Acta Universitatis
Lappeenrantaensis
830

Nadezda Belonogova

ACTIVE RESIDENTIAL CUSTOMER IN A FLEXIBLE ENERGY SYSTEM — A METHODOLOGY TO DETERMINE THE CUSTOMER BEHAVIOUR IN A MULTI-OBJECTIVE ENVIRONMENT

LUT University

Nadezda Belonogova

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Thesis for the degree of Doctor of Science (Technology) to be presented with due permission for public examination and criticism in the Auditorium of the Student Union House at Lappeenranta University of Technology, Lappeenranta, Finland on the 5th of December, 2018, at noon.

Acta Universitatis
Lappeenrantaensis 830

Supervisor Professor Jarmo Partanen
LUT School of Energy Systems
Lappeenranta University of Technology
Finland

Reviewers Professor Matti Lehtonen
School of Electrical Engineering
Aalto University
Finland

Research Professor Kari Mäki
VTT Technical Research Centre of Finland Ltd
Finland

Opponent Research Professor Kari Mäki
VTT Technical Research Centre of Finland Ltd
Finland

ISBN 978-952-335-306-0
ISBN 978-952-335-307-7 (PDF)
ISSN-L 1456-4491
ISSN 1456-4491

Lappeenrannan teknillinen yliopisto
LUT Yliopistopaino 2018

Abstract

Nadezda Belonogova
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Lappeenranta 2018

135 pages
Acta Universitatis Lappeenrantaensis 830
Diss. Lappeenranta University of Technology
ISBN 978-952-335-306-0, ISBN 978-952-335-307-7 (PDF), ISSN-L 1456-4491, ISSN 1456-4491

The transformation from passive into active end customers in modern energy systems has already started in many European countries, and it is a long process. The first step to engage residential customers to be active actors is to demonstrate the benefits that active participation in demand response in electricity markets can provide.

The operating environment of electric power systems and markets is evolving. The value and need for flexibility is increasing as the climate change is pushing intermittent renewables into the electricity grid at all voltage levels. At the same time, requirements regarding the security and reliability of power supply, along with cost-efficient and sustainable solutions, are tightening. One way to cope with these pressures is to adjust the electricity consumption to the variable generation. That is why the role of a single residential customer will be invaluable in the future energy system. Flexibility is required in electricity markets and ancillary services of many kinds. These will be referred to as demand response marketplaces.

Active customers located in the changing operating environment face challenging decisions: what flexibility options do they have now and what should they have in the near future? When, at which price, and in which time should these flexibility resources be offered to the smart grid environment so that the customers will benefit most?

Here, the role of the regulatory framework is crucial to channel the residential demand response in a predicted way; to be specific, how to direct the active customer behaviour in a way that satisfies the interests of the customers and the involved stakeholders of the energy system.

To address the above questions, this doctoral dissertation aims to solve the complex decision-making problem of an active customer in the evolving operating environment. The main contribution of the work is the established methodology that can be implemented to any type of residential customer located in any operating environment. The proposed methodology is divided into two stages. The first stage determines the most promising demand response marketplaces for the end customer from a list of marketplaces. The second stage aims at defining the optimal operating strategy in the selected marketplaces. Thus, the methodology provides tools to solve the complex decision-making problem of a single customer in the environment of multiple demand response marketplaces.

Another contribution of the dissertation is the simulation tool created on the basis of the methodology. The input data used in the simulations consisted of the automatic meter reading (AMR) data of 10 000 residential customers located in the Nordic electricity market environment. The results of the simulation tool give indications of the customer behaviour in the near future. This, in turn, is an important input for regulatory and decision-making entities to provide the customers with demand response services that both meet their interests and satisfy the interests of the energy system and electricity market operators.

Keywords: active customer, conflict of objectives, decision-making, demand response, multi-objective, flexibility

Acknowledgements

The research work of this doctoral dissertation was carried out at the Laboratory of Electricity Market and Power Systems in Lappeenranta University of Technology. The study was supported by a grant from the Finnish Graduate School of Electrical Engineering (GSEE), Fortum Foundation, and the Foundation of the Association of Electrical Engineers **(**Sähköinsinööriliiton Säätiö).

It has been an honour to have an opportunity to participate in a set of research projects over the course of this work: Smart Grids and Energy Markets (SGEM) coordinated by CLEEN Ltd with funding from the Finnish Funding Agency for Technology and Innovation, Tekes, in 2010 - 2015; DR pool, Demand response – Practical solutions and Impacts for DSOs in Finland, 2013–2015; FLEXe, funded by several organisations and Tekes, the Finnish Funding Agency for Technology and Innovation in 2015–2016; Multi-objective role of a BESS in an energy system, 2016–2017 in cooperation with Fingrid, Helen Sähköverkko, Helen and Landis+Gyr; R4 project in cooperation with Järvi-Suomen Energia, Kymenlaakson Sähköverkko, PKS Sähkönsiirto OY, and Savon Voima Verkko, in 2017-2019. I wish to thank the projects' partners for the interest in my work. The funding from these projects is also gratefully acknowledged.

I express my deepest gratitude to my supervisor, Professor Jarmo Partanen for his guidance, support, encouragement, patience, and belief in me. Thank you for showing me the long-term vision and keeping me on the track, while giving me research freedom to open up my mind and realize my potential. I have always left your office with a feeling of satisfaction and motivation to go on.

I would like to thank Professor Samuli Honkapuro for the fruitful conversations and your support. I have always felt tuned to the same frequency with you when having discussions. This has contributed to my self-esteem and confidence in what I am doing.

I wish to thank the preliminary examiners, Research Professor Kari Mäki and Professor Matti Lehtonen for your valuable comments, your willingness to engage in the work and bring it further to the final stage.

I would like to extend my appreciation to Dr. Petri Valtonen and Dr. Jussi Tuunanen for the rewarding cooperation at LUT during your working years here.

I thank my colleagues Mr. Ville Tikka, Mr. Janne Karppanen, Dr. Juha Haakana, Mr. Arun Narayanan, and Mr. Jouni Haapaniemi for creating a pleasant and fruitful environment at work.

My heartfelt gratitude goes to Dr. Hanna Niemelä. I have always admired your optimism, patience, creativity, and perseverance in all spheres of your life. I am lucky to have you in my life. I am deeply thankful for your genuine interest in my work, not just from the language point of view. All remaining errors are my own.

I would like to thank my parents-in-law, Eero and Pirkko, my sisters-in-law Henna, Annika, Anna-Maija and my brother-in-law Hannu, for letting me be myself and feel at home in Finland from the very first moments.

I owe a lot to my friends Hanna Koponen, Taina Haakana, and Marina Ängeslevä. Thank you for those deep discussions that we have had. You are of immense importance to me.

Special thanks go to my parents Ekaterina and Andrey and brother Denis for support and encouragement. My departed brother Ilja, you always remind me of my true potential.

Above all, I want to express my deepest gratitude to Jukka for your everlasting support, patience, understanding, and love during this long journey. Without you, it would not have been possible to reach this goal.

I want to dedicate this doctoral dissertation to our brilliant children Olivia, 7 years and Oskar, 4 years. I hope your life will be better than the one of the previous generations.

Nadezda Belonogova
November 2018
Lappeenranta, Finland

Contents

Nomenclature

Latin alphabet

E	active energy
h	hour
P	active power
s	seconds
t	time
T	temperature
r	interest rate
t	tons

Greek alphabet

α	hourly indices
β	share of the appliance being ON
λ	binary variable
η	efficiency

Subscripts

0	initial
BPM	balancing power market
BESS	battery energy storage system
ch	charging
DA	day-ahead
dch	discharging
E	energy

EV	electric vehicle
EWH	electric water heater
HP	heat pump
max	maximum
min	minimum
Opex	operational expenses
P	power
PB	power band
PV	photovoltaic
Q	reactive power
RT	round-trip
SH	space heating
uncontr	uncontrollable

Abbreviations

AMR	automatic meter reading
BESS	battery energy storage system
BRP	balance responsible party
CO_2	carbon dioxide
DC	direct current
DR	demand response
DSO	distribution system operator
ES	electric storage
EV	electric vehicle
FCR	Frequency Containment Reserve

FCR-N	Frequency Containment Reserve for Normal Operation
HEMS	home energy management system
HV	high voltage
HVAC	heating, ventilation and air-conditioning
HVDC	high voltage direct current
ICT	information and communications technology
GHG	greenhouse gas
kW	kilowatt
LV	low voltage
MG	microgeneration
MOP	multi-objective problem
MV	medium voltage
NPV	net present value
OPEX	operational expenses
PB	power band
PV	photovoltaic
P2P	peer-to-peer
RES	renewable energy system
RPC	reactive power compensation
RTP	real-time pricing
SOC	state of charge
TCL	thermostatically controlled load
TSO	transmission system operator
VC	voltage control

1 Introduction

Traditionally in the electricity grid, the amount of generation has followed the consumption levels. In the past, less attention was paid to the climate change, energy resource availability, CO_2 emissions, and other environmental problems. However, this attitude is radically changing in the modern society. Our awareness of the consequences and impact of the careless use of our planet's resources has increased significantly over the last few decades. There is an urgent need to change our daily habits already today in order to provide a sustainable future for the next generations. In response to the environmental problems that we have created, solutions and remedies are emerging in different spheres of life such as water and waste management , the use of organic food and materials (sustainable food), and penetration of renewable energy resources with the purpose of gradual substitution of the traditional fossil fuel resources.

It is clear today that the future energy system will rely on renewable energy resources. This is the key solution to fight against the environmental problems mentioned above. With the increasing proportion of highly intermittent renewable energy sources in the power sector, flexibility requirements in the power system are becoming tighter. At the same time, societal, political, and technological changes are occurring in the operating environment, which will have an impact on many players including a single customer. The changes can be seen in residential electricity consumption, covering for instance higher energy efficiency, changes in heating solutions and micro generation, electric vehicles, and stationary battery energy storage systems (Tuunanen 2015).

The transformation from passive to active customers has already started in many European countries, and it is a long process. The first steps to engage residential customers to become active actors is to let them become aware of their energy use, offer them an opportunity to change their behaviour, and eventually, demonstrate the benefits that such a change can provide them. The dissertation presents triggers for a transition path of a single residential customer into an active customer in a smart grid environment. The role and potential of a single customer in a smart grid environment are addressed and the impact of active customers on market players and grid operators is analysed.

Further, this doctoral dissertation aims to establish a methodology that gives answers to the major questions of why, what, and how things should be changed on a single customer's premises in order to support a transition to a sustainable energy system of the future.

1.1 Main objective of the work

The main objective of the work is to develop a methodology to forecast a dynamic electricity load of a single residential customer in a smart grid environment. The dynamic electricity load means that the load profile of a single customer changes under various triggers within certain boundaries. Thus, the objective of the dissertation is to analyse what load-changing triggers are applied to the customer, and further, what the load profile of a single customer looks like after the triggers.

In the coming years, the customer's load profile will change as a result of various technological changes such as energy efficiency, microgeneration and battery storage solutions, sustainable geothermal heating solutions, electrified mobility, and home energy management systems (HEMS).

In addition to that, the changing operating environment provides a single customer with an opportunity to participate in different electricity markets such as spot market, balancing power market, and frequency-controlled reserve markets. These two factors will dynamically change the load profile of a single customer, which will have a further impact on the operating environment and the customers themselves.

The sub-objectives of the work are to

1. Analyse the technical and social aspects of a single customer's behaviour.
2. Mathematically formulate the problem of a single customer's flexibility resources in a smart grid environment.
3. Build a methodology to define the most promising electricity marketplaces and an operating strategy in them for a single residential customer.
4. Build a simulation tool to test numerous scenarios and carry out a sensitivity analysis.

1.2 Outline of the work

This doctoral dissertation is organized as follows:

Chapter 2 introduces the concept of an active customer. It describes both technical and social aspects of a single residential customer's behaviour at the present moment, and the ongoing changes on the end customer's premises and the operating business environment.

Chapter 3 mathematically formulates the problem of controlling multiple flexible resources on a single customer's premises against multiple demand response marketplaces.

Chapter 4 establishes a methodology to solve the complex problem by dividing the whole problem into two main stages. Stage 1 of the methodology is described in this chapter.

Chapter 5 provides the results of stage 1, which eventually serve as an input to stage 2 of the methodology.

Chapter 6 presents stage 2 of the methodology at the case-specific level.

Chapter 7 summarizes the results of stage 2, and provides the implications of the results for a single customer and the involved stakeholders.

Finally, **Chapter 8** draws conclusions of the obtained results and states the contributions of the doctoral dissertation. The further research questions are listed.

The structure of the dissertation is presented in Figure 1.1.

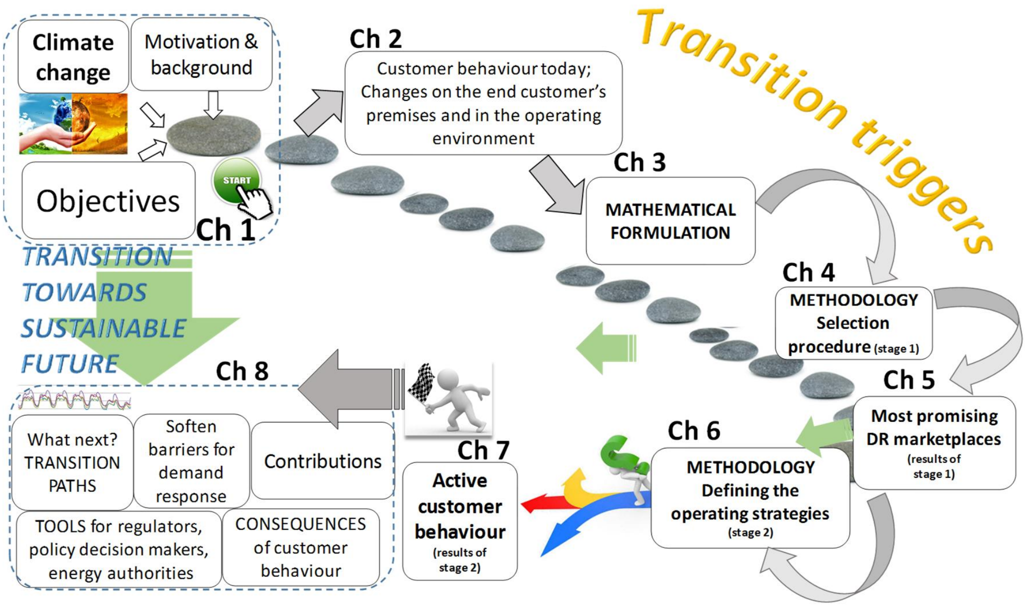

Figure 1.1. Transition triggers towards an active customer

1.3 Scientific contributions

The scientific contributions of the doctoral dissertation can be summarized as follows:

1. The complexity of the problem of a single residential customer's flexible energy resources in multiple demand response (DR) marketplaces is shown through the mathematical formulation of the problem.

2. A methodology to solve the problem is established. The methodology is not fixed to any specific environment and is thus suitable for any type of customer and DR marketplace.

3. As a result of the methodology, a simulation tool is built which is made flexible for the input parameters and thus allows to test numerous scenarios by varying the parameters. Furthermore, it enables to run a sensitivity and risk analysis, and thus,

identify possible risks and opportunities related to the operation in multiple DR marketplaces.

4. The results obtained from the methodology and the simulation tool allow to understand the conflict of objectives arising when the active customer is involved in multiple DR applications. Such information is important for the policymakers, regulators, and energy authorities, especially in the era of the evolving operating environment, changing customer behaviour and a need of creating new marketplaces, mechanisms, and drivers for a transition towards a sustainable energy system.

In addition, the following publications have been written in the course of writing the doctoral manuscript:

1. Belonogova N., Lassila J., and Partanen J. (2010), ”Effects of Demand Response on the End-Customer Distribution Fee,” in *CIRED Workshop 2010*, France.
2. Belonogova N., Lassila J., and Partanen J. (2010), “Effects of Demand Response on the Distribution Company Business,” *NORDAC Conference 2010*, Aalborg, Denmark.
3. Belonogova N., Kaipia T., Lassila J., and Partanen J. (2011), “Demand Response: Conflict between Distribution System Operator and Retailer,” *CIRED 2011*, Frankfurt, Germany.
4. Auväärt A., Rosin A., Belonogova N., and Lebedev D. (2011), “NordPoolSpot price pattern analysis for households energy management,” in *Proceedings of the 7th International Conference-Workshop Compatibility and Power Electronics, CPE 2011*.
5. Belonogova N., Valtonen P., Tuunanen J., Honkapuro S., and Partanen J. (2013), “Impact of Market-based Residential Load Control on the Distribution Network Business,” *CIRED 2013*, Stockholm, Sweden.
6. Belonogova N., Haakana J., Tikka V., Lassila J., and Partanen J. (2016), “Feasibility Studies of End-Customer's Local Energy Storage on Balancing Power Market,” *CIRED 2016*, Helsinki, Finland.
7. Belonogova N., Tikka V., Honkapuro S., Lassila J., Partanen J., Heine P., Pihkala A., Hellman H-P., Karppinen J., Siilin K., Matilainen J., Laasonen M., and Hyvärinen M. (2018), “Multi-objective role of BESS in an energy system,“ *CIRED Workshop 2018*, Ljubljana, Slovenia.
8. Belonogova N., Tikka V., Haapaniemi J., Haakana J., Honkapuro S., Partanen J., Heine P., Pihkala A., Hellman H-P., and Hyvärinen M. (2018), “Methodology to define a BESS operating strategy for the end-customer in the changing business environment,” in *the 15th International Conference on the European Energy Market*, Poland, 2018.

9. Belonogova N., Tikka V., Honkapuro S., Lassila J., Haakana J., Lana A., Romanenko A., Haapaniemi J., Narayanan A., Kaipia T., Niemelä H., and Partanen J (2018). *Final report: Multi-objective role of battery energy storages in an energy system*, LUT 2018.

The author has also been a co-author in the following publications on the closely related topics:

10. Järventausta, P., Repo, S., Trygg P., Rautiainen, A., Mutanen, A., Lummi K., Supponen, A., Heljo, J., Sorri, J., Harsia, P., Honkiniemi, M., Kallioharju, K., Piikkilä, V., Luoma, J., Partanen, J., Honkapuro, S., Valtonen, P., Tuunanen, J., and Belonogova N. (2015), *DR-pooli; Kysynnän jousto – Suomeen soveltuvat käytännön ratkaisut ja vaikutukset verkkoyhtiöille*, [DR pool; Demand response – Practical solutions and Impacts for DSOs in Finland], in Finnish, Research report
11. Haakana, J., Tikka, V., Tuunanen, J., Lassila, J., Belonogova, N., Partanen, J., Repo, S., and Pylvänäinen, J. (2016), "Analyzing the effects of the customer-side BESS from the perspective of electricity distribution networks" in *2016 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, Ljubljana, Slovenia.
12. Haakana, J., Tikka, V., Lassila, J., Tuunanen, J., Partanen, J., and Belonogova, N. (2016), "Power-based tariffs boosting customer-side energy storages" in *CIRED Workshop 2016*.

2 Concept of an active customer

As a starting point on the path illustrated in Figure 1.1, this chapter aims at giving answers to the following questions:

1. How can a single customer's behaviour be described today (2018)?
2. What changes are taking place on a single customer's premises?
3. What changes are occurring in the operating environment?
4. How can changes on a customer's premises be allocated to the changes in the operating environment?

2.1 Customer behaviour in the late 2010s

As it was stated in the introductory chapter, the amount of generation has traditionally followed the consumption levels in the electricity grid. In practice, this means that the consumption is given the freedom to remain as it is, while the generation is adjusted to the consumption levels. In particular, this concerns the residential consumption. Some large industrial and commercial customers participate already today in demand response programs offering their flexibility to various needs of the power system. However, in the residential sector, the customer has been passive until recently.

One of the reasons for the passive behaviour, along with the lacking incentives to activate it, is the diversity of residential electricity consumption, which poses challenges to quantify the flexibility of consumption. There are many types of electricity customers with various consumption patterns. Because of the wide variety of individual customers, a single residential customer's behaviour is a complicated issue to model and analyse. Numerous factors affect a single customer's load profile such as:

1. Weather,
2. Length of daylight,
3. Type of load,
4. Type of house, insulation,
5. Heating area, heating type,
6. Number of household members, working shifts,
7. Consumption habits, educational background, and
8. Green values, environmental concerns.

Over the past few decades, modelling of residential consumption has been given much attention in the literature both at a single customer (Paatero and Lund 2006), (Sadeghianpourhamami 2016), and appliance level (Paull 2010; D'hulst 2015). The models are applied by policy makers, energy suppliers, and energy service companies to define new policies and tariffs and provide new services for the customers. In addition, the distribution system operators also take advantage of residential load models for network planning and operating purposes (Tuunanen 2015), while the electricity retailers use the models to improve the bidding strategies in the wholesale markets and maximize the portfolio (Valtonen 2015).

In Finland, starting from 1 January 2014, every single residential customer is equipped with an AMR meter. This means that a lot of AMR measurement data will be available in the residential sector in the coming years. This is an important milestone in the history of the electricity power system. From now on, there is a vast potential not only to understand the customer behaviour but also to control it. In this regard, there is an urgent need to know how we can benefit from AMR data (Yildiz 2017). Thus far, AMR data have been used for instance for customer billing purposes and fault detection. For research purposes, the AMR data provide a solid base to:

- improve the accuracy of short-term load forecasting (Niska 2015),
- define the various clusters of residential customers (Mutanen 2011),
- estimate flexibility potential (Ponoćko and Milanović 2018), and
- identify which customers are eligible for demand response programs (Martinez-Pabon 2017).

That being said, today we know better than ever the various types and load profiles of residential customers, and even flexibility and controllability of individual appliances.

However, the customer electricity consumption behaviour is not defined by technical aspects only. It is also the behavioural aspects that shape the choices of the end customers and thereby define for what, when, and how much they consume electricity. The role of the human behaviour is also emphasized in (Pfenninger 2014), which focuses on modelling the energy systems of the twenty-first century.

