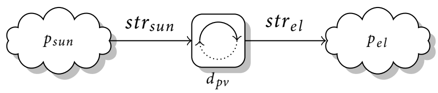

*Converting devices*

A converting device is basically a device with one or more streams in and one or more streams out with a certain ratio between the different streams. In this paragraph three different converting devices are modelled: a standard high-efficiency boiler, a microCHP and a PV panel.

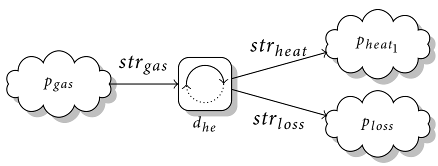
A PV panel $d_{pv} \in Dev_{conv}$ produces a certain amount of electricity. The output of a PV panel is often defined by the nominal output under standard test conditions, the so called Watt-peak (Wp). Standard test conditions are 1000 W/m$^2$ and an orthogonal incidence of the sunlight[1]. The efficiency of a PV panel is the Wp divided by 1000, the total electricity production of a PV panel is defined by the efficiency times the area and a correction factor when sunlight does not incide orthogonally. The sunlight intensity, the amount of sunlight imported, is given as the amount of sunlight per square meter (W/m$^2$). The panel is connected to a sun pool $p_{sun}$ and an electricity pool $p_{el}$. The PV panel has one stream $str_{sun} = (p_{sun}, d_{pv})$ in and one stream $str_{el} = (d_{pv}, p_{el})$, the multiplication factor depends on the efficiency, the

[1] http://en.wikipedia.org/wiki/Watt-peak

size of the panel and the positioning of the panel. The device only has one option, it consumes the amount of electricity imported by the exchanging device. This device is also stateless and therefore $Opt^{d_{pv}}_{state} = Opt^{d_{pv}}$. Note that the energy is not in balance for this device since the imported sun is a code for the sunlight intensity.




A high-efficiency boiler $d_{he} \in Dev_{conv}$ produces heat (hot water) using natural gas. The device imports gas from a pool $p_{gas}$ and delivers heat to a heat pool $p_{heat}$. Loss is delivered to a abstract pool $p_{loss}$. This results in one stream $str_{gas} = (p_{gas}, d_{he})$ in and two heat streams out: $str_{heat} = (d_{he}, p_{heat_1})$ and $str_{loss} = (d_{he}, p_{loss})$. When the boiler has an efficiency of 97% the multiplication factors for these three streams are 1, 0.97 and 0.03 respectively. The boiler has a very low startup time in comparison to the time interval lengths used, it produces immediately heat. Furthermore, boilers can often produce different amounts of heat; central heating requires a less high heat stream than the hot water tap. Therefore, the set $Opt^{d_{he}}$ has three different options *off*, $low$ and $high$. For every option, the boiler has a fixed amount of production, thus $Min = Max$ The concrete values for the three options are given by $Max = 0$, $Max = 15000$ and $Max = 30000$. The state represents the current state of production (*off*, $low$, $high$) and the device can divert from every state immediately to any other state: $Opt^{d_{he}}_{state} = Opt^{d_{he}}$.

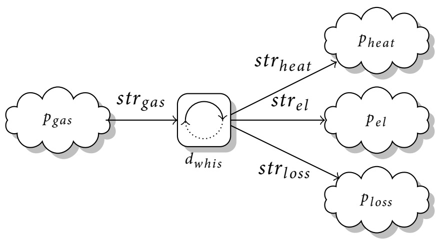



The modelled microCHP device is a Whispergen $d_{whis} \in Dev_{conv}$. We have chosen for this specific device, since a Whispergen[2] is available for testing, but other Stirling engine based microCHP devices have similar behavior. A Whispergen is a Stirling engine based microCHP with only one generation level. Thus, the generation has two modes: on and off (0 $W_e$ and 1000 $W_e$). The heat production is eight times the electricity production, 8000 $W$. The efficiency of the device is 97%, which is equal to the efficiency of a conventional boiler. Therefore, the device imports gas from a pool $p_{gas}$ via a stream $str_{gas} = (p_{gas}, d_{whis})$. It delivers electricity to a pool $p_{el}$, heat to a pool $p_{heat}$ and loss to a pool $p_{loss}$ via streams $str_{el} = (d_{whis}, p_{el})$, $str_{heat} = (d_{whis}, p_{heat})$ and $str_{loss} = (d_{whis}, p_{loss})$ respectively.

[2] http://www.whispergen.com

Taking multiplication factor 1 for the gas input, the loss output has multiplication factor 0.03. Furthermore, from the resulting 97%, $\frac{1}{9}$ is electricity. Therefore, the multiplication factor for the electricity output is 0.10 and for the heat output 0.87.






When the microCHP device starts, it does not immediately generate the full 1000 $W_e$ and 8000 $W_{th}$. During the startup time the generation increases from 0 $W_e$ to 1000 $W_e$. This is modelled as a linear increase. For stopping the same holds and we model this as a linear decrease from 1000 $W_e$ to 0 $W_e$. Starting and stopping takes a certain amount of time, these starting and stopping time are defined with $STARTTIME$ and $STOPTIME$ in the number of time intervals. Furthermore, once the machine is running it has to run for a certain amount of time and equivalently once the machine is stopped it has to cool down for a certain amount of time, defined with $MINRUNTIME$ and $MINOFFTIME$ respectively. A Whispergen consumes during the first minutes a small amount of electricity. However, this is left out of the model since the model is discrete and in most cases the production is higher than the consumption in the first interval. Two runs of the Whispergen annotated with these definitions are shown in Figure 3.3.

The microCHP has four different run levels ($on$, $off$, $starting$, $stopping$), the state of the device consists of the run level in combination with the number of time intervals the device is in the current run level.

$$state = \{runlevel, statetime\}, runlevel \in \{on, off, starting, stopping\}$$

According to the number of run levels, the set $Opt$ of the microCHP also has four options:

$$running, stopped, starting, stopping.$$

The $x_{d_{whis}}$ is fixed for every option $opt \in Opt_{d_{whis}}$, so $Min = Max$. For $running$ and $stopping$ $Max$ is 10000 and 0 respectively, for $starting$ and $stopping$ $Max$ depends on the $statetime$:

$$Max = (statetime/STARTTIME) * 10000, \qquad starting \in Opt^{d_{whis}}$$

$$Max = ((STOPTIME - statetime)/STOPTIME) * 10000, \qquad stopping \in Opt^{d_{whis}}$$

For this device only a subset of $Opt$ is valid for every state:

$$Opt^{d_{whis}}_{\{off, statetime\}} = \begin{cases} \{stopped\} & , if\ statetime \leq MINOFFTIME \\ \{stopped, starting\} & , if\ statetime > MINOFFTIME \end{cases}$$

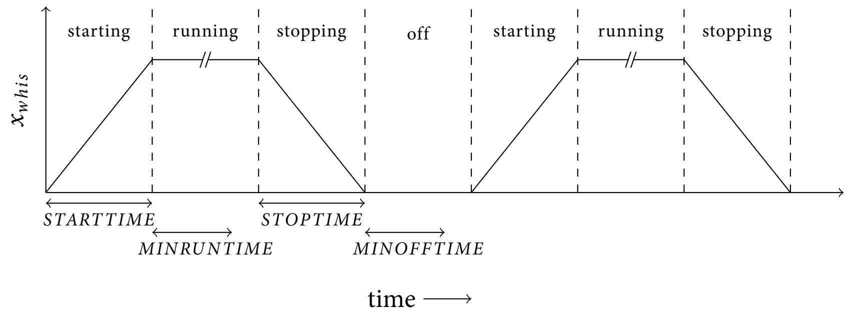



Figure 3.3: Electricity output during two runs of a Whispergen

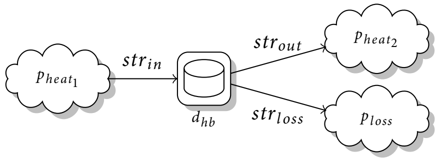
$$Opt^{d_{whis}}_{\{starting,statetime\}} = \begin{cases} \{running\} & , if\ statetime = STARTTIME \\ \{starting\} & , otherwise \end{cases}$$

$$Opt^{d_{whis}}_{\{running,statetime\}} = \begin{cases} \{running\} & , if\ statetime \leq MINRUNTIME \\ \{running, stopping\} & , if\ statetime > MINRUNTIME \end{cases}$$

$$Opt^{d_{whis}}_{\{stopping,statetime\}} = \begin{cases} \{stopped\} & , if\ statetime = STOPTIME \\ \{stopping\} & , otherwise \end{cases}$$

*Buffering devices*

Two different types of buffers are modelled, a heat buffer and an electricity buffer (battery). The heat buffer $d_{hb} \in Dev_{buf}$ can be filled from a pool $p_{heat_1}$ or heat can be drained from it flowing to a pool $p_{heat_2}$. Loss from the buffer flows to a loss pool $p_{loss}$. This device has one heat stream $str_{in} = (p_{heat_1}, d_{hb})$ in and two heat streams $str_{out} = (d_{hb}, p_{heat_2})$ and $str_{loss} = (d_{hb}, p_{loss})$ out. The state of the heat buffer consists of the State of Charge (SoC) and the amount of energy in the buffer. The set of options $Opt^{d_{hb}}$ consists of three options: heat flows in ($filling$), heat flows out ($draining$) or nothing happens (*off*) except the loss flows out. For the amount of heat flowing in and out an interval from 2 kWh to 30 kWh is defined; heating and hot tap water demand stay in this range and also the production of heat stays in this range. Therefore, the interval $[Min, Max]$ for $filling$ and $draining$ is $[2000, 30000]$. We assume that the amount of loss is 5% of the energy flowing in or out, i.e. 5% of the value of $x_d$. This comprises the loss in the tank and the loss in the pipes. The assumption means that the loss in the pipes is assumed to be the dominating factor. Since the loss is assumed to be 5% $M^{filling}_{(d_{hb},p_{loss})} = M^{draining}_{(d_{hb},p_{loss})} = 0.05$. The multiplication factors for the heat streams in and out are $M^{filling}_{(d_{hb},p_{heat_2})} = M^{draining}_{(p_{heat_1},d_{hb})} = 0$ and $M^{filling}_{(p_{heat_1},d_{hb})} = M^{draining}_{(d_{hb},p_{heat_2})} = 1$. For *off* there is a fixed amount of loss modelled, we chose a loss of 100 W, based on the minimum loss during filling ($2000 \times 0.05 = 100$). Therefore, $Min = Max = 100$ with a multiplication factor $M^{off}_{(d_{hb}, p_{loss})} = 1$ and zero for the other two. The new state can be calculated by the old SoC and the amount of energy flowing in and out. For most states holds that $Opt^{d_{hb}}_{state} = Opt^{d_{hb}}$, except when the buffer is empty (no heat can flow out) and when the buffer is full (no heat can flow in). When the heat buffer is placed in between the boiler and the heat consuming devices, there can flow heat in and out at the same time and these two streams are not related. To solve this, two independant variables for $x_d$ can be used for the device, i.e. the buffer is modelled as two separate devices. For the simulations described in Chapter 6 we used this version of the model, where there is an internal value $x_{d_{in}}$ for the stream in and an internal value $x_{d_{out}}$ for the stream out and the loss stream. The rest of the characteristics described above stay the same.




To model a battery $d_{kibam} \in Dev_{buf}$ the KiBaM (Kinetic Battery Model) [50] is used. This model also keeps, next to the State of Charge (SoC), track of maximum charge and discharge currents. Within KiBaM, the battery is modelled as two charge containers, one representing the bound charge and the other the unbound charge (see Figure 3.4). The two containers are connected with a pipe with a limited diameter at the bottom ($P1$ in the figure). Charge can flow from the unbound container to the bound container and vice-versa. The direction and speed of the flow depend on the fill-levels of both containers and is limited by the diameter of the pipe. Through another pipe in the unbound charge container ($P2$ in the figure), also with limited diameter, charge can flow in and out of the battery. It can be seen as if the containers are filled with water, this has the same behavior as the charge in the model. Due to the modelling of the battery using two containers, the influence of high charge and discharge currents and the recovery of the battery are incorporated in the model.

The total SoC ($batSoC$) is the sum of the content of both containers. However, the unbound charge has more influence on the clamp voltage and the maximum charge ($maxCharge$) and discharge currents ($maxDischarge$). The maximum discharge and charge currents are mainly limited by the level of the unbound charge container and the diameter of the pipe. The amount of charge flowing between the two containers define for what period a certain current can flow. E.g. when the discharge current is exactly the amount of charge flowing between the two containers the current can flow until the battery is completely empty, however, when the output flow is higher than the flow between the containers the unbound

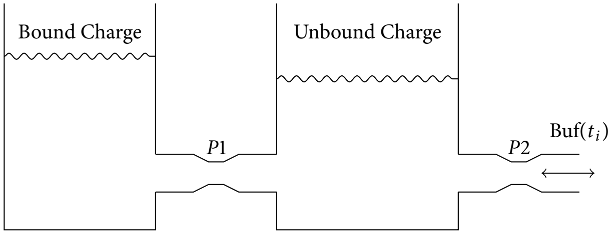



Figure 3.4: Schematic of the KiBaM battery model

charge container empties and the maximum flow out decreases.

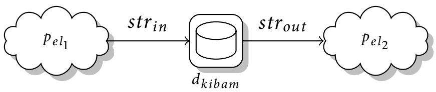
Because of this setup the model implements a couple of characteristics of batteries that most models disregard, e.g. that the battery supplies more energy with lower discharge currents before it is empty and that if it is emptied with high currents it restores after a while. Since the clamp voltage depends on the unbound charge level a battery is empty when the clamp voltage drops below a certain level. Furthermore, the SoC and the maximum currents can be calculated by the (measured) clamp voltage.

The battery is connected to two electricity pools $p_{el_1}$ and $p_{el_2}$, but this can be the same pool. Through an energy carrier stream out $str_{out} = (d_{kibam}, p_{el_1})$ electricity flows out of the battery, trough $str_{in} = (p_{el_2}, d_{kibam})$ electricity flows in. The loss is dealt with within the model itself. The state of the battery consists of the SoC of the bound container ($SoC_{bound}$) and the SoC of the unbound container ($SoC_{unbound}$). Based on the state the maximum discharge $maxDischarge(state)$ and the maximum charge $maxCharge(state)$ can be calculated. This results in a set of options $Opt^{d_{kibam}}$ consisting of two options $charge$ and $discharge$. The interval $[Min, Max]$ for these two options are $[0, maxCharge(state)]$ and $[0, maxDischarge(state)]$ respectively for the current state. Using the KiBaM model, the values of $maxCharge(state)$ and $maxDischarge(state)$ are calculated. The multiplication factors are

$$M^{charge}_{(d_{kibam}, p_{el_1})} = M^{discharge}_{(p_{el_2}, d_{kibam})} = 0$$

and

$$M^{charge}_{(p_{el_2}, d_{kibam})} = M^{discharge}_{(d_{kibam}, p_{el_1})} = 1.$$



*Consuming devices*

Four different consuming devices are modelled. The first consuming device can be used to model all types of normal, not smart devices $d_{ns} \in Dev_{cons}$. The demand of these devices are specified by an earliest (and preferable) start interval number $St_{d_{ns}}$, a runtime (number of intervals) $Ru_{d_{ns}}$, the energy consumption profile in the i-th interval the device is running $dem_{d_{ns}}(i)$ and accompanying multiplication factors. In case a device $d_{ns}$ has a periodic operation pattern (e.g. a refrigerator has a consumption profile with a length of approximately one hour, because it starts about once every hour) the profile $dem_{d_{ns}}$ only specifies the demand of one period. The demands in the later time intervals follow by repeating the profile. Thus, in this periodic case the length of the profile is shorter than the runtime. A consuming device has no stream out and can have multiple streams in. The state of the device consists of the number of intervals it has been running, since some devices can be preempted (temporarily switched off after it is switched on) or the start time can be delayed. Assuming $demSize_{d_{ns}}$ is the length of one demand period, the demand $dem_{state}$ in the $i$-th time interval can be calculated by:

$$dem_{state} = \begin{cases} 0 & , if\ i < St_{d_{ns}}\ or\ state \geq Ru_{d_{ns}} \\ dem_{d_{ns}}(state\%demSize_{d_{ns}}) & , otherwise \end{cases}$$

One option is supplying the demand. Optionally, when the demand is not zero, a preemption or delaying option is added.

Next, a smart freezer $d_{fr} \in Dev_{cons}$ is modelled. This freezer consumes electricity from a pool $p_{el}$ via an energy carrier stream $str_{in} = (p_{el}, d_{fr})$ with multiplication factor one. The freezer has a state containing the internal temperature $Temp$. The temperature $Temp$ has to be in the range $[-28, -18]$°C. The set of options $Opt$ consists of three options:

- *off* - 2 W electricity consumption, the temperature increases 0.1 °C per 4 minutes
- $on_{low}$ (Temp≥-23) - 100 W electricity consumption, the temperature decreases with 0.5 °C per 4 minutes
- $on_{high}$ (Temp<-23) - 140 W electricity consumption, the temperature decreases with 0.5 °C per 4 minutes

In Figure 3.5 the relation between these streams is given by a state diagram. Depending on the state a subset of the options is valid:

$$Opt^{d_{fr}}_{Temp \geq -18} = \{on_{low}\}$$

$$Opt^{d_{fr}}_{-23 \leq Temp < -18} = \{\mathit{off},\ on_{low}\}$$

$$Opt^{d_{fr}}_{-28 < Temp < -23} = \{\mathit{off},\ on_{high}\}$$

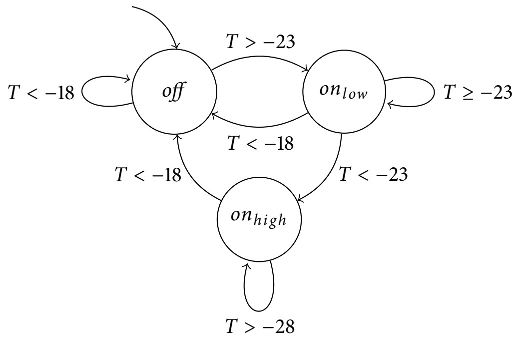



Figure 3.5: State diagram freezer

$$Opt^{d_{fr}}_{Temp \leq -28} = \{off\}$$

The new state can be calculated using the current $Temp$ and the chosen options. Without optimization, the freezer is switched on when the temperature reaches -18 °C and cools until the temperature is -23 °C.

Another interesting use-case is charging a large fleet of electrical cars. Therefore, also a plug-in electrical car $d_{pev} \in Dev_{cons}$ is modelled. The car consumes electricity from a pool $p_{el}$ via an energy carrier stream $str_{in} = (p_{el}, d_{pev})$ with multiplication factor one. An electrical car needs a certain number of intervals of charging and should be finished on a certain time. The number of intervals left until this finishing time is denoted by $endTime$. The state of the electrical car consists of the number of intervals left to charge $chargeLeft$ and the finishing time $endTime$. The set of options $Opt_{d_{pev}}$ consists of two options: charging ($charging$) or not charging ($off$). The charge power is 1500W, so $[Min, Max]$ is for $charging$ $[1500, 1500]$ and for $off$ $[0, 0]$. As long as the number of intervals left until the finishing time is higher than the number of charge intervals left, both options are valid. When the number of intervals left is equal to the number of charge intervals left, it is not allowed anymore to postpone charging:

$$Opt_{chargeLeft<endTime} = \{off, \ charging\}$$

$$Opt_{chargeLeft=endTime} = \{charging\}$$

The next state can be determined by simple decreasing $endTime$ with one and when the $charging$ option is chosen decrease $chargeLeft$ with one only.

The last modelled device is the loss device $d_{loss} \in Dev_{cons}$. The loss device consumes all loss that flows into a loss-pool $p_{loss}$ via a stream $str_{in} = (p_{loss}, d_{loss})$ in with multiplication factor one. It can consume as much loss as necessary, so there is only one option with as interval $[Min, Max] = [0, \infty)$.

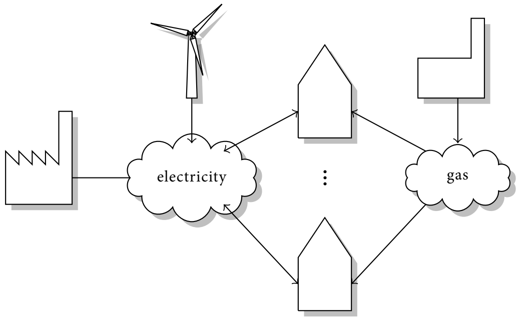



Figure 3.6: Smart Grid: combination of multiple buildings and energy-suppliers

## 3.2 Smart Grid

In the previous section a model for the energy streams in a building has been derived and described in detail. To analyze energy streams in a grid, caused by domestic usage, multiple buildings can be combined into a grid. To combine buildings into a grid, every exchanging device of every building is connected to a pool in the grid. In this way, the buildings can drain the required energy out of the grid (pools). These *global pools* also need to be in balance, so the net energy demand needs to be delivered to the pools by energy-suppliers. It is possible that there are multiple energy-suppliers per global pool, for example a wind turbine (with a fixed, fluctuating amount of production) and a conventional power plant. This total picture of a grid is shown in Figure 3.6. Such a grid model makes it e.g. possible to analyze the impact of optimizations algorithms and renewable sources on the production pattern of a power plant. Optionally, global storage devices can be connected to the pools (e.g. flywheel backup as grid frequency regulation [49]).

The electricity grid is complex, it consists of multiple voltage levels and generated electricity is fed in on different voltage levels. To model a complete electricity grid including multiple voltage levels, multiple pools can be used. Each pool models one voltage level. Between the pools converting devices convert electricity from one to another voltage level. These converting devices model the transformers between the voltage levels. These transformers have one stream in (a voltage level) and two streams out (another voltage level and loss). Within these devices the maximum capacity, the losses and whether they are bi-directional can be modelled with the valid options $Opt^d$. Furthermore, multiple neighborhoods can be modelled to analyze how much electricity is used locally, i.e. how much electricity streams via two transformers to another low voltage pool. This is shown in Figure 3.7.

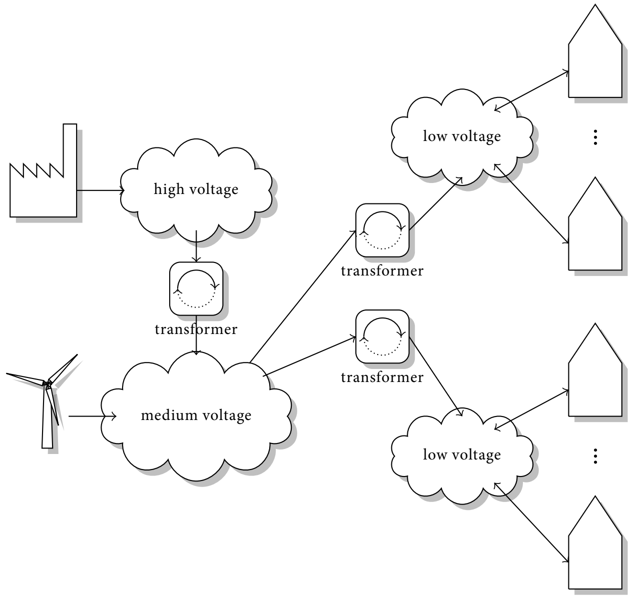



Figure 3.7: Smart Grid: multiple voltage levels, transformer limitations and locality

## 3.3 Conclusion

In this chapter a model of the energy infrastructure within a building and the energy supply towards the building is derived and described in detail. The basis of the model are the energy-carriers that model energy flowing towards and inside the buildings. These energy-carriers range from heat, gas and electricity to real and reactive electricity to analyze grid stability.

The energy demand within the building is split upto a device level. The devices within the building are divided into four groups: exchanging devices, consuming devices, buffering devices and converting devices. Furthermore, a flexible construction for defining the connections between devices is given. On a device level the behavior of the devices can be defined, as well as the flexibility in the behavior resulting in optimization potential.

Natural gas and district heating connections can be defined straightforward using the same construction as used for defining the connection between devices. Domestic energy generation using renewable sources can be modelled, as well as the influence of improving efficiency, e.g. of PV. Furthermore, local energy stock (e.g. oil fuel) can be incorporated when the fuel is modelled as an energy supplier with as state the amount of (oil in) stock.

On grid level, it is possible to model the different voltage levels, the transformers and the (capacity) limitations. The generators can feed in electricity on multiple voltage levels. Furthermore, local use of domestic generated electricity can be analyzed. Combining electricity demand, domestic generation, grid losses and renewable generation leads to desired production patterns for conventional power plants. The stability in the grid can be analyzed up to a certain level: the load of the grid and transformers can be analyzed, as well as the fluctuations in production profiles and electricity streams and the phase shift on different locations in the grid.

The proposed model is flexible and generic. The expectation is that future devices, techniques and scenarios can be incorporated into this model without fundamental adaptations of the model.

CHAPTER 4

# Control methodology

Abstract – *In this chapter the framework for the three-step control methodology is given. The framework has a hierarchical structure consisting of devices on the lowest level up to nodes on the highest level representing the electricity grid. The three steps are offline local prediction, offline global planning and realtime local control. In the first step, the energy consumption and production for every individual building in the grid is predicted on a device level. In a second step a planning for the devices in a building is made, based on the predictions of step one. These local plannings are aggregated to a global planning and in an iterative and hierarchical way these local plannings may be adapted to fulfill global optimizations and/or constraints. The result of this planning is an energy import/export profile for every building. In the last step, a local scheduler in every building schedules the devices realtime, using steering signals determined by the global planning as an input. The goal of the last step is to achieve an energy import/export profile close to the one which was the outcome of step two. The base of all three steps of the control methodology is a mathematical model of the energy streams using the energy infrastructure model of Chapter 3 in combination with mathematical optimization techniques. The last step has to try to work around prediction errors while keeping as close as possible to the planning. To achieve this we propose a Model Predictive Control (MPC) approach. Within a Model Predictive Control approach the realtime controller not only takes the current situation into account, but also a certain period in the future. The preferences and optimization potential of every device are expressed using cost functions. These cost functions express the desirability of possible choices. Furthermore, the steering signals of the global planner also are expressed as cost functions. Based on the cost functions and (technical and social) constraints the best decisions can be determined by the realtime controller.*

Parts of this chapter have been presented at [AM:12], [AM:16] and [AM:18].

In this chapter the three-step control methodology is introduced. The goal of this energy control methodology is to manage the energy import/export of domestic users to support the transition towards a society where electricity is supplied in a sustainable way. Therefore, the objectives of the control methodology are mainly based on electricity streams. However, since these streams are tightly interweaved with the other domestic energy streams, all domestic energy streams are incorporated in the control methodology.

The three-step control methodology is the result of a cooperation within a team of three PhD students. Each researcher developed the detailed implementation of a part of the control methodology, the integration and implementation of the overall control methodology is joined work. Since the first two steps of the control methodology are developed by colleagues, these steps are only described to the extend which is necessary to understand the overall control methodology. More detailed information can be found in papers mentioned as references. The focus of this chapter will be on the overall control methodology and the third and last step.

The remainder of this chapter is organized as follows: the next section outlines the requirements of the control methodology followed by a section describing related work and giving a motivation for the chosen control methodology. In Section 4.3 the overall control methodology is explained and the first two steps are described. The fourth section gives a detailed description of the third step and in Section 4.5 the cost functions used in the third step are studied more detailed. The last section gives some conclusions. The results of the three-step control methodology are presented and discussed in Chapter 6.

## 4.1 Requirements

The goal of the control methodology is to monitor, control and optimize the domestic import/export pattern of electricity and to reach objectives which may incorporate *local but also global goals*. In this context, local objectives concern energy streams within the building, e.g. lowering electricity import peaks and using locally (in or around the building) produced electricity in the building. Global objectives on the other hand concern energy streams of multiple buildings, e.g. on a neighborhood, city or even (parts of) a country level. These objectives can be on different levels, e.g. on a neighborhood level to consume local generated electricity locally or on a national level to optimize production patterns of large power plants. Thus, the control methodology optimizes the runtime of individual devices on a domestic level to work towards local and global objectives.

Since there are a lot of different (future) domestic technologies and building configurations, the control methodology should be able to work independently of configurations and it should be possible to incorporate new technologies. Furthermore, within the control methodology multiple objectives should be supported and the objective levels (scope) may differ. As a consequence, the control methodology needs to be very *flexible and generic*. Since there can be global objectives (e.g. in case of a VPP) and the actual control of devices is on domestic level, both a global and a local control is needed. Furthermore, the control methodology should be able to optimize for a single building up to a large group of buildings. Thus, the algorithms used in the control system should be *scalable* and the *amount of required communication should be limited*. The control methodology should try to exploit the potential of the devices as much as possible while *respecting the comfort constraints of the residents* and the technical constraints of the devices. Furthermore, the control system should consume significant less electricity than it saves.

Based on the way how the control methodology is used, extra requirements may arise. One possible application of the control methodology is to act actively on an electricity market for a group of buildings. To trade on such a market, an electricity profile must be specified one day in advance. Therefore, it should be possible to determine a forecast of the net electricity profile of the managed group of buildings one day in advance. Another application can be to react on fluctuations in the grid, for example caused by renewable generation, asking for a realtime management. Reacting on fluctuations requires a realtime control and the availability of sufficient generation capacity at every moment in time to be able to increase or decrease the consumption. To achieve sufficient capacity, again a planning must be determined in advance, in combination with realtime control to react on the fluctuations. Thus, a combination of *prediction of demand and generation of devices and a planning of the use of these devices is needed*.

Another important requirement is *damage control*. The control methodology should prevent oscillating behavior (fast repetitive on/off switching) caused by over-steering and large fluctuations (peaks), e.g. when a lot of buildings react on the same steering signal. Damage is often caused by prediction errors and/or using more potential then available (e.g. maximum electricity import is too low) or synchronous behavior (all buildings reacting at the same time). An example of such an unwanted situation is when problems are pushed to future time periods, e.g. the charging of electrical cars is moved forward, when the required charging power was predicted too low, until there is no shifting possibility anymore, possibly resulting in a higher peak usage than without optimization.

Furthermore, *limitations of the communication links* should be taken into account. Due to the latency of communication links, sending information from the local controllers to global controllers and sending the decision from the global controller back to the local controller requires a certain amount of time. However, deciding whether it is profitable to switch on a large consuming device (e.g. a washing machine) or reacting on fluctuation in generation need to be done virtually instantaneously. Thus, *the local controller has to be able to make these realtime decisions independent of the global controller* or these decision need to be taken on beforehand.

Summarizing, the requirements are:

1. local and global control and optimizations,
2. generic and flexible,
3. scalable,

4. respect the comfort of the residents,
5. combination of prediction, planning and control,
6. support damage control,
7. limited requirements on the communication links,
8. local controller must be able to work independently.

## 4.2 Related work

Several *control methodologies* for DG, energy storage, demand side load management or a combination of these can be found in literature. Roughly these control methodologies can be divided into two groups: 1) *agent-based market mechanisms* and 2) *discrete mathematical optimizations*. The advantage of agent-based market mechanisms is that no knowledge of the local situation is required on higher levels, only (aggregated) biddings for generation/consumption are communicated. The advantage of mathematical optimizations is that the steering is more direct and transparent, the effect of steering signals is better predictable. Another important difference is that in an agent based approach often every buildings works towards its own objectives where in a mathematical approach the buildings can work together to reach a global objective.

Most of the research considers agent based control methodologies. These agent based control methodologies propose an agent per device [54]. The agents give their price for energy production (switching an appliance off is seen as production); via a market principle it is decided which agents are allowed to produce. Since there are a lot of agents, the information is aggregated on different levels in a hierarchical way. The research described in [14] combines domestic generation, consumption and buffering of both heat and electricity. They propose an agent based system where buildings are divided into groups (microgrids) which are loosely connected to the conventional large-scale power grid. In first instance the goal is to maintain balance within the microgrid without using the large-scale power grid. Furthermore, agents use predictions to determine their cost function. Their field studies show that 50% of the domestic electricity demand can potentially follow a planned schedule (within certain boundaries). To reach this potential, there have to be incentives for the residents to allow some discomfort.

The PowerMatcher described in [43] and [38] additionally takes the network capacities into account. This control methodology is rather mature; it is a product capable of being used in field tests [63]. In this field tests, a peak reduction of 30% is reached when a temperature deviation of one degree of the thermostat in the buildings is allowed. To be able to reach objectives, business agents can be added that influence the biddings in the auction market.

In [27] the authors compare the results of individual (local) and overall (global) optimizations. They conclude that global optimizations lead to better results. Next, they claim that agent based control methodologies outperform non-agent based control methodologies since agent based control methodologies take more (domestic) information into account.

In literature, also some mathematical control methodologies are proposed. The research described in [18] proposes a methodology that is capable to aim for different objectives. For every device a cost function is determined for both heat and electricity. Using a Non Linear Problem definition the optimal on/off switch pattern is found. The authors of [37] address the problems of both agent and non-agent based solutions: non-agent based solution are less scalable and agent based solutions need local intelligence and are not transparent. Therefore, they propose a combination: aggregate data on multiple levels, while these levels contain some intelligence. The aggregation is done with a database, the control methodology is rule based. In [24] a control methodology is proposed using Stochastic Dynamic Programming (SDP). The stochastic part of the control methodology considers the uncertainty in predictions and the stochastic nature of (renewable) production and demand. The authors of [31] propose a control methodology based on Time Of Use (TOU) pricing, where electricity is cheaper during off-peak periods. They combine this approach with a domestic wireless sensor network: when a Smart Appliance would like to switch on, it has to send a request to a controller. This controller decides, based on the electricity price and the status of the other devices, whether the appliance is allowed to switch on. The TOU pricing can be seen as global steering signals, however it is a rough steering signal which is equal for a large group of buildings. Furthermore, it is not known in advance what the impact of the steering signals is.

In [12] a combination of existing tools together with a new developed platform is used. The electricity consumption and production per device is forecasted and using genetic algorithm the best runtime for every device is determined. The platform exists of two levels, a global level for global optimizations sends steering signals to the local level and a local level control which uses the global steering signals as input and determines the runtimes based on the steering signals while respecting local constraints.

Most control methodologies use some sort of prediction of demand and/or production. Due to the changes in the network and the introduction of new devices, current prediction models are not satisfactorily for planning and analysis [62]. In [48] a the prediction framework is proposed that combines deterministic (devices' operation), probabilistic (user behavior) and stochastic (weather and external parameters) prediction models. The energy profile following from devices' operation and weather predictions can be done rather good with neural networks, as described in [57] and [9]. The predictions follow the trend rather well.

### 4.2.1 POSITIONING OF OUR APPROACH

As described above, there are many research projects investigating energy efficiency optimization. From the mentioned research, simulations and field tests it can be concluded that the efficiency can be improved significantly, especially when all three types of technologies (consuming, buffering and generating) are combined. All control methodologies split the control into a local and a global part, most of them using a hierarchical structure for scalability. Furthermore, most control methodologies use an online algorithm deciding on device level and some control methodologies use prediction to adapt the production and demand patterns. However, this prediction data is only used on a local level and, therefore, on a global level hardly any prediction knowledge is available. What is lacking in current control methodologies in comparison to the control methodology proposed in this thesis is the predictability on a global level which is required for electricity market trading, i.e. insight in the effect of choices. This is also related to dependability.

To overcome these shortcomings we chose to use mathematical optimization techniques and a combination of prediction, offline global planning based on the predictions and online realtime control based on the global planning. The base of the control methodology is 1) using local information, 2) communication using multiple levels and 3) scalability. The goal of the control methodology is to work towards (global) objectives and the performance of the control methodology is measured by the extend the objectives are reached. We use 1) predictions on a device level to be able to predict the overall result, 2) planning to estimate the energy streams in the building and the grid and 3) realtime control to respond on changes (e.g. fluctuations in renewable generation) and work around predictions errors.

Based on the above considerations, the proposed control methodology uses three steps and is split up into a local and a global part: 1) local offline prediction, 2) global offline planning and 3) local online control. Because of scalability reasons, the global planning has a hierarchical structure and can aggregate data and plannings on different levels, e.g. within a neighborhood or city. The level on which the planning is determined and, thus, the highest level of the global controller determines the scope (e.g. a local scope or a neighborhood scope). Especially the three steps and the global planning differ from the control methodologies described in literature. Furthermore, the control methodology is not agent based and uses other mathematical optimization methods or heuristics than the control methodologies described above.

Due to the predictions and planning on beforehand, the predictability of the global electricity streams is improved. The combination of planning (aggregated knowledge on higher levels) and mathematical optimization result in better dependability and combination of planning and realtime control improves the damage control. Furthermore, the amount of communication can be limited due to the hierarchical structure. Finally, the requirements on the communication medium is low since the local controller can work independently and a lot of information can be sent on beforehand without high latency requirements. Therefore, our three-step control methodology fulfills all requirements mentioned in Section 4.2.

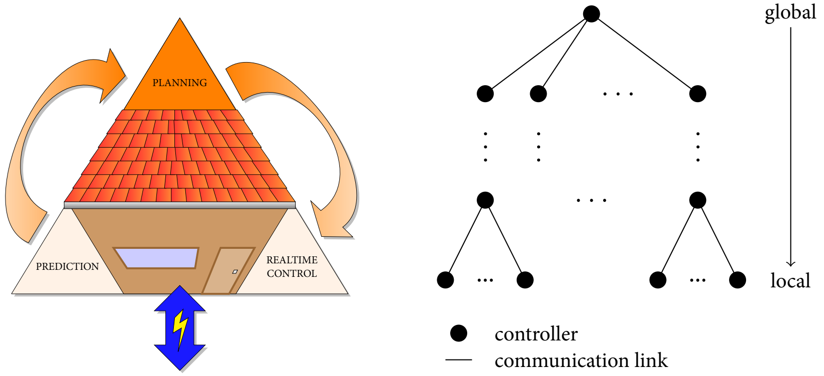
## 4.3 Three-step approach

As motivated in the previous section, the proposed control strategy consists of three steps. A schematic representation of the control methodology is given in Figure 4.1a. The base of the control methodology is a hierarchical tree structure of control nodes. The lowest level node is a node on a lowest (building) level, the local controller. The higher level nodes are placed through the Smart Grid up to the highest level of optimization required (neighborhood, city, national) and are part of the global controller. The tree can be an unbalanced tree and in practice the tree structure depends on the topographical and technical topology, e.g. the number of buildings behind a transformer and the number of district transformers connected to the medium voltage transformer. A schematic of this tree structure is given in Figure 4.1b.

We have chosen for a hierarchical structure for scalability reasons; the control methodology can be used for a large number of houses and the planning for only microCHPs is known to be NP-hard in the strong sense [17]. Heuristics are used, but even heuristics are computational intensive. Therefore, the problem is divided into subproblems, resulting in a tree structure. When houses are added, the tree grows relatively slow in comparison to the number of houses and when too many houses are added for the current depth of the tree an extra level can be added, resulting in more nodes but still limited requirements on the computational power per individual node. Furthermore, this tree structure follows the current topology of the grid and not all information has to be harvested by one single node (also a single point of failure). Depending on the communication infrastructure, also the amount of communication can be reduced since the information is sent to local (nearby) nodes. Due to the hierarchical structure of the communication and the iterative planning algorithms, it is possible to only optimize subtrees where still optimization possibilities exist, resulting in reduced overall communication. Another advantage of the tree structure is that the privacy sensitive information is kept locally, it is sent only to the nearby node where it is aggregated with other data and the detailed information of the customers is hidden.

In the first step of the three-step approach, a system located on the domestic level (i.e. the leaves of the tree) predicts the production and consumption pattern of all devices for the upcoming day. The prediction horizon is a parameter and can be changed, it is in first instance chosen to be one day since utilities need a predicted profile one day ahead and to be able to act on the day-ahead market. For every device a predicted energy profile is generated based on the historical usage pattern of the residents and external factors like the weather.

Note that non-smart devices are integrated to one device which has a consumption profile without optimization potential. The consumption and production profiles of these non-smart devices are required in the control methodology to determine the total consumption/production profile. The local controller aggregates these profiles and can send them to the controller one level higher, etc. The result of the first step is a prediction of the import/export profile on a building level. Note that in this step the devices are not yet controlled.




(a) Three-step approach (b) Control infrastructure

Figure 4.1: Proposed optimization infrastructure

In the second step, the output of the first step is used as input. The predicted production/consumptions patterns can be used by a global planner to exploit the optimization potential to work towards a global objective. Examples of objectives are peak shaving and shifting load away from certain time periods, the objectives are defined as preferred profiles. The global controller can make use of the hierarchical tree structure of control nodes, local or global algorithms and heuristics to optimize the electricity streams in the grid given the objective. In this way, it can give a prediction of the eventual electricity streams. To achieve this, each building sends its profile to its parent node, this node aggregates all received profiles and sends the aggregated profile upwards in the tree, etc. Based on the received profile and the objective, the root node determines steering signals for its children to ask them to work towards the global objective. Each intermediate node in the tree determines steering signals for its children based on the received steering signals. Finally, the building controllers (the leaf nodes) can determine an adjusted profile, incorporating the steering signals. This profile is sent upwards in the tree and when necessary the root node can adjust the steering signals again. Thus, the planning is an iterative, distributed methodology lead by the global controller. The objective of the planning methodology can be implemented by choosing to work towards an upfront defined consumption profile (optionally per subtree), but it can also incorporate freedom in the profile to cope with realtime optimization objectives (e.g. react on fluctuations of renewable sources). The latter can only be done in cooperation with the local controller (e.g. use only a part of the available energy buffer capacity). The position of the uppermost node and therefore the global controller determines the scope of the optimization (within the building, a neighborhood node, etc.). The result of the second step is a planning for each household for the upcoming day (which can be described by steering signals) and a prediction of the global electricity streams.

The third step uses the steering signals of the planning step as input, in combination with information about the status of the devices in the building and the grid. In this final step, a realtime control algorithm decides at which times devices are switched on/off, when and how much energy flows from or to the buffers and when and which generators are switched on. The local control algorithm has to take three different inputs into account while making these decisions. This realtime control algorithm 1) uses non-realtime steering signals from the global planning. Furthermore, 2) it can use realtime steering signals of the global controller, based on the status of the grid, to respond on fluctuations in the grid, e.g. caused by wind farms. Finally, the local controller 3) has to work around prediction errors and preserve the comfort of the residents in conflict situations. To reach its goals, the local controller can also use, next to realtime optimization algorithms, local (short-term) predictions and planning.

The combination of prediction, planning and realtime control exploits the potential of the overall system at the most beneficial times. The hierarchical structure with intelligence on the different levels ensures scalability, reduces the amount of communication and decreases the computation time of the planning.

As described above, the control methodology is very flexible and the proposed infrastructure supports different algorithms for the global and local controllers. On the one hand, one may chose to solve the global planning problem and the local optimization problems to optimality. However, especially for the planning part the resulting computation times are much too long. Therefore, multiple heuristics for the planning are considered, one of them is explained in the following subsections. Furthermore, the planning horizon can differ. The next two subsections give a short description of the first two steps of the control methodology. For every step, first the overall idea is given. Next, more explanation is given using a case of microCHP devices installed in buildings. These microCHP devices are combined with heat stores decoupling heat production and consumption up to a certain level. In this way, scheduling freedom for the microCHPs is introduced and, therefore, freedom in electricity production. The microCHP case is used to describe the concepts, however, the control methodology has also been tested for other use cases, for example Demand Side Management using freezers [5]. For more use cases we refer to Chapter 6.

### 4.3.1 PREDICTION MODEL

In the first step the energy production and consumption pattern of every individual device in the building is predicted. This prediction can be based on the preferable runtimes of the device itself, i.e. the runtime without optimization, or can be based on the proposed steering signals to determine the scheduling freedom or optimization potential. The predictions should be on a device level since the control is on a device level. To steer individual devices, it must be known what the potential and behavior of individual devices is. However, for which devices prediction are required depends on the objectives and level of the optimization; e.g. when heat is provided by gas-fired conventional boilers the runtime of this device and therefore the heat consumption is not crucial for the electricity import/export pattern. Furthermore, the electricity consumption of non-smart and/or non-controllable devices can be predicted jointly for all these device in a building, or when the optimization level is on the neighborhood level even for all non-controllable devices in the total neighborhood. Advantage of predictions on a higher level is that prediction errors level out.

Predictions can be performed on the local controller or when the devices are capable, on the devices themselves. For a neighborhood level the prediction of the consumption of non-smart devices is performed on the highest node involved, the central control node.

*Heat consumption prediction*

In this subsection we describe the prediction approach for a microCHP in more detail. Since a microCHP is responsible for the production of heat in a building, we need a prediction of the heat demand [6]. The heat demand for an individual household is predicted. The goal is to predict the heat profile for the next day as accurately as possible. Based on the prediction, a schedule for the microCHP can be calculated. The value of this schedule depends on the accuracy of the predictions and influences the electricity pattern of the building quite drastically.

There are several reasons why individual heat demand prediction is used. The first and most important reason is that the schedules for the generators are made locally. A second reason is that our approach is used for optimization of a large group of households. The group might consist of hundreds of thousands up to a million of households. It is then infeasible to perform a prediction per building centrally. It might be possible to do a prediction of a whole group, but eventually all individual generators must be scheduled, based on local heat demand. By moving the prediction to a local control system in the building, a scalable system is achieved and local information can be incorporated much better into the prediction.

The heat demand (of a household) depends on factors like weather, insulation and human behavior. The prediction model should be able to predict the heat demand one day ahead, based on recent observations. In other words, based on recent heat demand data and information about external factors like weather and insulation, the model should learn the relation between these factors and the heat demand.

The relation between external factors, behavior and the corresponding heat demand can be different for each building and household, since each building is different and has different insulation characteristics and every household is different and has different behavioral patterns. By predicting the heat demand per building locally, local information about the specific environmental and behavioral characteristics can be used to improve the prediction.

As mentioned, one important factor in the heat demand is the behavior of the household. However, due to human nature, this behavior is not static. People have different behavior on different days of the week, thus the model has to be flexible.

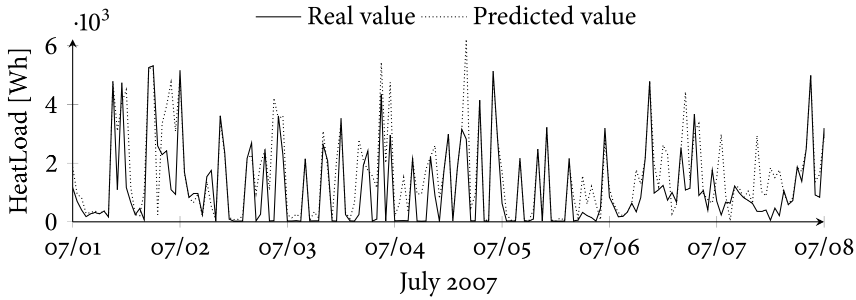



Figure 4.2: Heat demand prediction for a household from July 1 to July 8, 2007

Changes in behavior should be learned quickly in order to cope with changes, e.g. holidays.

Based on the requirements and characteristics of the prediction mentioned above is chosen for neural networks [6, 8]. Neural networks are computational models based on biological neurons [44]. They are able to learn, to generalize, or to cluster data. A network has to be configured (trained) such that the application of the network to a set of given inputs produces results the closest possible to the desired outputs (which are also given).

The output of our prediction model is the heat demand per hour. We assume that the most relevant factors for the heat demand are the behavior of the residents, the weather and the characteristics of the building. Therefore, information about these factors are thus candidates as input for our prediction model.

To learn the behavior of the residents, historical heat demand data is used as an input. Information about the weather can for example be represented with outdoor temperatures, wind speeds and solar radiation. Since buildings do not change that often, we consider the characteristics of the building static. Because of this, the neural network should be able to learn these characteristics since they are present in all input data used. In [9] and [6] multiple possible combinations of input sets and their influence on the predictions are presented. Furthermore, in [6] a different way of constructing the training set is presented. Common practice when generating a training set for neural network applications is to select a large, randomly selected set used for training. In our case, this translated to giving the network many samples to find as much general behavior as possible. However, since behavior is changing during the year, [6] shows that this is not the best way. Using only information of the last weeks as training information gives better prediction.

An example of a good prediction is depicted in Figure 4.2. Here, a prediction is made for a household on November 22, 2007 using historical heat demand data and outdoor temperatures as input. As can be seen in the figure, in this example the trend is followed quite good; in this week, the Mean Absolute Percentage Error is 5.84 and the Mean Percentage Error is 5.75. Due to human nature and unmeasurable influences, there is some deviation from the real heat demand.

*Scalability and complexity*

Since the predictions are done locally on a building level, scalability is not an issue. Concerning complexity, there are two different steps for neural networks: 1) training the network and 2) obtaining a prediction value given a certain input and a trained network. The second step, getting a prediction value, has a low complexity, a complete pattern for the next day can be determined within a second on an embedded platform. The complexity of the first step, training the network, depends on the amount of training data. There are two different strategies used for training the networks: a) train them once in a couple of months or b) train them every day. When they are trained once in a couple of months the amount of training data is large and training can take hours. But, since this is only once in a couple of months this is acceptable. When they are trained every day, the parameters of the previous network can be used as initial values and the amount of training data can be low and as a result training takes a few seconds.

### 4.3.2 GLOBAL PLANNING MODEL

The second step in the control methodology determines an offline planning for the devices on beforehand, using the predictions from the first step, the hierarchical structure of control nodes and the objective of the system. Initially, the local control nodes calculate a profile based on some initial price vectors for electricity and the predictions. They send this prediction data of the devices upwards in the tree to the root node via the intermediate nodes on the path. Note that the prices used in the control methodology are artificial prices, determined during the planning and only used to steer towards objectives. Every intermediate node can already perform preparatory computations on the data, for example aggregating the data into one profile.

The root node determines, based on the received information and the objective, a preferred profile. These objectives can be peak shaving, work towards the profile predicted on beforehand (useful for utilities), shift load based on the electricity prices (real prices, e.g. paid on the short-term markets), etc. To reach this preferred profile, the root node can steer the child nodes by sending steering signals: objective bounds or pricing signals. Objective bounds are upper and lower bounds on the consumption pattern in between which the consumption/production of a subtree should stay. Pricing signals are artificial electricity import/export pricing signals. The advantage of objective bounds is that the objective is explicitly represented, the advantage of pricing signals is that they are more general and easier to incorporate on the house level. The root node can decide to send each child-node the same signals/bounds or individual determined signals/bounds per child-node.

Intermediate nodes have to determine steering signals for their child-nodes, based on the received steering signals and optionally on local objectives or constraints (e.g. the amount of energy flowing through a certain link). Once on a certain level the intermediate node changes from objective bounds to pricing signals, all child nodes can only use pricing signals. The local nodes have to receive

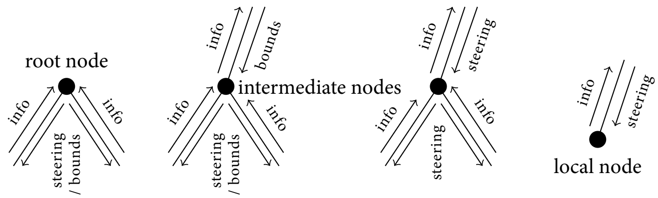


Figure 4.3: Possible information streams and steering signals in the planning tree

pricing signals (due to the optimization algorithms in the local nodes). Just as the root node, intermediate nodes can send each child-node the same signals/bounds or individual determined signals/bounds per child-node. This communication structure is shown in Figure 4.3. An important parameter in this structure is the level where is switched from objective bounds to pricing signals. The results in [5] indicate that the best results are reached by using objective bounds in the whole tree except for the lowest level of intermediate nodes and the buildings.

One of the prediction/planning algorithms implemented using this structure is described in detail in the remainder of this subsection. This algorithm uses an iterative approach. The consumption/production profiles are based on predictions and on the steering signals, these profiles are sent upwards. Based on these predicted production/consumption profiles, the root and intermediate nodes determine new bounds/steering signals and these are sent downwards to the local nodes. Based on these new steering signals, new profiles are determined. This process continues until the objectives are reached or the profile does not improve anymore.

*Iterative distributed dynamic programming*

The iterative distributed dynamic programming approach described below focusses on a planning for a large group of microCHP devices. Based on the heat demand prediction for a single building we plan the runs of the corresponding microCHP. This means that the exact periods in time are specified during which the microCHP should be switched on. This planning takes into account that the complete heat demand of the building has to be guaranteed. To create scheduling freedom, the microCHP is accompanied by a heat buffer so heat can be produced before it is consumed. Furthermore, the planning is restricted by technical constraints of the microCHP like minimal runtime and minimal off time. A complete explanation of these constraints can be found in [17].

Based on the heat demand prediction and given the electricity price vector, the planner makes for each building of a group of buildings (of size $N$) a production plan, satisfying the domestic, or local constraints (i.e. the heat demand constraints plus the technical, microCHP related, constraints). When we consider the generators in all the buildings as a Virtual Power Plant (VPP), a new dimension in the planning problem is introduced, since we now have to focus on the total electricity production of this group of buildings. As a consequence, the planning does not only need to satisfy local constraints, but also a global constraint on the total electricity production may be added. More precisely, the group of buildings should satisfy a predefined production plan $P$, that is based on the role the VPP wants to play in the overall electricity market.

We discretsize the problem by dividing the planning horizon of a single day into $N_T$ intervals for which a decision must be made for each microCHP in each building. Since a simplified version of the resulting discrete optimization problem is known to be NP-hard in the strong sense [17], we developed heuristics which find in reasonable time a planning for the group of buildings that is 'good enough'. In this context, we mean by 'good enough' that we approximate the predefined (discrete) production plan $P = (P_1, \dots, P_{N_T})$ well enough. As objective, we use the squared mismatch $ms$ to this plan $P$, which should be minimized:

$$ms = \sum_{j=1}^{N_T} \left( \sum_{n=1}^{N} e_{n,j} - P_j \right)^2,$$

where $e_{n,j}$ is the produced electricity in building $n$ during time period $j$ and $P_j$ the production plan for time period $j$.

The problem is to find production plans for local households which are subject to local constraints, whereas we want to minimize the global deviation of the total electricity production, measured by the squared mismatch $ms$. In this subsection we describe a heuristic that solves this problem by separating the two elements that make the problem difficult:

1. finding a local plan satisfying local constraints by a fast local optimization method;

2. minimizing the squared mismatch from the global production plan.

The two elements are combined in an Iterative Distributed Dynamic Programming approach. This separation in two steps uses the hierarchical structure and local computational capacity, resulting in a scalable planning method with a global perspective. The approach is explained in more detail by tackling the two single elements.

*Finding a local plan satisfying local constraints*

A local production plan that satisfies both technical (microCHP related) and domestic (heat demand) constraints can be found by using a Dynamic Programming approach. This approach uses a state $s_j$ to describe the household situation in time interval $j$. For more detail we refer to [15]. The states $s_{j+1}$ can be determined based on state $s_j$ and the decisions $x_j$ to have the microCHP running or not. From the state the relevant information on the run history and the total production until the current time period that are needed for the future decisions can be deducted. So, technical constraints of the microCHP and heat buffer constraints are covered by only allowing feasible states and state changes in the corresponding time periods.

Since the global production plan $P$ often is based on the electricity market (e.g. the Dutch APX market[1]), the costs in the Dynamic Programming formulation also are chosen to be electricity price related. However, the steering signal for production should be low when the price is high (steering signals are costs, the objective is cost reduction). More formally, if $p_j$ denotes the price on the electricity market in period $j$, we define the market related costs $c_j$ for state changes in time period $j$ by

$$c_j = \overline{p} - p_j,$$

where $\overline{p}$ is the maximum price during the day: $(\max_i p_i)$. The costs of a state change from period $j$ to period $j+1$ depend on the related decision $x_j$ and are given by $c_j x_j$. Now, for each interval $j$ and state $s_j$ the costs are defined by $F_j(s_j)$, which expresses the minimal costs needed to satisfy the heat demand from interval $j$ until the end of the planning horizon, i.e. the path with the lowest costs from this state to one of the states in the last time interval, assuming that the current situation is characterized by the state $s_j$.

In practice the number of states for a day ahead planning is not too large, if the time periods are chosen larger than or equal to five minutes. Via a backtracking algorithm the value of $F_0(s_0)$ (the starting state) can be calculated, which minimizes the total costs from the start of the planning period until the end of the planning period, i.e. the path with the lowest costs from the starting state to a state in the last time interval. This path gives the state changes and, thus, the corresponding decision values $x_j$ to switch the microCHP on or off, i.e. it gives a production plan for the building.

*Minimizing the squared mismatch from the global production plan*

By sending all local production plans to a global planner, the sum of all production plans of the group of buildings can be calculated and gives a global electricity output of the VPP, leading to a squared mismatch *ms* from the production plan $P$. In an iterative approach we aim to minimize this mismatch by iteratively steering the local production plans in a mismatch-reducing direction. As a consequence, most of the computation is still done locally at the buildings. On a central level the steering of the plans in a certain direction is calculated. To allow for scalability, the group of buildings is divided into a hierarchical structure. In this way a limited number of buildings can be regarded as a sub group, which is steered into the right direction independently from other sub groups. For simplicity we refer in the following to the plan $P$ as the production plan for a sub group of buildings.

To influence the outcome of the local Dynamic Programming approach, we adapt the steering signals in the following way. Artificial additional costs $a_j^i$ are added to the state change costs $c_j$ for time period $j$ in iteration $i$, if:

- the electricity output of the VPP is larger than the plan value $P_j$, and
- in the local building plan the microCHP is running at time period $j$.

[1]http://www.apxgroup.com

The values of $a_j^i$ are sent to the local planners and a new planning is determined by the local planners. In this way, microCHPs that are running in periods where the sub group plan is exceeded are stimulated to produce at other time periods. In the steering method, the additional costs $a_j^i$ that are used in the steering process, decrease with each iteration $i$, to minimize negative overshooting effects and guarantee a convergence.

*Scalability and complexity*

Due to the hierarchical structure of the planning algorithm with aggregation on every level it scales well. Although the algorithms per iteration require only limited computational power, a high number of iterations can increase the required computational power and communication significantly. The number of required iterations depends on the size of the groups, i.e. on the number of buildings connected to one subgrid controller. The choice of a proper group size is analyzed by extensive parameter value exploration and simulations show that the best group size is around 25. Furthermore, in [5] the required number of iterations and the required amount of communication is analyzed. It appeared that within ten iterations the objective profile was approximated quite well. Since for every iteration each building sends 1440 bytes of data with a header of 5 bytes, for 500 buildings this resulted in a total of 7.2 megabytes of communication for ten iterations. As the planning is only performed once per day (assuming no re-planning) the communication costs are acceptable.

## 4.4 Local control algorithms

The result of the second step, a planning on a device level for every individual building, can be used as input for the third step. The third step is a realtime control approach that manages devices, i.e. it decides every time interval which devices are switched on or off and how much energy flows from or to the buffers. The control is on a device level with online scheduling for fast reaction. The main task of the third step is to supply all energy demands of the residents and guard the selected comfort level of the residents. Within these requirements, the scheduling freedom is used to work towards the selected objective.

The third step can work stand alone or it can use the output of the second step as input, i.e. objectives can be local and global. One application of a stand alone operation can be an islanded operation, where no connection to the grid exists. In this case, the control methodology should keep the energy streams in balance. Another stand alone operation could focus on TOU pricing and try to make as much profit as possible (i.e. lowest bill). In that case, also the electricity prices are used as input. Note, that in this case these prices are the real electricity prices and not artificial steering signal prices (as received from the global planning).

Working towards global objectives can be done by using the planning made on beforehand in the second step. Next to these steering signals which are specified on beforehand, there also can be communication with higher level nodes in the hierarchical structure, e.g. to react realtime on fluctuations or to work around prediction errors on a higher level. However, this leads to higher requirements on the throughput and latency of the communication links.

The remainder of this section gives a detailed description of the developed control methodology. First, the idea behind the developed control methodology is given and next the control methodology itself is described. In Subsection 4.4.3 an optional extension of the control methodology to cope with predictions errors is given.