The challenge related to the social aspects is that they are not only dependent on a single residential customer, but also on all market actors in the operating environment. Here, a mutual interaction takes place in the sense that a single customer’s behaviour is shaped by the environment, and eventually, the environment is influenced by the customer behaviour (Figure 2.1).

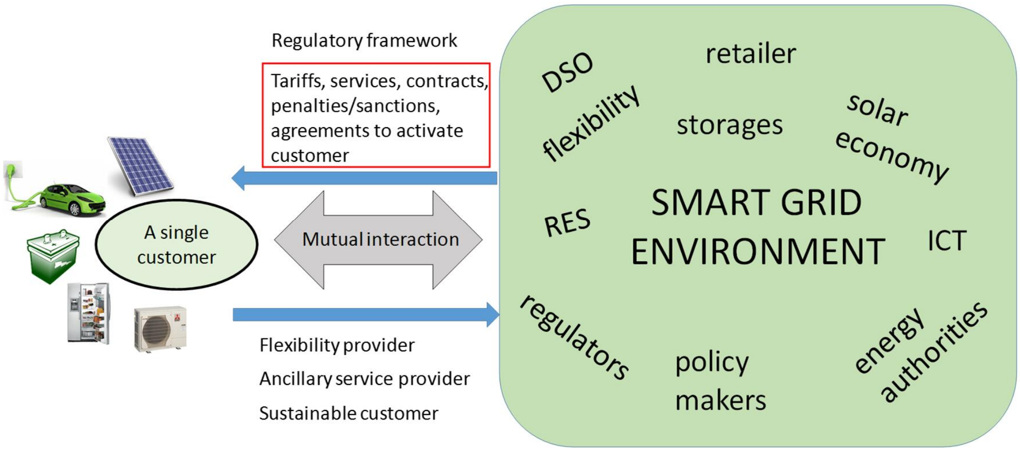

Figure 2.1.Mutual interaction between a single customer and a smart grid environment

For this reason, defining a customer behaviour is a very complicated task in practice. It not only requires modelling of the customer's end-use consumption but also taking into account the political, technological, economic, and environmental aspects of the environment the customer belongs to, and finally, estimating the choices that the customer is likely to make. Some examples of the choices are:

- switching from district heating to a ground source heat pump,

- acquisition of low-carbon technology (solar PV, stationary BESS, EV, heat pumps),

- switching the retailer,

- buying green energy,

- switching to another tariff, and

- sustainable behaviour.

The social aspects of a single customer's behaviour not only affect his/her load profile both in the short and long term, but they may also shape the load profile of the community the customer lives in. That way, for instance, local energy communities emerge, peer-to-peer energy markets are established, and microgrids are developed to enable such mechanisms.

To conclude, today, we can better understand the technical aspects of the customer behaviour for instance by exploiting the benefits of AMR data. Further, in addition to the technical aspects, this section discussed the social aspects and their role in shaping the customer behaviour. The next section focuses on how the changes on a single customer's premises are aggregated into the hidden flexibility potential and what the challenges related to load control on the residential customer's premises are.

2.2 Changes on a single customer's premises

The changes in the electricity use at the end customer level have been extensively described and discussed in (Tuunanen 2015). The major changes are enhanced energy efficiency and an increasing rate of microgeneration (namely, solar PV installations) in the LV networks (NREL 2016).

At the end customer level, many changes have taken place regarding the heating solution, installation of solar PV panels, and electric vehicle acquisition. In the literature, attempts have been made to distinguish the changes and estimate their impact on the energy stakeholders. For instance in (Chen 2015), a method has been developed to detect changes in the customer behaviour and when they have occurred (in which week of the year). Furthermore, the impact of heat pumps on the load profile has been modelled in (Laitinen 2011).

The changes have been driven by climate change, political decisions, and sustainability goals, pushing to develop new approaches for a transition to low fossil carbon societies (Suzuki 2016). A significant amount of research has focused on the effects of low-carbon technologies such as solar PV and electric vehicles on the CO_2 emissions (Barisa 2015), which further drive the changes.

However, such low carbon solutions do not exert only positive impacts on the environment. In fact, there are both risks and opportunities that such solutions on the end customer premises offer for the operating environment. The risks are related to the changing load profiles. The research in (Tuunanen 2015) addressed the impacts of future technologies on the energy and power levels. The general trend is that the power levels will likely increase whereas the energy levels will remain approximately at the same level, which, in turn, poses challenges to the DSO business and distribution grids.

Another challenge is the increasing rate of solar PV installations in the distribution grid, which puts stress on the network in terms of voltage quality and overloading. Consequently, the need for flexibility in the distribution grid is growing.

On the other hand, the flexibility of such entities as solar PV, batteries, and heat pumps is much better than that of traditional home appliances in terms of reaction time, accuracy, and responsiveness to the control signal. The flexibility of residential consumption has become one of the central issues in the topic of sustainability and smart grids over the last few years (D'hulst 2015; Gottwalt 2017; Sadeghianpourhamami 2016).

However, the major challenge with the residential load control lies in the rebound, or the payback effect. This phenomenon occurs after the load control event, and reflects the peak power when the residential loads are restored back to the normal operation. In the worst case, the payback effect may totally cancel the benefit of load control. Moreover, it can jeopardize the market and power system operators.

In Finland, direct load control of space heating loads was carried out already in the 1980s, when monopolistic utility companies had an incentive to avoid high peak powers. At the time, the load control was carried out based on the structure of the wholesale market and not based on the needs of the electricity grid. According to the wholesale tariff for electricity in 1987, peak powers were much more expensive than base and middle level powers, costing about 30 €/kW (Martikainen 1987). If the annual peak power exceeded the level of the previous year, the company had to pay a higher rate for electricity procurements for a number of years ahead unless the load level approached the peak power level. Therefore, utilities had a strong motivation to avoid new peak powers. Space heating load control has demonstrated significant potential to cut peak powers during cold winters, and it has delivered financial benefits. However, after the liberalization of the electricity markets in 1995, the retail and distribution sectors have been separated, and as a result, the DSOs' business is not dependent on electricity procurements anymore. The structure of the wholesale market changed from capacity-based payments to energy only payments, and the incentive for direct load control of space electric heating disappeared.

Owing to the undesired effects of the payback (or load response) after the load control event on both the power system and market operators, there have been attempts to model this phenomenon in order to make it predictable and thus manageable.

Responses of direct load control of electric heating loads were modelled in (Koponen 1997) using the measurements of direct load control tests carried out in winter 1996–1997 in three utility companies and using the simple physical models introduced in (Martikainen 1987). These models were also used in (Koponen 2006) for the optimization of control responses of full storage electric heating loads. Further, an overview of direct load control tests in the Scandinavian countries and dynamic load response modelling was presented in (Koponen 2012).

As the studies show, the payback has been modelled by using field test measurements of direct load control events. Furthermore, it is not only challenging to model load response without having such data but also to do this for a single end customer instead of an aggregated group of customers.

The good news is that the payback in an individual house equipped with automation control devices is not an uncontrollable phenomenon anymore. On the contrary, the payback profile can be adjusted to the objectives set by the end-user, such as minimization of power, energy and/or end user's comfort, or minimization of electricity cost.

This is yet another reason why it is a complicated task to model the response at a single customer level. Such a multi-objective load response optimization problem is beyond the scope of this doctoral dissertation. Instead, low-payback and high-payback energy scenarios are suggested as a possible approach to model the load response at a single customer level.

In the high-payback energy scenario, the payback energy is fully recovered at once as fast as possible, in other words, in the following hour, all payback energy is recovered (Figure 2.2).

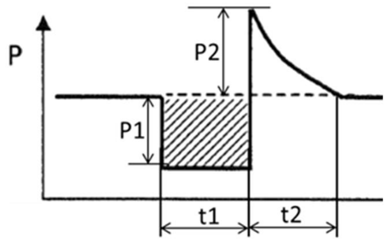

Figure 2.2. High-energy payback scenario (Martikainen 1987)

In the low-payback energy scenario, the payback energy is gradually recovered during the two or three following hours (Figure 2.3). This way, the payback energy and its impact are distributed among several hours.

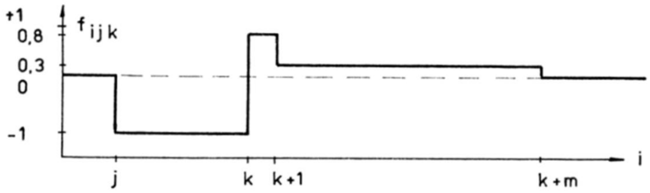

Figure 2.3. Low-energy payback scenario (Tamminen and Aho-Mantila 1979)

The duration of the load control will be limited by the customer comfort preferences, which mainly depend on the outdoor and indoor temperature.

This chapter discussed the changes taking place on the end customer's premises and briefly covered the hidden flexibility potential in the residential consumption and the payback challenge related to it. Thereby, the changes, opportunities, and challenges associated with a single customer's behaviour were covered.

These discussions bring us to the next step. Now, it is time to have a look at changes taking place in the operating environment where the single customer is located. In particular, the focus is on identifying and analyzing the major goals, interests, and challenges in the emerging flexible energy system. The next section provides the reasons for the need for changes in the operating environment from the viewpoint of energy stakeholders such as a DSO, a TSO, and a retailer.

2.3 Changes in the operating environment

The smart grid environment is emerging (Bayindir 2016; de Reuver 2016; Tricoire 2015). The global aim of the electricity power system and market players is to facilitate a sustainable and resilient smart grid environment with a high proportion of intermittent renewable energy resources as part of the least-cost solution for every involved party (Spiliotis 2016). The main challenge of the transition from traditional to a smart grid environment is the increasing need for flexibility resources to back up the intermittent energy resources (Eid 2016; Ela 2016; Alizadeh 2016; Papaefthymiou and Dragoon 2016).

Four evolutions cause an increasing need for flexibility in the electricity system. Firstly, the proportion of intermittent renewable energy is growing. Secondly, renewable electricity generation is increasingly injected into the electricity system in a decentralized manner. Thirdly, an increase in the electrical load is expected, caused by a shift from fossil-fuelled systems toward highly efficient electrical equipment for transport and heating (European Commission 2017). Fourthly, the number of traditional fossil-fuel based power plants is (European Environment Agency 2016). As a result of the combination of these four evolutions, maintaining the electricity power balance while respecting electricity grid constraints is becoming increasingly challenging (Cossent 2009). One of the ways to cope with the above-mentioned evolutions is demand response (Albadi and El-Saadany 2007).The need for flexibility in the smart grid as part of the least-cost solution means that the already available energy resources in the electricity grid have to be utilized at their full capacity. Single residential customers possess such promising flexibility resources.

The role of a single customer as a flexibility provider will be significant in the sustainable smart grid environment. The local flexible energy resources on the single customer's premises compete with the other flexibility options such as interconnectors, energy storage, commercial and industrial demand response, flexible generation, and back-up generation. For instance, interconnectors enable electricity transmission from an area with a surplus of electricity to an area with a deficit of electricity, and can thus satisfy the need for energy or power in that area. These connections can be for example HVDC (high-voltage direct current) interconnectors, DC (direct current) links, sea cables, or high-voltage overhead transmission lines.

In addition to these options, distribution network operation and electricity market rules have an impact on which flexibility options are activated and when.

For instance, one of the major coming changes in the distribution business environment is the shift from the energy- to the power-based tariff. The motivation behind introducing the power-based tariff in the residential sector is justified by the following reasons:

1. To cover the cost of distribution network operation and maintenance when the energy consumption decreases and power consumption increases in the residential sector as a result of enhanced energy efficiency, increasing amount of solar PV

installations, and other technological changes in the end customer premises (Tuunanen 2015; Honkapuro 2014).

2. To create motivation for the end customers to change their consumption behaviour in a beneficial way for the customers themselves, the distribution network, the DSO's business, the retailer, and other market and grid players in order to maximize the social welfare in the long term (Koliou 2015).
3. To solve the conflict of interests that a market-based demand response creates for a distribution network when flexible energy resources are activated according to electricity market-based incentives (day-ahead, balancing, frequency regulation markets) (Belonogova 2013).

As it was described in Section 2.2, direct load control was carried out in Finland already in the 1970–80s with exactly the same purpose of keeping the load consumption in the distribution network under the predefined level as a result of the peak power-based tariff structure in the utilities. In the coming years, a similar tariff will be imposed on end customers, meaning that the DSOs transfer the responsibility to the end customers. It also means that the end customers are given more freedom and choice in their actions.

The need for flexibility in the energy system calls for creation of new demand response (DR) marketplaces for small end customers. That is to say, the already available marketplaces for power generation plants and large industrial and commercial consumers should be made equally accessible also for the small residential customers in order to harness the residential flexibility. The possible DR market places are a day-ahead market, intra-day, balancing power market, frequency regulation service, peak load management, and greenhouse gas (GHG) emissions trading (to provide consumers financial incentives to reduce their carbon footprint).

Each demand response market can be characterized by a quantitative characteristic or attribute, such as:

- day-ahead market—volatility and price level,
- balancing power market—volatility and price level,
- frequency regulation service—requirements for response rate (droop function),
- power-based tariffs in the distribution system—price of kW, and
- GHG emissions trading—carbon tax.

These descriptive parameters may change in the future to the higher and the lower boundary. Depending on which combination of values/characteristics is used in the demand response analyses, a single customer's behaviour will vary correspondingly, which eventually has an impact on the definition of the role of a single customer (Figure 2.4).

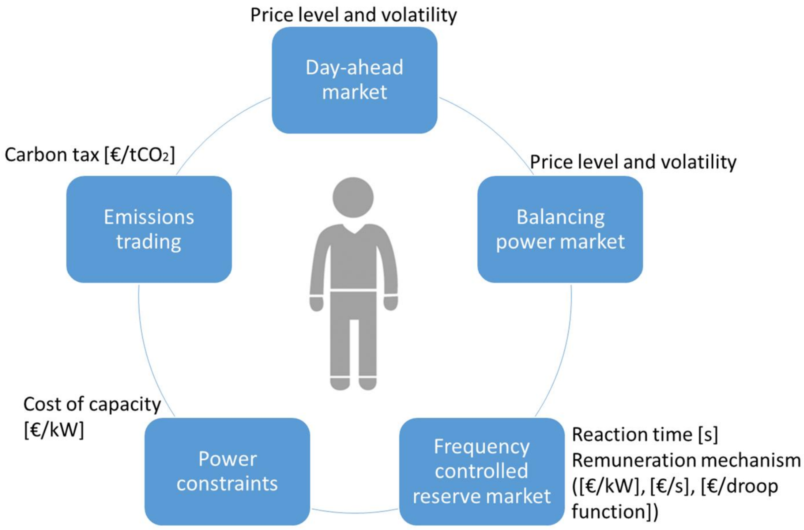

Figure 2.4. DR marketplaces and their attributes that affect customer behaviour.

For instance, a high price of kW for a single customer will create strong incentives for a customer to keep the consumption under the predefined level. This, in turn, limits the earning potential in the other DR markets such as day-ahead, balancing, and frequency reserve, and thereby lowers the participation rate of the customer in these applications (from here onwards, the term 'application' is used to refer to the activity exercised in a DR marketplace, such as energy arbitrage, frequency regulation, or peak shaving). However, if the prices in either of the markets are attractive for the customer and comparable with the cost of shifting to a higher power band level, then the chances of participation are better.

The above-listed attributes are included in the simulation tool developed further in the doctoral dissertation. The tool easily allows to change these parameters and thus simulate numerous scenarios, and also analyse changes in the customer behaviour.

2.4 Allocation of end customer flexibility resources to demand response services

The previous sections have shown that changes in the operating environment create new DR markets, whereas changes on a single customer's premises produce new flexibility options in electricity consumption.

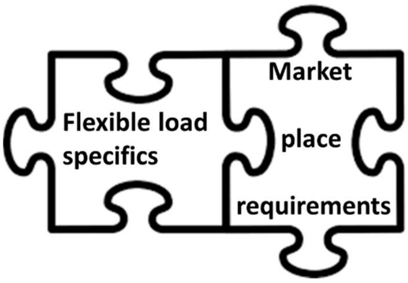

Figure 2.5. Principle of flexibility resource allocation to demand response marketplaces

Reasonable allocation of flexibility resources to the right applications requires:

a) On one side, definition of the requirements of the marketplaces where demand response services are offered, see Table 2.1.

Table 2.1. Requirements of demand response places.

DR place	Response time	Duration of DR
Day-ahead market	24h	1 hour
Balancing power market	15 min	1 hour
FCR (Frequency Containment Reserve) market	seconds	seconds, minutes
Network constraints	hours (load forecasting time window)	hour

a) On the other side, listing the end-user's flexibility resources and their characteristics in terms of response time, duration of the DR event, availability, and payback phenomena. In Table 2.2, the main load groups and appliances are listed with such load control characteristics as response time, duration of the DR event, payback, and availability. For instance in Finland, the stored electric space heating loads have typically been switched on during cheaper night-time hours according to the night-time tariff, which has been used by approximately half a million customers. However, according to the recommendations presented in (Pahkala 2018), the night-time tariff should be gradually eliminated in Finland by 30 April 2021, leaving thus space for a market-based, more dynamic load control.

Table 2.2. Characteristics of end-user flexibility resources.

Flexibility resource	**Response time**	**Duration of DR event**	**Payback**	**Availability**
Direct electric space heating	fast	minutes, depending on Toutdoor	yes	depending on Toutdoor
Stored electric space heating	fast	hours	yes	nights / in the coming years also days
Electric water heater (EWH)	fast	short	yes	nights
Refrigerator	fast	short	yes	according to the duty cycle
Heat pump	fast	short	yes	during use
BESS	fast	long	no	according to SOC levels
EV	fast	short/long	no	according to usage

b) Linking the flexibility resources to the demand response applications so that the appliance characteristics meet the requirements of the applications (Table 2.3).

Table 2.3. Allocation of end-user flexibility resources to demand response places (example).

DR place	**Flexibility resource**
day-ahead market	space electric heating, EWH , BESS, EV (Kahlen 2018),
balancing power market	space electric heating (M. Ali 2015), BESS, EV, EWH
FCR market	space electric heating, refrigerator, heat pump, EV, BESS (R. Ali 2014; Lakshmanan 2016; Xu 2014; Tindemans 2015)
power constraints	space electric heating, EWH, BESS, heat pump, solar PV

2.5 Conclusions

This chapter aimed to show the customer behaviour at the moment, the main challenges related to residential load control, and changes taking place on the end customer premises and in the operating environment.

The motivation behind the decision to focus on a single customer is based on the following objectives:

- to promote awareness among the energy stakeholders about a single customer's behaviour in the future flexible energy systems and the factors affecting it,
- to increase awareness of the end customer of potential multiple revenue streams,
- to engage the customer in providing flexibility services,
- to maximize the utilization rate of the residential flexibility options,
- to contribute to a sustainable and cost-efficient energy system, and
- to generate an environmental impact.

The factors that affect the customer behaviour and its impact on the system cost are summarized in Figure 2.6.

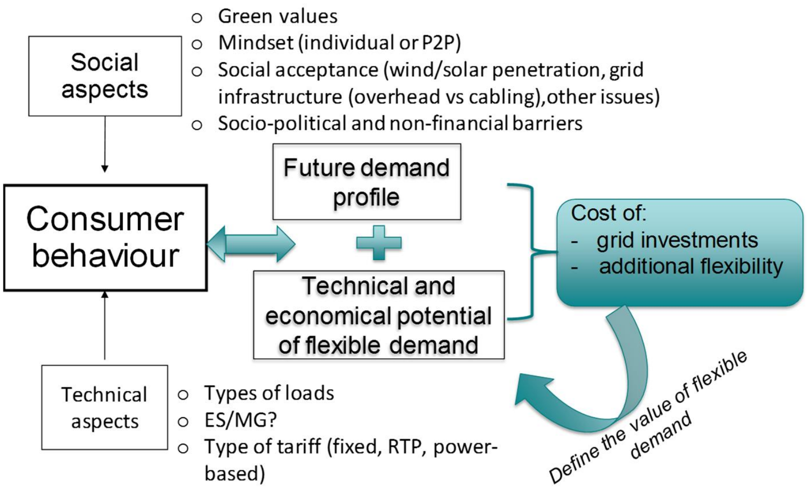

Figure 2.6. Creation of the consumer behaviour value chain

The figure above shows that the end consumer behaviour produces value to the energy system in the form of additional flexibility. This, in turn, has an impact not only on the operating environment such as investments in the electricity grid infrastructure or alternative flexibility options but also on the customers themselves. Therefore, the motivation behind the analysis of a single customer's behaviour is to understand how customers can use their flexibility so that both their interests and those of the involved energy stakeholders are met. The first step towards understanding such a complex value creation chain is to come down to the level of a single customer and mathematically formulate the problem (Figure 2.7), which is done in the following chapter.

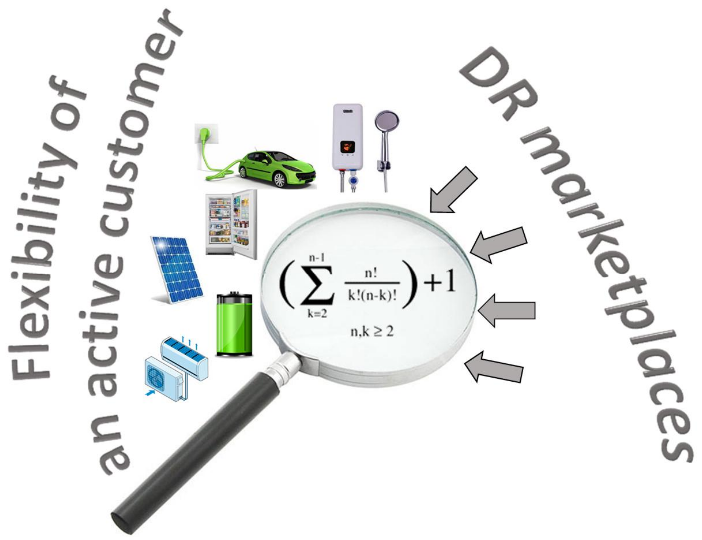

Figure 2.7. Active customer in the operating environment

3 Mathematical formulation of an active customer's decision-making problem in multiple demand response markets

The decision-making problem contains a customer with multiple flexibility resources such as controllable loads, BESS, EV, solar PV panels, and an operating environment with multiple DR marketplaces (as presented in Figure 2.4). The question is what decisions a single customer makes on how much flexibility, when, and to which market he offers it. The challenge here is the uncertainty, stochasticity, and multi-objective nature of the problem. The uncertainty is related to both a single customer (availability of the loads and their short-term behaviour) and the DR marketplace (prices, control signals). Control signals coming from the markets to the end customer are, for instance, to decrease or increase the consumption (energy or power) in a certain time period.

The major objective of this chapter is to show the complexity of the decision-making problem of an active customer without solving it. In our example case, a customer has multiple flexible resources such as a heat pump, an electric water heater, a space heating load, a BESS unit, an electric vehicle (EV), and solar PV panels on the rooftop.

As DR marketplaces, both energy-based and power-based markets are considered. In the energy-based market, the trading commodity is active energy whereas in the power-based market the trading commodity is power. The Nordic electricity market environment is used as an example for the mathematical formulation of the problem in this chapter. To this end, the day-ahead Elspot, the real-time balancing power, and the FCR-N hourly markets are considered in the formulation. However, this mathematical description is not fixed to the chosen case environment and can be applied to any other environment with different sets of customers and DR marketplaces.

3.1 General formulation

The algorithms for multi-objective optimization of residential electricity consumption found in the literature usually take into account conflicting local (end customer level) and global parameters (DR marketplace) such as maximizing the customer comfort and minimizing the electricity cost (see Appendix A).

However, the multi-objective problem in this doctoral dissertation addresses not only the relationship between local and global parameters but also the relationship between control signals coming from multiple applications (see Figure 3.1).

Figure 3.1 illustrates 15 multi-objective problems (MOP), which result from the participation of a single customer in five marketplaces. In each of the marketplaces, the customers have objectives of their own, such as minimization of the total cost or maximization of profit. At the same time, the customers also have objectives of their own to maintain the comfort level. When the customer participates in one marketplace, two objectives are activated: the customer's comfort and the goal in the marketplace. However, when the customer participates in two marketplaces, three objectives have to be activated. In addition to that, the arrows between the objectives illustrate the relationship between them: the objectives can be conflicting or non-conflicting depending on various factors.

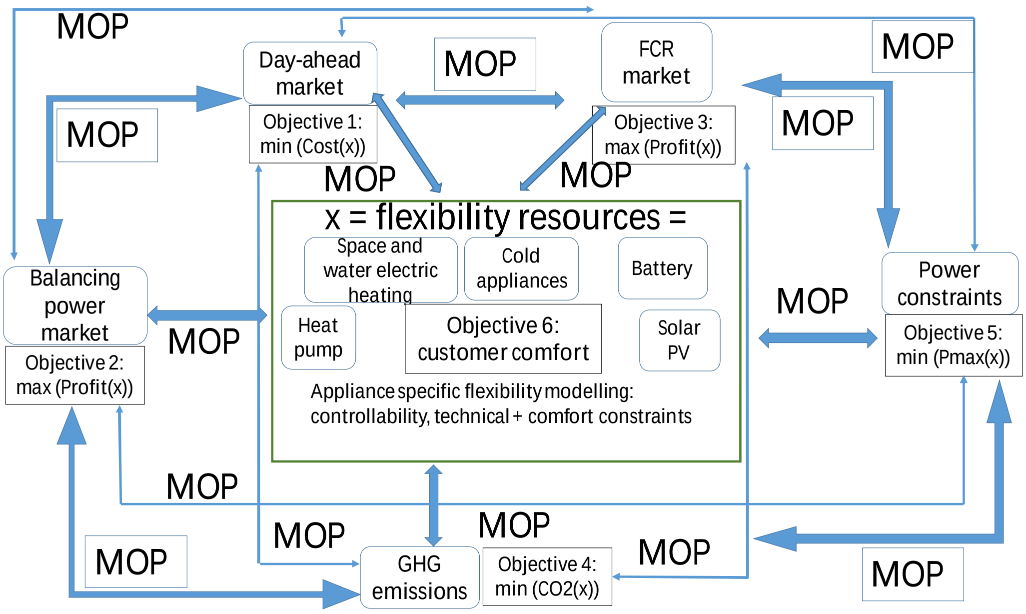

Figure 3.1. 15 multi-objective problems (MOP) of a single customer offering resources to multiple demand response services.

Therefore, it is a complicated task to solve such a multi-objective problem at once, in one iteration. There are no ready codes, libraries, or software tools available for the combination of all control signals presented in the previous section, neither there is any ready solution for this problem yet. The doctoral dissertation aims at bridging this gap.

The general mathematical formulation of the optimization problem presented in Figure 3.1 is given as a multi-objective optimization problem with five objective functions:

$$F = \min[f1(x_E), f2(x_E), f3(x_P), f4(x_E), f5(x_E), f6] \tag{3.1}$$

where x_E represents flexible energy resources on a single customer's premise, for instance:

$$x_E(t) = E_{HP}(t) + E_{EWH}(t) + E_{SH}(t) \pm E_{BESS}(t) \pm E_{EV}(t) - E_{solar\ PV}(t) \tag{3.2}$$

The components of (3.2) are:

t	time step
$E_{HP}(t)$	energy consumption of a heat pump
$E_{EWH}(t)$	energy consumption of an electric hot water heater
$E_{SH}(t)$	energy consumption of space electric heating loads (direct or fully stored)
$E_{BESS}(t)$	energy (charging or discharging) of a battery energy storage system (stationary)
$E_{EV}(t)$	energy (charging or discharging) of an electric vehicle
$E_{solar\ PV}(t)$	energy generated from solar PV panels

Finally, x_P represents flexible power resources such as thermostatically controlled loads (TCL), for instance a refrigerator's power consumption, and the charging/discharging power of a BESS unit.

The objective functions of (3.1) are:

1. $f1(x_E)$ – electricity cost minimization in the day-ahead market

$$f1(x_E) = \min[Cost(x_E)] = \min \sum_T Price(t) * (E_{uncontr}(\mathrm{t}) + x_E(\mathrm{t})) \tag{3.3}$$

2. $f2(x_E)$ – profit maximization in the balancing power market through energy arbitrage

$$f2(x_E) = \max[Profit(x_E)] = \max \sum_T \Delta Price(k) * x_E(t) \tag{3.4}$$

   where k is the number of times that the energy arbitrage was exercised in the market over the time period T and $\Delta Price(k)$ is the price difference of the energy arbitrage event k.

3. $f3(x_P)$ – profit maximization in the hourly FCR markets

$$f3(x_P) = \max[Profit(x_P)] = \max \sum_T \left(Price(t) * x_P(t)\right) \tag{3.5}$$

4. $f4(x_E)$ – power constraints on the end customer's premises (for instance, a power band). The objective is to minimize the annual cost of electricity purchased at a power-based tariff, which eventually results in minimization of peak power (on a weekly/monthly/yearly basis)

$$\begin{aligned} f4(x_E) &= \min[Pmax(x_E)] \\ &= \min[(E_{uncontr}(\mathrm{t}) + \mathrm{x_E}(t)) * C_p + \mathrm{E} * C_E] \end{aligned} \tag{3.6}$$

   where C_p and C_E are the power- and energy-based components of the end customer's retail tariff.

5. $f5(x)$ – minimization of greenhouse gas emissions caused by electricity consumption of a single household. This function results in minimization of the cost of electricity on which, for instance, a carbon tax is levied.

$$f5(x) = \min[CO_2] = \min(Cost(x)) \tag{3.7}$$

This objective function will be left out of the further consideration in this doctoral dissertation.

6. $f6$ – the objective to keep the comfort level of the end customer. This objective can be broken down into the following sub-objectives:
   a) keep security of supply,
   b) keep the indoor temperature in the interval set by the customer, for instance, by programming the cooling and heating devices accordingly,
   c) keep CO_2 at an acceptable level in the house,
   d) make hot water available when needed,
   e) make an EV available for the use when needed, and
   f) keep the battery state of charge (SOC) levels within the allowed limits

Before going into more detailed mathematical formulation, the main issues related to the decision-making problem of a single customer in multiple DR marketplaces will be discussed in the next section.

3.2 Decision-making: implicit vs. explicit demand response

The decision-making procedure can be technically applied for instance through a home management energy system (HEMS). The HEMS database can be divided into four main sections: customer's settings, flexible resources, and customer- and aggregator-driven applications (see Figure 3.2). The customer's settings represent the associated objectives and requirements. The section about flexible resources reflects the flexibility potential of the customer by providing information not only about which flexibility entities the customer has but also to which DR marketplaces they are contracted. Aggregator-driven applications represent the explicit demand response whereas customer-driven applications reflect the implicit demand response (Stromback 2017).

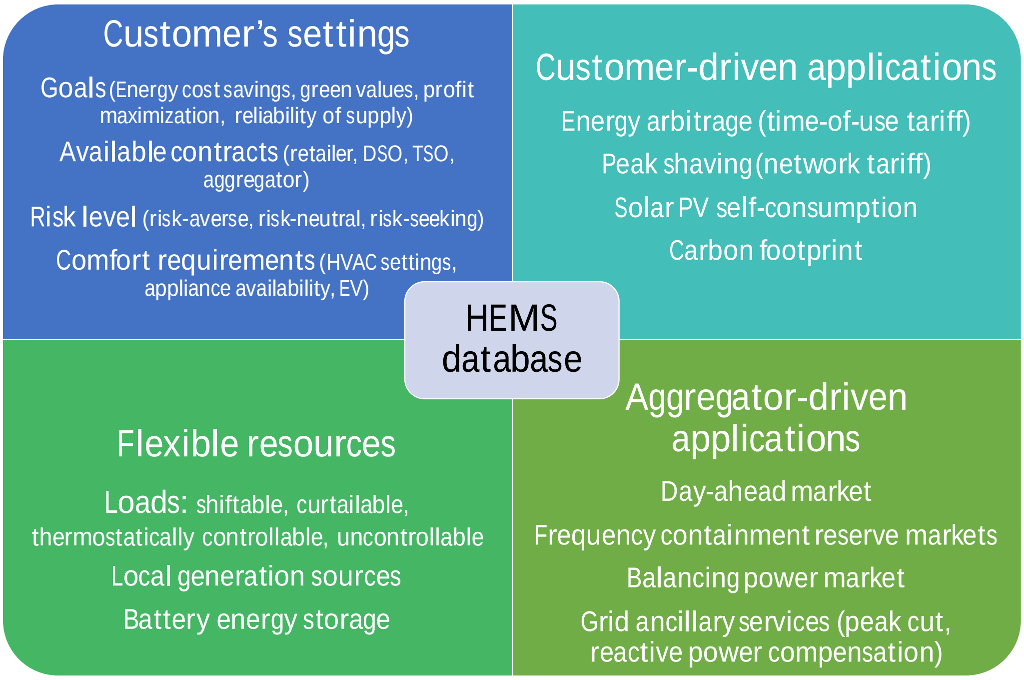

Figure 3.2. Structure of the HEMS database

A single customer can participate independently or through an aggregator party in DR marketplaces. In this regard, a decision-making process is divided into two mutually dependent parts: a customer-driven decision-making tool and an aggregator-driven decision-making tool (see Figure 3.3). These two units should be running in parallel and they affect each other's decisions.

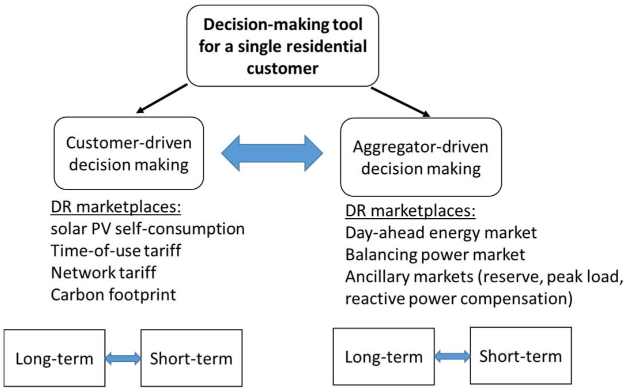

Figure 3.3. Interdependence between customer-driven and aggregator-driven decision-making tools

A customer-driven decision-making tool allocates the customer's flexible resources to applications where the customer can participate independently. An aggregator-driven tool allocates the resources to system-level applications (Figure 3.4). Information about the availability of the resources is constantly updated in both of the decision-making tools.

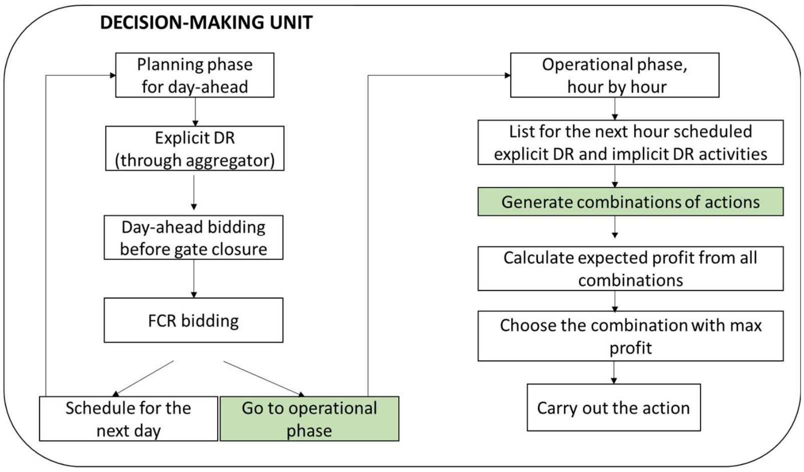

Figure 3.4. Decision-making logic of the HEMS

In order to develop a decision-making tool, the relationship between implicit and explicit demand response should be analysed. The specific details of explicit demand response and their impacts on the implicit demand response as well as their conflicting nature depend on the following issues:

1) Contract terms with the aggregator/supplier/DSO:

   - Is the flexibility service load-specific (e.g. only bound to electric water heaters, air-conditioning units, or space electric heating), time-specific (certain amount of energy and/or power has to be available in a specific time interval), or energy/power-specific (certain amount of energy/power should be available)?

- What is the process of load prequalification, activation, and finally, verification of the demand response action?

- What is the remuneration scheme: a fixed reward for availability, a reward paid for the provided flexibility, or penalty if not provided?

Because of lacking experience in the simultaneous operation of the implicit and explicit demand response, research and thereby information on the relationship and impacts between these two forms of demand response are scarce. However, some recommendations are given within the regulatory framework (USEF 2016) regarding the simultaneous execution of the implicit and explicit demand response:

2) Flexibility energy resources of a customer with a spot price-based tariff cannot be bid by the aggregator/supplier to a day-ahead market.

3) The flexibility resource can be traded in multiple markets but can only be sold once per resource and per time unit.

4) A flexible resource (asset) can only be operated by one aggregator at a time. If two or more aggregators operate the same flexible resource at the same time, it is uncertain and complicated which operation control should take precedence. Also it is not transparent how the activated flexibility (energy volume) should be allocated to (the BRP of) the right aggregator.

One has to keep in mind that presently, the DSOs cannot fully rely on the demand response potential in the residential sector when planning network development owing to the voluntary nature of the residential demand response (Finnish Energy 2017).

To conclude, the decision-making problems comprise not only the objectives of the customer and the stakeholders involved, but also the relationship between them, as it was shown in Figure 3.1. This relationship is discussed in more detail in the next section.

3.1 Conflict of objectives in the decision-making problem

This section presents an analytical discussion on the interests of multiple stakeholders and their relationship. It is assumed that a single customer is a service provider, while the multiple stakeholders such as the TSO, retailer and DSO are the service requesters. Each of them has their own objectives, which are developed further into tasks or service requests for the service provider. The service provider needs to apply such an operating strategy to his/her flexible resources that delivers him/her the maximum profit. The operating strategy defines which task(s) are executed, in which priority order, and in which time. Here, the regulatory framework and the market design will play an important role in the decision-making process of a single customer, since it is located between the service provider and service requesters (see Figure 3.5) and serves as a trigger to activate the resource to provide the service.

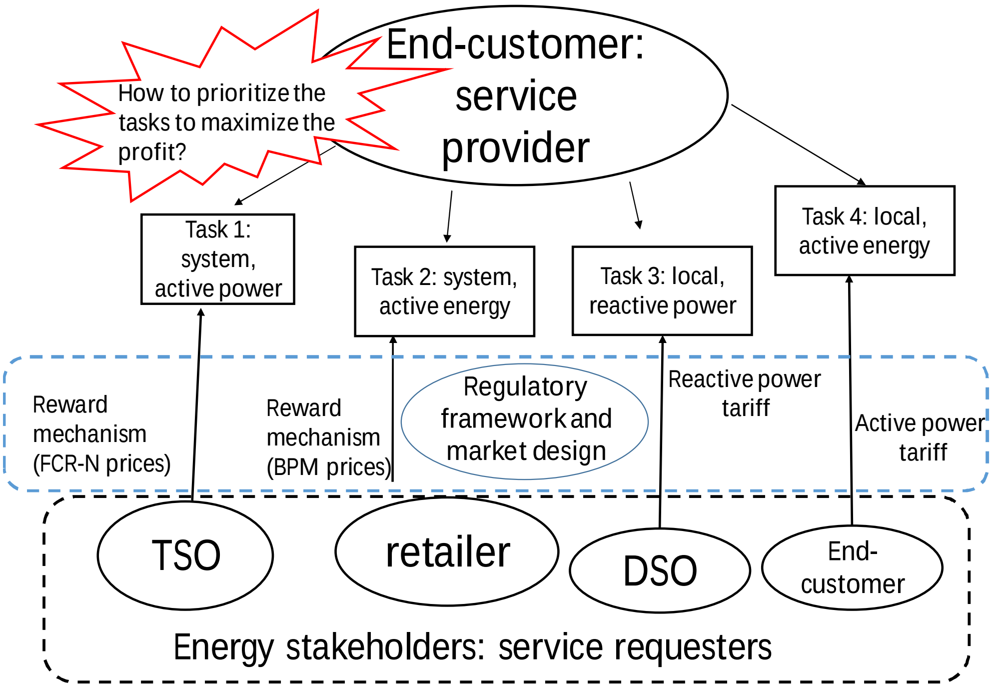

Figure 3.5. Regulatory framework to meet the interests of the service provider and service requesters

The obvious strategy for an end customer to maximize the profit is to prioritize the tasks in the descending order of the expected reward obtained from them; the first priority task delivers the highest reward and so on. However, in practice, this does not always have a positive impact on the social welfare neither does it serve the long-term objectives of the whole energy sector. Therefore, one of the global objectives of the regulatory framework and the market design is to enable such an operation of flexible energy resources that will not only meet the interests of the service provider (end customer), but also the involved stakeholders (service requesters), and thereby be beneficial from the socio-economic perspective.

The conflict of objectives may be of a technical and economic nature. A technical conflict means that the capacity allocated to one task is limited because of its usage in another, higher prioritized task. A conflict of this kind may also occur when a flexibility resource is requested to be activated in opposite directions by multiple players. For instance, an over-frequency period (a need for a load increase, or battery charging) may coincide with the peak shaving need on the end customer's premises (a load decrease, or battery discharging).

An economic type of conflict means that there is a limitation on providing the service to a task because of its low level of reward. When two or more tasks are executed during the same hour, a conflict may occur depending on the service requested. The relationship between tasks is conflicting or non-conflicting depending on the end customer- and system-level state, as well as reward level of the tasks. Figure 3.6 illustrates that in certain time moments there occurs a conflict between a system and a local tasks when a flexibility resource is requested to provide a service in opposite directions (for instance, a need to shave the power peak on the customer's premises coincides with the down-regulation hour in the power system). There can be another case of non-conflicting system and local tasks, when their type of service requires the flexibility resource to perform in the same mode (charging or discharging).

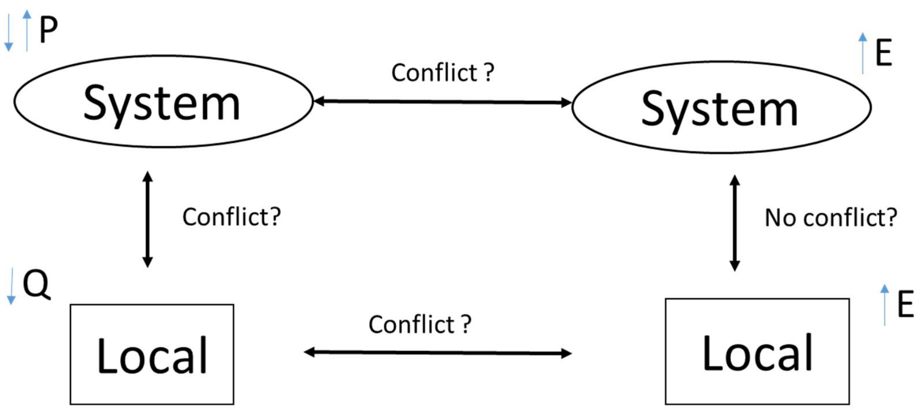

Figure 3.6. Relationship between the tasks depending on the system and local state (end customer's load profile)

With regard to a BESS unit, it can be operated simultaneously during the same hour in the energy-based and power-based applications as long as the SOC level is kept within the optimum level. To this end, SOC level correction measures are required.

A conflict of interests arises between energy-based applications in the case of energy capacity limitations. The priority is given to the alternative application if the benefit obtained from it is higher taking into account all the costs and penalties caused by not following the scheduled application.