### 4.4.1 IDEA

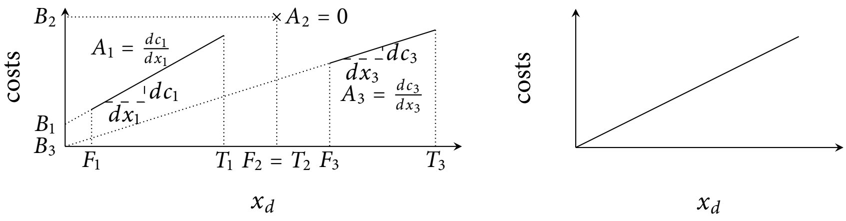
In Chapter 3 for every device a variable $x_d$ is introduced expressing the amount of energy flowing in and out of the device. However, not every value for $x_d$ is valid for a device, so constraints are introduced to define the valid values of $x_d$. Since devices often have multiple valid values for $x_d$ (multiple options), constraints are defined by intervals on which $x_d$ should be chosen ($Min \leq x_d \leq Max$). For every device, multiple intervals can be defined. An example of a $x_d$ with three valid intervals is given in Figure 4.4a. The value of $x_d$ in this example should be chosen on one of the intervals $Min_1 \leq x_d \leq Max_1$, $Min_2 \leq x_d \leq Max_2$ or $Min_3 \leq x_d \leq Max_3$.

The constraints introduced in the model of Chapter 3 force all technical and non-technical constraints to be satisfied (e.g. balance in the pools and supply all demand). However, within these constraints often multiple sets of values for $x_d$ for every device can be chosen. For example, all electricity can be imported from the grid or it can be (partly) drawn from a battery. Therefore, costs are assigned to every possible value of $x_d$. In other words, a cost function is defined for every device expressing the preferences of the residents, wearing of the devices, State of Charge (SoC) of the buffers, etc.

Thus, the third step of the control methodology is based on the use of artificial costs defined for every device. In combination with the (artificial) costs for electricity import/export the best option for every device can be chosen. Due to the artificial costs the optimization problem is reduced to a cost minimization problem with constraints; the costs are defined per option and the constraints are defined as given in the model description in Chapter 3.

*Cost functions*

The cost functions should express the 'quality' of the decision for a certain value of $x_d$. Some decisions are more preferable than others for the residents, e.g. temporarily switching off a television is less desirable than temporarily switching off the freezer. Furthermore, switching on and off a device too often may lead to wearing. Finally, the amount of electricity imported or exported is topic of desirability, depending on the objective. These preferences can be expressed using cost functions. The costs consist of costs for picking an option (e.g. switch a device off) and the costs for the energy stream (e.g. flows from/to buffers). Therefore, the costs for every option




(a) Artificial cost function

(b) Cost function electricity import

Figure 4.4: Example valid range for $x_d$ and corresponding costs

exist of a part $A$ depending on the internal energy stream $x_d$ of the device and a fixed part $B$ for choosing the options.: $A \times x_d + B$.

For example, consider the cost function with three intervals for $x_d$ given in Figure 4.4a. Since the costs differ per decision, every option $opt \in Opt^d_{state}$ has its own cost function. Therefore, each valid interval for $x_d$ has a corresponding cost function, in other words, the cost function used depends on the interval on which $x_d$ is chosen. In case of the cost function given in Figure 4.4a the costs for a (valid) value of $x_d$ are:

$$\begin{cases} A_1 \times x_d + B1 & , if\ Min_1 \leq x_d \leq Max_1 \\ A_2 \times x_d + B2 & , if\ Min_2 \leq x_d \leq Max_2 \\ A_3 \times x_d + B3 & , if\ Min_3 \leq x_d \leq Max_3 \end{cases}.$$

An example of a realistic cost function is given in Figure 4.4b. This is the cost function of electricity import: there are no costs for picking an option ($B = 0$), the costs only depend on the amount of electricity imported. Another example of a cost function is the cost function for a smart freezer (as defined in Chapter 3). This freezer has two options: cooling or not cooling. In other words, $x_d$ is valid on two intervals: $0 \leq x_d \leq 0$ and $150 \leq x_d \leq 150$ (the two intervals are actual two points). The costs for the energy stream ($A$) are zero (note that when the device is supplied the required electricity must be imported or supplied by a battery for certain costs). However, when the freezer deviates from the normal behavior that results in certain costs: when the freezer is cooling and it should stop cooling before it reached the minimum temperature this has certain costs ($B$), after all, it deviates from the normal behavior and stops cooling earlier. The same holds when the freezer is not cooling and it should start cooling before the maximum allowed temperature is reached (start cooling earlier). The costs for these deviations depend on the status of the freezer, i.e. they depend on the temperature of the freezer. When the freezer is cooling and it has almost reached its minimum temperature, the costs to stop cooling are lower than when the freezer just started cooling.

Since the complete third step is based on the artificial costs, a proper definition of these costs is very important. They should correctly express the energy demands, allowed discomfort, device requirements, etc. A detailed discussion about cost functions is given in Section 4.5. Note that these cost functions are also incorporated in the planning phase, the second step of the control methodology.



### 4.4.2 CONTROL METHODOLOGY

This subsection presents the formalized control methodology to control the devices in a single building as described in the previous section. The control methodology is executed iteratively every time interval, whereby the concrete parameters (e.g. the valid intervals for $x_d$) are determined at the beginning of the time interval. Note that some of these parameters may be influenced by the decisions of former time intervals and, therefore, the value of these parameters cannot be determined on beforehand.

As explained in the model in Chapter 3, every device expresses its demand/generation and its scheduling freedom using options. Within these options the allowed discomfort chosen by the residents is already included. These options specify the allowed intervals for the decision variables $x_d$ and the multiplication factors to derive the actual energy flow of each energy stream. In combination with the given connections between devices and pools, for every decision variable $x_d$ a valid value must be chosen in such a way that all pools are in balance.

The desirability of every optional value of $x_d$ is expressed using cost functions. The cost functions for the devices are chosen to be generic to be able to apply the approach to different technologies. Furthermore, they have to be determined for every time interval separately, since the production capacity, demand, buffer status and the costs can fluctuate over time. Finally, the global controller can send information about the global cost function of the grid to the local controller as steering signals. Combining this local and global information leads to a set of concrete cost functions for a time interval. We assume that cost functions of different devices are independent and that it is possible to determine cost functions for every device independently.

Following the above considerations, within every time interval the control algorithm induces an optimization problem of choosing for every device the best values for $x_d$ concerning the given constraints. The model of the devices, pools and energy streams as presented in Chapter 3, extended with a cost function for every option of every device, leads to a minimization problem. This minimization problem can be modelled as an Integer Linear Program (ILP). The optimization problem considers the given set of devices $Dev$ and for every device $d \in Dev$ a set of options $Opt^d_{state}$. The goal is to find a valid option for every device such that all pools are in balance and the costs are as low as possible. In other words, the defined model is extended with a cost function for every option and an optimization function that adds the costs of all chosen options. Using ILP optimization techniques the minimum value for the optimization function can be found within the given constraints. The two added functions, the optimization function and the cost function per option, are given below. The complete model is given in Appendix B.

$$minimize \sum_{d \in Dev} tc_d \tag{4.1}$$

$$s.t.\ \ tc_d = \sum_{opt \in Opt^d_{state}} A_{opt} \times x_{opt} + B_{opt} \times c_{opt} \tag{4.2}$$

Determining the best combination of options using these cost functions gives a lot of freedom and allows to incorporate almost every device in this control methodology, since in general devices can be modelled using state transitions and cost functions can be used to express preferences, wearing, etc. In general, options with high costs will not be chosen, except when it is really necessary to reach stability in the pools or when other options are even more expensive. Therefore, the cost functions cannot be defined completely independent. For example, to define "the costs of discomfort", some rule of thumb may be needed. This is done using standard energy prices where deviations from these prices express the desirability of the different options. The definition of cost functions, the effects of adding cost functions and the expressive power of cost functions are studied more detailed in Section 4.5.

### 4.4.3 MODEL PREDICTIVE CONTROL

One of the drawbacks of the above described approach is that the planning is based on predictions and therefore the planning often cannot be reached. A small prediction error can result in large deviations from the planning since the realtime controller does not have a look ahead feature, but locally tries to follow the planning [51] which is based on wrong information. More general, since the realtime controller only takes the current status of the system into account it may take decisions that are disadvantageous for later time periods. Therefore, a method is introduced to improve the realtime controller such that it not only takes the current status into account, but also a number of future states, based on improved short-term predictions. In this way, it might be possible to prevent disadvantageous decisions to some extent when working around prediction errors. Furthermore, since a larger horizon is considered, it can be observed earlier whether the prediction errors become too large and in such a situation it may be beneficial to determine a new global planning (step 1 and step 2).

The local control methodology can be extended with Model Predictive Control (MPC) [11] (in the Operations Research literature this is called Rolling Horizon (RH) [58]). The idea of MPC is to take a number of future time intervals into account while making a decision for the current time interval, using predictions of the future states. MPC is a widely spread technology in industry for control design [11]. Within the terminology of the three-step control methodology, MPC can be seen as a short-term planning on the local level. This planning starts with the status of all devices in the building and uses short-term (improved) predictions of the behavior of the devices given the current and past status of the system. The steering signals of the global planning, determined in the second step, are also used as input for this local planning. In this planning, every time interval is a *decision point*: in every interval for each device a valid option needs to be chosen. Furthermore, every time interval in which a new (short-term) planning is determined is called a *re-planning point*.



To apply MPC, first the constraints on the state variables are determined to be able to construct a valid state space. Using this state space, the best path from the current state to one of the end states can be determined. This results in the best options for the current time interval while taking future time intervals into account. The number of future time intervals taken into account is called the observed horizon. In the current implementation in every time interval this local re-planning is performed, i.e. every time interval is a re-planning point for the local planning.

In [58] the effect of the length of the observed horizon is analyzed. The authors conclude that a larger horizon may lead to worse results, where large depends on the fluctuations in the optimization problem. A larger horizon can lead to continuously postponing taking profit, continuously make a less profitable decision to gain more profit in the future. The authors of [58] conclude that by using certain heuristics the performance of longer horizons improve and outperform shorter horizons.

*MPC applied to the local control methodology*

The idea of MPC applied to the third step of our control methodology is to estimate the effects of decisions on future states. To integrate MPC in the realtime control step, we use predictions of the consumption and production profile of devices, similar to the ones used in the first step. Thus, the behavior is predicted when required, i.e. at the moment the MPC based algorithm is performed. Next to these (new) local predictions, MPC can use the steering signals determined during the planning step and predictions of realtime fluctuations in the grid. An advantage of short-term predictions is that they are easier and often more precise than long-term predictions, both for device behavior as for realtime fluctuations.

Let the observation horizon consist of $N+1$ time intervals, i.e. $T = \{0, 1, .., N\}$. The state of the building, the *building-state*, is the combination of the states of all devices. Given a certain building-state in a certain time interval, there is a set of possible choices per device. In general only a subset of all possible combinations of choices results in a valid next building-state, i.e. only a subset of combinations of choices respect the constraints of the energy model (e.g. balance per pool). Based on all valid combination of choices, the possible building-states at the beginning of the next time period can be calculated. Iteratively, now for each of these possible building-states the sets of choices per device can be determined taking into account the estimated device behavior. Given the valid combination of these choices, again the valid next building-states after two time periods can be calculated, etc.

Following these steps for the upcoming $N$ time intervals results in a state space. An example of such a state space for a freezer is given in Figure 4.5. The nodes represent all possible, valid states and the edges between them result from executing

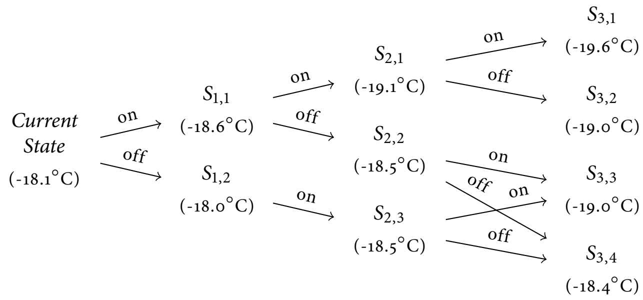



Figure 4.5: N future states of a freezer

a combination of chosen options for the devices. Therefore, based on the cost-functions of the devices the costs of every edge can be calculated, including the steering signals of the planning as import costs of electricity. If we now calculate the most cost effective path from the root node to an end state, the choice for the current time interval is calculated which belongs to the best sequence of decisions for the next N time periods. Since switching on and off a device has certain costs, it prevents the oscillating behavior. Furthermore, the methodology can work better around prediction errors since it prevents decisions in the current time interval that are very disadvantageous for future time intervals. This results in a more predictable and dependable behavior.

Note that this algorithm is executed every time interval, i.e. every time interval is a re-planning point. Thus, although a sequence of choices for the next $N$ time intervals is determined, only the choice for the current interval is executed. During the next time interval a new local re-planning is performed and a new sequence of time intervals is determined. In future work it may be investigated whether or not it is more profitable to execute not only the first decision but the decisions of a few future time periods, i.e. to do a re-planning only after a few time intervals.

Adding MPC is illustrated using a freezer. A freezer has an easy to estimate behavior; when it is switched off the temperature increases with a certain slope and when it is switched on the temperature decreases. This estimation is a simplified model of the real behavior and the influence of residents is neglected. An example of the estimation of the behavior of a freezer during three future states is illustrated in Figure 4.5, starting at $-18.1°$ C: when the freezer is switched on, the temperature drops by $0.5°$ C and when the freezer stays off the temperature increases by $0.1°$ C. Observing future states in this way, it can be determined whether it is preferable to switch on the freezer already now, although it is not necessary in the current time interval.

The MPC methodology can be incorporated in the earlier described ILP formulation by adding a time interval to $Opt^{d}_{state}$ and the accompanying constraints. In other words, one ILP is executed that enforces balanced pools in every time interval in the observed horizon and finds the most cost effective path through the state space.

This results in balance in every time interval and a valid chosen $x_d$ for every time interval for every device, i.e. per time interval the model is correct. However, not every state in time interval $t+1$ can be reached given the chosen state in time interval $t$. For example, when in the state space in Figure 4.5 the transition from $S_{1,1}$ to $S_{2,1}$ is chosen, the state transition from $S_{2,2}$ to $S_{3,3}$ cannot be chosen anymore. Therefore, constraints to guarantee a valid sequence of states are needed, or better, a correct sequence of choices must be guaranteed. This is done by adding constraints on the binary variables representing the chosen binary state variables $c_{d,i,t}$ for every device $d$, state $i$ and time $t$. These variables enforce that state $i$ for device $d$ at time $t$ only can be chosen (expressed by setting $c_{d,i,t} = 1$) when one of its valid predecessor states is chosen. In other words, a variable $c_{d,i,t}$ is only allowed to be larger than zero when one of the predecessor states is chosen. Therefore, for every state a constraint must be added enforcing this:

$$c_{d,i,t} - c_{pred_1} - \dots - c_{pred_N} \leq 0,$$

where $c_{pred_1} \dots c_{pred_N}$ are all possible immediate predecessor states.

For example, Figure 4.5 shows a state space for a freezer with on/off decision. In this case, the only valid preceding states of $S_{3,3}$ ($c_{d,3,3}$) are $S_{2,2}$ and $S_{2,3}$. Therefore, the added constraint becomes:

$$c_{d,3,3} - c_{d,2,2} - c_{d,2,3} \leq 0.$$

So, $c_{d,3,3}$ can only be chosen (become one) when one of the preceding states $c_{d,2,2}$ or $c_{d,2,3}$ is chosen. Only one of the two preceding states can be nonzero due to constraint (3.3) introduced in Chapter 3 that forces to choose only one state.

Next to adding these constraint, also the decision variables and options need to be annotated with the time interval. For every time interval a set of choices must be made, thus (4.1) is extended to:

$$tc_{d,t} = \sum_{opt \in Opt^d_{state,t}} A_{opt} \times x_{opt} + B_{opt} \times c_{opt}.$$

The optimization function observes the choices for all $N$ time intervals, thus (4.2) is extended to:

$$minimize \sum_{d \in D,\ t \in T} tc_{d,t}.$$

Furthermore, an index $t \in T$ is added to every variable, e.g. $x_d$ becomes $x_{d,t}$ and (3.4) becomes:

$$x_{d,t} = \sum_{opt \in Opt^d_{state,t}} x_{opt}.$$

Summarizing, by duplicating the model for each time period and every possible successor state and by adding constraints describing the possible state transitions an optimization model for a horizon can be achieved.

*Relaxation*

Note that the number of decision variables $x_{d,t}$ for the above model increases linearly with the number of states observed and the number of states is given by the product of the number of options of every device. Since devices often have more than one option, the number of decision variables increases very fast with the number of future states observed. Therefore, we relaxed the optimization problem by allowing $x_{d,t}$ for $t > 2$ to be non-integer. Since these states are based on predictions and these choices are not directly used this hopefully does not decrease the accuracy of the model too much. Simulations discussed in Section 6.1 show that this relaxation decreases the computational time significantly whereas the accuracy of the model decreases not significantly.

### 4.4.4 SCALABILITY AND COMPLEXITY

The basic approach used for step three (without MPC) is defined as a rather simple ILP optimization problem. This method is integrated in the simulator using a standard C library, GLPK[2]. The complexity of an ILP optimization problem is mainly defined by the number of integer variables and the number of constraints. The number of variables and constraints depend on the number of pools $NP$, the number of devices $ND$ and the total number of options for all devices together $NO$. Since for every option a variable $x_{opt}$ and a variable $c_{opt}$ is introduced, the number of variables is $2 \times NO$. For every pool there is a balancing constraint (NP), for every device a constraint to choose only one option (ND) and for every option there is a constraint to force the accompanying $x_{opt}$ to values of its own interval (NO). Furthermore, for certain devices some balancing constraints may have to be added (~ND). So, roughly the number of constraints is $NP + 2 \times ND + NO$.

For a single building this ILP can be solved within milliseconds, even on an embedded computer (see Section 6.2.5). So, complexity is no problem for this basic approach. Since the ILP is solved locally per building, scalability also is no issue.

However, when MPC is incorporated the complexity rises fast. Due to the large number of options per state, the state space explodes. Since for every state a number of $2 \times NO$ variables and $NP + 2 \times ND + NO$ constraints are required, this state space explosion leads to a lot of constraints and variables. Furthermore, state transition constraints are added to enforce a valid path through the state space. The exact number of variables and constraints depend strongly on the number of options and the number of predecessors of every state. However, simulations show a strong increase in simulation time with the number of observed time intervals. Relaxation of the algorithm decreased the simulation time significantly (by an order of magnitude).

The exploding complexity of the ILPs is mainly caused by the exploding state space. In the current, exact solution approach all states are taken into account. Improvements can be reached by decreasing the number of states, i.e. on beforehand decide to let certain states out of consideration. Therefore, we propose to create

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

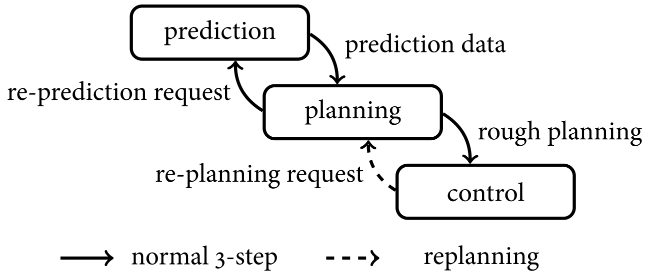



Figure 4.6: Interaction between the three steps in the control methodology

a heuristic approach to reach near-optimal solutions for the MPC version of the third step. This is left for future work.

### 4.4.5 RE-PLANNING

Despite the addition of MPC to the third step, it might happen that the prediction errors are too large to reach the planned profile for the building. However, other buildings often also have to deal with prediction errors. Therefore, in case serious mismatches occur within buildings or neighborhoods, the following re-planning approach may be applied: as the overall planned production/consumption pattern has to remain the same, it may be shifted within the overall tree, i.e. the production/consumption from one subtree may be shifted to another subtree.

It may not always be necessary to compute a new planning on the highest level of the tree. Re-planning is possible on every level in the tree working with objective bounds; a node getting objective bounds from its parent can divide the required consumption/production in an different way during the re-planning. Note that nodes getting steering signals cannot rearrange the production/consumption in their subtrees. The complete picture of the interaction between the three steps in the control methodology, including re-planning, is given in Figure 4.6. In the normal scenario, the prediction and planning step are executed iteratively until an acceptable planning is determined. Next, this planning is sent to the realtime controller. In case of a re-planning, the realtime controller initiates a new planning (the dashed arrow in the figure). This re-planning is similar to the initial planning: the prediction and planning step are executed iteratively until an acceptable planning is determined. The new planning is sent to the realtime controller.

When to initiate re-planning, on which level re-planning should be performed and its effects on the planning is topic of future work. Model Predictive Control can be seen as a local re-planning, especially when the MPC is only performed when necessary instead of in every time interval like in the current implementation.

## 4.5 Cost functions

In this section the cost functions of the devices used for the three-step control methodology are studied more detailed. First, it is discussed how cost functions should express the desirability of the different options. Next, in subsection 4.5.2 the actual cost functions for the devices modelled in Chapter 3 are derived. In subsection 4.5.3 the combination of cost functions of multiple devices and the effect of steering signals on individual devices using these combined cost functions are investigated. The last subsection gives a brief list of possible steering methods.

### 4.5.1 Expressing status with cost functions

The cost function of a device can express 1) the costs to deviate from the most desirable behavior, 2) the costs of state transitions (e.g. startup costs) and 3) costs to steer the behavior and reach some global objectives. Furthermore, the cost function of a device has to be independent of other devices to get a generic controller. In the following paragraphs the use of cost functions to express the above mentioned three points is described in more detail. Furthermore, using cost functions to maintain stability in more extreme situations is discussed.

The costs to deviate from the desirable, normal behavior are used to express the costs of a behavioral change for a certain device, only concerning the status of the device itself. For example, the costs for electricity import are fixed and independent on the amount of import ($A_{elec}$ is fixed, $B_{elec}$ is zero, see Figure 4.4b). However, the costs of switching a consuming device off depends on the type of the device and the priority; switching a TV off is less desirable than temporarily switching off the fridge. For buffers, the costs may fluctuate due to the SoC: draining energy from the buffer becomes more expensive when the SoC decreases. Furthermore, costs may be negative, e.g. charging a buffer gives a reward, just like exporting electricity to the grid. Therefore, it can be profitable to charge a buffer. For example, when the reward for charging a battery increases (when the SoC decreases) the costs for importing electricity may become lower than the reward for charging the battery: therefore it is profitable to charge the battery, the optimization algorithm of the third step minimizes the costs and thus chooses this option.

The costs for state transitions of the devices are used to prevent that costly transitions happen too often or at undesirable times. For example, starting a microCHP leads to wearing, starting it often and running it for short intervals leads to extra wearing. Switching off a device shortly after starting it may even be forbidden (modelled by very high costs shortly after starting).

The global optimization objectives are mostly specified via constraints or preferences on the electricity import/export from the grid. To steer import/export, the costs of the import/export from the grid can be adjusted: higher costs when less import is preferred or costs depending on the amount of import.

The cost functions can also be used to model more extreme situations. In some scenarios it may be desirable to allow a certain mismatch of energy consumption and demand, e.g. during a power cut. In such a scenario it is allowed to produce

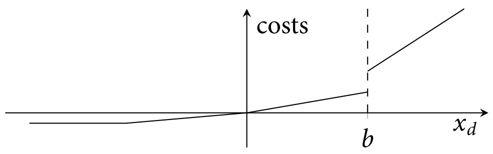



Figure 4.7: Electricity import costs for local peak shaving objective

more heat than can be consumed/stored. This heat surplus can be dumped to enable the production of electricity (with a generator) when this is strictly necessary. Surplus energy can be added very easily by adding "abstract" devices for heat surplus/shortage and electricity surplus/shortage without changing the model. Two separate devices for heat and electricity are used since heat surplus/shortage in general is independent from electricity surplus/shortage. Using these devices in a normal situation is prevented by giving them extremely high costs in normal situations, but this can be adapted if certain circumstances require such extreme behavior.

### 4.5.2 (SMART) DEVICES

In this subsection the cost functions for a number of devices are discussed. The models of these devices as described in 3.1.3 are extended, by adding costs to the options. All costs of the devices are related to the standard costs of energy, i.e. the costs for importing energy for a fixed price. These standard costs are set to 1000 units per W.

*Exchanging devices*

For the import and export of energy usually the standard costs are $A_{ex} = 1000$ and since there are no transition costs we set $B_{ex} = 0$. However, the import and export costs can be used to steer towards a (global) objective, especially the electricity import and export costs are used for this. So, the actual costs used in the controller depend on the global steering signals, the planning made on beforehand and the status of the building.

An example of a cost function for electricity import is given in Figure 4.7. This is a combined cost function for import and export of electricity; a negative value of $x_d$ means export of electricity. Due to the definition of this cost function, it works towards a local goal. When the imports are higher than a certain value ($x_d \geq b$), the relative import costs are much higher, i.e. the value of $A_{elec}$ in the cost function $A_{elec} \times x_d + B_{elec}$ is increased. Therefore, this cost function results in shaving the peaks of the electricity import. Due to the low export costs (low benefits), the locally produced electricity is used locally as much as possible.

*Buffering devices*

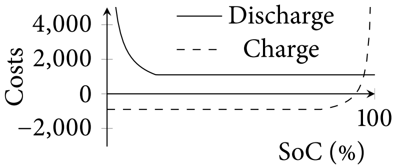
The cost function of the buffers depend on the State of Charge (SoC) of the buffer. Furthermore, the costs may increase for higher flows from or to the buffer since this may lead to more wearing. A battery wears out faster with higher flows whereas for a heat buffer the amount of energy flowing from or to the buffer has (almost) no influence on the wearing. However, in the current implementation, and more important, for the simulations in the next chapter, the used costs are chosen to be not depending on the amount of energy flow for both the heat buffer and the electricity buffer. In other words, the wearing of the battery is not taken into account in the simulations. This is left for future work. Therefore, the costs $A_{buf}$ only depend on the SoC and since there are no state transitions $B_{buf}$ is set to zero. The costs $A_{buf}$ as function of the SoC for both implemented buffers is given in Figure 4.8. The charge costs for the electricity buffer are -900, so only when electricity is available for less than 900 ("cheap" electricity) the buffer is charged, since only then the profit of charging the battery is higher than the costs of using this electricity. When the buffer is almost full, the charging costs increase so there is no profit in charging anymore and the buffer is not overcharged. For discharging it is the other way around, discharging costs are 1100 so only when other electricity is expensive the electricity from the battery is used. In other words, when no electricity generators are available in the building, the battery is charged when electricity is cheap (e.g. at night) and discharged when electricity is expensive (during peak periods or to supply the peaks in case of a peak shaving objective).

The cost function for the heat buffer is similar, except for the increasing benefits for charging when the SoC decreases. This is because the heat buffer is required for supplying heat demand, so it is necessary to fill the buffer when it gets empty (as opposed to electricity buffers). Often heat generators are used to fill the heat buffer and these heat generators might have transition costs. Furthermore, heat generators are often converting devices, so the total costs for the heat produced are higher than the standard costs (i.e. > 1000), since these converters use an energy-carrier stream as input with a price of 1000 and add converting costs to this. Therefore, the charge costs between 20% and 80% SoC are set to $A_{buf} = -1100$. Furthermore, when the buffer is almost empty an extra incentive (profit to charge) is required to start the generators and to fill the heat buffer (this is discussed more detailed in the next subsection). Since the heat buffer often is the only supply for heat demand, the discharge costs are set to the standard costs, i.e. $A_{buf} = 1000$. Only when the buffer is almost empty the discharge costs increase.

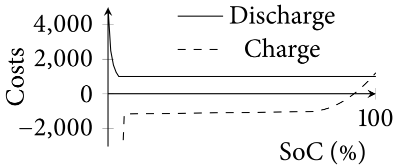
*Converting devices*

Three different converting devices are modelled: PV panels, a boiler and a microCHP. The costs of a PV panel are set to zero, since the production cannot be controlled and it is desirable to use all production.

The variable costs for the boiler are set to $A_{boiler} = 0$, since energy is not produced but only converted. When the boiler is switched on it consumes gas,




(a) Battery




(b) Heat buffer

Figure 4.8: The value of $A$ of the cost function of a buffer as function of SoC

which has to be imported resulting in certain import costs. However, to compensate for the usage and wearing of the device and to prevent it from switching on for short moments only, there are transition costs. The definition of these transition costs are important for the correct functioning of the device. A boiler can optionally be installed in combination with a heat buffer. When there is no heat buffer, the heat demand should be supplied by the boiler directly. Since the costs for not supplying a load are very high, the transition costs for the boiler are not important, it switches on anyway.

When a heat buffer is available the boiler fills the buffer and the heat demand is supplied by the heat buffer:


Therefore, the boiler should only be switched on when the buffer is almost empty and should switch off when the buffer is full. Thus, the transition costs should be synchronized with the heat buffer costs. Since the boiler is the only device that can fill the buffer and the heat from the boiler can only flow to the heat buffer, the interaction between these two devices is independent of the rest of the building and the interaction can be analyzed without taking the rest of the devices into account.

When the device is not running, it should only start when the buffer is almost empty. In the case the device is not running, there are two options: stay off or switch on. The costs to switch on are the costs $B_{boiler}$ of the boiler to switch on, the costs $A_{gas}$ for importing gas and the costs for charging the buffer $A_{buf}$ (a reward): $B_{boiler} + x_{boiler} \times A_{gas} + x_{boiler} \times A_{buf}$. The costs to stay off are zero. Since the goal is cost minimization, the boiler switches on when the costs to switch on are lower than the costs to stay off, i.e. when the costs to switch on drop below zero. The gas import price is normally 1000 and the standard charge costs for the buffer are −1100. The boiler should only switch on when the heat buffer is almost empty, i.e. when the charge costs are lower than −1100. Since the boiler produces $30 \times 10^3$ W heat,

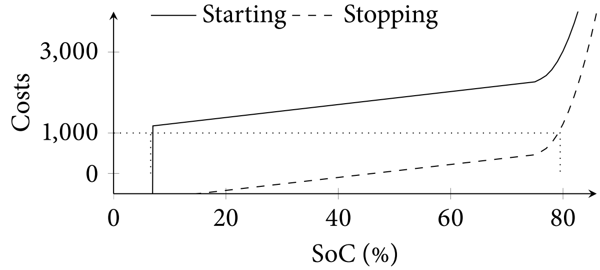



Figure 4.9: Break-even point for starting and stopping the microCHP as function of the SoC of the heat buffer and the electricity price

the gas import and heat buffer charge costs are $30 \times 10^3 \times A_{gas} + 30 \times 10^3 \times A_{buf} = 30 \times 10^3 \times 1000 + 30 \times 10^3 \times -1100 = -3 \times 10^6$. Thus, to prevent the boiler to switch on when the heat costs are $-1100$ the transition costs should be higher than $3 \times 10^6$, so the transition costs for switching on are set to $B_{boiler} = 5 \times 10^6$. When the device is already running there are no transition costs (i.e. $B_{boiler} = 0$) for both keep running as for switching off. Due to the definition of the boiler costs, the boiler switches on when the reward is high enough, i.e. when $A_{buf} < -1100$. Therefore, the boiler switches on when the buffer is almost empty. Furthermore, the boiler keeps running since the reward $A_{buf}$ is higher than the costs $A_{gas}$. Only when the buffer is almost full, the reward drops and the boiler is switched off.