It is crucial to keep in mind the role of the aggregator, who acts as a binding actor between the service provider (end customer) and the service requesters (TSO, DSO, retailer). In Finland, special attention has recently been paid to the aggregator's business models, in particular, in the recent report of the smart grid working group (Pahkala 2018). The group members have shown a positive attitude towards independent aggregators, who would accelerate the demand response activities, especially in the residential sector.

Apparently, the aggregator's business models will have an impact on the customer behaviour, which was discussed already in the previous chapter, where the interdependence between the implicit and explicit demand response was brought up. However, the further analysis of this type of impact is beyond the scope of this doctoral dissertation.

In the next section, the decision-making problem is formulated mathematically.

3.2 Building blocks of the problem formulation

The problem is divided into four main parts; description of variables in block A, definition of a decision-making procedure in block B, constraints in block C, and finally, derivation of an objective function in block D. The building blocks are illustrated in Figure 3.7.

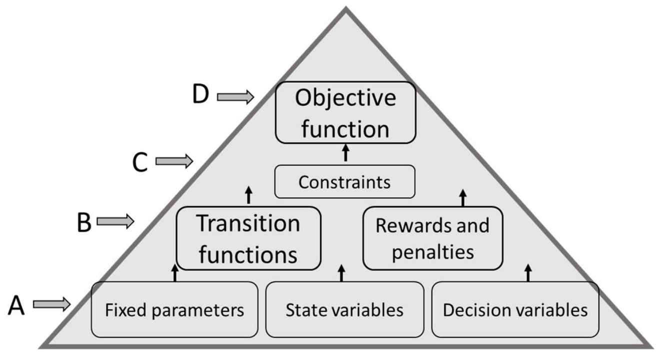

Figure 3.7. Building blocks of the problem formulation

3.2.1 Block A: Definition of variables

The variables are further divided into fixed parameters and state and decision variables. The fixed parameters and state variables reflect both the technological settings on the single customer's premises and the quantitative characteristics of DR marketplaces described in Figure 2.4. By changing these parameters, a decision maker can generate numerous scenarios regarding DR marketplaces and customer types.

The parameters and variables presented below represent an example of an end customer located in the Nordic electricity market environment.

1) Fixed parameters can be divided into appliance-related, BESS-related, EV-related, and solar PV-related ones, depending on which flexibility resources a customer has.

P_{max}^{SH}	installed capacity of space heating loads [kW]
P_{max}^{EWH}	nominal power of an electric water heater [kW]
P_{max}^{HP}	nominal power of a heat pump [kW]
P_{max}^{load}	fuse size of the customer's electricity connection point [kW]
$P_{ch/dch}^{BESS}$	Maximum charging and discharging power capacity of BESS [kW]
E_{max}^{BESS}	Max. SOC level, [kWh]
E_{min}^{BESS}	Min. SOC level, [kWh]
η_{RT}	round-trip efficiency of the battery [p.u.]
C_{Rate}	C-rate of the battery
$P_{solarPV}$	nominal power of solar PV [kWp]

2) State variables

A state variable is a time-varying characteristic of the model that represents the storage of mass/volume of the time-varying quantity of interest within the system/model. A number of different state variables taken together can be used to define the "state" of the system/model.

The dynamical model of a single residential customer is defined so that the state variable satisfies the Markov property. The Markov property means that the state S(t) at time t contains all necessary information about the system needed to propagate the behaviour of the system forward in time as new inputs become available, without the need to store information about any previous (before time t) inputs to the system (Ruelens 2016).

The following state variables are defined at hour t:

s_t^{BESS}	battery SOC level [kWh], or the amount of energy in the battery
s_t^{SH}	space heating, controllable load [kWh]
s_t^{HP}	heat pump, controllable load [kWh]
s_t^{EWH}	state of electric water heater [0,1] – off or on

s_t^{DA}	day-ahead spot market price [€/MWh]
s_t^{BPM}	power price in the balancing power market [€/MWh]
s_t^{FCR}	frequency regulation service, capacity price [€/MW]
s_t^{L}	total load [kWh] at time k

As a result, the state of the model can be defined using a state vector:

$$S_t = (s_t^{BESS}, s_t^{SH}, s_t^{HP}, s_t^{EWH}, s_t^{DA}, s_t^{BPM}, s_t^{FCR}, s_t^{L}) \tag{3.8}$$

3) Decision (control) variables

A control or decision variable is the one that can be changed by the user/decision maker with the aim of modifying/controlling the behaviour and/or response of the system. The following decision variables are defined at hour t:

$E_{DA}(t)$	total flexible energy used for the day-ahead market [kWh]
$E_{BPM}(t)$	total flexible energy used for the balancing power market [kWh]
$P_{FCR}(t)$	total power bid to the frequency reserve market [kW]
$E_{PB}(t)$	total energy used to cut the peak power to the pre-defined level [kWh]

Each decision variable can be further split into flexibility resources with the help of β values according to Table 2.3 in Section 2.4. These variables can take values between 0 and 1, where a value of 0 means that the energy/power capacity of the load is totally off, and 1 means that the energy/power capacity of the load is fully on during the time t in the marketplace:

$$\begin{aligned}
\boldsymbol{E_{DA}(t)} &= \beta_{HP}(t) * E_{HP}(t) + \beta_{EWH}(t) * E_{EWH}(t) + \beta_{SH}(t) * E_{SH}(t) \pm \beta_{BESS}(t) * E_{BESS}(t) \pm \beta_{EV}(t) * E_{EV}(t) - \beta_{solarPV}(t) * E_{solarPV}(t) \\
\boldsymbol{E_{BPM}(t)} &= \beta_{HP}(t) * E_{HP}(t) + \beta_{EWH}(t) * E_{EWH}(t) + \beta_{SH}(t) * E_{SH}(t) \pm \beta_{BESS}(t) * E_{BESS}(t) \pm \beta_{EV}(t) * E_{EV}(t) - \beta_{solarPV}(t) * E_{solarPV}(t) \\
\boldsymbol{P_{FCR}(t)} &= \beta_{HP}(t) * P_{HP}(t) + \beta_{EWH}(t) * P_{EWH}(t) + \beta_{SH}(t) * P_{SH}(t) \pm \beta_{BESS}(t) * P_{BESS}(t) \pm \beta_{EV}(t) * P_{EV}(t) - \beta_{solarPV}(t) * P_{solarPV}(t)
\end{aligned} \tag{3.9}$$

$$\boldsymbol{E_{PB}(t)} = \beta_{HP}(t) * E_{HP}(t) + \beta_{EWH}(t) * E_{EWH}(t) + \beta_{SH}(t) * E_{SH}(t) \\ \pm \beta_{BESS}(t) * E_{BESS}(t) \pm \beta_{EV}(t) * E_{EV}(t) \\ - \beta_{solarPV}(t) * E_{solarPV}(t)$$

$$\boldsymbol{E_{total}(t)} = E_{uncontr}(t) + \boldsymbol{E_{DA}(t)} + \boldsymbol{E_{BPM}(t)} + \boldsymbol{E_{FCR}(t)} + \boldsymbol{E_{PB}(t)}$$

As a result, a matrix of β variables can be formed for each hour of the day. The example below (0.10) shows that in hour t the customer participates 1) in the day-ahead market by decreasing the consumption of electric water heater by half, 2) in the balancing power market by offering 30% of the electric vehicle energy capacity, 3) in the FCR market by offering the 50% of total space heating power capacity, and finally, 4) the customer uses a BESS unit together with solar PV generation to keep the load under the pre-defined power constraints. Such a set of actions represents one combination, which is a theoretical one in this case.

$$\begin{bmatrix} & \beta_{HP}(t) & \beta_{EWH}(t) & \beta_{SH}(t) & \beta_{BESS}(t) & \beta_{EV}(t) & \beta_{solarPV}(t) \\ DA & 0 & 0.5 & 0 & 0 & 0 & 0 \\ BPM & 0 & 0 & 0 & 0 & 0.3 & 0 \\ FCR & 0 & 0 & 0.5 & 0 & 0 & 0 \\ PB & 1 & 0 & 0 & 1 & 0 & 1 \end{bmatrix} \quad (3.10)$$

Multiple possible combination matrices can be obtained for each hour. Each of the combinations leads to a different model propagation during the following 24-hour period. Thus, the number of combinations grows exponentially, and the problem becomes computationally very exhaustive.

However, the number of possible states/actions in each hour is limited by the economic and technical constraints, which are expressed by transition functions and constraints, respectively. Below, the transition functions are specified in block B.

3.2.2 Block B: Transition functions and penalties/rewards

The transition functions dictate how the state variables evolve over time. In other words, it is a question of which control signals arise from the DR marketplaces and how they trigger changes in the flexibility resources. Here, the main target is to specify the mechanism by which the controller chooses actions at different time epochs. Such a mechanism is often called a policy, a strategy, a profile, or a decision rule. The transition function, in other words, determines a condition for choosing the resource in one or another DR market in hour t in order to satisfy the objective function. Each state transition gets a reward or penalty function. The target is to minimize the penalties and maximize the rewards obtained during each state transition from hour t to the hour t+1:

$$F_{hour}(t, t+1) = \max[Reward(t, t+1) - Penalty(t, t+1)] \tag{3.11}$$

where $F_{hour}(t, t+1)$ is the transition function indicating which action or decision the end customer undertakes in hour t regarding the hour t+1 and expressed in €. For instance, the customer submits a bid to the balancing power market (through an aggregator) for the next hour. The bid contains information about the amount of energy available at that moment and price, which then allows to calculate the estimated reward from the market. At the same time, it is estimated that the bid activation results in exceeding of the power constraints of the end customer, which can be expressed in the form of a penalty.

In general, the reward is obtained when meeting the requirements of the DR marketplace to which the customer bids the resources. The reward can be in the form of profit gain or savings in costs.

A penalty is applied whenever requirements of a DR marketplace are not met or meeting the requirements in the DR marketplace causes violation of objectives/interests of another DR marketplace. A penalty can be represented for example in the form of loss of revenues or the customer's comfort. This issue is elaborated on in Section 3.1 about the conflict of objectives.

Table 3.1 presents a description of rewards and penalties from each DR marketplace covered in this work.

Table 3.1. Rewards and penalties from DR marketplaces

DR marketplace	**Reward**	**Penalty**
Day-ahead	Decreased cost of electricity through energy arbitrage	Increased cost of electricity because of consumption at a high price hour
BPM (balancing power market)	Profit obtained through energy arbitrage	Missing profit from not participating in BPM
FCR	Reward for availability of capacity	Cost of power purchase from another bidder
Grid tariffs	Avoid an increase in peak powers and power fees	One-time penalty defined according to the cost of capacity

The challenge of finding the optimal policy and selecting the optimal transition action is that both rewards and penalties may be obtained on different timescales depending on the DR marketplace. For instance, a reward obtained from the FCR market is an expected return from the frequency regulation during hour t, whereas a reward achieved because of keeping the consumption under the power constraints is equal to monthly or annual payments according to the power-based tariff. Therefore, in order to be comparable between each other, the rewards and penalties have to be converted into the same time level.

It is important to keep in mind that the quantitative values of penalties and rewards obtained from DR marketplaces are directly dependent on their attributes presented in Figure 2.4. The outcome of the simulations is also strongly dependent on those values.

The constraints presented further place technical limitations on the transition actions.

3.2.3 Block C: Constraints

Above, Figure 3.1 demonstrated that there are multiple objectives when a customer participates in multiple markets. Furthermore, there are numerous combinations that the customer can have. One combination represents the information about which flexibility resources the customer offers and to which marketplaces. In this work, the number of DR marketplaces is chosen to be four. However, in the future, there can be more than four marketplaces, which increases the number of possible combinations exponentially. This makes the mathematical problem description a very laborious task. The number of possible combinations, without taking into account constraints, can be calculated as (Brualdi 2009):

$$Ncombinations = \left(\sum_{k=0}^{m} \binom{n}{k}\right)^{y} \tag{3.12}$$

$$\binom{n}{k} = \frac{n!}{k!\,(n-k)!} \tag{3.13}$$

where n is the number of DR marketplaces, m is the number of marketplaces, in which the simultaneous participation is possible, and y is the number of flexibility resources. Assuming that there are two flexibility resources on a single customer's premises that can be bid to five DR marketplaces, and to two of the DR marketplaces simultaneously, the number of combinations is 256 when using (3.12) and (0.13).

Therefore, in order to limit the number of combinations, certain constraints are introduced. Furthermore, the constraints are defined not for each combination separately but for each appliance and for each DR marketplace. This approach also eases the task when more flexibility resources or DR marketplaces are taken into account. There is no need to describe every single combination, but it suffices to list the constraints for new resources and new DR markets. The constraints are divided into three groups: 1) customer-related, 2) DR marketplace-related, and 3) relationship between DR marketplaces.

Customer-related constraints

The constraints can be divided into appliance-specific and total consumption-specific ones. The first type means that the power consumption of each controllable load cannot exceed its nominal value, whereas the second type means that the total power consumption at the connection point to the grid cannot exceed the fuse size of a single customer in every moment.

For all types of flexibility resources the same constraint takes place. The total consumed power from the grid cannot exceed the fuse size of a single customer, which is 3x25 A or 3x35 A, depending on the size of the customer:

$$P_{TOTAL}(t) \leq P_{MAX} \tag{3.14}$$

$$P_{MAX} = 3 * 25A(\ 35A) * 220V = 16.5\ (23.1)kW$$

Depending on the appliance, there may be different constraints, which can be classified into three main groups:

a) time-specific: appliance should be available for use for a certain time period,
b) volume-specific: the consumption of the appliance should not go below or above the pre-defined limits, and
c) frequency of usage: appliance can be used for various DR applications N times per day.

For example, the constraints for an electric vehicle of the customer are that a) it has to be fully charged by 8 a.m. in the working days, b) its maximum charging/discharging power cannot exceed 10 kW, and c) the maximum amount of charge/discharge cycles per day is limited to 2.

DR marketplace-related constraints

These constraints reflect the rules of operation in the marketplace.

For instance, in the balancing power market in Finland, both up- and down-regulating bids have to be submitted 45 minutes before the hour of delivery at the latest (Fingrid 2018b).

In the FCR-N hourly market, the bids are submitted by 18:30 the day before the operation for each hour of the day (Fingrid 2018a). In case of not providing the accepted power bid, the penalty has to be paid equal to the hourly price in the market.

The size of the power bid is limited by the ability of the flexibility resource to provide that power. The general rule is that there should be that much of energy capacity in the resource as to be able to provide the bid power in both directions continuously during a specific activation period. In the Nordic countries it is currently 30 min. Discussions are going on about decreasing the length of the activation period to 15 min (European Union Electricity Market Glossary 2018).

Constraints related to the relationship between DR marketplaces

The third type of constraints describes the relationship between the DR marketplaces or applications (Figure 3.8).

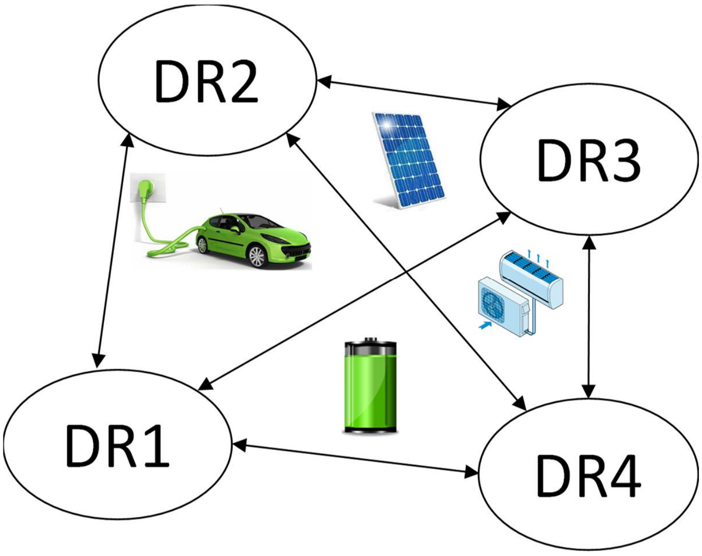

Figure 3.8.Constraints related to the relationship between demand response marketplaces

This type of constraint is applied when the customer participates in more than one DR marketplace.

The applications (activities) exercised in the DR marketplaces can be divided into local- and system-level ones according to Figure 3.9.

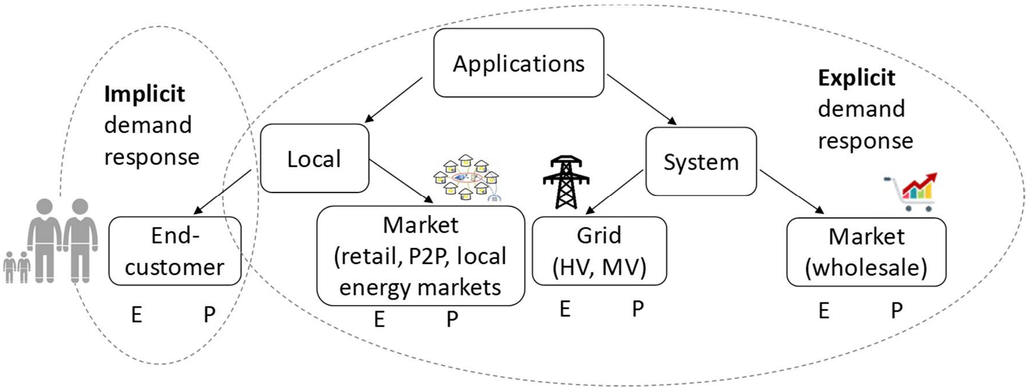

Figure 3.9. Classification of applications. E: energy-intensive; P: power-intensive (active or reactive)

The market-related applications can be active power-based (frequency regulation, reactive power compensation) or energy-based applications (day-ahead and intraday wholesale markets, peak shaving). The grid-related applications can be further divided into active power (peak shaving, interruption management), reactive power (voltage control, reactive power compensation) and other power quality related applications. The local tasks at the end customer level can be, for instance, maximization of solar PV self-consumption, peak shaving, and reduction of carbon footprint.

The major topics of operating flexible resources in multiple DR marketplaces are the conflict of objectives between the applications, the priority order of multiple applications, and the decision-making procedure.

The main suggestion is that the nature of the relationship (conflicting or non-conflicting) between the two applications does not depend on the flexibility resource that is used against them. Instead, it depends on the objectives set in the applications. A conflict may arise when participation in one marketplace limits return or violates the objective in the other marketplace.

However, in a case when the objectives in the two marketplaces are conflicting with each other, the strength of the conflict depends on the type of flexibility resource and the load profile of the single customer.

The following possible combinations of the two DR marketplaces will be considered here:

1) two energy-based markets,
2) two power-based markets, and
3) an energy- and a power-based market.

1. **Two energy-based markets**

Since both applications are exercised in energy-based DR marketplaces, the same energy cannot be used in both markets during the same hour. The day-ahead and balancing power markets are considered as an example. Equation (0.15) shows that the same flexibility resource x cannot be offered to both markets during hour t, but, instead, can be offered in parts:

$$\beta_x^{DA}(t) + \beta_x^{BPM}(t) \leq 1 \tag{3.15}$$

For instance, 30% of flexibility x can be offered to the day-ahead market and 70% is left for the balancing power market. This strategy was also considered for instance in (M. Ali 2015).

The objective function is

$$f12(x) = \min[Cost\big(E_{DA}(t)\big) - Profit\big(E_{BPM}(t)\big))] \tag{3.16}$$

and the decision variables are as in (3.9)

$$\begin{aligned}
E_{DA}(t) = {} & \beta_{HP}^{DA}(t) * E_{HP}(t) + \beta_{EWH}^{DA}(t) * E_{EWH}(t) \\
& + \beta_{SH}^{DA}(t) * E_{SH}(t) \pm \beta_{BESS}^{DA}(t) * E_{BESS}(t) \\
& \pm \beta_{EV}^{DA}(t) * E_{EV}(t) - \beta_{solarPV}^{DA}(t) * E_{solarPV}(t) \\
E_{BPM}(t) = {} & \beta_{HP}^{BPM}(t) * E_{HP}(t) + \beta_{EWH}^{BPM}(t) * E_{EWH}(t) \\
& + \beta_{SH}^{BPM}(t) * E_{SH}(t) \pm \beta_{BESS}^{BPM}(t) * E_{BESS}(t) \\
& \pm \beta_{EV}^{BPM}(t) * E_{EV}(t) \\
& - \beta_{solarPV}^{BPM}(t) * E_{solarPV}(t)
\end{aligned} \tag{3.17}$$

A conflict between the objectives arises when minimization of the energy cost in one marketplace limits the profit maximization in the other marketplace. Figure 3.10 illustrates an example when maximizing the profit in the balancing power market results in a higher energy cost in the day-ahead market. Furthermore, there may be several trade-off solutions when both objectives are met to a certain extent.

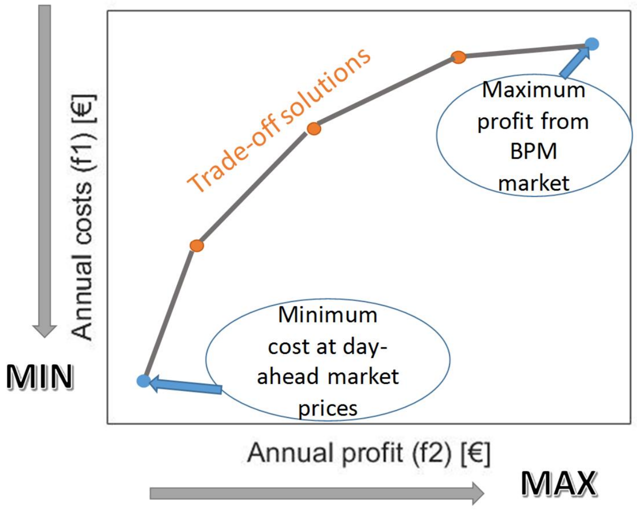

Figure 3.10.Conflict of objectives between two energy-based markets

It has to be kept in mind that the example provided above is only an indicative one and not fixed to any specific market.