For the microCHP, the costs are built up a bit more complex. Just as for the boiler the costs for conversion $A_{mchp}$ are set to 0 and the startup costs should be high enough. The heat production when the microCHP is starting is $2.6 \times 10^3$ W, so the startup costs should be at least $2.6 \times 10^3 \times 100 = 2.6 \times 10^5$. Therefore, the costs $B_{mchp}$ to switch on are determined as $4 \times 10^5$ when the cool down period has elapsed and $1 \times 10^6$ otherwise. To compensate for the loss of the microCHP, the costs $B_{mchp}$ to switch off are $2 \times 10^5$ (or $5 \times 10^6$ when the minimum runtime is not elapsed).

This cost function of the microCHP device results in a comparable behavior as for the boiler: the costs for switching on the microCHP are the import of gas ($9300 \times 10^3$) and the switching costs ($4 \times 10^5$), in total $9.7 \times 10^6$. Since the 1000 W with a normal electricity import prices accounts for $1000 \times -1000 = -1 \times 10^6$, the heat supply has to deliver $8.7 \times 10^6$ to be break even, in other words $8.7 \times 10^6 / 8 \times 10^3 = 1087$ per W. The same calculation can be made for switching off the microCHP. So, with normal electricity price the microCHP switches on when the buffer is almost empty and switches off when the buffer is almost full, but with changing electricity prices these break even points shift. This is shown in Figure 4.9.

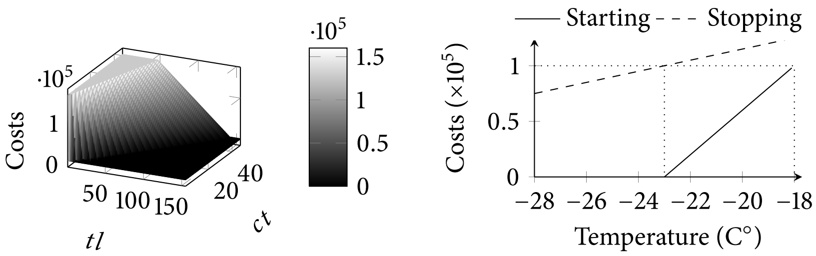
*Consuming devices*

Also for four consuming devices (the standard consuming device, the freezer, the electrical car and the loss device) cost functions are defined. The cost of the loss device is set to zero, it just consumes the loss.

The standard consuming device has a certain demand in every time interval, depending on a given consumption profile. When the demand of a standard consuming device is nonzero, the demand can be supplied or optionally shifted in time: there are two valid values for $x_d$, $x_d = 0$ or $x_d = demand$. We have chosen for a cost function that depends on the priority. Furthermore, it is preferable to shift the load from devices which are already preempted. The costs for supplying the standard consuming device are zero, both $A_{cons}$ and $B_{cons}$, since this is the normal behavior. For shifting the load in time, the value of $A_{cons}$ is not relevant, since in the case of not supplying the device we get $x_d = 0$. Switching off the device results in less costs for importing energy. So, to ensure that not supplying a device is not more preferable than supplying it, the value of $B_{cons}$ should be at least equal to the costs of supplying it, i.e. $demand \times 1000$. Whether the demand can be shifted depends on whether the device is preemptable and whether it has already been supplied before. If the device is preemptable, the demand can always be shifted. If the device is non-preemptable the demand can only be shifted if the device is not yet started, i.e. it is not supplied before. The value of $B_{cons}$ depends, next to the costs mentioned above, on the priority of the device to assure that lower priority devices are switched off before higher priority devices. Thus, the value of $B_{cons}$ is increased with $B_{cons} = 3 \times 10^6 + priority \times 2 \times 10^5$ (priority running from 1 to 5). Furthermore, the value of $B_{cons}$ depends on whether the demand of the device is also shifted the previous time interval, i.e. state transition costs. When the device consumed energy in the previous time interval, the costs are increased by $1 \times 10^6$ resulting in preference to keep already shifted devices shifted instead of shift multiple devices one after each other.

The costs of shifting the load of an electrical car depends on the required number of intervals of charge left $ct$ (# time intervals) and the time left before the car must be completely charged $tl$ (# time intervals). For the option to charge the car, the value of both $A_{car}$ and $B_{car}$ are set to zero. For shifting the load in time, the value of $A_{car}$ does not matter since the value of $x_d$ is zero. So, the value of $B_{car}$ should compensate for the reward for not supplying the car (less electricity supply) and the costs for shifting the charging in time. Therefore, the value of $B_{car}$ is set to $B_{car} = 16 \times 10^4 - (tl - ct)/ct \times 8 \times 10^4$. The value of $B_{car}$ as function of $ct$ and $tl$ is shown in 4.10a. As with the standard consuming device, the costs for shifting should be higher than the costs for supplying the device ($1000 \times demand$). This cost function results in charging when the electricity is cheap or when there is no time left to shift the load in time.

For the freezer, the costs depend on the temperature and the current state (switching costs). When the freezer is switched on (i.e. cooling), the costs for staying on are zero, both $A_{freezer}$ and $B_{freezer}$. To switch a running freezer off, the costs for $A_{freezer}$ are zero and the switching costs depend on the temperature $temp$:




(a) Costs for not charging an electrical car

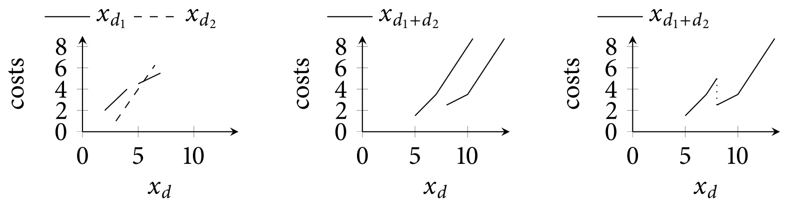
(b) Costs for switching on/off the freezer as function of the temperature

Figure 4.10: Costs for shifting load in time

$B_{freezer} = 1\times10^5 + (23 + temp) \times 5\times10^3$ (lower temperatures means lower switch off costs). When a freezer is switched off, switching it on has no costs but keeping it off (shifting load) has costs for shifting the load: $B_{freezer} = 1\times10^5 + (18 + temp) \times 2\times10^4$ (higher temperatures means high costs to not switch on). The resulting costs are shown in Figure 4.10b. Since a running freezer consumes 100 W electricity, a running freezer results in $1 \times 10^5$ costs for electricity (import) with standard costs. Using this, it can be calculated that with normal electricity costs the freezer switches on when the temperature reaches -18 °C and switches off when -23 °C and when electricity prices are higher, the freezer switches off with higher temperatures, when electricity is cheap, the freezer switches on with lower temperatures.

### 4.5.3 STEERING THE COST FUNCTIONS

In this subsection the combination of and interaction between multiple cost functions are studied and the influence of steering signals on (combined) cost functions is analyzed. When one smart device is installed in the building, the device can simply be steered by the import/export costs for energy. However, often multiple smart devices are present in a building and they are all influenced by a single steering signal, the (artificial) import price of electricity. The building controller decides based on this single steering signal which (smart) devices are switched on and which devices are switched off. Therefore, all smart devices in a building are seen as one aggregated device by the global controller. To analyze the influence of the energy costs on the smart devices the cost functions should also be aggregated, i.e. the cost functions are added. This section studies what these combined cost functions look like, how multiple smart devices in a building react on a single steering signal and how multiple (supplying and consuming) smart devices interact with each other in a single building. In this subsection, first the analytical consequences of adding cost functions is studied, next the combination of multiple cost functions is analyzed.




(a) Two separate functions (b) All parts of the combined function (c) The resulting combined function

Figure 4.11: Combining two non-continuous, partial linear functions

*Adding cost functions*

Adding the cost functions of two devices means adding two non-continuous partial linear functions. In other words, the two functions for $x_{d_1}$ and $x_{d_2}$ are combined in one function $x_{d_1+d_2}$. Note that combining two cost functions is only possible when they are of the same type, e.g. both electricity consuming.

To combine two non-continuous partial linear functions, both functions must be split up in continuous linear parts, resulting in a set of linear parts $lp_1$ for $x_{d_1}$ and $lp_2$ for $x_{d_2}$. The sum of the two functions consists of all possible combinations of parts $(i, j)$ with $i \in lp_1$ and $j \in lp_2$. The combination for $x_{d_1+d_2}$ of two parts $i$ having cost function $A_i \times x_i + B_i,\ Min_i \leq x_i \leq Max_i$ and $j$ having cost function $A_j \times x_j + B_j,\ Min_j \leq x_j \leq Max_j$ is given by:

$$\begin{cases} A_i \times x_c + B_i + B_j & , Min_i + Min_j \leq x_c \leq Min_j + Max_i \\ A_j \times x_c + B_i + B_j + A_i \times Max_i & , Min_j + Max_i \leq x_c \leq Max_i + Max_j \end{cases},$$

assuming $A_i \leq A_j$ without loss of generality. This is shown in Figure 4.11, the left figure shows the two separate functions and the two right figures show the combined function. The function of $x_{d_1}$ consists of two intervals and the function of $x_{d_2}$ of one interval, so the resulting cost functions consists of four intervals (see Figure 4.11b). As can be seen in the figure, there can be an overlap between different parts of the function. However, since the optimization function has a minimization objective, always the lowest of the two overlapping parts is picked (see Figure 4.11c).

*Examples of combined cost functions*

Using this method, cost functions of a couple of devices are combined to analyze the usability of these combined functions. This is done for two electricity consuming devices and for the electricity supply with the choice between three sources.

To analyze how useful a combined cost function of two consuming devices is, the cost functions of a freezer and another consuming device are combined. In this scenario, the temperature in the freezer is -20 and currently it is switched on consuming 100 W. The other consuming device is a fan with a consumption of 150W and the costs for switching off are $1.5 \times 10^5$. Therefore, the freezer has two options: switch off or continue running:

$$x_d = 0,\ A = 0,\ B = 1.1 \times 10^5 \ or \ x_d = 100,\ A = B = 0$$

The fan also has two options: switch on or shift the load:

$$x_d = 150,\ A = B = 0 \ or \ x_d = 0,\ A = 0,\ B = 1.5 \times 10^5$$

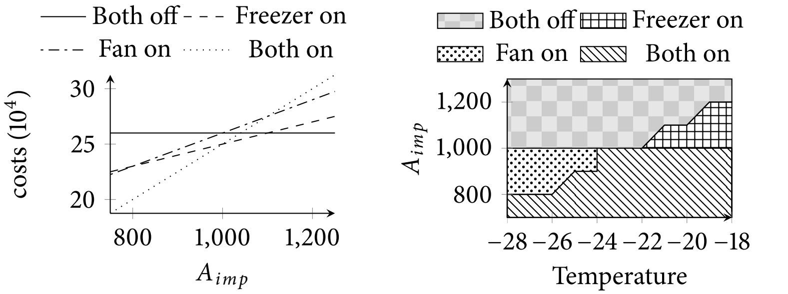
The combination of these two devices lead to four options: both off ($B = 2.6 \times 10^5$), only the freezer on ($B = 1.5 \times 10^5$), only the fan on ($B = 1.1 \times 10^5$), both on ($B = 0$).

To study how the electricity import price influences the decision which of the devices will be supplied or not, we have to incorporate the electricity import price in the costs. For this calculation we assume that the only source of electricity is importing it. The costs for switching both devices off do not change since no electricity is consumed. When the freezer is switched on and the fan not, the costs for switching the fan off are $1.5 \times 10^5$ (B) and the costs for supplying the freezer are $100 \times A_{imp}$, given electricity costs of $A_{imp}$: with standard electricity costs (1000) the overall costs are $1.5 \times 10^5 + 100 * 1000 = 2.5 \times 10^5$. For the three other scenarios the costs can be calculated in the same way:

1. both off: $2.6 \times 10^5 + 0 \times A_{imp}$,
2. only the freezer on: $1.5 \times 10^5 + 100 \times A_{imp}$,
3. only the fan on: $1.1 \times 10^5 + 150 \times A_{imp}$,
4. both on: $250 \times A_{imp}$.

Figure 4.12a shows the total costs for the four scenarios as function of $A_{imp}$. As can be seen in the picture, when the costs for $A_{imp}$ are lower than 1000, both devices will be switched on. When the costs for $A_{imp}$ are between 1000 and 1100 only the freezer will be switched on and when the costs are higher than 1100 both devices will be switched off. So, in the combined cost function with one steering signal for both devices, the fan cannot be switched on while the freezer is switched off. However, it may be not required to switch a device on while a more desirable device is switched off.

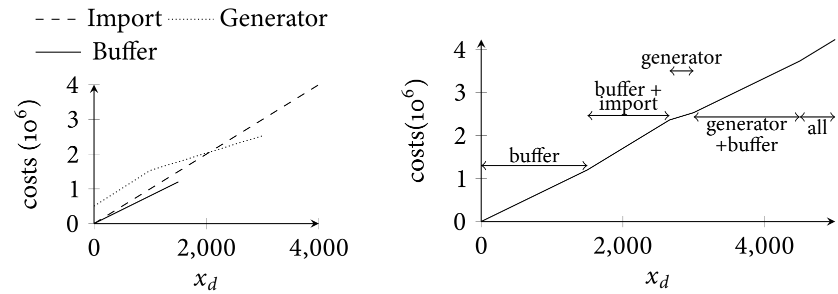
As explained in Section 4.5.2, the costs $B$ for switching off the freezer while it is running depend on the temperature of the freezer. In Figure 4.12b it is shown for multiple values of costs for $A_{imp}$ and multiple temperatures for the freezer whether both the fan and the freezer will be switched on, only the freezer will be switched on, only the fan will be switched on or whether both devices are switched off. As can be seen in the figure, when the costs are high both devices are switched off and when the costs are low both devices are switched on. Furthermore, when the temperature of the freezer is high it is more preferable to switch off the fan, but when the temperature is low it is more preferable to switch off the freezer.




(a) Combined costs of a freezer and a fan as function of import price

(b) Decision which devices are switched on as function of the freezer temperature and the import price

Figure 4.12: Combined behavior of a freezer and a fan




(a) Cost functions of three electricity sources

(b) Combined function for the three sources

Figure 4.13: Combination of multiple electricity supply sources

In Figure 4.13 the cost functions of three electricity supply sources are shown: electricity import, a generator and a battery. The battery is the cheapest source (when it is full), but has a limited capacity. The combined function given in Figure 4.13b, shows which (mix of) source(s) is used for a certain electricity consumption.

When the above mentioned consumers (fan and freezer) and sources (import, generator and battery) are combined, the amount of consumption depends on the price, but the price (per unit) depends on the amount of consumption. For example, matching the above mentioned costs for demand and supply, both the fan and the battery would be supplied since the battery can deliver enough cheap electricity for both. However, when the capacity of the buffer would have been limited on 100 W, only the freezer would have been supplied.

### 4.5.4 STEERING SIGNALS

Within the complete control methodology the structure and the number of steering signals are important. Three important parameters are identified within this structure and number of steering signals:

- division between steering signals and objective bounds,
- individual steering signals per device, individual steering signals per building or one steering signal per subtree,
- on/off steering signals or cost-based steering signals.

We have chosen for steering signals since they are more generic and less information about the devices is required on a higher level. Within the tree as long as possible objective bounds are used, only on the lowest (building) level steering signals are required. Furthermore, one steering signal per building is used to limit the number of steering signals and the amount of communication. Whether individual steering signals per building or one steering signal per subtree is preferable is studied using simulations described in the results chapter.

## 4.6 CONCLUSIONS

The framework for the control methodology proposed in this chapter results in a flexible and generic methodology to work towards global and/or local objectives. The hierarchical structure of the framework ensures scalability and limits the required communication. The three-step approach enables a well-established prediction of the consumption/production profile one day ahead to be able to act on electricity markets. The prediction and planning determine whether or to what extent the preferred profile is reachable, resulting in a prediction of the profile. Furthermore, the realtime part is able to react on realtime signals, e.g. due to fluctuation caused by renewable sources. The addition of Model Predictive Control to the last step of the control methodology strengthens the ability of the realtime control to work around prediction errors. Furthermore, it increases the stability (reduction of oscillation) by not only taking the current situation into consideration, but also a prediction of the future (PI-control).

The cost functions for devices in combination with the options per device are a very flexible way to express the status of the device and desirability of different options. Since the cost functions are similar for every type of device (exchanging, converting, buffering and consuming), new devices can be incorporated in this approach. Furthermore, the control methodology acts on a homogeneous set of cost functions that keeps the algorithms much easier and less computationally intensive. Finally, cost functions of multiple devices can be combined into one cost function to study the effects of a single (price) steering signal on a group of (different) devices.

The combination of offline prediction, offline planning and online control results in a solution that meets the requirements set at the beginning of this chapter.

CHAPTER 5

# Simulator

Abstract – *In this chapter the simulator developed to analyze future scenarios and control methodologies is described. The simulator is based on the model derived in Chapter 3 and uses discrete simulations. The design is kept the closest to the model possible, individual buildings are identified on a device level and multiple buildings are combined into a (smart) grid. Only the voltage levels in the grid and the transformers between the voltage levels are left for future work. Within the simulator, a framework with hooks for control methodologies is included. This framework consists of prediction and management capabilities of devices together with a tree-structured network of control nodes which can communicate with each other and execute algorithms. To increase the ease of use, a number of features are added to the simulator, such as logging for easy evaluation of the results. Furthermore, the elements (e.g. devices) are parameterized so one implementation can be used to simulate different versions of the element. Finally, stochastic variations can be added to the devices so with only a small set of building models a realistic mix of buildings can be simulated. This results in a simulator that can simulate a grid of buildings up to a device level and can keep track of all energy streams. The simulator is generic, it can simulate various domestic technologies and control methodologies and it is easy to extend the simulator with implementations of new technologies. The simulator is able to simulate a large group of buildings within reasonable time.*

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This chapter gives a description of the simulator based on the model described in Chapter 3. The goal of the simulator is to create a tool to analyze the effect of control methodologies steering residential generation and storage technologies for a large fleet of buildings. Furthermore, the simulator is able to compare scenarios and to analyze the characteristics of a scenario (e.g. peak usage), for example a large scale

Parts of this chapter have been presented at [AM:14] and [AM:4].

introduction of electrical cars can be analyzed. The simulator is built from scratch instead of using an existing simulation platform for which a motivation is also given in this chapter.



The model described in Chapter 3 models a complete electricity grid from generation by power plants via the transport and storage on different voltage levels up to buildings on a device level. Within the simulator this model is implemented and extended with controllers. There can be controllers on different levels: on a domestic level and on different levels within the grid. These controllers can communicate via multiple (hierarchical) communication structures. Furthermore, the framework for the controllers should also be generic to allow different communication structures, control methodologies and algorithms.

In the remainder of this chapter the developed simulator is described in more detail. The next section describes the requirements for the simulator, followed by a section with a short overview of the related work and a motivation to develop a simulator from scratch. Section 5.3 gives the implementation details. The last section ends up with conclusions.

## 5.1 Requirements

The motivation for building the simulator was to be able to get a realistic, generic and flexible simulation tool, where the simulated situation should be an accurate representation of the actual situation. As the model of the grid and buildings described in Chapter 3 is quite flexible and is able to represent different types of normal houses (family/single-person houses, big/small houses, etc.) and other buildings (schools, offices, shops, etc.) on a detailed level and multiple buildings can be grouped together to form a grid, e.g. a city with a realistic mix of buildings, we chose this model as the base of our simulator.

We decided to use a discrete time simulation instead of continuous time simulation. A continuous time simulation also requires a continuous analysis and control which is more complex than taking a decision for a certain time period. Furthermore, continuous predictions of energy demand and production used within the optimization methods are less accurate since exact timestamps for the demand and production are predicted; discrete predictions predict the aggregated demand during a certain period. Moreover, there is no need for a continuous control algorithm since the actual controller installed in buildings will probably also work on a discrete time base.

A third way of simulating is event-based simulations. Where discrete time simulation is based on time intervals, the new situation is calculated every time interval, event-based simulations are based on events. The advantage of event-bases simulations is that only when the status of the system changes (a load is switched on, a battery is almost empty, etc.) the new control signals are determined and the new situation is calculated. However, with event-based simulation 1) the period to decide for is unknown since it is not known when the next event will take place (and therefore e.g. the maximum discharge current of a battery) and 2) events are highly correlated resulting in many events for which the whole system needs to be analyzed (e.g. a high discharge current of a battery changes the status of the battery quickly resulting in many events). When there are a lot of such events, the advantage of event-based simulation over discrete simulation disappears.

For a discrete simulation the simulation horizon is discretisized resulting in a set of consecutive time intervals. The number of intervals depends on the length of the planning horizon and the chosen length of the time intervals, e.g. a five minute time-base and a 24 hour horizon results in 288 time intervals. The model describes the status of the building at one moment in time and gives the options for the following time interval. A control algorithm has to decide about the amount of energy flowing in the following time interval by selecting an option for every device in such a way that all pools are in balance.

Each building is individually addressed because every building has its own characteristics and internal state. The buildings should be, in comparison to the model, extended with a local controller. The grid can optionally also be extended with global controllers on different levels, communicating with the local controllers and/or each other, like the situation sketched as a Virtual Power Plant (VPP) described in [59].

The control methodology, algorithms and (communication) structure should be generic and flexible, just like the rest of the model. Multiple approaches (agent-based, optimization algorithms, etc.) and communication structures (different tree structures), should easily be incorporated into the simulator. So, the simulator should offer hooks to insert controllers on different levels and an adjustable communication structure for the controllers.

There are a lot of different possible scenarios (different combinations of buildings, building controllers, etc.). To be flexible, the simulator should be easily adaptable to new types of micro-generators, controllers and other supported elements. It should be easy to simulate different scenarios, combinations of different buildings and present results of local controllers and global objectives.

To analyze the results of the used control methodologies, the simulator has to keep track of the energy streams within the building and within the grid. In this way the production patterns of power plants and the electricity streams through the grid(transformers) can be derived. This data can be used to determine the properties of the controllers.

The simulator should be capable of simulating both the impact of local control algorithms within a single building in detail, and the overall effect of a global control algorithm on a large number of buildings. For the latter, not all details of individual buildings may be necessary. However, within a simulation of a single building these details are essential. So, the level of detail of stored data needs to be adjustable.

As we have chosen for a discrete simulation, the length of the time intervals mainly influences the amount of data (since it influences the number of intervals) and the precision of the results. Therefore, the choice of the used time discretization reflects the tradeoff between precision and data usage. The minimum possible time interval length may be a second, but this has to be adjustable. In many cases, a five minute time interval is a good tradeoff between precision and data usage [66]. The precision of the data itself does not form a major issue, since almost all data can be stored as integers representing watts. Since different parts of the simulations (buildings, devices, etc.) can be defined using different time interval lengths, all parts should be synchronized towards the same time interval length.



The speed and memory usage of the simulator are also important characteristics of the simulator. For the VPP simulations it should be possible to simulate a large fleet of buildings in detail. As an average windmill park produces around 50 MW, in order to have an applicable VPP with micro-generators that is comparable to such a windmill park, a generation potential of 50 MW is necessary. Therefore, the number of buildings that can be simulated within a reasonable time (hours) on a normal PC should be at least 50.000, leading to requirements on CPU and memory usage. However, improved and more complex optimization algorithms decrease the simulation speed, leading to even higher requirements to meet the speed and memory usage constraints.

Finally, the network communication of the control methodologies needs to be monitored (between local and global controllers) to verify the used protocols and define the requirements for the communication network.

Summarized we have the following requirements:

1. flexible, generic, extendable and scalable,
2. a communication and control framework to integrate control algorithms,
3. adjustable time interval length for the discrete time simulation,
4. adjustable simulator output,
5. high simulation speed with reasonable memory usage,
6. easy to use.

## 5.2 Related work

Simulation solutions already exist in a lot of different areas, e.g. optimizations for logistics, 3D modeling or process management. However, most simulation software is domain specific and can not easily be ported to different application areas.

The focus of our research is on simulating the effect of (domestic) energy streams on the system as a whole. Commercial software is available to simulate heat and electricity load of large buildings. These systems are often used to optimize Heating Ventilation Air Conditioning (HVAC) systems and façade control systems or to build more energy efficient buildings and take into account the structure of the building and the materials used [3, 55]. However, our goal is not to simulate the expected heat and electricity load, but to simulate the control methodologies to supply these loads resulting from the structure of the building. Other energy simulation software focuses on a specific technology, for example wind parks or solar cells.

The Advanced Local Energy Planning (ALEP) simulation framework [40] is an initiative of the International Energy Agency and is developed in cooperation with multiple countries. This simulation framework focusses on the local energy supply, it can analyze which mix of generators can be used best for certain (remote) areas. It takes next to technical constraints, also management and social issues into account. The goal of the tool is to analyze the impact of different generation components in an area. Another free tool is HOMER, an optimization model for distributed power [47]. It is a model that simplifies the task of evaluating design options for both off-grid and grid-connected power systems for remote, stand-alone, and distributed generation applications. It can also take buffering and deferrable loads into account. The goal of the tool is to find the best combination of supply components and parameters for these components. Thus, these two tools have another focus and do not meet all of our requirements.

In [37] a custom simulation system for the coordination of decentralized energy conversion is described. Like in our approach, a custom made simulator is developed. However, few details about the underlying design are given and only a device specific example is given. Our approach has a more flexible design. Different control strategies can easily be added and the design is more flexible to future technologies.

We have chosen not to use simulation frameworks like Tortuga [64] or SimPy (Simulation in Python). Although these frameworks may provide some generic functionality required for a simulation, they still require to create a specific model within the limitations of the framework. We considered it easier and more promising to create an own model in a familiar environment and still have the flexibility to reuse work in the literature. Furthermore, our aim is to have a simulator that is very fast and memory efficient. The simulator does not only have to perform discrete time simulations, but it uses time consuming local and/or global algorithms/solvers as well. The access to data, which is required by these algorithms/solvers, needs to be fast. Since especially a clever way to access the data in memory based on the model structure is hard to incorporate in an existing simulation framework, we decided to spend effort in the development of an own simulator. The proposed simulator incorporates algorithms and solvers, rather than that it communicates with other programs. This incorporation increases simulation speed compared to existing simulation platforms with slower data exchange. Incorporating algorithms and solvers into the simulator also eases the adaptation of the algorithms to run them on the eventual embedded systems of the control nodes.

A further advantage of a tailored simulator is that its overhead is reduced to necessary features imposed by the stated requirements. Although the simulator is composed of generic parts, it is specifically tailored for the energy infrastructure. The memory and disk usage is efficient, since no unnecessary elements are created or stored.

Preferably the simulator is usable on multiple platforms, which makes distributing the simulations easier. For this reason, we chose C++ as programming language, using Nokia's QT library. This library provides efficient, cross platform libraries for data storage, network communication and user interfaces. Furthermore, the C++ programming language enables us to use other C and C++ libraries.

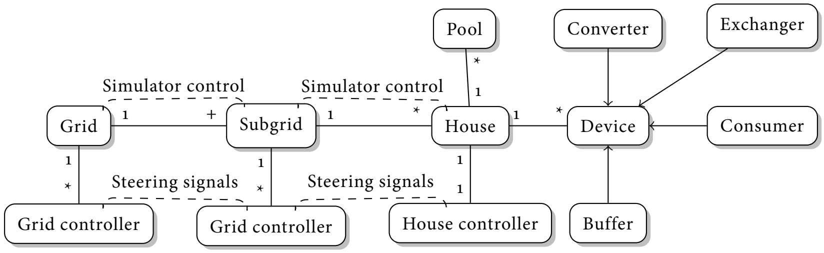



Figure 5.1: Class diagram of the simulator

Finally, the simulator needs flexibility in adding, for example, new algorithms or other types of generators. The generic modelling approach allows adaptations in the model without directly asking for a large change in the simulation environment. This prevents that such adaptations suddenly lead to a huge increase in memory usage or a large decrease in speed.

In related work regarding energy-optimizing control strategies the focus is mostly on agent based approaches [39, 43]. An example of an agent-based system is the PowerMatcher [43], which creates a virtual market to determine who can produce/consume energy and for which price. Important in such an approach is the stability and reliability of the bidding system, which is often simulated. The simulator described in this thesis has a more generic approach, where the focus is on the control of the system and the influence of that control system on the whole system. Due to the flexible design of our simulator, the PowerMatcher bidding system could be embedded in our simulator.

## 5.3 Simulator structure

In this section a description is given of the implementation and special features of the simulator. In the first subsection, the general idea behind the simulator, the structure of the simulator and design details are given. Next, the required functionality of controllers and how the controllers can be added to the simulation is discussed. In subsection 5.3.3, added features to make simulations easier to configure and to make simulations more realistic are discussed, followed by a subsection with a description of the steps during a simulation. Finally, in the last three subsections some speed optimizations, the Graphical User Interface and the verifications of the correctness of the simulator are given. A main aspect in this section is to show how the simulator is built up taking into consideration that flexibility, ease of use and speed should be achieved.

### 5.3.1 DESIGN DETAILS

In this subsection the design details of the simulator are given. The simulator is designed in an object-oriented manner, using C++ and Nokia's QT library. In the rest of this subsection, first the idea behind the simulator is sketched. Then, the main parts of the simulator are described: devices, buildings, the grid and the control.

*Simulator idea*

The structure of the classes is kept the closest possible to the model described in Chapter 3. For each model-entity discussed in this chapter (and shown in Figure 3.1 and Figure 3.7), a separate class is built: a building consists of pools and devices, multiple buildings are combined into a grid. The class diagram of the simulator structure is given in Figure 5.1. For every element in the simulation an object is instantiated; for the grid one object is instantiated, for every simulated building an own building-object is instantiated and for every device in every building a device-object is instantiated. These parts are discussed in more detail below.