2. **Energy-based and power-based market**

The difference between the energy-based and power-based applications is that the flexibility provider (end customer) is rewarded in one of them based on the provided energy capacity and in another based on the provided power capacity. Moreover, the conflict of objectives is of a different nature compared with the previous case. To be specific, there is no competition for the single energy-intensive resource as it was in the previous case with two energy-based markets. Instead, a conflict arises because the energy offered to the energy-based market may cause undesired changes in peak powers in the power-based market. The objective function aims at minimizing the energy-based cost and maximizing the power-based profit (0.18).

$$f13(x) = \min[Cost(x_E(t)) - Profit(x_P(t))] \qquad (3.18)$$

However, the objective function may take another form depending on the DR marketplace objective. For instance, it could be minimizing the total energy cost at the power-based tariff while minimizing the energy cost at the energy-based market prices, for instance, day-ahead market (Figure 3.11).

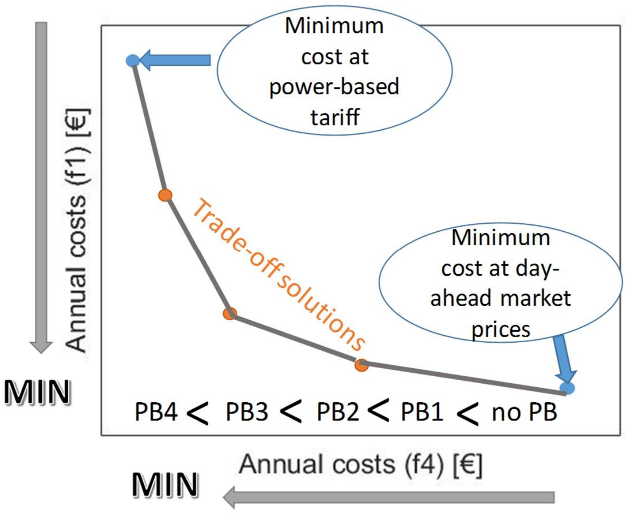

Figure 3.11.Trade-off solutions in the energy- and power-based applications

3. Two power-based markets

The relationship between two power-based markets can be of a different nature depending on the objectives set in them. If both the objectives aim at minimizing or maximizing the power in the specified time period, the marketplaces are non-conflicting. However, there is a conflict if the objective function in one market aims at minimizing the power and maximizing it in the other (see Figure 3.12).

The example objective function is shown in (3.22), where the total objective is to maximize the profit in one application and minimize the power-related cost in another:

$$f34(x) = \max[Profit(x_P) - Cost(x_P)] \tag{3.19}$$

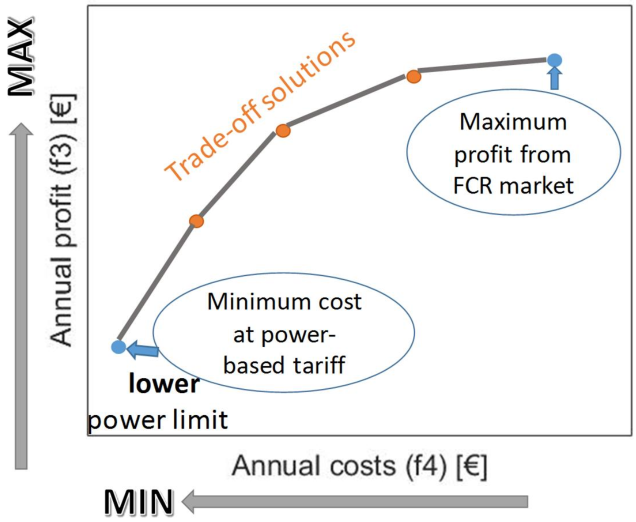

Figure 3.12. Decision-making problem with conflicting objectives for profit maximization in the FCR market and electricity cost minimization at the power-based tariff

Now, when the constraints related to the customer, DR marketplaces, and the relationship between DR marketplaces are presented, the next step is to derive the objective function of the decision-making problem.

3.2.4 Block D: Objective function

The main objective of the problem of operating multiple flexibility resources in multiple marketplaces is to minimize the total energy costs over the decision horizon, $\forall t\,\{1 \ldots T\}$, given as the sum of all components of the total function such as:

$$\begin{aligned} F = \min[&\lambda_{DA} * Cost_{DA}(E_{DA}(t)) + \\ &\left(-\lambda_{BPM} * Profit_{BPM}(E_{BPM}(t))\right) + \\ &\left(-\lambda_{FCR} * Profit_{FCR}(P_{FCR}(t))\right) + \\ &(\lambda_{PB} * \mathrm{Cost}_{PB}(\max[\mathrm{E}(1{:}\,\mathrm{T})]))] \end{aligned} \tag{3.20}$$

where λ_{DA}, λ_{BPM}, λ_{FCR}, and λ_{PB} are binary variables (0;1) for each DR application that show whether the application is included in the analyses or not. A decision horizon is time T over which the energy costs are minimized.

A decision maker can enter the binary variables manually. In addition, the optimization algorithm can go through all possible combinations of DR applications and select the ones that yield the most promising results.

3.3 Conclusions

The objective of this chapter was to demonstrate the complexity of the problem. The participation of various flexibility loads in multiple DR marketplaces was mathematically described. The building blocks of the problem were identified and described in detail. Although the mathematical formulation was applied to the Nordic electricity markets, no specific rules and reward mechanisms were considered, which makes the formulation generic and applicable to any other operating environment. The main idea was to show that the participation of an end customer with various flexibility resources in multiple DR markets can lead to numerous combinations and result in various conflicts between the objectives of the marketplaces, which makes the problem a complicated one to solve.

In the literature, a significant amount of research has focused on solving this type of problem (see Appendix A). To name but a few, such optimization methods as predictive control algorithms (Alimohammadisagvand 2016), mixed integer linear programming (Ikegami 2010), an evolutionary algorithm (Gomes 2004), and heuristic optimization (Logenthiran 2012) were applied to find the optimum strategy of using various flexibility resources against specific objectives. Machine learning is also attracting interest in the field of residential demand response. For instance, (Ruelens 2016) has implemented reinforcement learning to develop control strategies for residential demand response at the household level. These strategies are limited to thermostatically controlled loads (TCL) participating in three demand response applications: dynamic pricing, day-ahead scheduling, and energy saving.

Moreover, computationally time-consuming and complicated optimization algorithms have been used to solve problems that are of high time (e.g. minute-resolution data) and space (specific household type, or specific appliance) resolution. Such data are seldom available, especially on a large scale. Furthermore, the challenge of this kind of a detailed analysis of the problem is that such an approach does not help to understand:

a) the nature of the whole problem and interdependence between its parts,
b) the relationship between different type of DR marketplaces, and
c) the outcome for various types of customers.

Moreover, most often, the goal of the optimization is to find such a combination of the input parameters and such a decision that yield the desired output according to the optimization function. However, the optimized solution does not necessarily help to understand the role of different input factors on the results.

After formulating the problem mathematically, the following aim is to develop a simplified although practical solving approach to handle this complex, dynamic, and stochastic problem. The methodology to solve the problem is established in the following chapter.

4 Methodology to define the end customer’s potential in multiple DR marketplaces

This chapter presents the methodology to solve the problem of controlling flexibility resources on a single customer’s premises against multiple incentives. The main tasks of the chapter are:

1. Develop a methodology to solve the problem and justify the methods,
2. List the limitations of the methodology, and
3. Describe the first stage of the methodology.

The main purpose of this chapter is to establish a methodology that provides a strategy for a particular single customer to participate in multiple demand response marketplaces. Given the technical specifications of electrical loads and preferences of a customer, the methodology generates a preferable set of marketplaces and the operation strategy. Eventually, there can be as many strategies as there are customers. However, the idea of this chapter is to produce a universal decision-making tool to establish a strategy for any type of customer.

4.1 Establishment of a methodology

The multiple flexibility resources, for instance, four controllable appliances on the customer’s premises (a heat pump, direct electric heating, a BESS, and a refrigerator), against five control signals result in a huge number of combinations, which is a very complicated task to calculate and analyse as a closed-form problem. Besides the large number of combinations, there can be numerous alternatives within each combination depending on the customer type and size of flexibility (BESS, solar PV, size of hot water storage).

The complexity of the problem requires that the methodology is divided into two stages. The first stage provides a strategy to select the most promising DR marketplaces for a particular type of customer. The output of the first stage serves as an input to the second stage of the methodology.

The second stage provides a strategy to operate the flexible resources in the selected DR marketplaces on a day-to-day basis. After selecting the promising DR marketplaces and setting the constraints, the number of possible combinations reduces further and makes the problem easier to understand, mathematically formulate, and solve.

The structure of the proposed methodology is presented in Figure 4.1.

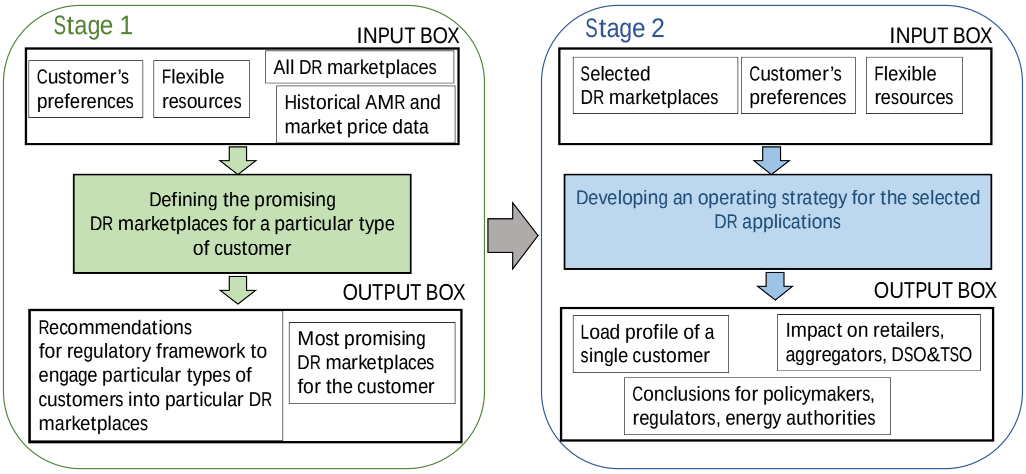

Figure 4.1. Structure of the proposed methodology

A similar approach can be found in strategic planning of the electricity distribution networks, where first the strategic decisions are made on which technologies to use in the network and after that, how to implement the technologies (Lassila 2009).

4.2 Limitations of the methodology

The following limitations are out of the scope of this doctoral dissertation, even though they play a major role in shaping the customer’s role in a smart grid environment. The reason for not including them is purely to keep the task manageable, as involving all these aspects would considerably complicate the work. However, these questions are on the list of future research topics.

The limitations of the methodology are dictated by the following issues, which strongly affect the outcome of the calculations:

1. The technological trend, which determines the cost of use of the flexibility options on a single customer’s premises. In the coming years, it is expected that the technology prices, meaning the cost of home appliances, storage, and microgeneration solutions, will decrease as the market expands. The learning rate of the technology is expected to be steep in the coming years (Schmidt 2017).
2. Electricity market price level and volatility. These, again, are affected by many issues such as the generation mix, storage, and flexibility solutions, and the efficiency of electricity network operation (grid and transmission capacity of interconnectors).

3. Regulatory framework for residential demand response, which sets the contract and agreement terms between a single customer and the involved stakeholder and establishes a remuneration scheme for a customer participating in multiple electricity marketplaces.
4. The electricity market framework is constantly changing, which means that in the future there may be more or fewer electricity marketplaces than at the present time. For instance, there may be one single flexibility market instead of intra-day and balancing power markets. On the other hand, there may be additional marketplaces with varying gate closure times to accommodate flexibility options in a more dynamic way. Hence, depending on the number of electricity markets, the number of control price signals varies.
5. Market price forecasting in the short (hours) and long term (years) is outside the scope of this study. Thus, the calculation results present a theoretical economic potential of demand response for a single customer.
6. The residential customer is assumed to be a price taker so that they do not impact the prices in the DR marketplaces. However, depending on the participation rate of the customers, a customer may become a price maker and eventually affect the prices in the markets.

The description of stage 1 is provided in the rest of the chapter.

4.3 Selection procedure of DR marketplaces (stage 1)

In this stage, the promising DR applications are selected for a given customer type.

The input parameters are the customer’s preferences and the available flexibility resources on his/her premises. The customer’s preferences contain part of the end customer’s objectives stated earlier in Chapter 0, that is, the comfort requirements and the risk level. This information together with the available flexibility resources and DR marketplaces is used to carry out a simulation. As a result, a rating of the DR profitability in all marketplaces is obtained, and the profitable and non-profitable DR marketplaces are revealed.

The necessary conditions for a DR marketplace to be attractive for an end customer are:

1) With the selected application, the annual cost of electricity for a single customer should not be higher than the cost of electricity without participation in that application.

2) Annual income from any selected application should be higher than zero.

3) Customer’s comfort requirements should be followed in every moment.

Each simulation case includes only one flexibility entity and one DR marketplace. At this stage, combinations of applications and multiple flexibility entities are not considered. The flow of the stage is presented in Figure 4.2.

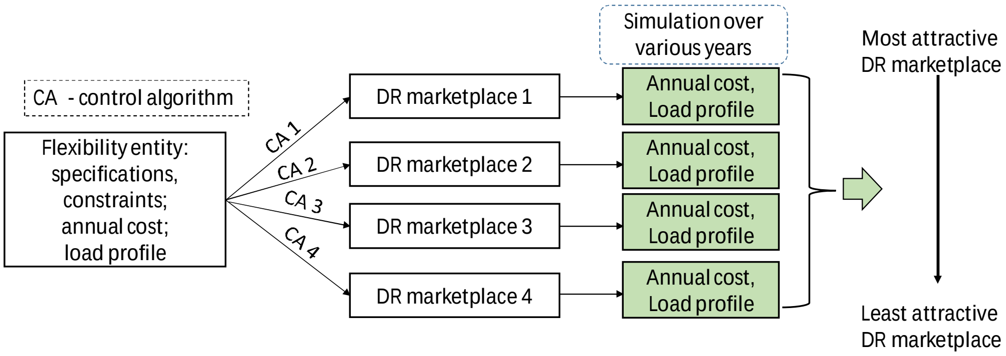

Figure 4.2. Flow of stage 1 of the methodology

The flexibility entity can be a particular customer type, an individual appliance, a BESS unit of any size, an EV, or any other demand, which can be increased or decreased at certain times. This approach is beneficial because it is universal and not fixed to any particular type of load or DR marketplace.

The DR marketplaces with their control algorithms are presented in the following sections. The applications considered in the doctoral dissertation are energy arbitrage in the day-ahead and balancing power markets, frequency regulation in the FCR-N hourly market, and peak shaving against the power-based tariff.

The control logic aims to reveal the maximum theoretical earning potential. This means that the customer's preferences are not taken into account. The motivation behind this simplified approach is straightforward. It is based on the hypothesis that the theoretical earning potential is, in most cases, higher than the optimized one. This is because the optimized operating strategy usually takes into account constraints related to customer's preferences and technical specifications of the controllable appliances, whereas the algorithm to calculate the theoretical maximum earning potential does not take those constraints into account. In case the theoretical potential is low in a particular DR marketplace, there is no need to develop an optimized strategy of load control in that marketplace, and thus, it can be left out of the second stage of the methodology.

4.3.1 Energy arbitrage in day-ahead and real-time markets

This section presents the energy arbitrage application in the energy-based markets. Energy arbitrage means gaining profit by shifting the energy from the high-price hour to the low-price hour.

The control logic of the energy arbitrage application in the day-ahead and real-time markets (balancing power market) is valid for both shiftable loads and BESS units (Figure 4.3).

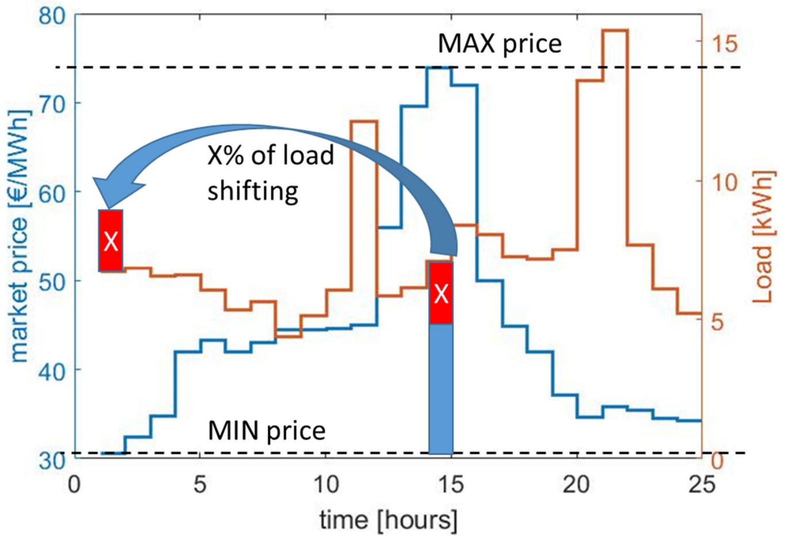

Figure 4.3. Price-based load shifting from the maximum to the minimum price of the day

The theoretical earning potential over T days is estimated using the following equation:

$$Profit_T = \sum_{d=1}^{T} E_{contr}(d) * \Delta Price(d) - OPEX_{flex}(d) \tag{4.1}$$

where $E_{contr}(d)$ is the shiftable part of the load in day d, $\Delta Price(d)$ is the price difference between the minimum and maximum prices of the day, and $OPEX_{flex}(d)$ is the operational cost of the control of the flexibility resource. In the case of shiftable loads, the cost of load control can expressed by the constraints set by the comfort of customers, whereas in the case of a BESS unit, the cost of control is expressed by:

$$OPEX_{flex}(d) = E_{contr}(d) * price_{kWh} \tag{4.2}$$

where $price_{kWh}$ is the price of energy stored in the battery.

In (Belonogova 2016), it was shown that the operation of a battery in the energy (or price) arbitrage is profitable only when the price difference $\Delta Price(d)$ is equal to or larger than the $price_{kWh}$ of energy stored in the battery.

4.3.2 Frequency regulation in the FCR-N hourly market

The frequency containment reserve (FCR) markets are power-based DR marketplaces, which means that power-intensive appliances and BESS units are suitable resources for this market. Opposite to the energy arbitrage application, the algorithm to define the theoretical earning potential in the market is developed separately for the BESS and power-intensive load units.

To this end, the three main scenarios are considered:

1) A customer has no BESS unit on his/her premises yet. The question is whether it is feasible to purchase a battery for the frequency regulation task.

This question is solved by analysing the net present value as:

$$NPV = \sum_{t=1}^{Lifetime} \frac{Revenues(FCR-N)_t}{(1+r)^t} - C_o \tag{4.3}$$

where

NPV	net present value [years]
$Lifetime$	calendar-based lifetime of the battery [years]
$Revenues(FCR-N)_t$	annual revenues from the FCR-N hourly market [€/a]
r	interest rate [p.u.]
C_o	investment costs in the battery [€]

A positive NPV shows the profitability of using BESS in the FCR-N market, while a negative NPV indicates that it is not feasible to purchase a battery for the frequency regulation in the FCR-N hourly market. The advantage of the NPV approach is that it allows finding the break-even point in feasibility studies, showing at which unit cost of battery technology and at which price level in the FCR-N market the profitability occurs.

2) A customer has already purchased a BESS. The question is how much profit the participation in the FCR-N hourly market delivers to the customer.

In this scenario, two options are possible. In the first one, the battery is used so intensively in the FCR-N hourly market that it wears out before its calendar lifetime reaches the end. This means that the operational cost of the BESS includes the replacement cost in addition to the loss component. In the second option, the lifetime cycles of the battery do not run out before the end of the calendar lifetime, and thereby the operational costs contain only the loss-related component (Lassila 2012):

$$C_{Opex}(1) = C_{BESS}/\eta_{RT} + (1-\eta_{RT}) * c_{w-electricity}$$
$$C_{Opex}(2) = (1-\eta_{RT}) * c_{w-electricity} \tag{4.4}$$

where

C_{BESS} battery price per discharged energy [€/kWh]

η_{RT} round-trip efficiency [p.u.]

$c_{w-electricity}$ price of electricity from the grid [€/kWh]

The annual profit from the FCR-N hourly market is then calculated as the difference between the revenues and the operational costs of the BESS unit:

$$Profit_{FCR-N} = \sum_{t=1}^{8765h} Price_{FCR-N}(t) * Power_{FCR-N}(t) - C_{Opex} * \sum_{t=1}^{8765h} Energy_{FCR-N}(t) \tag{4.5}$$

3) A customer participates in the FCR-N hourly market with the thermostatically controllable loads (TCL).

For the load, the main aim is to build an algorithm to estimate how much power is available for the frequency regulation. For the sake of simplicity, this task is executed at the level of a group of customers, not a single customer. The estimation provides the following answers:

1. Annual revenue that a TSO gets from a group of customers participating in the FCR-N hourly markets and

2. Approximate reward that a single customer gets for providing his/her load available for the FCR-N hourly market.

A lot of attention has been paid to the use of TCL in frequency regulation (He Hao 2014; Heleno 2016; Lakshmanan 2016). The aggregated TCL can be modelled as time-varying thermal energy storage (Mathieu 2015). This approach was simplified and implemented in this work (see Figure 4.4).