A simulation has a configurable number of time intervals. All required classes are instantiated, connected and adjusted to each other during the initiation phase. The simulation can start with preliminary controller actions, for example to make a (rough) planning on beforehand, optionally based on predictions of the generation and consumption per device. During the simulation itself, every time interval the devices first determine their set of possible actions $Opt^d_{state}$ based on their internal state and then sent these options to the controller. The controller selects, optionally consulting other controllers, for every device an option and sends this option to the device. Next, every device updates its internal state based on the chosen option and finishes the current time interval. A simulation controller monitors and manages this work-flow, it *triggers* the elements in the correct order when a time interval has started.

*Devices*

The base elements of the model are the devices in the building. In the model, four types of devices are defined: exchanging, converting, buffering and consuming devices. However, the devices in the building have a lot of common functionality and they need a common interface to communicate with the building controller. Via this interface, for example, the options can be requested and the chosen options can be communicated back. Furthermore, a common interface for the Graphical User Interface (GUI) and for the simulation control is required. Therefore, an abstract *device* class is defined. This class implements common functionality (initialization, configuration, speed optimizations) of all devices and it defines the methods for the communication interface. Furthermore, it implements some tools for pool administration, the instantiation of devices during simulation initialization and for the GUI.

For every of the four types of devices a class is defined, each with their own characteristics and extending the functionality of the abstract device class (i.e. inheritance). These classes are also defined abstract. An actual device can be implemented by extending one of the four device type classes. Due to the inheritance, the device already has a lot of basic functionality, amongst others functionality to configure the device using the GUI. Moreover, it is already a device that can be added to the simulation and that can be simulated. However, it has no functionality, i.e. no energy carriers streams (in or out) are defined for the device and only one option is available ($[Min, Max] = [0, 0]$). Because of the predefined functionality, the energy carrier streams $Str$ with their energy type $ec \in EC$ and the multiplication factors $M_{str}$ can be defined rather easily without a lot of code required. Next, functionality (i.e. methods) for configuration, functionality to keep track of the internal state and functionality to add the correct options to the set $Opt^{d}_{state}$ every time interval need to be added. Finally, it must be configured which parts of the device can be configured via the GUI. The methods are in fact for this functionality already defined in the abstract classes, but without functionality. So, these methods need to be overridden and the functionality need to be implemented, optionally using extra functions.

A device describes the behavior of the device; in the building it is configured what the priority is, when it has to start running and for how long.

*Building*

A building consists of devices, pools and energy streams between pools and devices. Within the building-object it is configured which devices and pools are available in the building. Furthermore, for consuming devices $Dev_{cons}$ the building keeps track of the priority and start- and runtime of the devices. The advantage of defining this in the building instead of in the device is that one device implementation can be used multiple times for different buildings with different start- and stop-times. For the other types of devices (exchanging, converting and buffering) this already holds since no start- and runtimes or other building specific parameters are required for these devices.

For every pool in the building, an instance of the *pool* class is instantiated with a certain energy type $ec \in EC$. This instance keeps a list of all energy streams connected to this pool $p \in P$, i.e. a list with devices $d \in Dev$ that have a stream connected to this pool.

*Grid*

To create a grid, multiple buildings are combined into a grid. This is done in two levels: multiple buildings are connected to a subgrid and multiple subgrids are connected to a grid. There is one instance of the *grid* class, but there can be multiple instances of the *subgrid* class.

Subgrids and grids consist of multiple pools, one pool for every type of energy-carrier defined for the simulation in $EC$. So, all buildings connected to the same subgrid are connected to the same electricity pool. Furthermore, all subgrids are connected to one electricity pool in the grid.

The maximum number of buildings that can connect to one subgrid is a parameter that can be defined at initialization of the simulation. So, the number of subgrids depend on the number of buildings and the number of buildings that can be connected to one subgrid. Furthermore, there can be multiple levels of subgrids in the simulation. The maximum number of buildings that can connect to one subgrid also holds for the grid; when there are more subgrids than can be connected to the grid, an extra level of subgrids is added (see Figure 5.2).

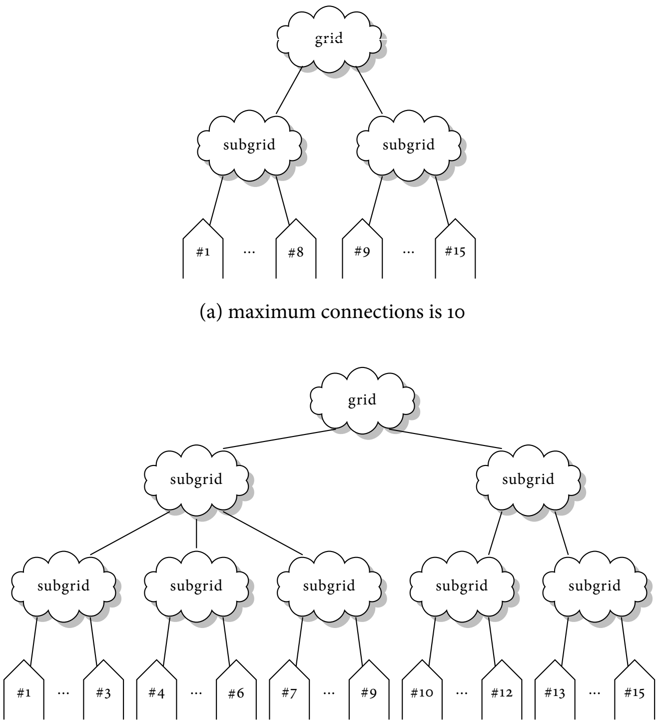
Except for generation in the buildings, large generators can only be connected to pools in the grid, i.e. on the top level (the grid pools) electricity can flow in the pool and on the lowest level buildings can have an energy flow from or to the pools of the subgrids on the lowest level. Therefore, multiple voltage levels and generation on different voltage levels are not yet implemented. The implementation of a various number of pools outside the building (e.g. voltage levels), transformers between these pools and generation/buffering connected to different levels is left as future work. Because of the generic setup of the model and the simulator we expect this can be added rather easily.

*Control*

To incorporate control methodologies and algorithms to the simulations, controllers are added on different levels in the simulation. There are controllers in the buildings, in the subgrids and in the grid. These controllers are defined as abstract classes, defining the interface and implementing a minimum functionality. Building controllers can communicate with devices, the interface in the form of methods is already defined in the abstract classes. Furthermore, all controllers (building controllers, subgrid controllers and grid controllers) can communicate with each other. In first instance we only implemented a vertical communication path, i.e. controllers only can communicate with controllers on a higher or lower level (e.g. building controllers cannot communicate with each other). A control methodology can be added to the simulator by defining classes for the controllers that extend the abstract classes and that implements the control methodology. Since it can be defined how much buildings can be connected to one subgrid, the hierarchical structure of the control methodology can be analyzed (e.g. best group size).

### 5.3.2 CONTROLLER

An important element of the simulator is the control. Nowadays, there is not always control available in buildings that monitors and manages all devices. However, there are already certain controllers present in buildings monitoring and managing devices. In this subsection, first these existing controls are discussed. Next, the controller framework implemented in the simulator is explained. Finally, a link between the implemented controller framework and reality is given.




(a) maximum connections is 10



(b) maximum connections is 3

Figure 5.2: Hierarchical structure of the grid infrastructure for 15 houses

*Controllers in current buildings*

Nowadays, in most buildings the electricity streams are not monitored nor managed. The electricity demand just appears when residents switch on consuming devices, generation appears when a micro-generator switches on (e.g. the microCHP). These two together give the total electricity flow in the building. Using the current electricity infrastructure, the electricity surplus or shortage is simply exchanged with the grid. However, for heat demand, a controller is present in the building. The heat demand also just appears, i.e. the demand is not known in advance to the controller (e.g. a resident takes a shower or there is a heating demand). This heat demand can either be supplied directly by a boiler or by a heat buffer. A controller in the boiler detects the demand and switches on the boiler on the required production level. Furthermore, modern boilers have sophisticated controllers to regulate the temperature in the building in an efficient way (e.g. use different run levels of the boiler).

When the heat demand is supplied by the heat buffer, a controller decides when to start the heat generator (e.g. microCHP), i.e. when the heat buffer level drops below a certain level the generator is started. In other words, the only decision to be taken is when to start the generator and that decision is optionally based on the level of the heat buffer.

Hence, in current buildings already basic (local) control algorithms are present. In the simulator, this can be simulated using a basic *control algorithm* available in the simulator.

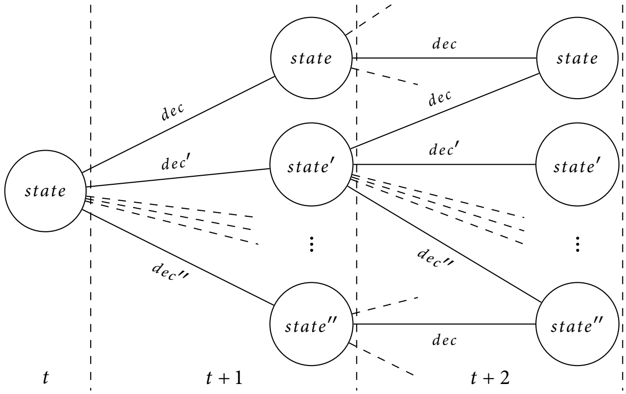
### *Controller framework in the simulator*

The basic control algorithm is very straightforward and only reacts on local measured data. In the simulator, more sophisticated control algorithms can also optimize runtimes of converting and consuming devices and make use of the buffers. In every time interval a valid option has to be chosen for each device and it has to be guaranteed that the pools are in balance. Within the simulator, the building controller can query the options of every device and it knows to which pool each energy-carrier stream of every device is connected. Based on this information the controller has to choose for every device an option which ensures that the pools stay in balance. In other words, there is always, although a simple one, a building controller required, even when no smart devices are installed.

To work towards global objectives, controllers on the different levels can communicate in a hierarchical way. Building controllers can communicate with the subgrid controller of the subgrid they are connected to, these subgrid controllers can communicate with the controller of the (sub)grid they are connected to. Building controllers can for example send prediction data upwards in the tree, the (sub)(sub)(sub)(sub)(sub)(sub)(sub)(sub)(sub)grid controller can send steering signals downwards the tree.

In the simulator, devices also have functionality for predicting their generation/consumption profile. Furthermore, devices can make predictions depending on the steering signals. Based on the predictions, the options for the current state can be derived. Next, the options for the successor states can be determined. This results in a tree-shaped state-space based on predictions, where every edge is a decision for a valid option (see Figure 5.3). Using this state-space and the known steering signals, the predicted consumption/production profile can be determined. The state-space can have a horizon from one time interval up to the complete simulation horizon and can be queried by the building controller.

In this way, local controllers with a realtime control methodology (only the current time interval) can be implemented, but also a prediction and planning on beforehand using a hierarchical structured communication infrastructure for the building controllers, the subgrid controllers and the grid controller as root node. Note that subgrid controllers can be connected to other subgrid controllers, buildings and the grid. A subgrid controller has a notion of the types of controllers it is connected to.




$$state = \{state^d | \forall d \in Dev\}$$
$$dec = \{opt \in Opt^d | \forall d \in Dev\}$$

Figure 5.3: Tree-shaped state-space of three time intervals $t$, $t+1$ and $t+2$ based on predictions

*Future controllers in practice*

The expectation is that in future scenarios when the Smart Grid is implemented, such a controller framework is available. Furthermore, in buildings a combination of smart and non-smart devices will be available. The building controllers might be implemented in the smart meter, communicating with the smart devices or in a dedicated device. The full functionality as described above is only available for the smart devices. The non-smart devices can be neglected by the control methodology, but to predict and optimize the total import/export pattern the consumption/production pattern of non-smart devices can be predicted within the building controller. After all, non-smart devices have no optimization potential and therefore only one option in every state.

### 5.3.3 FEATURES FOR EASE OF USE

To make the simulator easier to use and faster to configure, a number of features are added. Three features are discussed in this subsection:

- logging,
- parameterization and configuration,
- stochastic variations.

*Logging*

Logging the data is one of the requirements of the simulator to analyze the results of the simulations. It is useful to be able to choose the level of logging; for large scale simulations the detailed information of all buildings is not necessary, it slows down the simulation and produces too much data. Therefore, every element of the simulator can log the status of its variables for every time interval. Which variables are logged depends on the implementation of the element. After the simulation all data is stored in an UML results file and can be read by the GUI or via a standard UML tool. However, logging can be disabled per element in order to reduce the memory usage. When the logging of an element is disabled, the logging of lower level elements, which are part of this element, is also disabled. In this way, for example the logging of individual buildings can be switched off without disabling it in all individual devices.

*Parameterization and configuration*

Within an implementation of an element, parameters can be defined. A concrete version of an implementation, with values defined for the parameters, is called a configuration. So, within the implementation of a device, an actual C++ class, freedom can be gained by parameters. A configuration is an instance of a device with values defined for the parameters.

For the current microCHP implementation for example, the electricity output and the ratio between electricity and heat are parameters. In this way multiple versions of an element can be defined with one single implementation. This can be used to optimize the parameters for an element or for a quick exploration of different possibilities for some features. For example, there is one implementation for non-smart consuming devices. They are defined by the energy-carriers they consume and a consumption profile for every energy carrier. This can be defined as parameters. So, only one implementation of a non-smart device can be used to configure all non-smart devices in the building, resulting in different configurations of one implementation (non-smart device) modelling different devices. The start- and runtime of consuming devices is defined in the building they are installed in. Thus, from one implemented device (non-smart device) there exist multiple configurations (e.g. coffee maker, washing machine, etc.) and every configuration can be used in multiple buildings.

The parameters of a configuration can be defined at run-time and multiple configurations of the same implementation can be used during one simulation. A building configuration combines the above described elements to one building. It defines which device configurations are installed, which pools are present, how devices and pools are connected and what local controller configurations are available. For all consuming devices the runtimes and the priorities are also defined. Finally, the grid configuration combines building configurations and the global controller configuration. For every building configuration the multiplicity of particular configurations can be defined within the grid. For example, when five different building configurations are defined, the grid can consist of a mixture of these five building configurations.

All configurations are saved in configuration files. So, a building consists of a set of references to configuration files, one for every device. These references are stored in the building configuration file together with the above mentioned characteristics (e.g. runtimes and priority). Similarly, grid configuration files consist of references to building configuration files with per reference the multiplicity. An example of a configuration file for a device and an example of a configuration file for a building is given in Appendix C.

Once a device is implemented, configuration files can be generated and updated via the GUI. Also building and grid configurations can be defined via the GUI, which is much easier than by hand. More details about the GUI are given in Subsection 5.3.6.

#### *Stochastic variations*

Since a limited set of configurations for individual buildings is used to form a grid, stochastic variations are useful in order to get a more realistic reflection of real world behavior. To introduce stochastic variations, random variates are generated and applied to the data in the configurations. Several distributions are available (Uniform, Exponential, Weibull, Normal and Poisson) which gives several options to create realistic variations. For each device the start- and runtime can be varied. Next, a single stochastic variation per building is applied to all values of the energy profiles resulting in variations in the overall energy consumption of buildings (high/low overall energy usage for the building). On top of this variation, a second variation can be applied on the energy profile with a different random variate for each device and each time period (stochastic human variations). These variations can also be used to emulate prediction errors; use the standard profile as prediction and the profile with variation as actual production/consumption pattern.

### 5.3.4 SIMULATION FLOW

The simulation flow consists of two steps, the initialization and the simulation. During the initialization phase the configuration files are read and based on these files the required elements are initialized; objects are created and parameters are set. After the initialization the actual simulation starts. During the simulation phase, the chosen simulation horizon and time interval length result in the number of time intervals to be simulated. The model is simulated for the determined number of time intervals; i.e. for every time interval the options of the devices, controller behavior and the resulting energy flows are calculated. In the rest of this subsection these two phases are discussed in more detail.

#### *Initialization*

In the initialization phase all required elements for the simulation are initiated. The elements are initiated based on configurations. These configurations are saved in configuration files. The initialization starts with the configuration for the simulation itself. The simulation configuration defines which grid configuration is used and some required additional information (e.g. the time interval length and simulations horizon). An example simulation and grid configuration is shown in Appendix C.

The corresponding building configuration files define which device configurations are installed, etc. Within a large scale simulation, in general only a few different building configurations are used, but with the stochastic variations we still get a realistic set of buildings.

The length of the time intervals used to specify the behavior of the elements of the simulation can differ. For example, the demand of a heat consuming device is specified in 15 minute intervals, the demand of an electricity consuming device is specified in 1 minute intervals and for the simulation itself a time interval length of 5 minutes is chosen. The interval length is one of the predefined parameters in the abstract *device* class. Every configuration of an element is based on the used time interval length and therefore this has to be synchronized, i.e. all devices must be configured using the same time interval length. The used time interval length in a simulation is the time interval length configured in the simulation configuration file. The parameters of all elements have to be adjusted to this time interval length. For example, the energy profile of a consuming device is based on the length of the time intervals and has to be recalculated for the time interval of the simulation when this is a different length. In the simulation configuration the simulated time interval length is specified, during initialization the time intervals of all elements are synchronized to this length.

*Simulation*

After the initialization, the simulation starts. During the simulation, the elements of the model are triggered one by one. There are two types of triggers: pre-simulation triggers and simulation triggers (ticks).

Before the actual time intervals of the planning horizon are simulated, a pre-simulation step can be done. In this step the controllers (first global and then local) get the opportunity to perform a pre-simulation step. An example of such a step can be a planning for the complete simulation horizon based on the predictions of the devices (on a local or global level). Thus, when the global controller is triggered for the pre-simulation step it can already communicate with the local controllers and query the local controllers for certain (calculated) data, but the global controller initiates the communication and calculations. For the local controller this works similar; it can communicate with the global controller and triggers it to execute algorithms, but the local controller initiates this.

After these pre-simulation steps, the actual simulation of the simulation horizon starts. Starting at the first time interval, every time interval all elements receive a signal to update their internal state. The order in which the elements update their internal state is very important. First, if present and applicable depending on the optimization method, the global controller queries all building controllers (optionally in the hierarchical way via subgrid controllers) what their expected profile is and can send a steering signal. Next, the building controllers query all devices what their options are and optionally together with the global steering signals determine the best combination of options for the devices. In these two control steps also the consumption/generation predictions and state-space prediction of the individual buildings can be used again to determine the best option. Finally, the devices update their internal state depending on the option chosen by the building controller. Communication between grid and building controllers can also take place on a less regularly way, for example requesting a new planning for the rest of the simulation horizon when there is too much deviation from the current planning.

### 5.3.5 SPEED OPTIMIZATIONS

When the size of the simulations increases, the required simulation time and the required memory increases significantly. We discovered two different bottlenecks during the simulation. The first one is that the time required for the initiation increases with the number of buildings simulated. The second one is that the required simulation time and memory increases due to different factors: more logging leads to more memory usage, more buildings lead to a longer simulation time and more memory usage and more complicated control methodologies lead to a higher simulation time. For both bottlenecks we added some optimizations to the simulator.

During the initialization of the simulation, the configurations for all elements are read from the configuration files. For every building, multiple configuration files have to be accessed, one for every device (approximately 15 per building). Since file access is very slow and every configuration is often used multiple times (e.g. only a limited number of building configurations is used), all elements are extended with a copy functionality. When an element is used a second time, it is copied from the previous instantiation. This decreases the number of disk accesses significantly resulting a significant lower initiation time. Another advantage of copying objects is that a lot of information is stored using QLists[1], which have optimizations for memory usage when they are copied. They are only actually copied when the data in the QList is changed, until then only one shared instance of the list is kept in memory. This is for example useful when a device configuration is used multiple times (e.g. a fridge for all houses), the consumption profile of the fridge is only stored once for all devices. Therefore, the copying optimization also leads to a significant lower memory usage. To simulate realistic buildings, the variation is added after the initiation of all configurations, so after copying the elements.

Decreasing the required simulation time and memory is harder to tackle, e.g. complicated control or optimization algorithms require a certain computation time. To overcome this, the simulator is converted to a client-server model. The clients can run on different computers, all connected to the server. This server-client design is shown in Figure 5.4. When a simulation is started on the server, the subgrids and buildings are split up over all connected clients. Next, the server

[1] http://doc.qt.nokia.com/latest/qlist.html

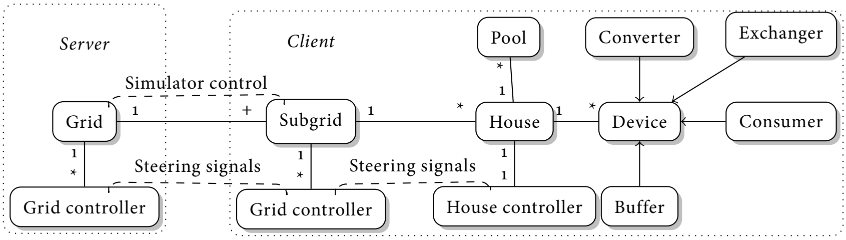



Figure 5.4: Class diagram of the network simulator



sends the configuration files to the clients when needed. Whether the clients need updated configuration files is verified using a hash of the configuration files. When all configuration files are sent and the clients are initiated, the simulations start. The structure and execution order of the simulation is equal to the structure and execution order of the stand-alone simulation.

The simulation control still runs on the server, but the buildings themselves are simulated on the clients. During the simulation of a time interval, each controller performs its specific tasks and each model entity is requested to update its state. The completion of each time interval of all clients is reported back to the server to keep all clients synchronized, so only simple time interval synchronization messages are sent between the grid and the subgrids. The grid controller can also communicate with the subgrid controllers on each client. After the last time interval, all information required at the server in order to aggregate the subgrid results and to be able to display the simulation results is sent to the server. Here, the user can interact with the GUI to display or save the simulation results. This can be done without a lot of overhead (see Section 5.3.8). A more detailed description of this server-client solution, including used protocols, etc., can be found in [7].

### 5.3.6 GUI

To ease the usage of the simulator, a GUI is developed for defining configurations and running simulations. As mentioned earlier, a simulation needs to be configured. Each instance of a class within the model is responsible for generating a GUI element so that device specific parameters can be configured. In the GUI, a grid can be constructed by defining which building types are used and how many instances of each building type are present in the grid. For each building it can be configured which devices and pools are present and the connection between devices and pools can be configured. Furthermore, building specific attributes like the usage of consuming devices can be configured per building.

The GUI is a graphical user interface to the functionality of the simulator. Via the GUI, configurations of devices can be added, edited or removed. Especially

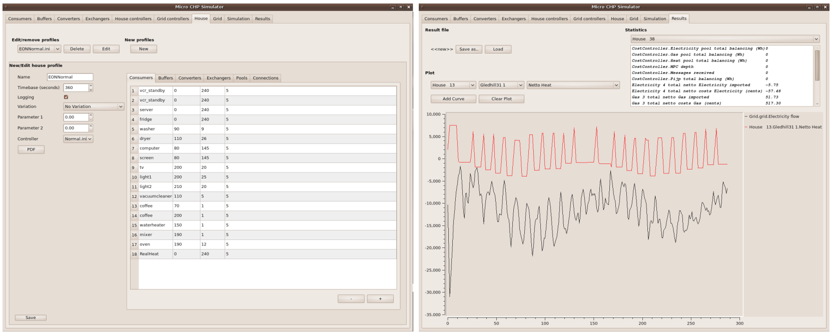


Figure 5.5: Screenshots of the simulator

making a correct configuration file that defines the connections between the devices and pools is hard to do by hand. The GUI automatically adds the required pools, i.e. when an electricity consuming device is added to the building configuration while there is no electricity pool present yet, an electricity pool is added. Furthermore, all energy carrier streams of every device are automatically connected to a pool of the correct type. These standard configurations can of course be changed, but in this way the configuration is always valid. The GUI enforce that energy carrier streams of the devices are connected to pools of the correct type.

Every element of the simulator has its own window in the GUI. For abstract parts, an actual implementation can be selected and a configuration for that implementation can be defined. Configurations of non-abstract parts can be defined by just setting the parameters. Within the simulation window the parameters of the simulation can be set (time interval length, number of intervals) and the simulation can be started. The result window visualizes the results of the simulation and the results can be stored there. Two screen shots of the simulator can be seen in Figure 5.5. The first screen shot shows the configuration screen for a building where all available consuming devices, converting devices, etc. can be configured. The second screen shot shows the results interface where the results can be studied and compared.

### 5.3.7 VERIFICATION

The last step of building a simulator is the verification: are the simulations correct, does the simulator do what is described in the model and are all energy streams correct? The simulator is verified in two ways, first of all assertions are incorporated in the code and secondly the simulation results are verified by hand. In the *pool* class and *building* class multiple assertions are incorporated to verify whether all energy streams are in balance. Assertions are statements in C++ that can verify boolean expressions, for example $streamIn == streamOut$. When an assertion

Table 5.1: Simulation speed (seconds)

| # buildings | 1 | 100 | 500 | 1000 |
|---|---|---|---|---|
| stand-alone | 1 | 47 | 234 | 490 |
| network, one client | 1 | 50 | 246 | 491 |
| network, two clients | - | 28 | 123 | 245 |
| network, three clients | - | 20 | 88 | 170 |

condition is not true, an error flag is raised.

Furthermore, for a number of scenarios the results are extensively studied to analyze whether the results are correct: from a device level up to the total energy import and output on a grid level. Essential in the simulations is a correct behavior of devices: every new implemented device has to be verified by a test defined in advance to analyze whether the behavior is correct and only the correct and valid options are given in every state.

### 5.3.8 PERFORMANCE INDICATORS

Simulation speed and memory usage are important factors for the simulator, especially when large scale scenarios are simulated or for state-space exploration of parameters. The optimizations described in subsection 5.3.5 increased the speed for only the stand-alone version significantly: without these optimizations it was not possible to simulate the reference case used for the results in Table 5.1.

The network version increases the simulation speed even more by spreading the computational load over multiple computers. The initialization steps and the collection of the results give a certain overhead, but the increase in simulation time compensates this easily, especially for a large number of buildings. The simulation times for a reference case are given in Table 5.1. The simulation times scale roughly linearly with the number of clients. However, due to the synchronization in every time interval the slowest client (computation time plus communication) is the bottleneck and defines the speedup.

## 5.4 Conclusions

In this chapter a simulator is presented to simulate and analyze energy streams in buildings and grids. The implemented simulator meets the requirements set on beforehand. I.e., the result is a generic and flexible tool that is able to simulate a realistic, accurate representation of the actual situation. The parameterized elements, configuration files and stochastic variations increase the ease of use and strengthen the ability to perform realistic simulations, with a minimum implementation and configuration effort. The simulator simulates a configured horizon using a discrete time simulation, with a configurable time interval length. Each building and every device is addressed individually and the simulator keeps track of all energy streams.

The control framework enables adding control algorithms that can manage individual devices and can communicate with each other and central control nodes in a hierarchical way.

This simulator is able to analyze the developed control methodology and study the potential of domestic optimizations in different future scenarios. Some results of the simulations are presented in Chapter 6.

CHAPTER 6

# Experiments and results

Abstract – *In this chapter the results of simulations and prototype tests are presented. The simulation results are used to analyze the behavior of the simulator, investigate the effect of parameters of the three-step control methodology and the control methodology itself and to study the potential of domestic optimizations. The results show that the simulator works correctly and that it is possible to exploit the optimization potential of buildings in the low-voltage network using our three-step control methodology. Furthermore, two different types of prototypes have been built: a lab prototype and some field tests. The lab prototype has been used to investigate whether it is possible to create an islanded situation using a microCHP and a battery. The goal of such a setting is to decrease the discomfort during possible power cuts by supplying a selection of devices by the battery and the microCHP. Furthermore, on the lab prototype the control methodology has been implemented to verify whether it is possible to use the control methodology to optimize the behavior of actual devices. The tests show that it is possible to create and maintain an islanded situation and that the control methodology can optimize the behavior of actual devices. Finally, the field tests lead to a number of "lessons learned" when new technologies like a microCHP are installed in houses.*

In this chapter the results of simulations and prototype tests are presented. The goal of the simulations are to test the simulator, analyze the effectiveness of the three-step control methodology, evaluate the parameters of the control methodology and study the optimization potential of a large group of buildings. Two different types of prototypes have been built: a lab installation and a number of field installations in real houses. The lab installation has been used to verify assumptions made and test (a simplified version of) the control methodology on real hardware. Furthermore,

Parts of this chapter have been presented at [AM:15], [AM:16] and [AM:17].

the ability of a microCHP device to act as a generator in islanded mode has been investigated. The field installations have been used to get experience with new technologies installed in normal houses.

The remainder of this chapter is organized as follows: in the first section the cases used for simulation are described and the results of the simulations are presented. Next, in Section 6.2 the prototype, the field tests and the results are discussed. The last section finishes this chapter with conclusions.

## 6.1 Simulations

The use cases described in this section have been simulated using the simulator described in Chapter 5 and the control methodology described in Chapter 4. The goals of the simulations were to study the behavior of the simulator and the effect of (different parameters of) the three-step control methodology; in particular:

1. analyze the behavior of the simulator: e.g. accuracy, realistic behavior, etc.,
2. analyze the performance of the three-step control methodology using local and global objectives,
3. compare the performance of local optimization with the performance of global optimization,
4. study the difference in performance between control with and control without (global) planning,
5. compare different types of steering signals (one shared steering signal or individual steering signals),
6. study the improvements reached with MPC and compare different parameters for MPC,
7. study the potential of domestic optimization.