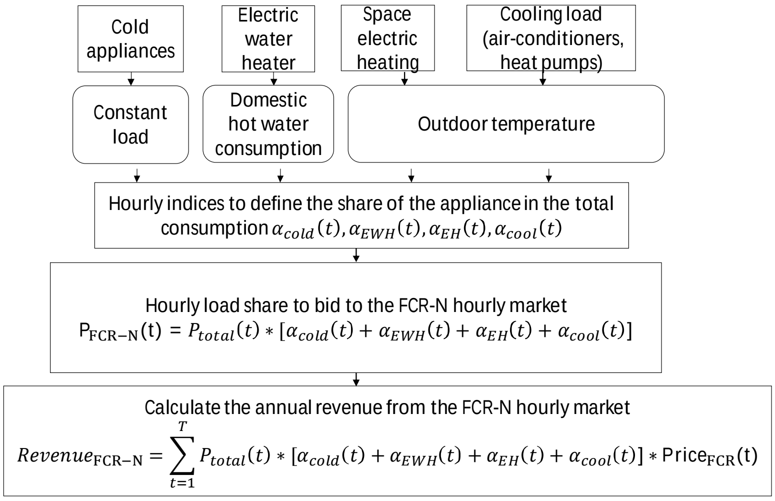

Figure 4.4. Procedure to define the annual revenue from the FCR-N hourly market for a group of customers with thermostatically controllable loads (TCL)

The procedure to define the total power available for the frequency regulation in hour t from a group of customers can be divided into several steps. First, the dependence of the TCL consumption, and thereby the availability for control, on the exogenous factors is quantitatively formulated by using the hourly indices $\alpha_{COLD}(t)$, $\alpha_{EWH}(t)$, $\alpha_{EH}(t)$,and $\alpha_{COOL}(t)$. For instance, the electricity consumption of an electric water heater depends on the domestic hot water consumption, and the space heating and cooling loads depend on the outdoor temperature, whereas the electricity consumption of cold appliances (refrigerator, freezer) depends, to some extent, on the use of these appliances (opening of the refrigerator door); nevertheless, the latter TCL are assumed to be constant in this doctoral dissertation. The hourly indices are expressed in p.u. values, indicating which proportion of the total load the TCL constitute. Summing up the indices and multiplying by the total hourly power consumption yields the proportion of the TCL of the total power consumption in hour t.

In order to obtain the profit, the operational expenses (OPEX) of using the flexibility resources have to be taken into account. The OPEX of the loads participating in the frequency regulation task can be presented as a sum of loss of comfort and a faster degradation rate of appliances (lifetime component), which are being switched on and off on a more regular basis, according to the frequency deviation from the dead band.

$$OPEX_{loads} = Lifetime + Comfort \tag{4.6}$$

The comfort component was taken into account in the process of defining the hourly indices. The impact of a frequent use of the appliances on their lifetime is difficult to estimate, and therefore, it is left out of these analyses.

After the size of power provided to the FCR-N hourly market is obtained and the earning logic is defined, the operating logic in the market is described. Submission of the bid to the market contains information about the offered power capacity [MW] and price bid [€/MW]. The general rule used in the simulations is that whenever the hourly price in the market is higher than the price bid offered by a customer/aggregator, the bid is accepted and the resource must be made available for the frequency regulation task in that specific hour. Such parameters as frequency, dead band, droop slope, reaction time, and activation time and period, define the power gain of the load/BESS unit in each second of the hour. A more detailed explanation of the operation in the FCR-N hourly market can be found in (Belonogova 2018).

4.3.3 Peak shaving task

The logic of load control in the peak shaving task is straightforward: keep the consumption under the pre-defined power level. The reward for such flexibility comes from the power-based tariff.

The methodology starts with definition of the scenario (see Figure 4.5).

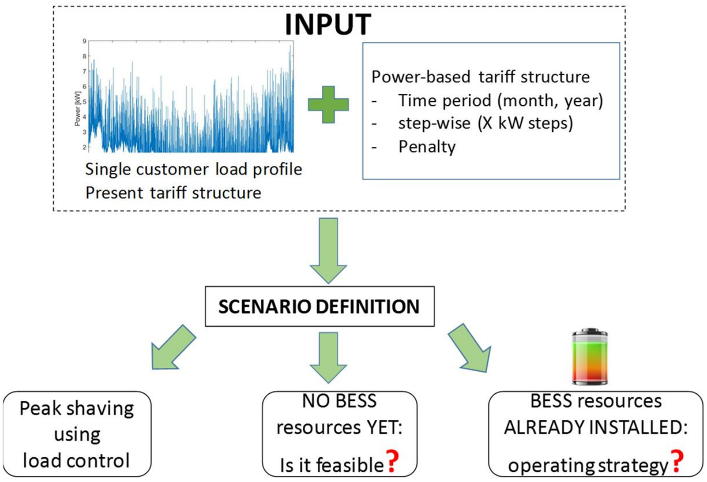

Figure 4.5. Scenario definition in the peak shaving task

Three main scenarios can be distinguished:

1) A customer manages the peak shaving task by the means of load control.

2) A customer has no BESS unit on his/her premises yet. The question is whether it is feasible to purchase a battery for the peak shaving task.
3) A customer has already purchased a BESS. The question is what the most economical operating strategy is when a battery is used solely for a peak shaving task.

In the last two scenarios, the assumption is that the battery resource is used only for the peak shaving task. Another assumption is that there are no solar PV panels installed on the customer's premises.

Many research questions arise within the topic of peak shaving on a single customer's premises. However, the established algorithm has the following limitations:

- Definition of the optimal power band for a particular single customer,
- Definition of the most economically reasonable flexibility resources to achieve the power band: controllable loads, a BESS unit, or a BESS unit with solar PV panels,
- Analysis of the changes of the customer behaviour in response to subscribing to a power-based tariff, and
- Estimation of the impacts of modified residential consumption on the energy system and its players in the short and long term.

Nevertheless, the developed algorithm and the simulation tool will make it possible to overcome these limitations and provide answers to these questions.

For all the three scenarios, the necessary task is to define the energy required from the flexibility resources (controllable loads or BESS) to achieve a shift from power band 1 PB_1 to power band 2 PB_2. It can be expressed using the peak operating time:

$$\sum_{t=tstart}^{tend} Energy_{flex}(t) = t_{peak} * [PB_1(k) - PB_2(k)] \qquad (4.7)$$

Figure 4.6 illustrates definition of the peak operating time in an example of a one-month period of consumption of a single customer. The figure shows the hourly consumption sorted in a descending order.

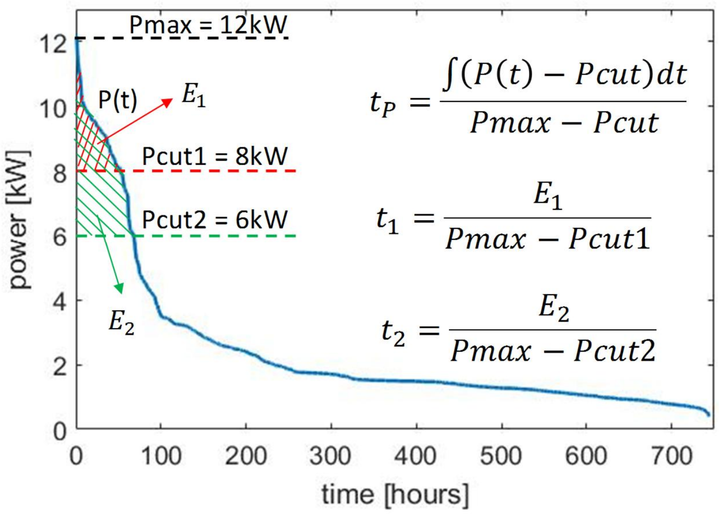

Figure 4.6. Definition of a peak operating time in a one-month period

The next part of the methodology covers procedures that give answers to the questions risen in scenarios 1 (load control), 2 (no BESS) and 3 (BESS installed).

Scenario 1

This scenario is the most challenging one out of the three, because it not only requires modelling of loads but also modelling of load control responses (also termed as payback effect) on a single customer's premises. These topics have been extensively studied in the project RESPONSE, which was carried out in 2015–2018. The outcome of the study was that both the physical (building, weather, and socioeconomic data) and data-driven approaches (the use of smart meter data and other measurement data) should be adopted to identify the flexibility potential on a single customer's premises (Koponen 2018). The direct load control carried out in Finland in the 1980s demonstrated that there is a significant flexibility potential in the residential sector so that in most cases the customers do not even notice that their loads are being controlled. For instance, electric sauna and direct electric heating loads in a household can be switched on alternatingly in order to keep the peak power under the predefined limit.

Yet another challenge related to the peak shaving with load control is the availability of load on a regular basis over a longer period of time. For example, when the load control takes place for the needs of the distribution network (e.g. congestion management) and the flexibility is harnessed from multiple residential (or other type) customers, in most cases, the unavailability of one resource can be substituted by another resource. Yet the single customer is the only actor responsible for his/her peak power level, and thus, the availability of load for control is of higher importance.

The savings obtained from the peak power reduction can be calculated in the same way as in scenarios 2 and 3. The major open question is the estimation of the operational expenses of the load control, which depend on the appliances used for the control, timing, duration, and frequency of the load control. Moreover, a longer period of time is required to quantify the expenses of the load control (for instance, what is the impact on the lifetime of appliances in a case when they are frequently being switched on and off).

However, the main objective of this section is on demonstrating the methodology and earning logic in the peak shaving task, rather than providing quantitative results. Therefore, this scenario will be omitted from the further analyses, and the load in the peak shaving task will be assumed non-controllable.

Scenario 2

In scenario 2, the feasibility of purchasing a BESS is verified by comparing the savings obtained from the peak shaving application over the lifetime of the battery with the investment costs of the battery (see Figure 4.7).

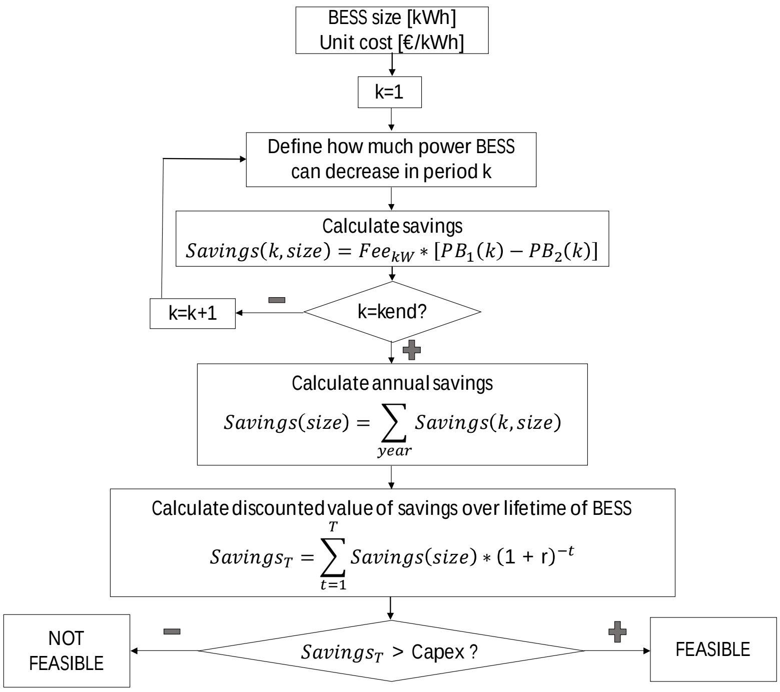

Figure 4.7. Scenario 2: procedure to define the feasibility of purchasing a BESS unit for peak shaving

Scenario 3

In scenario 3, the earning potential, or profit from the peak shaving, is defined in two steps. In the first step (see Figure 4.8), the price of stored energy in the battery is defined by estimating whether the lifetime of the battery is limited by the calendar-based age or the cycle-based age using (4.4).

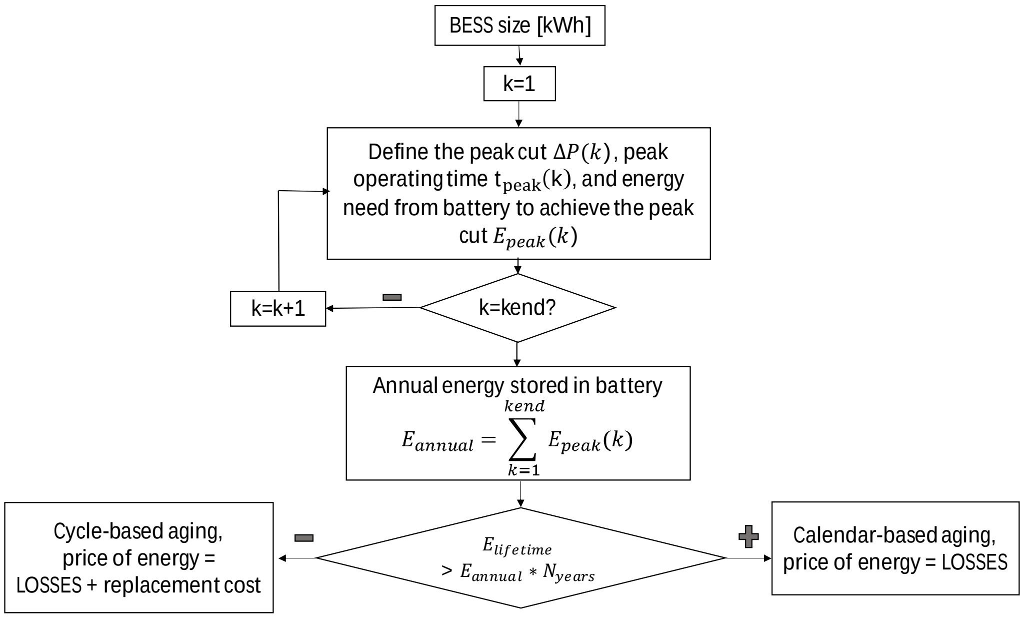

Figure 4.8. Step 1 in scenario 3: procedure to define the price of energy stored in a battery

After defining the price of energy stored in the battery in step 1, the profit is calculated in step 2. The objective here is to maximize the profit obtained from the peak shaving task over a time period k:

$$PB_{optimal} \sim \max_{k} Profit_{PS}(k) \tag{4.8}$$

The time period k is selected according to the tariff structure. For instance, if the billing is based on the hourly peak power of one month, the time period k is equal to one month.

The profit from the peak shaving task can be expressed as the change in power fees resulting from shifting to a lower power band minus operational expenses of using flexibility resources for that purpose:

$$Profit_{PS}(k) = Savings\big(\Delta PB(k)\big) - OPEX_{flex}(k) = Fee_{kW} * \big(PB_1(k) - PB_2(k)\big) - C_{Opex} * \sum_{t=tstart}^{tend} Energy_{flex}(t) \tag{4.9}$$

where

$Profit_{PS}$(k)	profit from the peak shaving task [€] obtained during period k
$Savings(\Delta PB(k))$	savings from the power band change [€] obtained during period k
$OPEX_{flex}(k)$	operational cost of the use of flexibility resources [€]
Fee_{kW}	power fee of the tariff [€/kW, k time period]
$PB_1(k)$	original power band during the time period k [kW]
$PB_2(k)$	new power band as a result of peak shaving, time period k [kW]
C_{Opex}	cost of energy required from the flexibility resources [€/kWh]
$\sum_{t=tstart}^{tend} Energy_{flex}(t)$	energy required to cut the peak power over the time period k [kWh]; tstart and tend—start and end hours of the period k

The operational expenses depend on the amount of energy required from the flexibility resources and the price of that energy.

Combining the equations above, the following objective function is obtained:

$$Profit_{PS}(k) = \max[\big(PB_1(k) - PB_2(k)\big) * (Fee_{kW} - C_{Opex} * t_{peak})] \tag{4.10}$$

The objective function shows that the profit depends on three main factors:

1) The value of the power-based fee Fee_{kW}. The higher is the cost of capacity [€/kW] for a single customer, the more the customer benefits from the peak shaving application.
2) Cost of using flexibility resources C_{Opex}. The lower is the cost of flexibility, the higher is the profit.
3) Peak operating time t_{peak} of a selected power band level, or customer load profile. The smaller is the value, the more customer benefits from the power-based tariff and the peak shaving task. Customers with short peak operating times have a sharp peak profile, whereas customers with long operating times have a wide peak profile.

The impact of the two parameters on the profit from peak shaving will be analysed in the doctoral dissertation: power-based fee and peak operating time.

4.4 Conclusions

In this chapter, the methodology to solve the complex decision-making problem of a single customer in multiple DR marketplaces was established. The methodology was divided into two stages: 1) selection of the most promising DR marketplaces and 2) definition of the operating strategy in the selected DR marketplaces. The DR applications under consideration were energy arbitrage in the energy-based markets, such as the day-ahead market and the balancing power market, frequency regulation in the FCR-N hourly market, and peak shaving against the power-based tariff. The control logic and the procedure to determine the theoretical earning potential in each of the applications were presented. Now, it is time to implement the developed elements of stage 1 of the methodology on real-world data and find out what the most attractive DR marketplaces are for a single residential customer. This is done in the next chapter.

5 Results of the selection procedure (stage 1)

The objective of this chapter is to define the economic feasibility of a single customer's participation in individual marketplaces, and after that, to select the most promising DR marketplaces for the customer. At this stage, the assumption is that the customer participates only in one marketplace at a time.

The methodology described in Section 4.3 was applied to actual residential customers equipped with the AMR. Hourly power measurements of 10 000 customers were used in the simulations. The customers have various types of heating solutions (non-electric, direct, stored, fully stored, heat pumps), and their annual electricity consumption is limited to 50 MWh/a. The distribution of the customers' annual electricity consumption is presented in Figure 5.1 It can be seen that approximately 4000 customers have an annual consumption of less than 5000 kWh/a. Further, about 2000 customers have an annual consumption between 5000 kWh/a and 10 000 kWh/a, and the rest of the customers' consumption varies from 10 to 50 MWh/a.

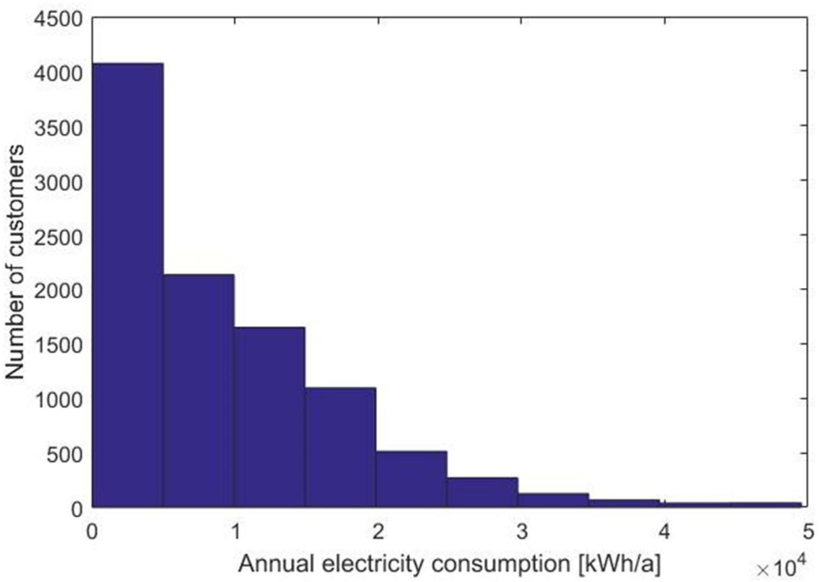

Figure 5.1. Annual electricity consumption of 10 000 customers

The customers can be divided into four groups: 1) households with holiday homes, 2) households in agricultural areas, 3) households in sparsely inhabited rural areas, and 4) households in small villages. In the simulations, the AMR data of the customers were used for two years, 2016 and 2017.

The Nordic electricity market was chosen as an operating environment in which the customers are located. The day-ahead Elspot market is operated by NordPoolSpot, whereas the balancing power market and the FCR-N hourly market are operated by the Finnish TSO Fingrid. The market prices of the years 2012–2017 were applied in the analysis. The power-based tariff structure was assumed to be based on the customers' hourly value of the monthly peak power (Figure 5.2).

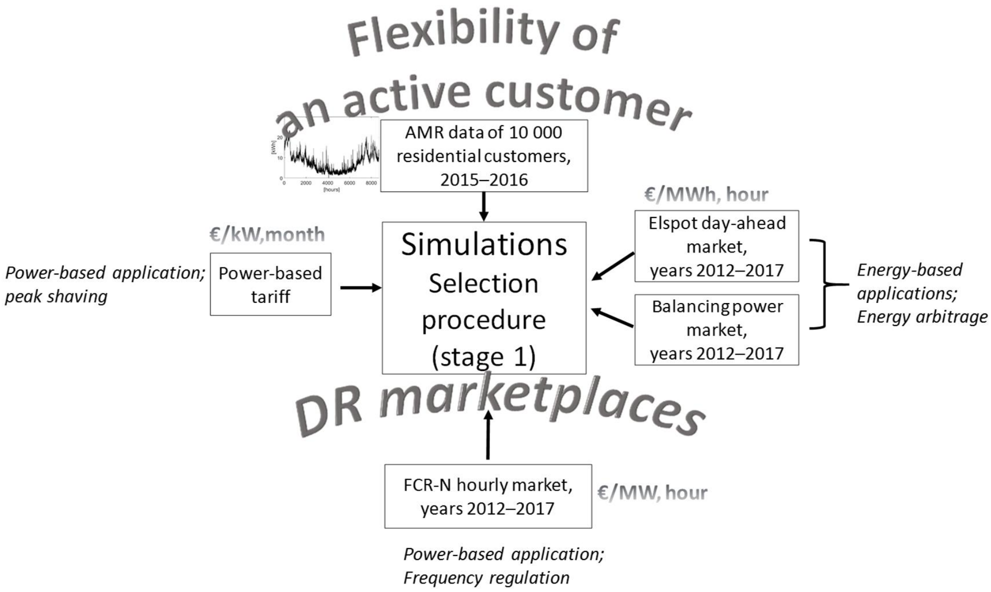

Figure 5.2. Input data for the DR marketplace selection procedure (stage 1)

In total, two energy-based and two power-based DR marketplaces from the operating environment of the Nordic electricity market were used for the simulations.

5.1 Energy arbitrage in the day-ahead market

The main factor affecting the profitability of load control in the Elspot market is the price volatility in the market. The price volatility in the Elspot market has been decreasing over the past few years. Some of the reasons for the volatility were discussed in (Rautiainen 2017). These are, for instance, an increase in wind power installations from 448 MW at the end of 2013 to 1553 MW at the end of 2016, the overall decrease in Elspot prices, and commissioning of the 700 MW HVDC transmission line NordBalt between Sweden (SE4) and Lithuania, which enables power transfer from Sweden to Finland through the Baltic countries.

In these simulations, only shiftable loads were exercising the energy arbitrage in the Elspot market. The BESS was excluded from the consideration, because the price difference in the Elspot market is not enough to cover the operational costs of the battery, and thus, its operation is not profitable in the market.

Figure 5.3 shows the maximum theoretical earning potential of 10 000 customers exercising the daily energy arbitrage in the Elspot market for the market years 2012–2017 and the consumption data of 2015 and 2016.

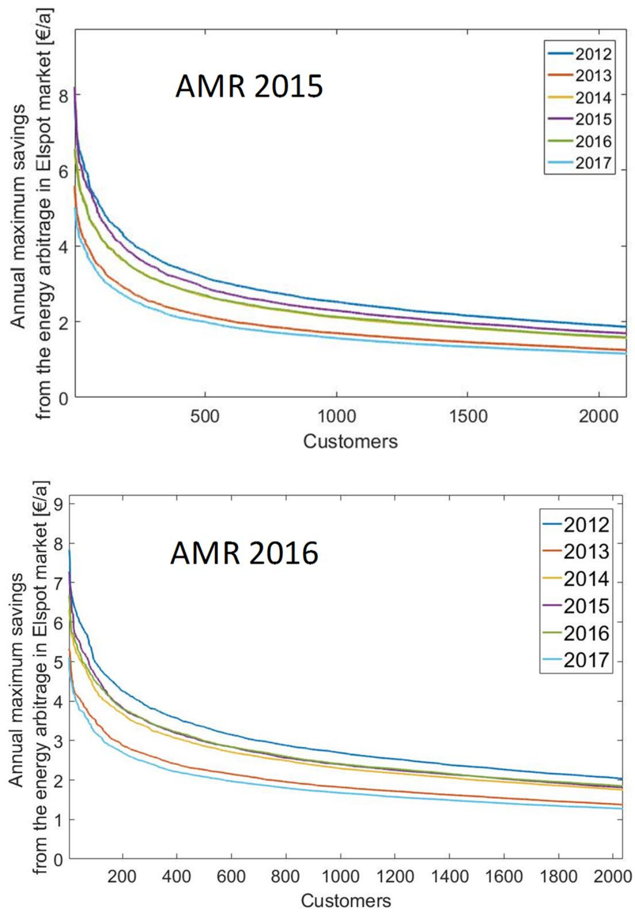

Figure 5.3. Annual theoretical maximum earning from the Elspot market-based load control

It can be seen that the results remain almost the same regardless of the year of the consumption data and the year of the market prices. Furthermore, it can be seen that in the year 2012 the annual earnings were 1–2 € higher than in the year 2017, which can be explained by the decreasing price volatility. Again, these calculations do not take into account constraints such as the comfort of the customer and the payback effect of load control, which would only further decrease the revenues.

Figure 5.4 illustrates the daily largest price difference in the Elspot market over a one-year period and the hourly consumption of the largest single customer (annual consumption 50 MWh/a) during the daily peak price hour. For instance, if the hourly consumption was 16 kWh during a peak price hour of the day and the maximum price difference was 80€/MWh, the 10 % load shifting would deliver 1.6 kWh*0.08€/kWh=0.128 € in that particular day.

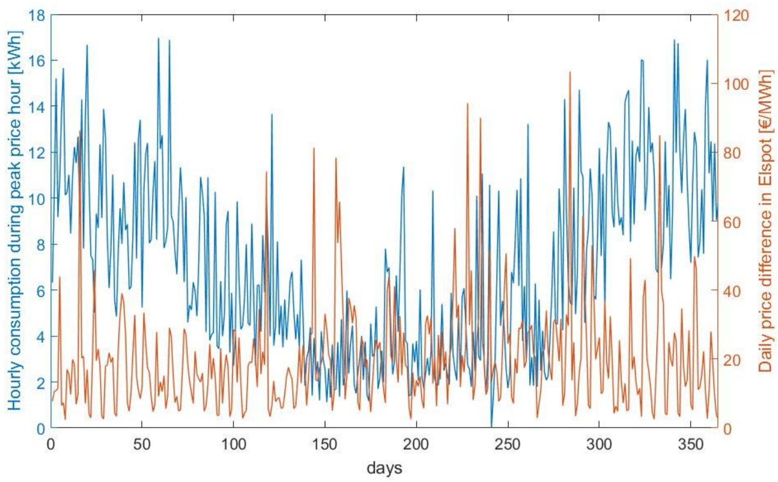

Figure 5.4. Hourly consumption vs. daily price difference in the Elspot market for the largest customer (annual consumption 50 MWh/a); annual profit 8€/a from 10% load shifting

The distribution of hourly powers during a daily peak price hour for the same large customer is presented in Figure 5.5. The histogram shows that the highest peak powers of 16–18 kW occur only for less than ten times per year. Instead, the hourly powers in the range of 2–4 kW occur even 70 times per year. Most probably, this is the customer with stored electric heating loads, which turn on at night-time when the prices are low. Such customers usually choose a day-night tariff instead of a spot price-based tariff.

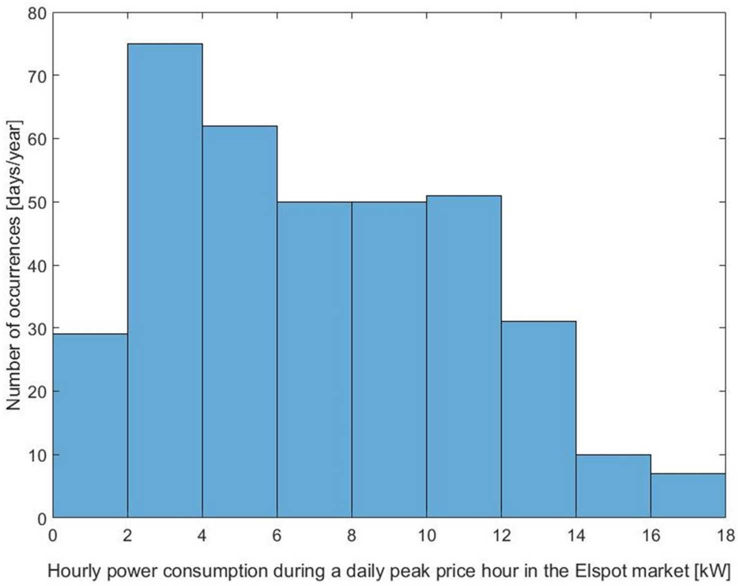

Figure 5.5. Distribution of hourly powers during a peak price hour for the customer with annual consumption of 50 MWh/a

The annual return from the energy arbitrage was also calculated from the retailer's perspective. In contrast to the previous case, where the customers had a spot price-based tariff, it was assumed that the 10 000 residential customers have a fixed-price tariff. In this case, instead of the end customers, it is the retailer who profits from the energy arbitrage. For instance, in 2017, the retailer received 3 million € of the income from the 10 000 customers at the Elspot area prices. Assuming the profit margin in the retailer's business to be 5%, the profit of the retailer is 150 000 €. At the same time, the profit on the energy arbitrage exercised by the same 10 000 residential customers was 7133 €, which constitutes 4% of the profit. This brings us to the conclusion that the economic feasibility of the Elspot market-based load control is very low for both the single customer and the aggregator.

5.2 Energy arbitrage in a balancing power market

In the balancing power market, the price volatility is higher than in the day-ahead Elspot market. However, from 2013 onwards the price level has been decreasing as can be seen from Figure 5.4. The number of hours when the price is higher than 200 €/MWh (yellow bar) has been decreasing over the past few years. This trend has a direct impact on the profitability of load control.

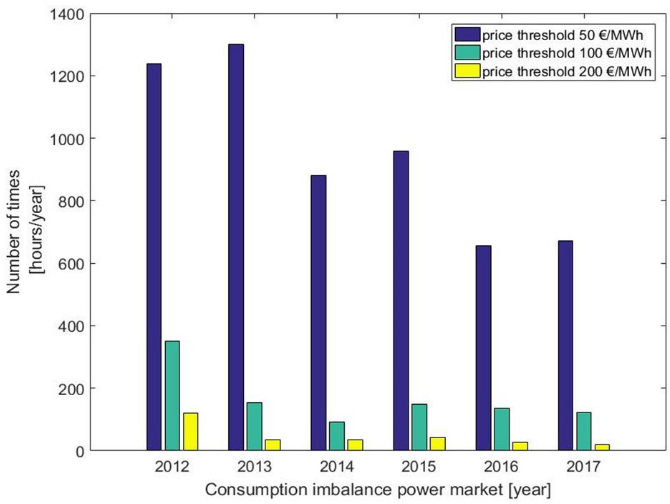

Figure 5.6. Number of times per year when the market price is higher than the price threshold

The annual revenues shown in Figure 5.7 are thus higher, but still not very significant and not attractive for an end customer. It is assumed that a customer participates in the market through a retailer or an aggregator. In this case, the revenues obtained will be even lower because of the margin price that an aggregator would charge a single customer.

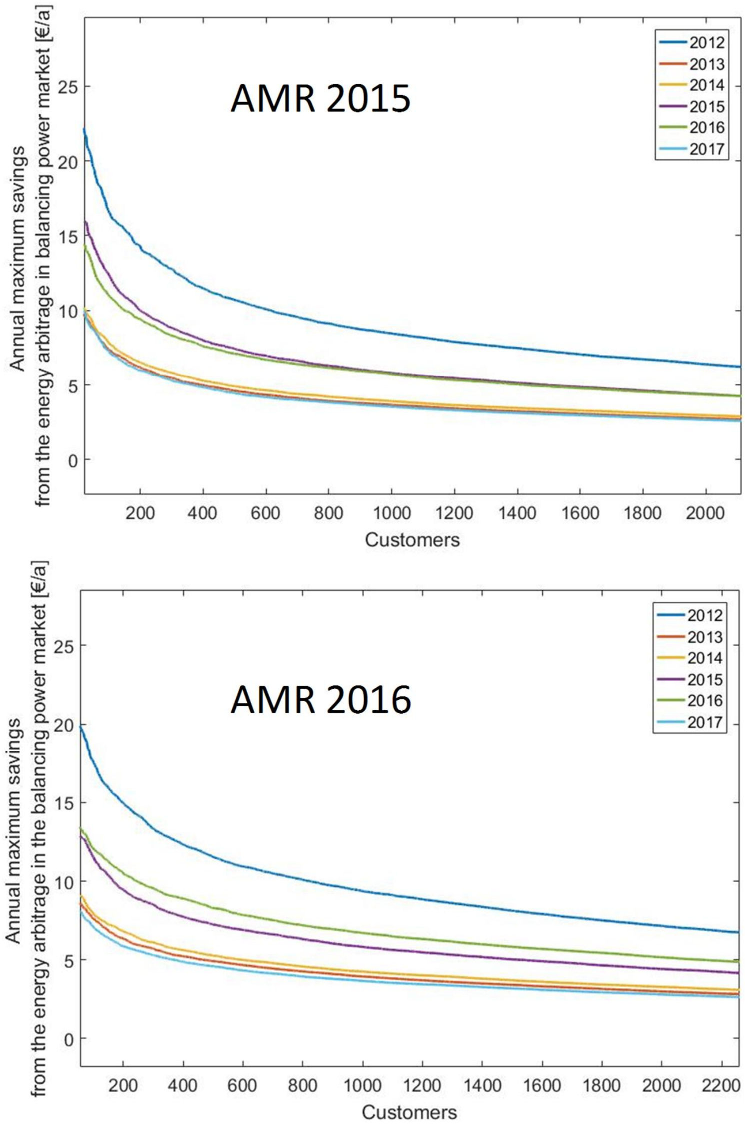

Figure 5.7. Annual theoretical maximum earning from the energy arbitrage in the balancing power market

The distribution of hourly powers during a daily peak price hour for the largest customer together with the annual consumption profile is presented in Figure 5.8. The idea of the figure is to show that the more occurrences of the high hourly consumption hours there are during the high price hours, the more the end customer profits from the market-based load control over the period of one year. For example, the highest peak powers of 16 kW almost never coincide with the peak price hour in the market. Instead, low hourly powers in the range of 2–3 kW occur most often during the peak up-regulating price hours. The fact that the load profile of the end customer is not in phase with the price pattern in the balancing power market strongly affects the profitability of the load control for both the end customer and the retailer.

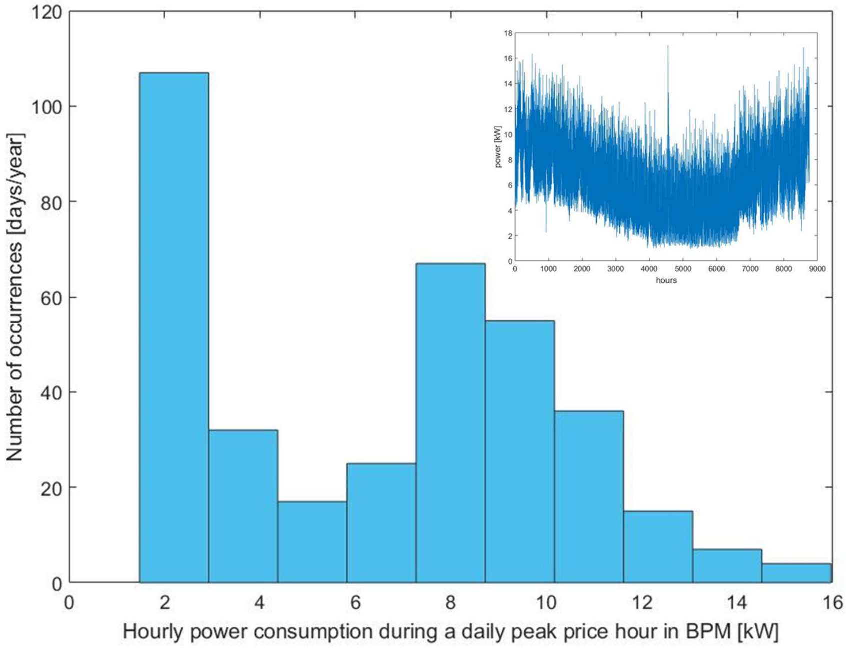

Figure 5.8. Distribution of the hourly powers during a peak price hour for the customer with the annual consumption of 50 MWh/a

Several examples of other types of customers are presented in Figure 5.9.

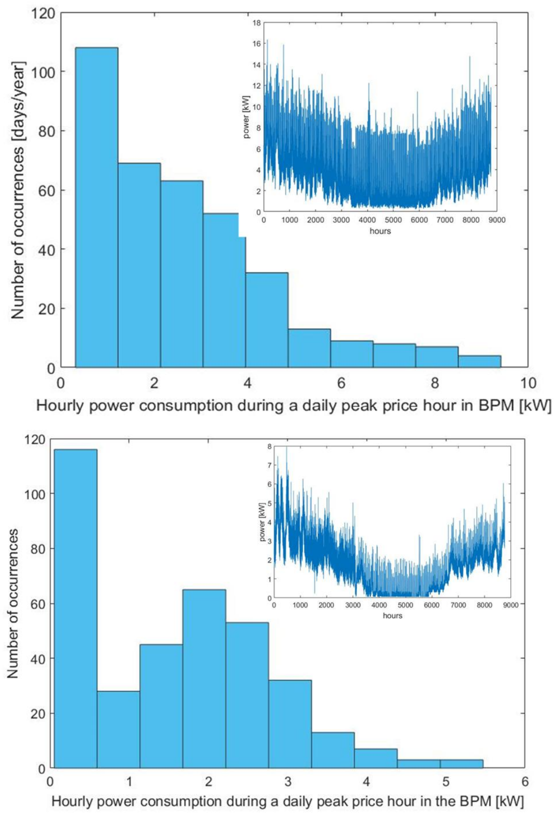

Figure 5.9. Distribution of the hourly powers during a peak price hour for the two example customers

To sum up, the profitability of load control in the balancing power market is slightly higher than in the day-ahead market as a result of the higher price volatility, but still insufficient for the end customer to get engaged in this type of application on a regular basis.

5.3 Frequency regulation

The results of the methodology part reported in Section 4.3.2 are presented here for the three scenarios: 1) economic feasibility of purchasing a BESS, 2) earning potential in the FCR-N hourly market with an already installed BESS, and 3) earning potential of the TCL in the FCR-N hourly market. The analyses were carried out for the market prices for the years 2012–2017. Various price bids were considered in the simulations. The price bid is expressed in €/MW, hour, and it is the price at which the flexibility provider (aggregator) offers its product (flexibility). If the price in the market is higher than the price bid, the bid is accepted and the flexibility provider is paid according to the market price (not the price bid).

5.3.1 Feasibility studies (scenario 1)

In this scenario, the assumption is that there is not yet a BESS unit on the customer's premises and he/she considers whether it is a profitable investment to make. Another assumption is that the price level in the FCR-N hourly market stays approximately the same during the payback time period. However, this is not true in reality. As it is seen in Figure 5.10, the annual revenues decrease, which means that the price level in the FCR-N market tends to fall over the past few years.

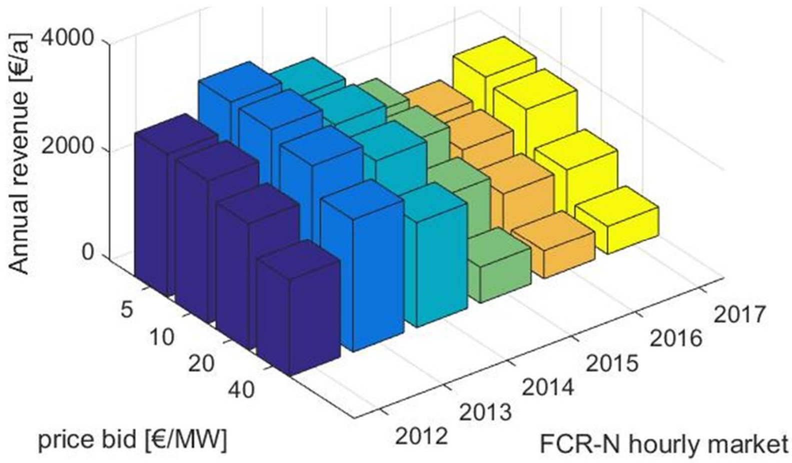

Figure 5.10. Annual revenues from the FCR-N hourly market for a 10 kWh BESS

The payback period for a BESS unit of 10 kWh is illustrated in Figure 5.11 for various price bids in the FCR-N hourly market (price level of year 2017) and various costs of battery technology.

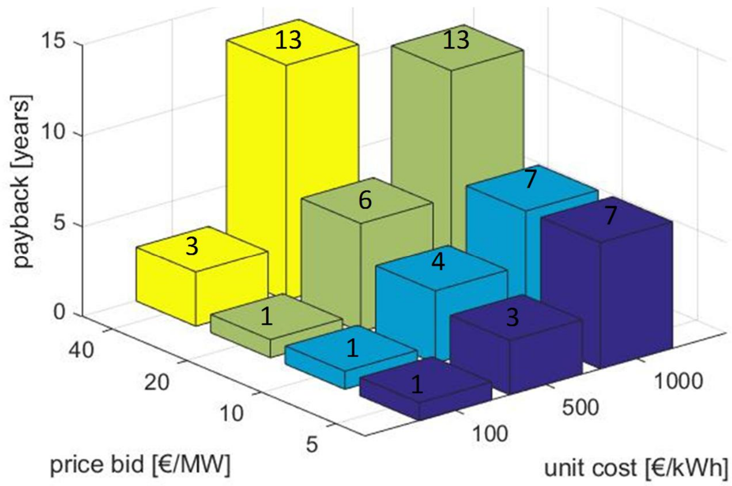

Figure 5.11. Payback period for a 10 kWh battery

The main guideline is that whenever the payback period is shorter than the lifetime of the battery, it is profitable to invest in the battery purchase. Assuming the lifetime to be 10 years, the investment in the 10 kWh battery is profitable at the battery unit cost of 1000 €/kWh and with the operating strategy in the FCR-N hourly market at the price bid of 10 €/MW (payback 7 years). Another example, if the unit cost of the battery is 500 €/kWh, it is feasible to purchase it for the frequency regulation task in the FCR-N hourly market, if the price bid level is under 20 €/MW (green bar, payback 6 years). If the battery capacity is bid at 40 €/MW and higher (yellow bar, payback 13 years), the number of hours at this price level in the market is so low that the revenues generated do not cover the investment costs of the battery over its lifetime anymore.

The main conclusion is that the lower is the unit price of the battery, the less annual revenues it requires to cover the investment costs. Thus, it can be operated at higher price bids than the more expensive batteries.

5.3.2 Definition of an operating strategy (scenario 2)

There is a BESS already installed at the end customer level. The question is how much profit the BESS participation in the FCR-N hourly market delivers to the end customer.

The input parameters used in the simulations are:

dead band width	49.95–50.05 Hz
reaction time	2 s

activation time	180 s
droop slope	0.05 Hz
BESS size	2, 5, 10, and 20 kWh
round-trip efficiency	95 %
calendar lifetime	10 years
cycle lifetime	5000 cycles
price bids	5, 10, 20, and 40 €/MW

The annual energy stored in the BESS for the frequency regulation task for various BESS sizes and price bids is presented in Figure 5.12.