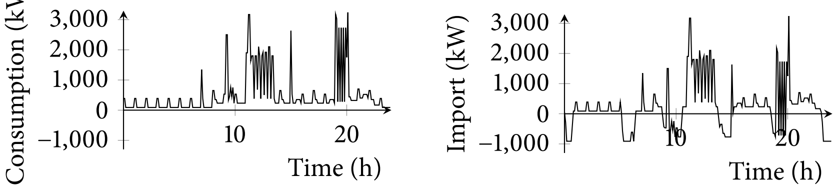
As explained before, the electricity grid always has to be in balance, i.e. for all time intervals generation should match with consumption. Therefore, utility companies predict the aggregated electricity profile of all their customers on beforehand. Deviations from this prediction cause an imbalance which leads to penalties for the one causing the imbalance. Currently, utilities have sophisticated prediction models to predict the electricity profile resulting in rather good predictions. However, when smart devices are installed in buildings, the predictability of the electricity profile could decrease. Moreover, when local intelligence in buildings optimizes the behavior of local devices (i.e. change the time periods they run) the predictability could decrease even more resulting in high penalties for the utilities and more important in more imbalance and therefore more generation by less efficient peak power plants. In other words, when (local or global) control methodologies are introduced they should 1) not decrease the predictability or 2) give a prediction of the electricity profile on beforehand and stick to that prediction. When the objective of a control methodology is to react on imbalance caused by others, e.g. deviations from the predicted profile of wind turbines, it is important to keep the predictability of the group of buildings in mind: when the imbalance of the wind turbines is compensated but the group of buildings deviate from their predicted profile, the overall result is that there still is imbalance. Thus, we should avoid to deviate from the planned production/consumption profile. The three-step control methodology proposed in this thesis can work towards two different kinds of objectives: 1) reach a predefined profile (e.g. VPP) and/or 2) react on deviations from the planning of others (e.g. react on fluctuation of renewable sources). Note that for the second objective type still the predefined profile must be taken into account, i.e. reacting on deviation from others should not cause deviation from the predicted profile of the controlled devices.

We have verified the three-step control methodology for a number of use cases. Within every use case, a number of different scenarios can be distinguished. The different scenarios have different parameters/settings of the control methodology to study the influence of the parameters/settings on the performance of the control methodology. Especially the amount and level of control can differ. Furthermore, the predictions can be a perfect prediction (no deviations of the actual profiles from the predicted consumption/production profiles) or the actual profiles can differ from the predicted profile due to prediction errors. Note, that in general a perfect planning without prediction errors determines the maximum reachable optimization, i.e. an upper bound on the optimization.

To represent which type of optimization is used, whether prediction errors are used or not, etc. a quadruple of characters is used, i.e. a code to represent the parameters/settings of the control methodology. The first character defines whether prediction errors occur in the scenario, i.e. the predictions are perfect predictions or subject to prediction errors. This is defined by $P$: $P_n$ means no prediction errors and $P_y$ means that the actual profile deviates from the predicted profile.

The second character represents the characteristics of the local controller. In every scenario a local controller is present, even when no optimization objective is incorporated, to ensure the correct functioning of every device. The settings of the local controller are defined with $L$, when the local controller does not work towards an objective it is defined with $L_{-1}$. Furthermore, the local controller can work towards an objective and optionally the local controller can be extended with MPC. Optimization of the local controller without MPC can be seen as MPC with an observed horizon of 0, therefore the setting of the local controller is given by $L_N$, where $N$ is the observed horizon of MPC ($L_0$ is the local controller without MPC). As explained in Chapter 4, the objective of the local controller is incorporated in the electricity import price, both with local and with global objectives. Note that the local controller does not make a planning, it just reacts on the electricity price (optionally using MPC) and thus always is a realtime controller.

The third character represents the settings of the global controller and are given by $G$: $G_{-1}$ means no global controller, $G_p$ means that the global controller makes a planning on beforehand, $G_r$ means that the global controller uses realtime




(a) Consumption profile (b) Import from the grid

Figure 6.1: Reference use case

optimizations techniques (e.g. react on fluctuations) and $G_{pr}$ means that both a planning is made and the global controller uses realtime optimization techniques. Note that when a global controller is used, also a local controller is required to react on the steering signals.

Finally, the last character $I$ represents whether imbalance caused by others is used: $I_n$ means that no imbalance from others, $I_y$ means that imbalance caused by others is taken into account.

Six use cases are used for verification: a reference use case, a case with a freezer, a case with electrical cars, a case with microCHPs, a case with multiple smart devices in every house and an islanding use case. These use cases comprise all three types of devices; use cases with a small consumer, a large consumer, a generator with energy buffer and the combination of these devices are used. The use cases are chosen such that the parameters/settings to be compared have a significant influence on the performance. The simulation results show the influence of the parameters/settings on the performance for a particular use case. Therefore, the use cases are chosen such that the results can be extrapolated to a more generic case. In the remainder of this section the use cases are described more detailed and the simulation results are presented.

### 6.1.1 REFERENCE USE CASE

The first use case is a reference case, a simulation of a standard house without optimization objectives or prediction errors: $P_n L_{-1} G_{-1} I_n$. In this use case a standard house is simulated with an average heat and electricity consumption profile (this profile is based on [66]). Only the last step of the three-step control methodology is used, the realtime control. This realtime control has no optimization objective in this case, the only task of the controller is to supply all demand. The electricity demand profile is built up by the consumption of many used devices in normal houses (fridge, freezer, coffee maker, etc.).

In the house a smart freezer, a microCHP device and a heat buffer as described in the previous chapters are available. Since there is no optimization objective, the freezer should run like a normal freezer. The heat buffer must supply the

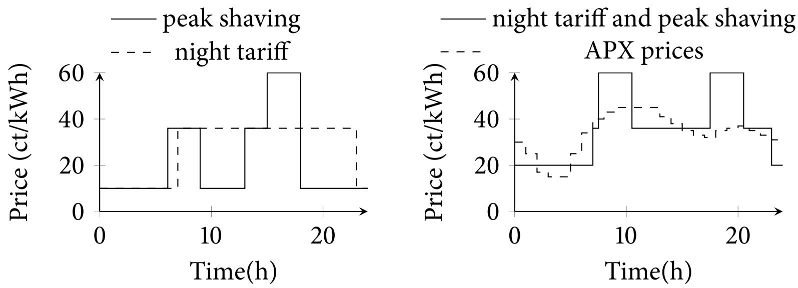



Figure 6.2: Electricity import pricing schemes freezer use case

heat demand, the microCHP device should run at the periods following from the technical constraints of the microCHP: when the buffer is almost empty, the microCHP device runs until the buffer is full.

The goal of this use case is to analyze whether the simulator works as expected and whether the basic version of the realtime controller (third step of the control methodology) is able to control devices in a standard scenario.

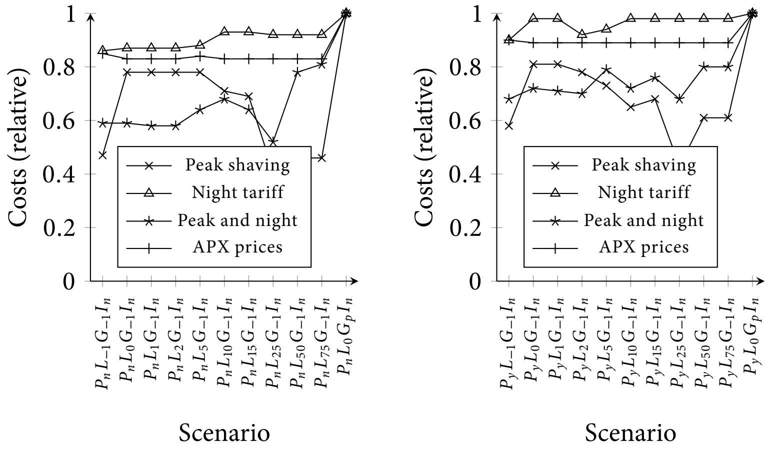
*Results*

The given consumption profile and the import profile from the grid resulting from the simulation are shown in Figure 6.1. Note that a negative import means an electricity flow from the house to the grid. This occurs when the microCHP device produces more electricity than is consumed in the house. A detailed inspection of the simulation results led to the conclusion that the simulator works as expected and that the realtime control part of the three-step control methodology is able to manage (the different types of) devices correctly in regular houses. During the simulation no devices are switches off (no load is shifted), the freezer behaves like a normal freezer and the microCHP device runs on the times it should run.

### 6.1.2 FREEZER USE CASE

The freezer use case simulates a single house optimizing the runtime of a freezer. The model of a freezer described in Chapter 3 and the accompanying cost function described in Chapter 4 are used. The chosen time interval length is four minutes and 360 time intervals are simulated (24 hours). The (local) objective of this use case is to minimize the electricity costs of the freezer.

Four different pricing schemes are used with different levels of variation. The first scheme has five price levels based on a normal consumption pattern (peak shaving), the second scheme has two levels (night tariff), the third combines the first two (night tariff and peak shaving) and the last pricing scheme is based on the




(a) Without prediction errors (b) With prediction errors

Figure 6.3: Simulations MPC controlled freezer (inverse proportional from the best case, higher is better)

APX prices from April 15th 2009 (APX prices). These pricing schemes are shown in Figure 6.2.

In first instance the goal of this use case is to study whether the tree-step control methodology works can optimize the behavior of a freezer on a local level. Furthermore, optimizations without global planning ($G_{-1}$) are compared with optimizations based on a planning ($G_p$). Note that in this scenario only one house is simulated, the global planning is in fact the planning for this single house and could be seen as a local planning. Furthermore, scenarios with and without prediction errors are simulated, whereby these prediction errors apply to both the predictions used for the planning as well as the predictions used for MPC. Next, the influence of MPC is studied and different parameters for MPC are compared: different lengths of the observed horizon and the addition of relaxation. Finally, the computation time is studied.

To reach the mentioned goals, each pricing scheme is simulated using different scenarios:

- **No optimization** - $P_nL_{-1}G_{-1}I_n$,
- **Realtime optimization** - $P_nL_0G_{-1}I_n$ and $P_yL_0G_{-1}I_n$,
- **Realtime optimization with MPC** - $P_nL_{>0}G_{-1}I_n$ and $P_yL_{>0}G_{-1}I_n$,
- **Planning** - $P_yL_0G_pI_n$
- **Planning with MPC** - $P_yL_{>0}G_pI_n$.

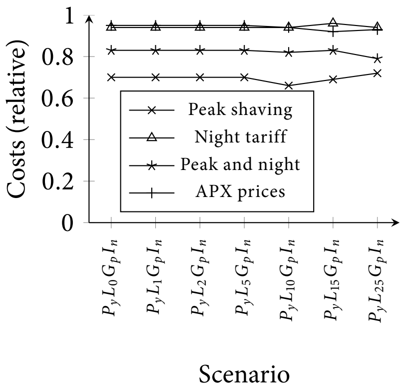



Figure 6.4: Simulations MPC controlled freezer, Combination MPC and planning with prediction errors

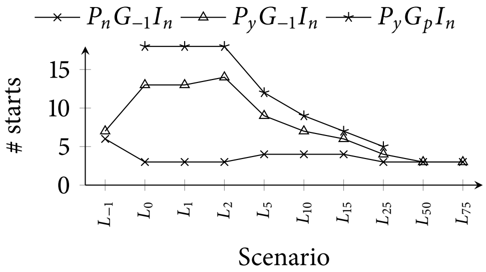
*Results*

The results of the scenarios are compared based on the objective. More precisely, the average electricity price for the consumed electricity is compared. Furthermore, the number of starts of the freezer are compared (irregularity of the resulting schedule, wearing of the device).

A planning and perfect prediction results in the best solution (lowest costs), therefore all costs of the scenarios are expressed inverse proportional to the costs of these scenarios (higher is better). These results are given in Figure 6.3 and Figure 6.4. The number of starts for three of the simulated scenarios are shown in Figure 6.5a.

As can be seen in Figure 6.3a and 6.3b, for almost all cases the local optimization without MPC gives better results than the scenarios without optimization. Furthermore, very often, adding MPC improves the results, but only for a part of the observed horizons. When prediction errors occur, MPC improves the results more than without prediction errors, especially concerning the number of starts. A longer horizon (N>10) often gives worse results, the best value of N depends on the amount of fluctuation in the pricing scheme. For slow or fast fluctuation (night tariff and APX prices) the value of N almost has no influence. The peak shaving with night tariff scheme has faster fluctuations than the night tariff scheme and therefore the negative influence is earlier gone. However the costs are not significant lower for higher values of N, the number of starts decrease significantly when N≥5, up to 70%. Overall, without using planning, an observation horizon for MPC of N=5 or N=10 seems to be the best choice.

Figure 6.4 shows the results for the simulations of the scenarios using planning and realtime control with MPC while prediction errors are taken into account. Note that with the used implementation of the planning algorithm, MPC does




(a) # starts

| | No relax. | Relax. |
|---|---|---|
| $L_0$ | 0.6 | 0.6 |
| $L_1$ | 0.6 | 0.6 |
| $L_2$ | 0.6 | 0.6 |
| $L_5$ | 1.3 | 1.3 |
| $L_{10}$ | 11.5 | 11.3 |
| $L_{15}$ | 41.1 | 38.9 |
| $L_{25}$ | 197.5 | 176.7 |
| $L_{50}$ | 1114.6 | 933.8 |

(b) Simulation time

Figure 6.5: Simulations MPC controlled freezer

not influence the results of the planning when no prediction errors are taken into account, i.e. the resulting values for these cases are 1 (best solution). When MPC and planning are combined, the behavior improves significantly. When planning is used without MPC, prediction errors lead to very irregular behavior, resulting in a lot of starts (see Figure 6.5a). This can be caused by the fact that planning assumes a complete different state of the freezer, the actions in the planning do not fit anymore. For example, when it is the planning that the freezer is at a high temperature and it should start cooling, the planning stresses to cool the freezer. However, in reality it might be that the freezer is at lower temperatures and the steering signals cause the freezer to cool until it reaches the minimum temperature, then it has to stop cooling, a few time intervals later it reaches a bit higher temperatures and starts cooling again, etc. Combining the planning with MPC decreases the costs often only slightly, but the number of starts decreases significantly if N is chosen to be larger than 10 (more than 50% in all scenarios).

Since the state space can increase significantly when MPC is added, the complexity of the resulting ILP can increase and therefore the computation time. To overcome this, relaxation of the MPC methodology is proposed in Chapter 4. In Figure 6.5b the computation times for multiple values of N with and without relaxation are shown. For small N, the computation times decrease only slightly when relaxation is added, since the ILP is rather easy and the state space limited due to the temperature bounds of the freezer. Therefore, the other parts of the simulation dominate. However, for an observed horizon of $N > 15$ the computational time decreases significantly (>10%). The results, average costs and number of starts, do not differ significantly when relaxation is used. Thus, for these scenarios relaxation does not influence the quality of the results but does decrease the computational time.

Summarizing, realtime optimizations improve the results compared to the scenario without optimizations, planning improves the results even more. However, when prediction errors are incorporated the number of starts increase. Thus, the three-step control methodology can work towards local objectives (decrease the costs), especially the combination of planning and realtime optimization. However, this might cause an irregular behavior and therefore reduce the stability. When the last step of the three-step control methodology is extended with MPC the results improve significantly. Especially the combination of planning, realtime control and MPC improves the results and mainly results in a more stable behavior of devices (without the fast on/off switching behavior). The optimal length of the planning horizon depends on the frequency of the fluctuations, but N=5 or N=10 is often a good trade off between computational time and the results. Using an ILP leads to high computational times while the future states are only predictions and subject to prediction errors. Relaxing the integer constraints for t>2 in the ILP results in significantly lower computational times with almost the same results.

In [5] a large number of houses of the type described in this use case are combined. In the resulting use case the complete three-step control methodology with the iterative planning algorithm was applied ($P_n L_0 G_p I_n$) to reach a flat consumption pattern for a large number (5000) of freezers. The goal of that study was to investigate the influence of the number of steering signals (one per building or one shared signal for all buildings in a subtree) and to find the optimal level in the tree to switch from objective bounds to steering signals. The results of the simulations show that the best level to switch from objective bounds to steering signals is the lowest level, i.e. one level above the building controllers. Furthermore, the best results can be reached when individual steering signals for every house are used.

### 6.1.3 ELECTRICAL CAR USE CASE

The car use case concerns charging 100 electrical cars when they arrive at home in the afternoon/evening. The optimization objective is to flatten the required charge power pattern. Without management all cars would start charging when they arrive at home. We chose for a group of 200 houses since this is the typical number behind a lowest-level-transformer (220V) in the Netherlands. The choice for 100 electrical cars is based on a penetration level of 50%. The time interval length is chosen as five minutes and the simulation horizon is 13 hours (5pm to 6am).

All cars have the same charge current (1.5 kW) but the required charging time differs between one and four hours (based on current available electrical cars) with a total charge time of 261 hours (391 kWh). The way the charge time is assigned is described in detail in Appendix D. The cars arrive at home between 5pm and 8pm and they must be fully charged at 6am the next morning. The assignment of the arrival times is also described in detail in Appendix D.

The goal of this use case is to investigate the ability to flatten the overall charge pattern, with and without prediction errors. Furthermore, the influence of different levels of optimization for a large group of buildings on the overall results are investigated: i.e. every house its own peak shaving objective (local level) or a shared peak shaving objective (global level). Finally, the difference between one shared steering signal and an individual steering signal per house is studied.

Table 6.1: Results car use case global realtime control

| | $P_nL_0G_rI_n$ (predicted average number of cars charging) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 |
| imbalance ($kW^2.10^3$) | 12 | 10 | 7 | 7 | 7 | 11 | 12 | 19 |
| load factor | 0.59 | 0.59 | 0.61 | 0.61 | 0.65 | 0.65 | 0.65 | 0.63 |

Table 6.2: Results car use case local control and global planning

| | $P_nL_{-1}G_{-1}I_n$ | $P_nL_0G_{-1}I_n$ | $P_nL_0G_{-1}I_n$+rand. | $P_nL_0G_pI_n$ |
|---|---|---|---|---|
| imbalance ($kW^2.10^3$) | 223 | 364 | 29 | 2 |
| load factor | 0.27 | 0.20 | 0.42 | 0.84 |

This use case is simulated with four different levels of optimization. The simulated optimization levels are:

- **no optimization** - $P_nL_{-1}G_{-1}I_n$,
- **local realtime optimization** - $P_nL_0G_{-1}I_n$,
- **global realtime optimization** - $P_nL_0G_rI_n$,
- **planning** - $P_nL_0G_pI_n$ and $P_yL_0G_pI_n$,

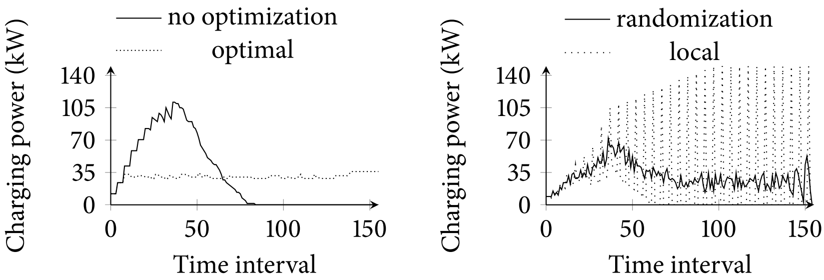
*Results*

Since the objective is to reduce the peaks, the results are evaluated based on the average/peak ratio of the total charge current (the average demand divided by the highest peak, higher is better) and the imbalance. The definition of imbalance can be found in Appendix D.

The results of the simulations are shown in Figure 6.6, Table 6.1 and Table 6.2 and discussed more detailed in the following paragraphs.

When no optimization is used, all cars start charging the moment they arrive at home. This results in a peak in the beginning as can be seen in Figure 6.6a.

When only a local controller is used ($P_nL_0G_{-1}I_n$), the decision of the local controller whether to shift charging in time or not, is based on the status of the charger. This results in an inferior charge pattern (see Figure 6.6b). This is caused by the fact that every car need to be charged at 6am, the state of all individual chargers converge to the same state. Therefore, when all states are converged, they make the same decision resulting in identical behavior of all devices and therefore high peaks. However, when a random factor is added to the cost function the results are much




(a) Scenario without optimization and the optimal charge schedule

(b) Scenario local optimization and randomization

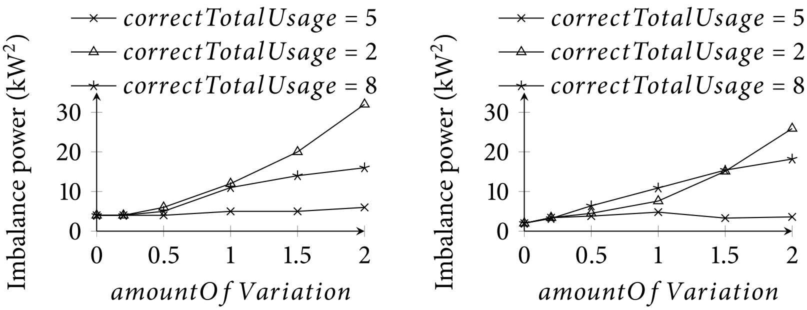
Figure 6.6: Total charge power use case 2

better. Due to the large number of cars the randomization results in an uniform distribution (since the random function is uniform distributed) and therefore in a somewhat flattened profile.

The global realtime control algorithm $G_r$ determines every time interval a steering signal. Based on a prediction of the total required charge power the average charge power per interval is determined (once, at the begin of the optimization period). Every time interval, all local controllers send their status to the global controller. Based on this information and the predicted average charge power, the steering signal can be determined, i.e. a signal is determined such that the predicted average number of cars will charge. Using this approach, at least the predicted number of cars will charge since the status of at least the predicted number of cars are such that they react. However, if some cars have identical status, more than the aimed number of cars may react on the steering signal. Furthermore, the prediction of the total required charging power can be wrong. Therefore, a predicted number of cars charging between 15 and 22 are simulated. The results of these simulations are given in Table 6.1. As can be seen, a too low prediction of the predicted charge power results in a better performance than a too high prediction (due to the fact that more than the desired number of chargers can react on the steering signal).

When the iterative planning is used, a large number of iterations results in a best schedule. The simulations show that in this case the best case results in 2000 kW$^2$ imbalance, both when one shared steering signal is used as well as when individual steering signals are used. However, this large amount of iterations is not realistic due to the exhaustive communication this requires. A reasonable tradeoff between quality of the schedule and communication costs results in an imbalance of 4000 kW$^2$ using one steering signal and 2000 kW$^2$ using individual steering signals.

Next, a prediction error is introduced. The number of charge intervals is calculated and used as prediction, during simulation a prediction error is added to this number. How this prediction error is calculated can be found in Appendix D.




(a) One shared steering signal

(b) Individual steering signals

Figure 6.7: Resulting charge power planning and prediction errors

The prediction error uses two important parameters: *correctTotalUsage* and *amountOfVariation*. The parameter *correctTotalUsage* defines whether the total charge power is equal (only variation), lower or higher. Three different values for the parameter are simulated: 5 (equal usage), 2 (more charge power) and 8 (less charge power). The parameter *amountOfVariation* defines the amount of prediction errors, a higher value means that the predictions are worse.

The results of the simulations ($P_y L_1 G_p I_n$) are given in Figure 6.7, Figure 6.7a shows the results using one shared steering signal for all houses and Figure 6.7b shows the results using an individual steering signal for every house. As can be seen in the figures, both the scenario using one steering signal and the scenario using individual steering signals follow the same trend, but the scenario using individual steering signals performs better for all amounts of variation. When only variation is added while the total charge power is equal, the planning can be followed quite well and only a little extra imbalance is introduced. When the total charge power also deviates, the imbalance power increases significantly. Just as with the realtime global control, when more charge power is required than predicted the errors are larger than when less charge power is required.

The simulations of this use case show that it is possible to flatten the consumption pattern of a large group of electrical cars, the load factor increases from 0.27 to 0.84 and the level of the peak decreases from 111 kW to 36 kW, a decrease of 67%. Local optimization gives very bad results: due to similarities between the chargers and situations, the optimization functions converge resulting in very high peaks. Using randomization improves these results, but that worsens the predictability. Global optimizations perform much better, both in the scenario with global realtime control as well as the global planning. The global planning performs much better than the global realtime control and it does not require realtime communication. The planning can be made on beforehand and during the day no communication is required. For both global scenarios prediction errors worsen the results, but a too low prediction performs better than a too high prediction. For the best scenario one single steering signal performs as good as individual steering signals. However, when less iterations are used and prediction errors are introduced, the individual steering signals perform better than one shared steering signal.





### 6.1.4 MICROCHP USE CASE

In the use case of this section a group of 200 houses is simulated, which may be regarded as a local unit behind the lowest transformer level in the electricity grid. Since this group of houses is geographically located around the same place, we assume a high level of similarity between the characteristics of these houses. For this reason the microCHP and heat buffer that are used in each house have the same parameter settings. The heat demand in the houses differs per house; however, the total demand is similar (the maximum and minimum total heat demands are 63064 Wh and 43544 Wh respectively). The time interval length in this use case is six minutes and the simulation horizon 24 hours.

The optimization objective of the use case is twofold. On the one hand, for the group of houses a plan is constructed which leads to a more or less stable (flat) electricity output for a complete day, which has to be followed by the realtime control. On the other hand, during the planning the global planner does not exploit all scheduling freedom so some opportunities for realtime optimizations are left. The second objective is to react on realtime fluctuations.

The model and cost functions of the microCHP and heat buffer used are described in previous chapters. The heat buffer capacity is 10 kWh, the initial levels differ per house. How the initial buffer levels and the heat demand for the houses is determined is described in Appendix D.

The goal of the simulation is to investigate the ability to reduce the overall imbalance and the influence of prediction errors using microCHPs. Furthermore, the computational time of MPC is determined and the influence of relaxation is studied.

The global planning determines a production profile for the fleet of microCHP devices for the complete day on beforehand. Therefore, this use case is similar to the Virtual Power Plant scenario (see Section 4.3.2). The objective is to stick to this planning. Next, an extra imbalance $I_y$ is introduced, emulating imbalance caused by prediction errors in the production of wind turbines. This imbalance pattern is used to analyze how much imbalance can be compensated. Since the heat demand defines the amount of generation, no extra or less electricity can be generated by the houses, the generation can only be shifted in time. Therefore, the integral of the introduced imbalance pattern is set to zero. The introduced imbalance is generated randomly between +20 kW and -20 kW and normalized so the integral is zero. So, the objective is to 1) stick to the planning and 2) on top of that compensate for the introduced imbalance.

In this use case individual steering signals are used (one per house) and a global level of optimization. Furthermore, scenarios with and without prediction errors are simulated and scenarios with and without introduced imbalance. Finally, scenarios with different observation horizons of MPC are simulated.

Table 6.3: Imbalance for the scenarios of the microCHP use case ($kW^2$)

| | MPC observed horizon | | | | |
|---|---|---|---|---|---|
| | $L_0$ | $L_1$ | $L_2$ | $L_5$ | $L_{10}$ |
| $P_n G_p I_n$ | 1473 | 773 | 710 | 4917 | 12095 |
| $P_n G_p I_y$ | 4307 | - | - | - | - |
| $P_y G_p I_n$ | 1566* | 1411 | 1114 | 4706 | 12132 |
| $P_y G_p I_y$ | 4156* | - | - | - | - |
| $P_n G_{pr} I_y$ | 3186 | - | - | - | - |
| $P_y G_{pr} I_y$ | 3159* | 2968 | 2646 | 4450 | 11931 |

* Heat demand shifted in time

*Results*

The results of the different scenarios are compared based on the resulting imbalance (see definition Appendix D). For the realtime global optimization all microCHPs send their status to the global controller. The global controller determines steering signals for all individual houses, based on the status of the global controllers, the planning and the amount of introduced imbalance at that moment in time.

The simulation results can be found in Table 6.3. As can be seen in the table, the initial case (no introduced imbalance, $I_n$) already results in 1473 kW$^2$ imbalance (1566 kW$^2$ in case of prediction errors). This is caused by the fact that the planning is made on a half hour base, the heat profile and decisions are aggregated for the time interval of half an hour, resulting in rounding errors in comparison with the realtime control. Therefore, realtime control cannot stick to the planning. When extra imbalance is introduced ($I_n$, 2689 kW$^2$) the total imbalance is 4307 kW$^2$ (4156 kW$^2$ in case of prediction errors). The pattern of the imbalance is given in Figure 6.8. When the global controller uses global realtime control to compensate for the introduced imbalance, the imbalance decreases to 3186 kW$^2$ (3159 kW$^2$ in case of prediction errors), a reduction of 26%. These results can probably be improved when the planning is also based on six minute time intervals, but in the current implementation of the planning algorithm this cannot be solved due to the complexity, it is infeasible. An example of the planning, the introduced imbalance and the actual production is given in Figure 6.8.

Using Model Predictive Control (MPC) in this use case increases the results also significantly. The imbalance in the reference case ($P_n L_N G_p I_n$) is decreased by 50% for N=2. In the case of global realtime control ($P_y L_N G_{pr} I_y$), the total imbalance is even lower than the introduced imbalance: the overall imbalance of the system is decreased. The results for $N > 2$ worsen fast with a growing observed horizon, this is probably caused by the definition of the cost function: when more intervals are observed, the starting and stopping costs $B$ are smoothened over multiple time intervals. A compensation for this is included in the control methodology, but this behavior should be investigated more detailed. However, this is left for future work.

The computation times when using MPC with and without relaxation are shown

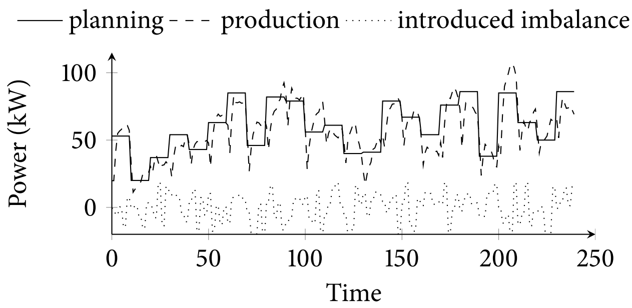



Figure 6.8: MicroCHP use case: planning and resulting production pattern

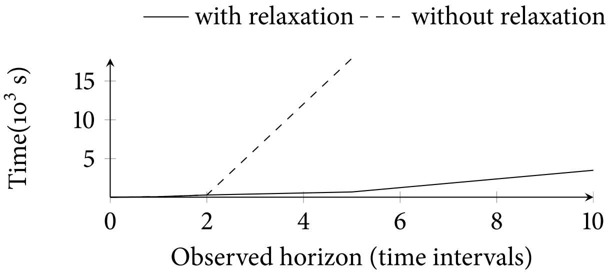



Figure 6.9: MicroCHP use case: computational times MPC

in Figure 6.9. As can be seen in the picture, the relaxation decreases the computation times considerably. In this use case, the state space can become much larger than in the freezer use case since the state space is not limited by the freezer temperature but by the buffer level, resulting in much broader bounds. The results (imbalance) are similar for the scenarios with and without relaxation.

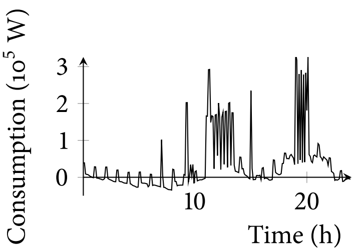
This use case shows that realtime global imbalance compensation has large potential, it can reduce the imbalance up to 26%. When MPC is added, the imbalance is even reduced with 50%. However, this is for limited observation horizons, the behavior of MPC for larger observed horizons need to be studied. Prediction errors worsen the overall behavior, but this can be compensated by using MPC. In this scenario, where the state space is quite large, the influence of relaxation on the computation time of MPC is considerable, whereas the observed results are similar.

### 6.1.5 COMBINATION OF DEVICES USE CASE

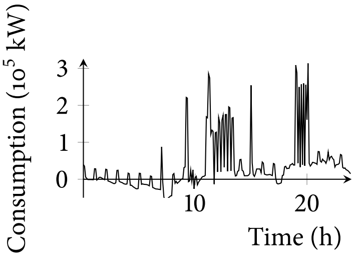
In this section we consider a use case which is a combination of the previous four use cases. The use case simulates 100 houses, all with a normal consumption profile as described in the first use case. The time interval length is six minutes and 24 hours are simulated (240 time intervals). The consumption of every house is similar

Table 6.4: Results combination of devices use case

| Influenced device | none | freezer | microCHP | car | all |
|---|---|---|---|---|---|
| imbalance ($kWh^2 \times 10^3$) | 137 | 135 | 130 | 128 | 119 |




(a) Without optimization



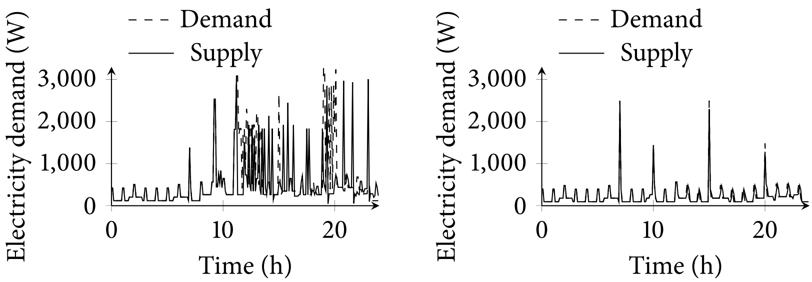

(b) All devices influenced

Figure 6.10: Overall electricity flow of combined devices use case

to the profile shown in the first use case. Furthermore, every house has a smart freezer and a microCHP device with heat buffer installed. The heat consumption is as described in the previous use case. Furthermore, electrical cars as described in the third use case are added, including the arrival time between 5pm and 8pm and the required number of charge intervals. Only the number of charge intervals is reduced by a factor two since we consider the situation that the cars must be charged before midnight (this is the end of the simulation horizon). The objective of this use case is to reduce the peaks in the electricity profile and to work towards a flat electricity profile for the overall consumption pattern of the 100 houses.

The goal is to study how well multiple smart devices can be steered using a single steering signal. In this use case one individual steering signal per house is used. The steering signals are determined using the iterative planning method described in the previous chapter. Furthermore, perfect prediction is used ($P_n$) in this scenario since the goal of this use case is to study the influence of a single steering signal per house on multiple smart devices in the house.

To compare the influence of one steering signal on a single smart device and the influence of one steering signal on multiple smart devices in the same building, five different scenarios are simulated. In the first scenario, none of the devices can be optimized by the steering signals. This is achieved by changing the cost functions and make the costs for deviation from normal behavior very high. Therefore, the microCHP device only switches on when the buffer is almost empty, the freezer behaves like a normal freezer and the car just starts charging when it arrives at home. In the next three scenarios only the behavior of one smart devices can be optimized. Finally, in the last scenario all devices can be optimized by the steering signals.




(a) Normal scenario

(b) Reduced scenario

Figure 6.11: Demand and supply in an islanded scenario

*Results*

To compare the results of the different scenarios the deviation from the average is used as measure, i.e. the imbalance. The definition of imbalance for this use case can also be found in Appendix D. The load factor cannot be used since the electricity consumption profile can be negative: more electricity is produced than is consumed.

In Table 6.4 the results for the five use cases are given and Figure 6.10 shows the overall electricity consumption profile for the scenario without optimization and the scenario where all devices can be optimized. As can be seen in the figure, the consumption profile is very irregular with high, short peaks. It is very hard to level out these peaks, especially since the base consumption profile of all houses is the same. Therefore, the imbalance in all scenarios is rather high. However, as can be seen in the table the devices influence the imbalance positively. In the four scenarios with optimization the imbalance decreases with 1.5%, 5.1%, 6.6% and 13.1%. These results show that, as discussed in Chapter 4, a single steering signal can optimize multiple devices in the same building. Although not all possible combinations of statuses of devices can be reached with one steering signal (as explained in 4.5.3), the optimization potential of the combined devices is almost as big as the sum of the individual optimization potentials (13.2% - 13.1%).

### 6.1.6 ISLANDING USE CASE

The use case described in this section simulates a house disconnected from the grid. The consumption profile is similar to the consumption profile described in the first use case. However, in this house no smart freezer is available. Furthermore, an electricity buffer (battery) of 2 kWh is added. For this battery the model and cost function described in the previous chapters is used. The objective of this use case is to use the microCHP device as backup generator and supply as much demand as possible. The time interval length is six minutes and the simulated horizon 24 hours. Since a disconnected scenario is simulated, only the last step of the three-step control methodology is used without prediction and planning ($P_n L_0 G_{-2} I_n$).

The goal of this use case is to study whether it is possible to use a microCHP device as backup generator in combination with a battery and decrease the discomfort during a power cut as much as possible. The heat generation is not taken into account in this use case. In other words, it is assumed that excess heat can be dumped. Two different scenarios are simulated: 1) a scenario with a normal electricity demand and 2) a scenario with less electricity demand, i.e. large consumers like the washing machine are disabled.

*Results*

The results of the two scenarios are shown in Figure 6.11. In the figure the demand and the supply are given. As can be seen in the picture, almost all load can be supplied using the microCHP device and the battery: in the normal scenario 98% of the load is supplied and in the scenario with less electricity demand all demand is supplied, in the latter even without shifting load in time. In this use case, the microCHP device is started with electricity from the battery when the battery is almost empty and it runs until the battery is completely filled, where the heat production is not taken into account. The simulations show that it is theoretically possible to decrease discomfort by supplying a part of the devices with the proposed configuration of a microCHP and a battery. These simulations show that, concerning the load/generation balancing, islanded operation with a microCHP device is possible and the comfort level can be increased significantly. For this use case it is assumed that it is possible to start a microCHP device using a battery and that the battery is capable of maintaining a stable 230V/50Hz. Furthermore, it is assumed that the battery can be charged by the microCHP device. These assumptions have been verified within the prototype tests, the results of these tests are described in the next section.

## 6.2 Prototype and field tests

In this section the prototypes built in our lab are described and the results of the prototype and field tests are discussed. The goal of the tests was to verify assumptions, check whether the proposed algorithms also work on a prototype and getting experience with the new technologies installed in normal houses.

The base of the prototypes of both the lab installation and the house installations is a microCHP device and a heat store, since these smart devices are already commercially available. We used two different types of prototypes, one installation in a laboratory and multiple installations in regular houses replacing the conventional heat supply. The control methodologies have been tested first on the laboratory installation (a real test environment) and next they have been implemented on the installations in houses.

Four different installations have been used, one lab prototype on the University of Twente campus and three installations installed in the field in normal houses. The lab prototype and two installations are based on a Whispergen microCHP device, the last field installation is based on a Baxi microCHP device. Since the lab tests have been done with a Whispergen and the Baxi field installation is only installed recently, in this section we focus on the Whispergen installations.



### 6.2.1 TEST GOALS

The first research goal of the lab test was to verify whether it is possible to create an islanded situation, i.e. whether it is possible to run the microCHP device without a grid connection. As mentioned in the first chapter, this was the initial research question of the whole project. In order to balance the load and generation of the Whispergen in islanded operation the tolerance of the Whispergen must be known. Tolerance is defined by the percentage of mismatch between load and generation for which the generation stays within the accepted limits for the voltage and frequency[1]. Furthermore, also the Rate of Change of Frequency (RoCoF) is limited, with the consequence that the Whispergen switches off when the frequency changes too fast. Knowing these limitations, the second step was to test whether it is possible to start and run the microCHP device using a battery setup. The final islanded test was whether it is possible to create and maintain an islanded situation for a longer period while switching on and off devices and managing the energy streams.

The second goal of the prototype tests was to verify whether the proposed algorithms are also applicable in a real world scenario and what has to be adapted within the algorithms to convert them from the simulator to the prototype.

The goal of the field installations was to get experience with installing these devices in normal houses and to investigate how they perform in comparison to the conventional installation and how residents react on the new technology.

### 6.2.2 TEST BED CONFIGURATION

The proposed configuration for our test emulates a normal house (except for the electrical equipment for balancing tests and measurements). With this testbed both the balancing tests and the islanding tests can be performed.

The basis of the testbed is a normal heat Whispergen/Gledhill combination as would be installed in a normal house. The exact types of the used machines are:

- Whispergen Mark 5A[2] (microCHP)
- Gledhill BoilerMate BMA-225-mCHP[3] (heat buffer)

The Whispergen is connected to the Gledhill and the Gledhill supplies all heat demand, both for central heating and hot water taps. In the lab configuration the Gledhill is connected to one radiator and a hot water tap. The radiator is represented by a forced heat-exchanger on the roof of the building.

[1] G83 limitations: 207 - 264V, 47 ± 0.5% - 50.5 ± 0.5% Hz
[2] http://www.whispergen.com
[3] http://www.gledhill.net

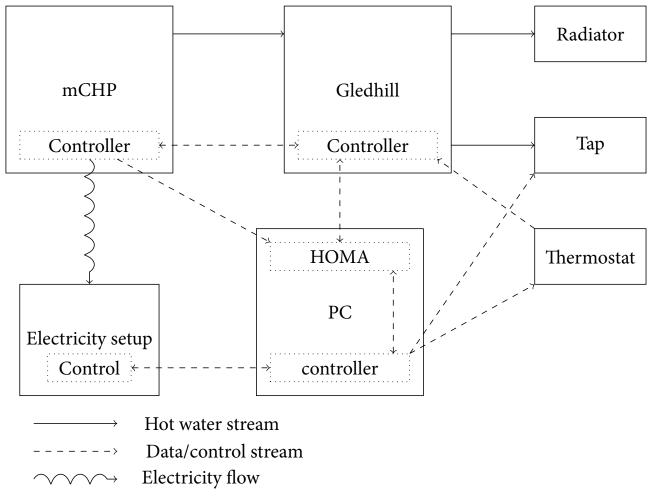



Figure 6.12: Setup configuration

For a Whispergen/heatstore combination an extra controller is required. Such a controller is built-in in the Gledhill. The normal thermostat is connected to this controller and this controller 1) starts the pump to stream water to the radiator(s) based on the thermostat signal and 2) decides when the Whispergen has to be switched on and off based on the level in the hot water tank and the heat demand.

For the communication with the controller of the Whispergen HOMA Software B.V.[4] developed a software product. This software product communicates with this controller to gather information about the Whispergen and Gledhill. Furthermore, the software can send a request to switch on or off the Whispergen to the controller. The controller decides whether the request can be honored or not. In this way the Gledhill controller stays leading and assures that the heat demand is always supplied and the temperature in the water tank does not become too high. The HOMA software runs on a separate computer, which in our testbed is a normal computer but in actual installations is an embedded PC. Adding HOMA software to the installation is not really necessary in normal situations, although it is very useful for global optimization algorithms (see previous chapter) and to monitor the installation. We used the software to get information about the status of the Whispergen/Gledhill and to switch on/off the Whispergen.

The above described configuration can be installed in normal houses to replace a conventional high-efficiency boiler and has been installed in several test houses. In these installations the Whispergen is connected to the electricity grid via a normal outlet. When it is starting it drains electricity from the grid and when it is running the electricity flows back to the grid via the same outlet.

[4] http://www.homa-sw.com

For the lab tests a couple of extra hardware devices have been added to be able to perform certain tests. A controller has been implemented on a PC (next to HOMA software) for the islanded control. The hot water tap is connected to an electrical valve that can be controlled by the control software (controller). The thermostat input is also generated by a computer controlled relay, so whether heat is exchanged on the roof or not does not depend on the temperature, but is managed by the control software. Furthermore, an electricity setup is added for the balancing tests to connect a battery and to switch on/off devices (loads). These control signals and the electricity setup are discussed more detailed the next subsection. A schematic overview of our testbed configuration is given in Figure 6.12.

*Additional hardware laboratory*

In the laboratory configuration a number of additions to the normal installation are made. To perform the balancing tests a battery with AC/DC converter is added. Furthermore, adjustable reactive and resistive loads are added. For the islanding tests, computer controlled equipment is added to control both heat and electricity demand. Finally, measurement equipment is added. A complete picture of the setup is given in Figure 6.13, in the remainder of this section the setup is discussed more detailed.

To measure the actual amount of generated electricity and to study the startup characteristics a current meter is added. The current can be measured on various places, depending on the test. Because both resistive and reactive load must be balanced this measurement equipment must be able to measure both real and reactive load. This can be either a combined voltage and current meter capable of measuring both loads or two meters that output not an RMS value but the actual sine wave so the phase shift can be measured. We used a power analyzer to measure voltage, current, real and reactive load at the same time. This power analyzer can be connected to the PC via a serial link, so the measurement values can be logged.

The requirements for the battery equipment are very strong, especially for the AC/DC converter part. Next to the high currents and capacity, especially the combined discharge/charge capabilities in combination with the stabilization capabilities are difficult. On one hand the battery must be charged in case of electricity surplus and discharged to supply shortage. On the other hand, the converter has to stabilize the 230V/50Hz. Battery solutions exist for both separate requirements, but as far as we know there is no battery solution that can stabilize the 230V/50Hz while it is charging the battery.

This equipment consists of a battery, an inverter and a charger. The inverter inverts the 12V= from the battery to the 230V/50Hz, supplies the shortage and stabilizes the 230V/50Hz. The converter charges the battery with the surplus. This can also be seen at the left side Figure 6.13. This solution is a combination of devices from Victron[5]:

- Battery - 12V/120Ah AGM Deep Cycle Battery (≈1.5 kWh)

[5] http://www.victronenergy.com/

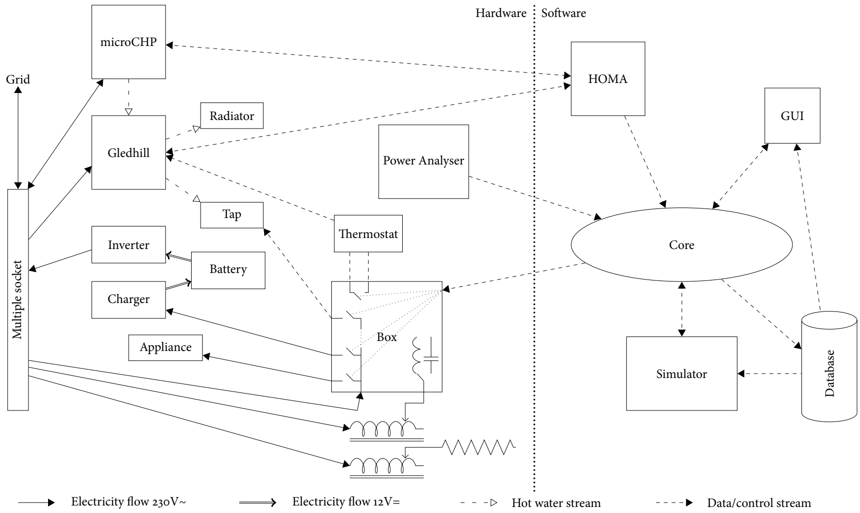



Figure 6.13: Hardware and software connection diagram

- Inverter - Phoenix Inverter 12/1200 (max. 1200VA discharge)
- Charger - Phoenix Charger 12/30 (360 W charge)

The advantage of this solution is that the stabilization requirement is met and the battery can be charged. Disadvantage is that the battery is continuously charged, even when there is no electricity surplus. This causes that the battery is charged with electricity supplied by the inverter, so the battery is charged with electricity drawn from the battery. To overcome this, the charger is connected to one of the controlled outlets for devices. So, the control algorithm can switch on and off the charger by switching on and off the outlet. The control algorithm should switch on the charger when there is more production than load and switch off the charger otherwise. Simulations show that the algorithms are able to support this setup, in the case that there is always enough load to get rid of all produced electricity (since only 360W can be led to the battery). The control algorithm described in Chapter 4 is adjusted to support this scenario, i.e. the cost functions of the devices are redefined to fit the correct behavior.

The computer equipment for the heat and electricity demand has been built in a box, together with the reactive loads. For the reactive loads, a coil and a capacitor have been used. The coil and capacitor are built in the box and a normal plug comes out of the box to connect this load to an electricity supply (e.g. the grid). A hand controlled switch on top of the box decides whether the coil or the capacitor is used as load. The amount of reactive load can be adjusted using a variac. The variac is delivered with an outlet and a plug, so the coil/capacitor plug can be connected to the outlet of the variac and the plug of the variac can be connected to the rest of the testbed (e.g. via the multiple socket). For the resistive load an (old-fashioned) electrical heater is used, also controlled via a variac.

For the load control functionality a relays card has been used. This relays card consists of eight relays and is connected via serial link with the computer. The control software can switch on/off the relays. The box has a second plug that is used to supply the connected devices that are switched on. This plug can be connected to the rest of the testbed to connect the switched on devices with the rest of the testbed. Six relays are connected with outlets that are built-on the outside of the box. When a relay is closed, the accompanying outlet is supplied with electricity drained from the second plug. The seventh relay is used to open and close the hot water tap valve and the last relay is used for the thermostat signal.

### 6.2.3 SOFTWARE

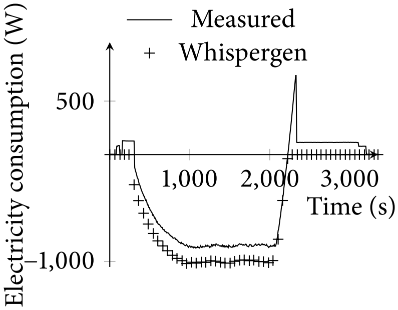
The hardware prototype is controlled via software. The core of the software delivers an interface to the hardware which can be used by other programs. This core part connects to HOMA software, determines the status of the Gledhill/Whispergen every minute and can send requests to start/stop the Whispergen. Furthermore, also the control algorithms are implemented in this part of the software. The data characterizing the prediction can be sent to a global controller via a TCP/IP connection. The local scheduler receives steering signals in the same way.

In the laboratory the core part of the software can also open/close the relays and can therefore manage devices, the hot water tap valve, the central heating demand and the thermostat signal. Furthermore, it reads the values of the power analyzer every second. All information is time stamped and stored into a database.

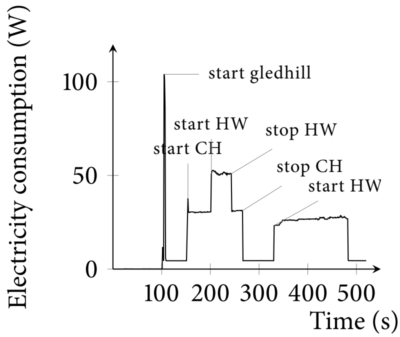
For the laboratory setup a second software part is developed, the simulation part. This simulation part of the software can emulate a house by switching on/off devices and by managing the heat demand (via the core). These two parts are connected via TCP/IP to allow them to run on different computers. Furthermore, a GUI in Python is built that can connect to the core to monitor the current situation and can give commands manually (switch on/off devices, the Whispergen or the heat demand). A schematic representation of the hard- and software is given in Figure 6.13.

### 6.2.4 TEST RESULTS

This section describes test results achieved with the different installations. Two different types of tests have been done with the lab prototype. First, it has been tested whether it is possible to create an islanded situation. Next, tests with the algorithm have been performed. Finally, the results of the field tests are presented, mainly the lessons learned during installation and usage of the technologies. In Figure 6.14 the electricity usage of the microCHP and Gledhill are shown. Figure 6.14a shows the electricity usage of a microCHP: first electricity is drawn, once the




(a) Whispergen




(b) Gledhill (HW=Hot tap Water demand, CH=Central Heating demand

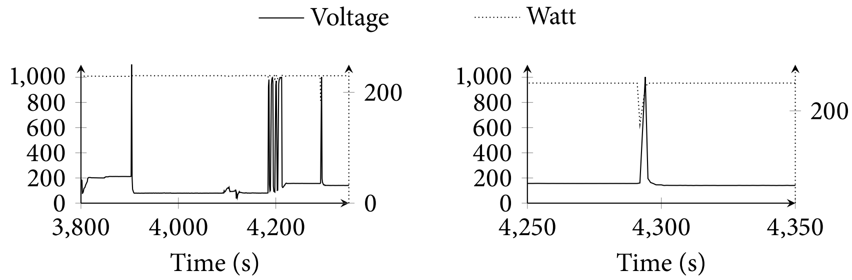
Figure 6.14: Whispergen and Gledhill electricity usage

device is running it produces electricity and when the devices stops it consumes electricity. During the startup phase the microCHP has a number of high demand peaks, these cannot be seen in this figure due to the time scale. In Figure 6.15a these peaks can be seen. Figure 6.14b shows the electricity usage of a Gledhill. The electricity demand of a Gledhill depends on the heat demand, this is caused by the pumps for the water flow.

The goal of the first test was to verify whether it is possible to switch on/off devices while the voltage/frequency stays stable enough and whether it is possible to charge the battery with the Victron equipment. With the inverter it is possible to start the Whispergen and to emulate an islanded house. In this scenario, the control algorithm has to decide which devices to supply and when to start the Whispergen. Furthermore, the control software must also decide when to switch on the battery charger and which devices need to be switched off when the Whispergen starts (the Whispergen draws high startup currents and thus other devices need to be switched off). Finally, since it is not possible to start the Whispergen when the heat buffer is full, we may have to decide to dump heat to be able to afterwards start the microCHP. This simplified version of the control algorithm is used since it is easier to implement and monitor.

After installing and connecting the Whispergen and Gledhill, they ran as expected. Stabilizing the generation and consumption to create an islanded situation without using a battery is not possible. Starting a Whispergen with electricity supplied by an inverter is possible and can maintain 230V/50Hz good enough, even when devices are switched on and off.

The tests show that it is actually possible to create and maintain an islanded situation. An islanded situation has been created during multiple hours with the testbed. However, it is rather hard to start the Whispergen with the current battery




(a) Required supply during startup

(b) Zoomed in on a peak

Figure 6.15: Electricity flow out of the Victron equipment when starting the Whispergen

equipment. The high startup current leads to a voltage dip (see Figure 6.15 and especially Figure 6.15b). The Whispergen protection against islanded operation (legislation) causes the machine to switch off. A second outcome of the test is that the control algorithm is able to control the devices in a house: switch on/off a generator, switch on/off devices and control the battery, even when the used battery equipment is not optimal (charge 360W or nothing). The different aspects of islanded situation have been verified and are functioning as specified: it is possible to create an islanded situation, it is possible to start the Whispergen in an islanded situation, it is possible to maintain the islanded situation while the Whispergen is running and devices are switched on/off and it is possible to charge the battery in an islanded situation. The assumption that it is possible to start a microCHP using a battery used for the simulations seems to be valid.

In a second test, the controller has been tested in a grid connected situation. Using the simulator, a fixed heat demand profile has been emulated. The heat demand of the previous day is used as prediction. Next, a planning is determined using a Dynamic Programming methodology. The objective is to shift production as much as possible to daylight hours (prevent noise at night). Furthermore, short runs are avoided (wearing of the machine), so only switch on signals are given (i.e. the generator runs until the buffer is filled). The planning is used as input for a simplified realtime control algorithm. The planned and actual free capacity (inverse of the level) in the Gledhill for two different days is given in Figure 6.16 and Figure 6.17. The runtime of the microCHP can be deducted from the free capacity: when the free capacity decreases the microCHP is running.

The heat demand prediction for the day in Figure 6.16 was accurate, but for the day in Figure 6.17 a peak in demand was predicted wrongly: a delay in the hardware shifted the heat demand in time. Therefore, the planned and actual free capacity in Figure 6.16 are similar and, more important, the planned and actual runtimes of the microCHP are equal. Furthermore, the microCHP is started on initiative of the

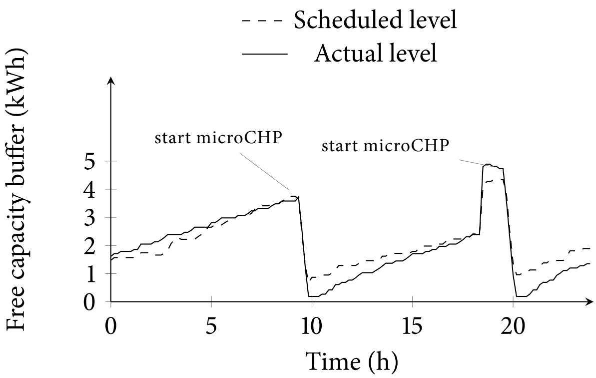



Figure 6.16: Planned and actual free buffer capacity with good heat prediction

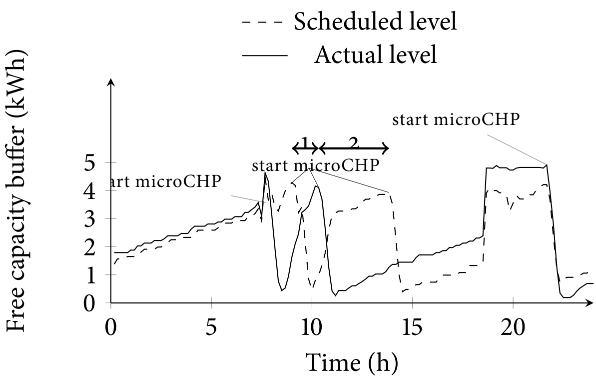



Figure 6.17: Planned and actual free buffer capacity with less good heat prediction 1) wrong predicted peak in demand 2) effect of wrong prediction

scheduler, since it was not required to switch on the microCHP due to the buffer level at time $t = 9.3$.

The wrong predicted peak in Figure 6.17 leads to a deviation in planned runtime of the microCHP of four consecutive hours. However, since the planning was to run the microCHP until $t = 10$, after the peak in demand. But, since the peak was too late, the microCHP had to be switched off because the heat buffer was filled ($t = 8.5$). The planning was to run until $t = 10$, there are steering signals and the microCHP switches on again at $t = 9.7$. As a consequence, the heat demand between $t = 10$ and $t = 12$ is directly supplied while the microCHP is running (in contradiction to the planning). Therefore, it is not possible to switch on the microCHP at $t = 14$.

Summarizing, the models and assumptions are accurate enough to determine a planning and it is possible to control the microCHP. However, when the heat demand deviates from the prediction, the planned and actual runtimes of the microCHP deviate as well.

The lab tests show that it is actually possible to create and maintain an islanded situation. Furthermore, the control algorithm is able to control the devices in a house: switch on/off a generator, switch on/off devices and control the battery, even when the battery equipment is not optimal (charge 360W or nothing). The assumptions made for the simulations seems to be valid. The second lab test shows that it is possible to determine a planning based on a prediction one day ahead. However, the prediction needs to be accurate, a wrongly predicted peak (for only a few minutes!) can have a severe impact on the runtime. Therefore, when the planning and actual situation deviate too much re-planning is required. Re-planning in the situation in Figure 6.17 at $t = 8.5$ would have prevented the start at $t = 9.7$ and as a consequence the planning would have been followed better.

The field tests show that it is possible to replace a conventional boiler with a microCHP with heat buffer. However, after installing the microCHP the settings of the microCHP must be correct to supply all heat demand, especially during winter days. Otherwise, the installation cannot keep up with the heat demand resulting in a too low temperature in the house. Furthermore, although it seems to be a small change to replace the boiler by a microCHP, it has certain impacts on the residents. In the Netherlands people are not used to large heat buffers which are required to have a larger optimization potential of microCHPs. These heat buffers are often placed in places in the house which are not heated, for example the attic. Due to heat losses of the buffer at places which are not heated, the heat demand increases. Furthermore, due to the lower heat production capacity, the machine runs for longer periods. This, in combination with a more noisy operation, can lead to integration problems. Finally, we experienced that new technologies have to prove themselves, even more than existing technologies. When something is going wrong or the energy bill is higher, people often think that it is caused by the new technology, even when there are good reasons to assume that the conventional technologies would have caused the same problems or increased energy bills.

### 6.2.5 LOCAL CONTROL NODE

The goal of the three-step control methodology is to increase the overall energy efficiency. As a consequence, the introduction of a control system with distributed control should save more energy (or increase the efficiency) than required for its own operation. Therefore, a proof of concept distributed control system has been designed which can be placed in buildings. This Local Control Node (LCN) can communicate with all (controllable) devices and the global controller. Furthermore, it runs the local control software. In other words, the LCN is responsible for the energy profile predictions, its corresponding optimization potential and the realtime control.

The power consumption of the LCN, including the control hardware of the devices, should be kept low. For our LCN, an E-Box 3300 using only 5 W is used in combination with the PlugWise[6] measuring and switching hardware, using up to 9 W in total. Although the system is low-power, it still has enough computational power to run our algorithms. The prediction algorithms require between 4 up to roughly 7000 milliseconds to run. A complete planning process can be executed within a couple of minutes. Since the system consists of off-the-shelf components, the power usage could be reduced even further.

Assuming that the system is switched on continuously, the minimal saving of the system must be 79 kWh per year. These savings can be obtained using different kinds of techniques. First, user awareness of their energy consumption already may lead to a reduction of energy usage. Due to the connectivity possibilities of the LCN, constant information about the electricity consumption can be displayed on a TV, LCD display or can be accessed via the web/smart phones etc. Tests in the Netherlands show that energy aware households can save up to 200 kWh[7]. Furthermore, since the electricity consumption is analyzed by the LCN, energy wasted by devices in stand-by mode can be reduced further by switching them off when people are not at home. A typical Dutch household consumes 400 kWh on stand-by devices, of which 50% can be saved by really switching off devices.

Besides the power savings, the LCN can react on improved energy profiles, which can be supplied more efficiently, leading to reduced $CO_2$ emission while generating the required electricity. About half of a household's electricity demand is dedicated to controllable loads (fridges, heaters, washing machines, etc.) [14], which could be scheduled (within certain limits). Thus, although no electricity is saved, less $CO_2$ may be required to generate the same amount of electricity if the load in the household can be controlled up to some limit.

Summarizing, although adding a smart energy-management node requires some extra energy, more energy can be saved with the system. Furthermore, the LCN allows a large part of the whole energy consumption to be generated more efficiently. Finally, on top of the environmental benefits, also more comfort may be offered to the residents.

## 6.3 Conclusions

The simulations show that the simulator works as expected and the control methodology is able to monitor and manage the behavior of devices. Different (types of) devices have been tested and all devices are managed correctly within the limitations of the comfort level. The control methodology is able to work towards objectives, it actually improves the resulting energy profile in all simulated scenarios. Global optimizations work better than local optimization in all scenarios, since buildings tend to shift the production and consumption to the same point in time in case all buildings optimize only their own behavior. However, this could be caused by the large similarities between the simulated houses. Planning improves the results significantly in comparison to only realtime optimization. It is both possible to

[6] http://www.plugwise.com/
[7] http://www.milieucentraal.nl/pagina?onderwerp=Apparaten

work towards pre-defined energy profiles as well as to react on realtime fluctuations. Even when realtime fluctuations are compensated, a planning where scheduling freedom is used improves the results.

Model Predictive Control (MPC) improves the results significantly: the imbalance decreased up to 50% in the simulated scenarios. MPC is especially useful to work around prediction errors. Beside that the results expressed in the objective (e.g. imbalance) are improved, the main advantage of MPC is that the behavior of the devices improves: much less starts and stops result in a more stable behavior. However, adding MPC increases the required computational power significantly. This can be overcome partly by introducing relaxation, which decreases the computational power without decreasing the quality of the results notably.

Individual steering signals per house give better results than one shared steering signal for all houses. Especially without global control one single steering signal results in identical behavior. With global control the results of a single steering signal already improve, although both with and without planning the results are much better using individual steering signals.

The simulations show that it is possible to use the domestic optimization potential to work towards (global) objectives. In the case of charging electrical cars the peak is reduced by 67% and the load factor increased from 0.27 to 0.84. Furthermore, using a group of microCHP devices it is possible to both work towards a pre-defined production profile and to compensate for realtime fluctuations. The use case with multiple devices shows that it is possible to exploit the optimization potential of multiple smart devices in one house: i.e. the exploited optimization potential of the devices together is almost as high as the sum of the exploited potential of single device optimizations. The simulation of an islanded situation shows that it is theoretically possible to create an islanded house using a microCHP and a battery to decrease the discomfort of the residents.

Prototype tests show that it is possible to start a microCHP device off grid. However, the requirements for such a start are high: the voltage and frequency must be stable otherwise the microCHP switches off. Therefore, the inverter needs enough capacity and the battery must supply enough current. Furthermore, it is possible to create an islanded situation using a battery and a microCHP for electricity supply. The battery can be charged with electricity from the microCHP while the inverter creates a stable 230V/50Hz. Multiple devices can be supplied and switched on and off during the islanded situation. A simplified version of the control methodology can be used to decide when to start the microCHP device and which devices to supply.

During a grid connected situation the simple control methodology is able to influence the behavior of an actual device, for example the runtime of a microCHP device can be shifted in time.

CHAPTER 7

# Conclusions

This chapter evaluates and concludes this thesis. In the first section a short summary and evaluation of this thesis is given. Next, in Section 7.2 the conclusions are stated and in Section 7.3 the main contributions of this thesis are discussed. Finally, Section 7.4 gives possible directions for future work.

## 7.1 Evaluation

Concerns about climate change, increasing energy prices and dependability of energy supply ask for drastic changes in the energy supply chain, but also in the current demand-supply philosophy. Current trends in energy consumptions result in an increasing and more fluctuating electricity usage, causing a decreasing efficiency of conventional power plants and increasing requirements on the grid and generation capacity. Furthermore, in order to meet the $CO_2$ emission reductions aimed for in the 20-20-20 agreements [22], at least a large part of the electricity should be generated by renewable sources which are to a large extent uncontrollable. This introduces even more challenges to maintain a reliable, dependable and affordable electricity supply. Therefore, new ways 1) to achieve a more efficient use of the generated electricity of existing power plants, 2) to facilitate the large scale introduction of renewable sources and 3) to allow a large scale introduction of new technologies for consumption and storage of energy, is required, while maintaining grid stability and ensuring a reliable and affordable supply.

The current grid is developed based on a demand-supply philosophy in which all electricity is generated in a few large central power plants and is transported top-down and one-way to the consumers. The consumers' side of the supply chain is static, consumers switch on devices and the generation side has to supply the demand. However, to increase the efficiency of current power plants and to allow the introduction of uncontrollable renewable sources, the consumer side of the supply chain should become more flexible; i.e. consumption should be adjusted to generation. To achieve this, the current electricity grid should be transformed into a Smart Grid and domestic customers should be transformed from static consumers into active participants in the energy supply chain. In Chapter 2 the characteristics of Smart Grids are studied. The main goals of a Smart Grid are to support the introduction of renewable generation and to keep up with the growing electricity demand and at the same time maintaining a stable, reliable and affordable electricity supply. Next to two-way electricity streams through the grid, there is also a two-way communication stream between all parties involved: between the central power plants, the grid operators, the renewable generation all the way up to the customers. Using this two-way communication, the consumption can be adjusted to the generation: the decrease in flexibility on the generation side can be compensated by a more flexible electricity grid and a more flexible consumer side. Essential in a Smart Grid is a monitoring and management system that monitors and manages all parts of the grid, from central generation and large scale renewable generation, via transportation up to consumption/generation at the consumers, in a cooperative way. The emergence of smartening the grid and updating the electricity supply chain is emphasized by the numerous initiatives worldwide, from the European Union, from governments, from industry as well as from the academic world. However, to reach a smarter grid, a number of technical (e.g. scalability and dependability), economical (e.g. who has to pay), political (e.g. is it allowed) and ethical (e.g. privacy issues) challenges have to be addressed. To tackle the technical challenges and to realize a monitoring and management system, ICT is seen as one of the key enabling technologies.

An important component of monitoring and management systems for Smart Grids is, next to sensors and actuators, a control methodology consisting of algorithms to gather information, process this information and optimize the overall electricity streams. Such a control methodology, capable of exploiting all potentials in a reliable and dependable way, should meet a number of requirements. The control methodology should work with both local and global objectives and should be very generic and flexible. Furthermore, since a large number of buildings is involved, the control methodology needs to be scalable. To be acceptable for the residents, it should also respect the comfort level of the residents. Furthermore, to get a dependable and reliable control methodology capable of damage control, a combination of prediction, planning and control is required. Finally, the requirements on the communication links should be limited and in case of failing communication links the local controller needs to be capable of working independently.

To study the potential of domestic optimizations and to setup a base for an optimization model, we derived a model of the energy infrastructure within a building and the energy supply towards the building in Chapter 3. Since all types of energy streams in the buildings and grid should be taken into account, the model is based on streams of energy-carriers through the grid and inside the buildings. To incorporate all possible devices into the model, we distinguish between devices that can exchange, convert, buffer and consume energy-carriers. The behavior and flexibility is modelled on a device level in order to make it possible to study the optimization potential per device and to make a planning for every individual device without harming the comfort of end-users. To be able to derive a scalable control methodology, the model exists of multiple (hierarchical) levels. First, multiple devices are combined into a building to be able to analyze the situation on a domestic level and to work towards local objectives. Multiple buildings can be combined into neighborhoods and multiple neighborhoods can be combined into cities. Also the voltage levels in the grid are modelled, including the transformers with their characteristics. In this way it is possible to analyze the energy streams through the grid and transformers and detect overloaded grid lines and transformers. The combination of electricity demand, domestic generation, grid losses and renewable generation leads to production patterns for conventional power plants. The stability of the grid can be analyzed at a timescale of minutes: the load of the grid and transformers can be analyzed, as well as the fluctuations in production profiles and electricity streams. The proposed model is flexible, generic and expressive. We expect that future devices, technologies and scenarios can be incorporated into this model without changing the basic model. Furthermore, all energy streams on an intermediate level can be analyzed. Therefore, the effects of the introduction of new technologies, new grid architectures and control methodologies on the power plants, the required capacities and the stability on a watt-level of the grid can be studied.

In Chapter 4 a three-step control methodology is introduced. It is based on 1) local offline prediction, 2) global offline planning and 3) local online control. The proposed three-step control methodology for Smart Grids exploits the scheduling freedom of domestic devices. The hierarchical tree structure of the framework ensures scalability and limits the required communication. Furthermore, in combination with the optimizations based on cost functions it results in a flexible and generic control methodology. The separation in local and global controllers distributes the required computational power and ensures the comfort and privacy of the end-users. The three-step approach enables a prediction of the consumption/production profile one day ahead to be able to act on electricity markets and the realtime part is able to react on realtime signals, e.g. fluctuation caused by renewable sources. The combination of offline prediction, offline planning and online control results in a flexible, generic and predictable solution. The addition of Model Predictive Control to the last step of the control methodology strengthens the ability of the realtime control to react on prediction errors. Furthermore, it increases the stability (reduction of oscillation) by not only taking the current situation into consideration, but also a prediction of the future (PI-control).

Based on the model derived in Chapter 3, a simulator has been designed to simulate and analyze energy streams in buildings and grids (Chapter 5). The implemented simulator is a realistic, generic and flexible tool, that is able to analyze a realistic, accurate representation of the actual situation. With this simulator we were able to verify the developed control methodology and to study the potential of domestic optimizations in possible future scenarios.

Simulations show that the control methodology is able to work towards objectives, it actually improves the resulting energy profile. Simulations also show that global optimizations work better than local optimization and planning improves the results significantly in comparison to only realtime control. It is possible to work towards pre-defined energy profiles as well as to react on realtime fluctuations. Even when realtime fluctuations are compensated, a planning in which scheduling freedom is incorporated within the schedule improves the results. MPC improves the results of the control methodology significantly and is especially useful to react on prediction errors. The main advantage of MPC is that it results in a more stable behavior of devices and much less starts and stops of the devices. Furthermore, individual steering signals per house give better results than one shared steering signal for all buildings.

## 7.2 Conclusions

Based on the evaluation given above, the research questions introduced in Chapter 1 can be answered:

- *What is the optimization potential of domestic technologies?*
  The simulations show that domestic technologies have a huge potential. However, to exploit this potential the current consuming devices should be replaced by smart devices and moreover, the generating, buffering and smart consuming devices should be connected to a controller to exploit their flexibility.

- *Can this potential be used for the objectives mentioned?*
  This potential can be exploited using local and global controllers in a control framework. Simulations show that peaks caused by charging electrical cars can be decreased by 67% and a group of microCHPs is able to compensate (parts of) the imbalance resulting from wind turbines.

- *Is it possible to create a control methodology to exploit this potential?*
  This thesis shows that it is possible to create a control methodology to indeed exploit the potential. In Chapter 4 the control methodology has been described, based on the model derived in Chapter 3. Simulations and prototype tests described in Chapter 6 show that the control methodology can exploit the potential.

- *What is the best structure for such a control methodology and which algorithms should be used?*
  The control methodology proposed uses an hierarchical tree structure for scalability and communication reasons, as is quite common in literature. Main differences with control methodologies proposed in literature are the underlying mathematical analysis and optimization techniques and the three-step approach. This results in a reliable and predictable behavior. Therefore, both offline objectives and realtime objectives can be used: it is possible to determine a production or consumption profile 24 hours in advance to trade on electricity markets and to react realtime on fluctuations.

Summarizing, optimizing the behavior of distributed generation, storage and consumption technologies has the potential to increase the efficiency of conventional power plants and to facilitate the introduction of large scale renewable generation. A large scale introduction of new technologies for production, consumption and storage allows maintaining grid stability and ensures a reliable and affordable supply. The control methodology proposed in this thesis is able to optimize the behavior of domestic devices to work towards local and global objectives in a predictable way. We think that the three-step approach with the hierarchical tree structure of control nodes is a good solution for a scalable, generic and efficient Smart Grid control methodology.

A Smart Grid is a key solution to keep up with the trends in electricity consumption and to facilitate the shift towards a more sustainable supply.

## 7.3 Main contributions of this thesis

The main contributions of this thesis are:

- *A mathematical model of (domestic) energy streams.*
  The model is based on energy-carriers that model energy flows towards and inside the buildings. These energy-carriers range from heat, gas and electricity to real and reactive power to analyze grid stability. The energy demand within the building is modeled up to device level. The devices within the building are divided into four groups: exchanging devices, consuming devices, buffering devices and converting devices. Furthermore, a flexible construction for defining the connections between devices is given. On a device level the behavior of the devices can be defined, as well as the flexibility in the behavior resulting in optimization potential. Domestic energy generation using renewable sources can be modelled, as well as its influence of improving efficiency, e.g. of PV. On grid level, it is possible to model the different voltage levels, the transformers and the (capacity) limitations. The generators can feed in electricity on multiple voltage levels. Furthermore, local use of domestic generated electricity can be analyzed. (*Chapter 3*)

- *A generic simulator able to simulate multiple scenarios, technologies and control methodologies.*
  A simulator has been developed for the energy streams within a Smart Grid. The simulator is based on discretization of the configured horizon, with a configurable time interval length. Each building is addressed individually and the simulator keeps track of all energy streams. The parameterized elements, configuration files and stochastic variations increase the ease of use and strengthen the ability to perform realistic simulations, with a minimum implementation and configuration effort. The control framework enables adding control algorithms that can manage individual devices and can communicate with each other and central control nodes in a hierarchical way. (*Chapter 5*)

- *A control methodology to exploit the domestic potential on a large scale.*
  A three-step control methodology has been proposed that is able to exploit the domestic potential. The hierarchical structure results in a scalable solution and the addition of MPC to the last step leads to an increase of the performance. Due to the used cost functions the control methodology is flexible and generic. (*Chapter 4*)

- *An overview of the domestic optimization potential by simulations.*
  The performance of the three-step control methodology has been studied in a number of use cases. In the case of charging electrical cars the electricity supply peak is reduced by 67% and the load factor increased from 0.27 to 0.84. Furthermore, a use case with a group of microCHP devices shows that it is possible to both work towards a pre-defined production profile and compensate for realtime fluctuations. (*Chapter 6*)

- *A lab prototype and field tests to proof the concept and to verify assumptions.*
  Prototype tests show that it is possible to start a microCHP device in an islanded situation and that the control methodology is able to influence the behavior of an actual device. (*Chapter 6*)

## 7.4 Recommendations for future work

Although the combination of model, simulator and control methodology shows promising results, there are still several directions for future work. First, the developed simulator can be improved. The underlying model is flexible and expressive, but not all parts of the model are incorporated in the simulator. Especially the grid part of the model needs more attention in the simulator.

The three-step approach and the hierarchical tree structure of the control methodology give promising results and due to this setup the requirements for the control methodology are met. However, individual algorithms of the approach can be improved. The last step of the control methodology uses an algorithm giving an optimal solution, but this requires quite some computational power. Although the distribution of the required computational power by the hierarchical structure and the local control decreases the computational requirements per node significantly, the computational power required for MPC in the realtime step is quite high. Therefore, heuristics for the realtime control should be developed. Furthermore, the synchronization between the different steps can be improved, especially between the planning and control step, for example by using the same level of detail in the used models. Next, more and better re-planning rules should be developed.

Another possible improvement of the proposed control methodology is to allow horizontal communication within a level, i.e. allow communication between buildings. In this way, a group of cooperating buildings can improve the ability to react on prediction errors and can introduce extra flexibility to react on fluctuations.

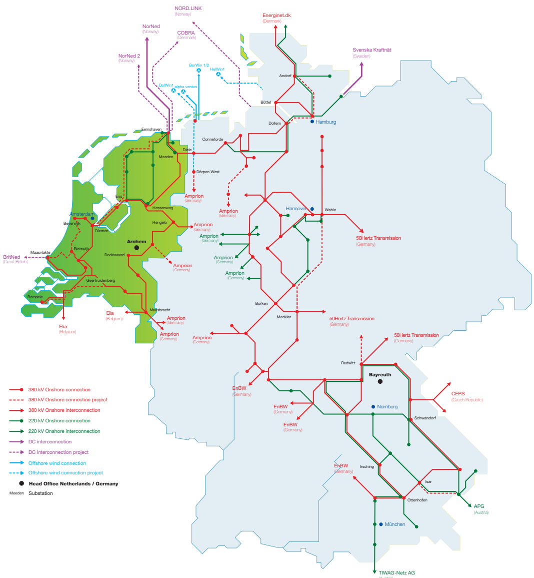
The definition of the cost functions should be studied in more detail, as they are very important for the correct operation of the control methodology. In particular when MPC is added the definition of the cost functions needs to be improved.

When these improvements to the control methodology are implemented, more real world tests should be performed. With field tests it can be studied how realistic our model and control methodology is, e.g. how much scheduling freedom really is available in buildings, whether people are willing to exploit this freedom and whether they are willing to decrease their comfort level to gain more scheduling freedom (of course based on an incentive).

Finally, possible stakeholders should be identified, business cases defined and legislational issues should be identified and solved. For an actual implementation of a Smart Grid, it must be clear who gets the benefits of the Smart Grid, who is paying for the Smart Grid and why people should cooperate with a Smart Grid. Only when these questions have clear answers we foresee a bright future for Smart Grids.

# Appendix A

# Dutch electricity grid



# APPENDIX B

# Complete model

The model of the energy infrastructure derived in Chapter 3 consists of two parts: the definition of the infrastructure and the definition of the devices (and the options related to the status). The infrastructure stays the same over time, at least within the studied horizon whereas the status of the devices changes over time. As a consequence, the complete model (including $Obt_{state}$) defines a snapshot in time. Since the goal is to study a certain period of time, the studied horizon can be discretisized resulting in a set of consecutive time intervals. In every time interval the status of the devices and the corresponding choices need to be deducted, based on the status in the previous state and the choices made. This model is given below, divided in the fixed and changing part in the first two sections. The last sections gives the extension to the model to incorporate the optimization algorithms explained in Chapter 4.

## B.1 Infrastructure model

In the house a set of energy-carriers $EC$ is defined. For every energy-carrier $ec \in EC$ at least one pool is defined, resulting in a set of pools $P$:

$$P = \{\cup P_{ec}\},$$

where $P_{ec} = \{p_{ec_1}, ..., p_{ec_{N_{ec}}}\}$. Furthermore, a set of devices is present in every house. These devices are split up in exchanging, converting, buffering and consuming devices:

$$Dev = Dev_{ex} \cup Dev_{conv} \cup Dev_{buf} \cup Dev_{cons},$$

where $Dev_{ex} = \{d_{ex_1}, ..., d_{ex_{N_{ex}}}\}$, $Dev_{conv} = \{d_{conv_1}, ..., d_{conv_{N_{conv}}}\}$, $Dev_{buf} = \{d_{buf_1}, ..., d_{buf_{N_{buf}}}\}$ and $Dev_{cons} = \{d_{cons_1}, ..., d_{cons_{N_{cons}}}\}$. These devices are connected to the pools via streams. Streams are uni-directional, there are streams from the device to the pool and vice-versa:

$$str = (p,d),\ str \in Str,\ p \in P,\ d \in Dev,$$

$$Str = Str^{p} \cup Str^{d}.$$

The amount of energy flowing through a stream is defined by $x_{(p,d)}$ and $x_{(d,p)}$. Since the pools are abstract devices introduced for modelling purpose they cannot contain energy, the sum of the energy flowing in should be zero:

$$\sum_{(p,d)\in Str^{p}} x_{(p,d)} = \sum_{(d,p)\in Str^{d}} x_{(d,p)}\ \forall p \in P.$$

## B.2 Device behavior model

For every device $d \in Dev$ an internal energy stream $x_d$ is defined. Not all values for $x_d$ are valid, therefore a set of option $Opt^{d}$ is defined for every device. Since only one option can be chosen, variable $c_{opt} \in \{0,1\}$ is introduced:

$$\sum_{opt\in Opt^{d}_{state}} c_{opt} = 1.$$

An option exists of a valid interval for $x_d$:

$$c_{opt} \times Min_{opt} \leq x_{opt} \leq c_{opt} \times Max_{opt}.$$

The internal value $x_d$ is the sum of all values of $x_{opt}$ (note that only one can be non-zero):

$$x_d = \sum_{opt\in Opt^{d}} x_{opt}. \tag{B.1}$$

The flow through every stream in and every stream out of a device is defined by the internal energy stream $x_d$ and a multiplication factor $M^{opt}_{str}$:

$$x_{(p,d)} = \sum_{opt\in Opt^{d}} M^{opt}_{(p,d)} x_{opt},$$

$$x_{(d,p)} = \sum_{opt\in Opt^{d}} M^{opt}_{(d,p)} x_{opt}.$$

Since the state of a device changes, only a subset $Opt^{d}_{state}$ of all options $Opt^{d}$ is valid in a certain state. All options that are not valid in a certain state should not be chosen:

$$c_{opt} = 0,\ \forall opt \in Opt^{d} \setminus Opt^{d}_{state},$$

where $state$ is the current state.

## B.3 Optimization algorithms

The model defined above introduces technical and non-technical constraints due to the balancing constraints for the pools and the definition of valid options for every device. Within these constraints there is some freedom of choice; to choose the best option for every device, costs are introduced for every option. Using an ILP minimization definition, the options with the lowest costs are chosen:

$$minimize \sum_{d \in Dev} tc_d, \tag{B.2}$$

$$s.t.\ \ tc_d = \sum_{opt \in Opt^d_{state}} A_{opt} \times x_{opt} + B_{opt} \times c_{opt}. \tag{B.3}$$

### B.3.1 Model predictive control

In Model Predictive Control not only the current state is taken into account, but also some future states. Therefore, the options, internal energy streams and the minimization function are annotated with time. For every time interval a set of choices must be made, thus (B.2) is extended to:

$$tc_{d,t} = \sum_{opt \in Opt^d_{state,t}} A_{opt} \times x_{opt} + B_{opt} \times c_{opt}.$$

The optimization function observes the choices for all $N$ time intervals, thus (B.3) is extended to:

$$minimize \sum_{d \in D,\ t \in T} tc_{d,t}.$$

Furthermore, an index $t \in T$ is added to every variable, e.g. $x_d$ becomes $x_{d,t}$ and (B.1) becomes:

$$x_{d,t} = \sum_{opt \in Opt^d_{state,t}} x_{opt}.$$

Finally, not every state in time $t+1$ can be picked when the state in $t$ is chosen, only successor states can be picked:

$$c_{d,i,t} - c_{pred_1} - \ldots - c_{pred_N} \le 0,$$

where $c_{pred_1} \ldots c_{pred_N}$ are all predecessor states of state $c_{d,i,t}$.

APPENDIX C

# Configuration files simulator

Listing C.1: Simulator configuration file

```
[General]
//type of configuration file (simulation)
className=Simulation
//name of the configuration
name=JournalSim
//the timebase is set to 300 seconds
timebase=300
//the simulated number of intervals is 288
timeintervals=288

[Grid]
//the location of the grid configuration file
filename=configurations/grids/JournalSim.ini
```

Listing C.2: Grid configuration file

```
[General]
//type of configuration (grid)
className=Grid
//name of the configuration
name=JournalSim
//number of different building configurations is 3
numberOfBuildings=3

//first building configuration
[Building0]
//location of the configuration file
filename=configurations/buildings/SimBuilding1.ini
```

```
//number of buildings with this configuration
number=75

//second buildings configuration
[Building1]
//location of the configuration file
filename=configurations/buildings/SimBuilding2.ini
//number of buildings with this configuration
number=60

[Building2]
//location of the configuration file
filename=configurations/buildings/SimBuilding3.ini
//number of buildings with this configuration
number=95
```

Listing C.3: Device configuration file

```
[General]
//type of configuration file
className=StdAppliance
//name of the configured device
name=HeatDemand1
//extensive logging is switched on
logging=true
//the time base is 3600 seconds
timebase=3600
//the device cannot be preempted
preemption=false
//the device does not use variations
useU1=false
//variation parameters
u2Type=0
u2Param1=0
u2Param2=0
u3Type=0
u3Param1=0
u3Param2=0
//the device has one stream in/out
numberOfStreams=1

//configuration of the stream
[Stream0]
//type of energy carrier (heat)
streamType=1
//name of the stream
name=Heat
//consumption profile
profile=890, 2075, 2445,//etc.
```

Listing C.4: Building configuration file

```
[General]
//type of configuration file
className=Building
//name of the configuration
name=SimBuilding1
//the time base is set to 360 seconds
timebase=360
//extensive logging is switched on
logging=true
//no variation is used
variationType=0
//variation parameters
variationParameter1=0
variationParameter2=0
//5 devices are present in this building
numberOfDevices=5
//4 pools are present in this building
numberOfPools=4

//first device
[Device0]
//location of the configuration
fileName=configurations/consumers/HeatDemand1.ini
//starttime of the device (time intervals)
starttime=0
//runtime of the device
runtime=240
//priority of this device
priority=0

[Device1]
//location of the configuration file
fileName=configurations/buffers/Gledhill1.ini
//no more parameters

[Device2]
fileName=configurations/converters/Whispergen.ini

//... more devices

//first pool
[Pool0]
//energy carrier is heat
poolType=1
//the name of the pool
```

```
poolName=Heat pool
//the devices connected to this pool
//(device 0, stream with name heat
// device 1, stream with name Heat out)
poolConnections=0.Heat, 1.Heat out

//... more pools

//the controller present in this building
[BuildingController]
//locaton of the configuration file
fileName=configurations/buildingControllers/Normal.ini
```

# APPENDIX D

# Details simulated use cases

In this appendix the details of the use cases described in Chapter 6 are given. These details are used to define the input sets and the measures to compare the results of different scenarios.

## D.1 Electrical car use case

In this use case a large number of cars need to be charged. Not all cars need the same amount of charging. Therefore, the charge time is chosen between one hour for the first car to four hours for the last car with a total charge time of 261 hours (391 kWh). All houses are numbered from 0 to 99, these numbers are used to determine the required intervals of charging per car. In detail, the following charge times are assigned to the vehicles

```
if(#car >= 90)
        chargeIntervals = 48;
else
        chargeIntervals = 12 + 2x(#car/5);
        if(#car%2 == 1)
                chargeIntervals++;,
```

where `#car` is the number of the car (0-99) and `chargeIntervals` is the number of intervals the car needs to be charged.

Furthermore, not all cars arrive at home at the same time, they arrive between 5pm and 8pm. Since the charge time depends on the number of the car, the arrival time should be randomly distributed. To randomize the arrival times, the pseudo-random development of the coefficients of $\pi$ are used (so the use case can be reproduced):

```
arrivalTime = 204 + piCoef[#car] x 4,
```

where `piCoef` is an array with the coefficients of $\pi$ (`[1,4,1,...]`) and the number of time intervals between 5pm and the time the car arrives at home is given by `arrivalTime`. With this information the use case (arrival time and charge time) can be generated.

To simulate use cases with prediction errors, a reproducible way of defining the prediction error is needed. For these prediction errors the pseudo-random development of the coefficients of $\pi$ is again used:

```
correctTotalUsage = 5;
amountOfVariation = 0.2;
variation = (piCoef[#car+6] − correctTotalUsage)
            x amountOfVariation;
```

The first 6 coefficients are not used to prevent a relation between starting time and prediction error (6 is arbitrary chosen, multiple values are simulated, all with similar results). The prediction error uses two important parameters: `correctTotalUsage` and `amountOfVariation`. The parameter `correctTotalUsage` defines whether the total charge power is equal (only variation), lower or higher. Three different values for the parameter are simulated: 5 (equal usage), 2 (more charge power) and 8 (less charge power). The parameter `amountOfVariation` defines the amount of prediction errors, a higher value means that the predictions are worse. The eventual variable `variation` defines the prediction error, this value is added to the `chargeIntervals` parameters.

As measure for the quality of the eventual electricity profile, the imbalance is used. The imbalance power in this case is defined as the deviation of the actual load power from the average load power (391 kWh/13 hours ≈ 30 kW, 20 cars charging):

```
for(int i=0;i<#timeIntervalsSimulated;i++)
        imbalance += (ElectricityDelivered[i] − 30.000)^2;
```

, where `#timeIntervalsSimulated` is the number of time intervals simulated and `ElectricityDelivered[i]` the total electricity delivered in time interval `i`.

## D.2 MicroCHP use case

In this use case 200 houses with a microCHP and a heat buffer are simulated. Every house has a different initial buffer level. To calculate the initial buffer levels, the house numbers are used: all houses are numbered from 0 to 199, resulting in a house number `#house` for every house. Initial buffer levels vary between 1 and 9 kWh, according to the following (in kWh):

```
initialLevel = (#house%10);
if(#house%10<5)
        initialLevel++;
```

The heat demand of every house is generated as in Algorithm 1 in [16], using $s = 0$, $w = 4$ and $I_{season} = I_{winter}$ for houses 0 - 99 and $s = 1$, $w = 4$ and $I_{season} = I_{winter}$ for houses 100 - 199, resulting in heat demand profiles with two peaks (one around 7-10 am and one around 6-9 pm).

The results of the different scenarios for this use case are also compared using the imbalance. In this use case, the eventual imbalance is defined as the deviation from the predicted generation pattern:

```
for(int i=0;i<#timeIntervalsSimulated;i++)
        imbalance += (plannedProd[i] - actualProd[i]
                      + introducedImbalance[i])^2;
```

, where `introducedImbalance[i]` is the introduced imbalance in time interval `i`, `actualProd[i]` the actual production in time interval `i` and `plannedProd[i]` the planned production in time interval `i`.

## D.3 Combination of devices use case

This scenario compares scenarios with multiple smart devices in every house and one single steering signal for every house. The results of the different scenarios are also compared using the imbalance: the imbalance in this use case is defined as follows:

```
for(int i=0;i<#timeIntervalsSimulated;i++)
        imbalance += (average - consumption[i])^2;
```

, where `average` is the average consumption during the day and `consumption[i]` the total consumption at time interval `i`.

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