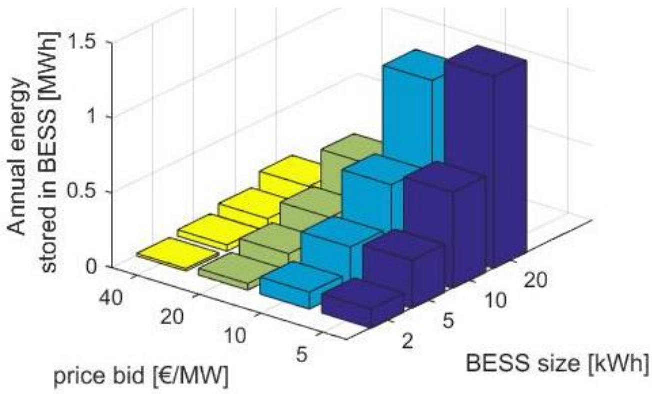

Figure 5.12. Annual energy stored in a BESS operated for the frequency regulation

The simulations show that the annual energy stored in a BESS operated for the frequency regulation application decreases as the price bid increases. This is because the number of high-price hours is lower than the number of low-price hours in the market. At this point, it is important to estimate whether the cycling lifetime is shorter or longer than the calendar lifetime and whether there is a need for battery replacement. This has a direct impact on the price of energy stored in the battery (according to (4.4) in Section 4.3.2) used further to calculate the OPEX and profit. The minimum annual energy stored in the BESS was calculated as in (Belonogova 2016):

$$E_{stored\_min} = \frac{Total\ stored\ energy\ over\ the\ lifetime\ [kWh]}{Lifetime\ [years]} = \frac{BESS_{capacity} * \eta_{RT} * N_{cycles}}{Lifetime} \quad (5.1)$$

For the batteries of the sizes 2, 5, 10, and 20 kWh, the minimum annual energy was 950 kWh/a, 2375 kWh/a, 4750 kWh/a, and 9500 kWh/a, respectively. Combining these results with the annual energy illustrated in Figure 5.12, it can be concluded that the battery is heavily underutilized when used only for the frequency regulation task. The same result was obtained in (Belonogova 2018), although a large-scale battery was used in the analyses in those studies.

Therefore, the operational expenses will be calculated at the price of energy taking only the loss component into account, and without replacement costs. The price of energy is assumed to be 5cents/kWh in the calculations. The OPEX calculation results are presented in Figure 5.13.

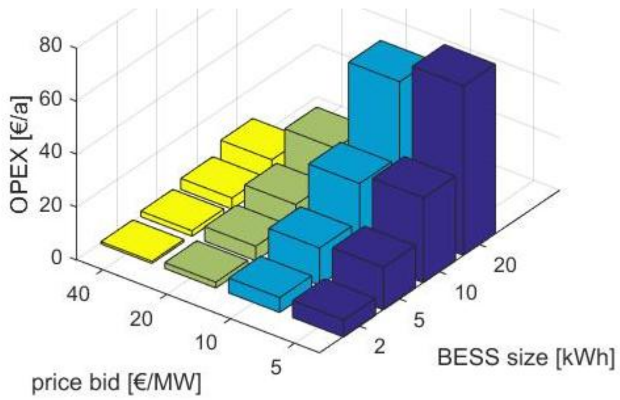

Figure 5.13. Operational expenses of a BESS operating in the FCR-N hourly market

The OPEX component follows the shape of the results of the annual energy in Figure 5.12 as it is directly proportional to the energy.

Further, the profit obtained from the FCR-N hourly market is given in Figure 5.14.

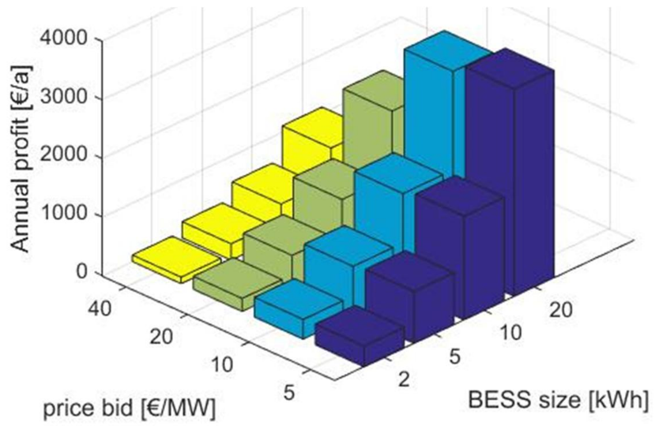

Figure 5.14. Annual profit in the FCR-N hourly market

The results show that a 2 kWh battery can earn 350 €/a, if operated at the price bid of 5 €/MW, while a 10 kWh battery operated at the price bid of 10 €/MW yields approximately 2000 €/a.

The key finding of the results obtained in this chapter is that already today (2018) it is profitable for a BESS to operate in the FCR-N hourly market. However, the battery is heavily underutilized if used only for this application, and thus, there is an opportunity to use it in other applications to increase the revenue streams and improve the cost-benefit ratio of the battery operation.

5.3.3 Earning potential of TCL loads (scenario 3)

The customer decides not to purchase a BESS but they still consider participating in the FCR-N hourly market with the TCL loads. The simulations were carried out for the market year 2016 and with the various price bids of 5, 10, 20, and 40 €/MW. Further, two sets of hourly indices reflecting the proportion of TCL in the total hourly consumption are used in the simulations. The space heating and cooling loads and household refrigerators were considered in the analyses. For the sake of simplicity, the electric water heater was excluded from the consideration. Below, the hourly indices reflecting the proportion of the TCL in the total hourly consumption are presented. The hourly indices for the refrigerator loads are given in kWs, while the other indices are given in p.u. values because of their dependency on the outdoor temperature.

1) Set 1

$$\alpha_{COOL}(t) = \begin{cases} 0.1, & 20℃ \leq T_{out} < 30℃ \\ 0.15, & if\ T_{out} \geq 30℃ \end{cases}$$

$$\alpha_{HEAT}(t) = \begin{cases} 0.1, & 0 < T_{out} \leq 10 \\ 0.15, & -10°C < T_{out} \leq 0 \\ 0.2\,, & T_{out} \leq -10°C \end{cases}$$

The refrigerator's available power is considered to be $\alpha_{COLD}(t) = 0.06kW$.

2) Set 2. The indices are increased by two times compared with the previous assumptions, as follows:

$$\alpha_{COOL}(t) = \begin{cases} 0.2, & 20°C \leq T_{out} < 30°C \\ 0.3, & if\ T_{out} \geq 30°C \end{cases}$$

$$\alpha_{HEAT}(t) = \begin{cases} 0.2, & 0 < T_{out} \leq 10 \\ 0.3, & -10°C < T_{out} \leq 0 \\ 0.4\,, & T_{out} \leq -10°C \end{cases}$$

The refrigerator's available power is considered to be $\alpha_{COLD}(t) = 0.08\ kW$

As an example, $\alpha_{HEAT}(t)$ indices are presented in Figure 5.15.

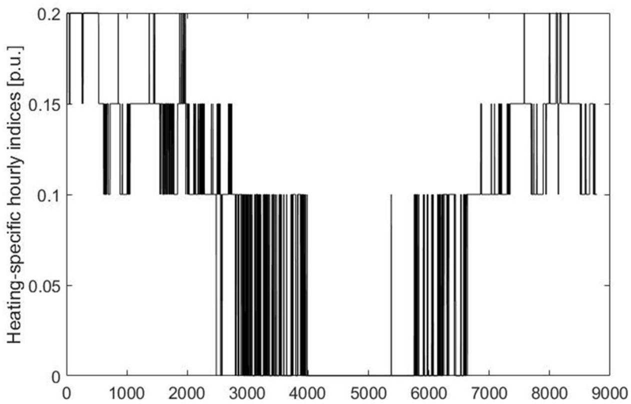

Figure 5.15. Example of electric heating-specific hourly indices

The estimated proportion of the hourly electricity consumption of a group of 10 000 customers is presented in Figure 5.16 (set 1) and Figure 5.17 (set 2).

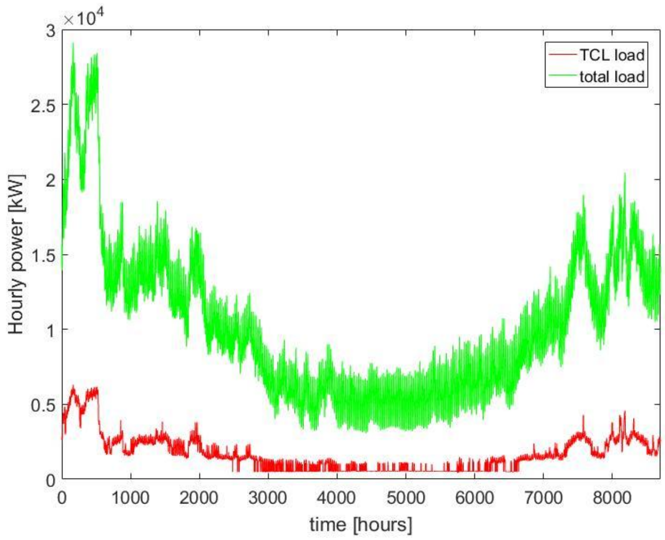

Figure 5.16. Hourly TCL available for the FCR-N hourly market, set 1 of the hourly indices

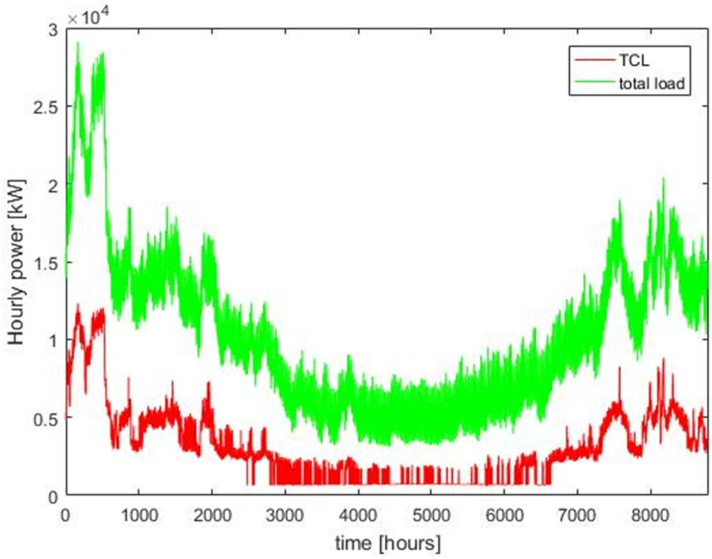

Figure 5.17. Hourly TCL available for the FCR-N hourly market, set 2 of the hourly indices

The annual revenues from the FCR-N hourly market delivered to the aggregator at various price bids are presented for the two sets in Figure 5.18 and Figure 5.19.

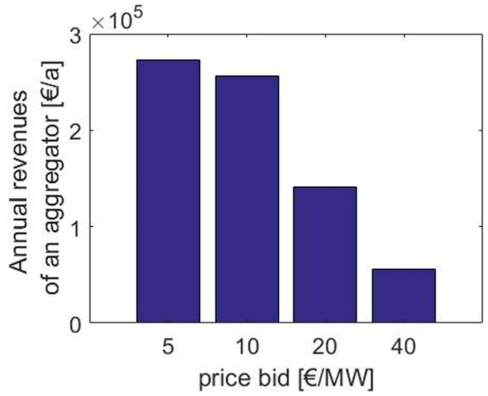

Figure 5.18. Annual revenues from the FCR-N hourly market, year 2016 (set 1)

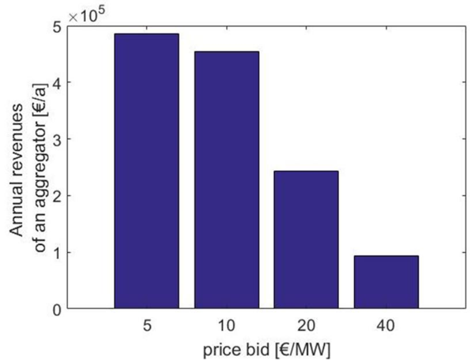

Figure 5.19. Annual revenues from the FCR-N hourly market, year 2016 (set 2)

The figures show that the annual revenues that the aggregator of the 10 000 customers' TCL receives from the FCR-N hourly market vary from 280 000 to 480 000 € if the TCL is bid at the price level 5 €/MW. The next figures show how the annual revenue vary for each single customer, if their TCL is bid at the price of 5 and 10 €/MW (Figure 5.20 and Figure 5.21).

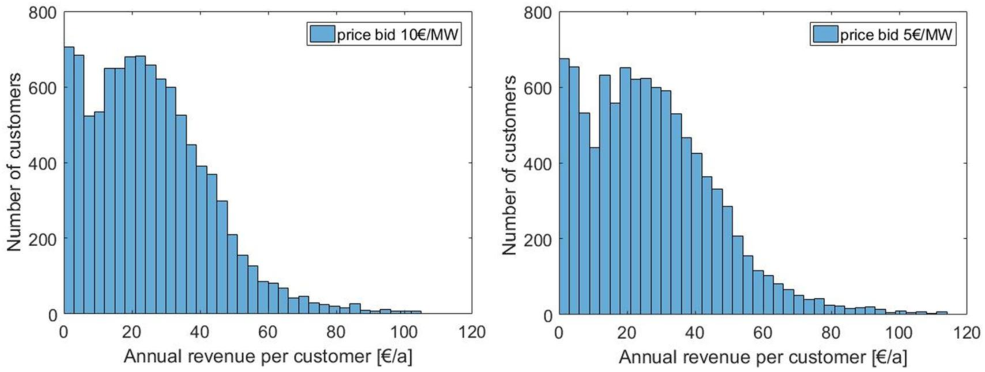

Figure 5.20. Distribution of annual revenues for a single customer at the price bid of 10 €/MW and 5 €/MW (set 1)

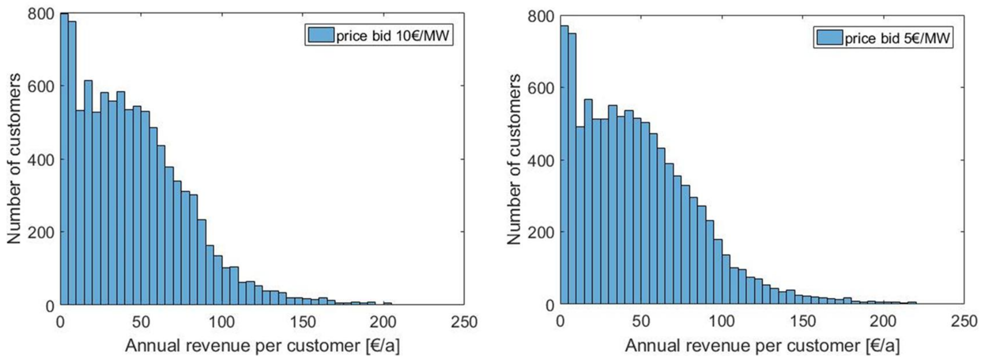

Figure 5.21. Distribution of annual revenues for a single customer at the price bid of 10 €/MW and 5 €/MW (set 2)

The results show that the size of power set available to the FCR-N hourly market has a direct impact on the annual revenue. At the same time, based on the prices of the year 2016, the price bid at which the loads are offered to the market should be 10 €/MW at highest in order to obtain reasonable revenues. If bided at higher prices, the number of operating hours and the revenues decrease dramatically (as seen in Figure 5.18 and Figure 5.19).

Considering the annual revenues for a single customer, most of the customers get less than 60–120 €/a, depending on the availability of TCL. Furthermore, most of the customers stay within the range of 10–40 €/a (set 1) and 20–80 €/a (set 2), which is much more than the savings obtained from the energy-based markets (Elspot and balancing power market). Still, revenues of this size may not be enough for a single customer to get engaged in a marketplace of such type. Eventually, the size of the revenues that the end customer receives depends on the contract terms with the aggregator, in particular, the reward mechanism that the aggregator offers for the end customer. The type of reward, that is, whether it is a fixed price-based reward to the end customer for making the TCL available for frequency regulation or a dynamic price-based reward according to the provided flexibility of TCL, has an impact on the profit earned by the customer and the customer's interest in engaging in demand response services. Here, the role of the regulatory framework is important in order to guide the end customer's behaviour so that the involved parties' interests are met.

5.4 Peak shaving task

In Section 4.3.3 it was concluded that the profit obtained from the peak shaving task depends on three factors: the power fee, the price of energy stored in the flexibility resources, and the peak operating time. To demonstrate this impact, the results are presented for two groups of customers, with two different annual consumption levels, 30–40 MWh/a and 7–8 MWh/a and with different load profiles, for example different peak operating times (Figure 5.22).

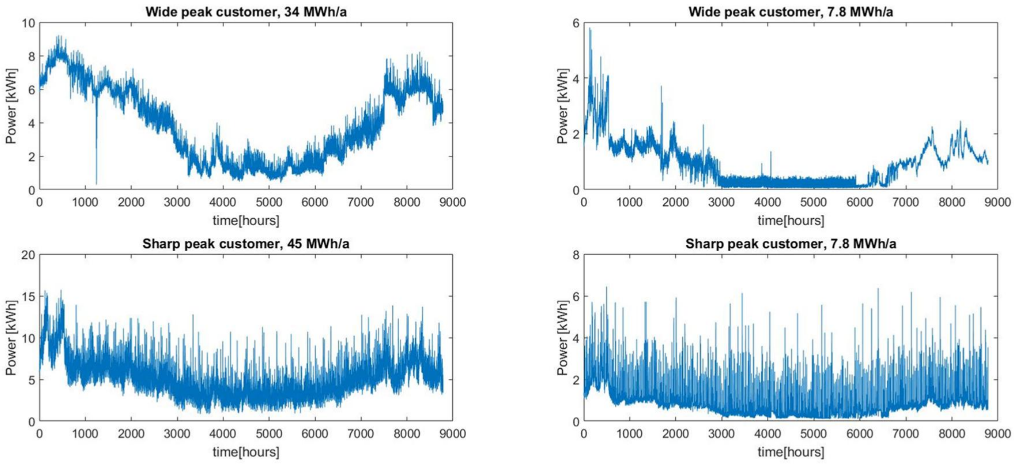

Figure 5.22. Annual consumption of four customers

According to the methodology presented in Section 4.3.3, there are two alternative scenarios: 1) no BESS resources yet 2) there is already a BESS resource installed. The size of the BESS was not calculated but various sizes were suggested instead as an input to the developed algorithm. In the future, the methodology could be developed further by finding a BESS of an optimal size for each customer.

5.4.1 Feasibility studies (scenario 1)

The procedure of scenario 1 was presented in Figure 4.7, where it was shown that in order for the BESS to be feasible, the investment costs in the battery have to cover the savings obtained from the peak shaving task over the lifetime of the battery.

The savings were calculated for various power-based fees, and the investment costs were calculated for different unit price values of the battery. The lifetime of the battery was assumed to be ten years, and the interest rate 4.5%. The results are presented in Figure 5.23. It is economically feasible for a single customer to purchase a battery whenever a bar representing the estimated savings is above the line representing the investment costs. The estimated savings are calculated over the battery lifetime. The results show that the profitability of a BESS in a peak shaving application improves with the increasing power fee and the decreasing unit price of the battery technology. It is obvious that customers with short peak operating times (sharp peak profile) benefit more from the peak shaving than customers with long peak operating times (wide peak profile). For instance, for a customer with a short peak operating time and an annual consumption of 45 MWh/a, purchasing a 5 kWh battery is profitable at the battery unit price of 200 €/kWh and a power fee of higher than 5 €/kW, month. However, at the unit price of 500 €/kWh (upper capex line), the battery purchase becomes profitable only if the power fee is at least 15 €/kW, month. The power fees of 5 €/kW and 10 €/kW yield lower savings over the lifetime of the battery, 1000 € and 2000 €, respectively, which the capex of 2500 € does not cover.

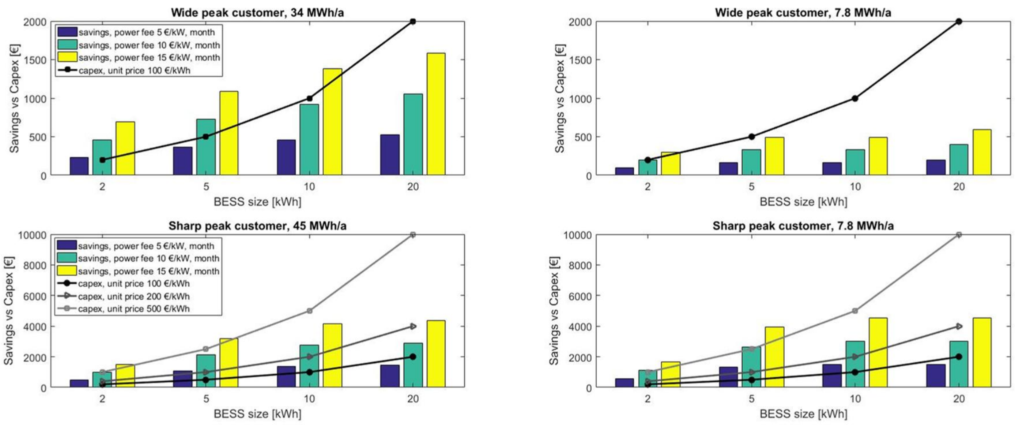

Figure 5.23. Results of the profitability studies of BESS purchase for four selected customers

In the simulations, the change in power fees throughout the lifetime of the battery was not taken into account. This can have an impact on the savings and thereby on the results of the feasibility studies.

5.4.2 **Definition of the earning potential (scenario 2)**

In this scenario, it is assumed that the customer already has a BESS unit installed. The objective is now to define the earning potential of the BESS operated for the peak shaving task. The algorithm is divided into two steps: 1) definition of the price of energy stored in the BESS (BESS operation limited by the calendar- or cycle-based lifetime), and 2) calculation of the profit.

The specifications of the BESS unit used in the simulations cover the following information: the number of lifetime cycles is 5000, the round-trip efficiency is 95 %, and the minimum and maximum SOC levels are 5 % and 95 %, respectively.

1) Definition of the price of energy stored in the BESS.

First, it was calculated how much energy is required to cut the monthly peak power by 1–5 kW for each of the four customers. The monthly peak power was assumed to be the maximum hourly value of each month. The energy defined for each month separately is illustrated in (Figure 5.24).

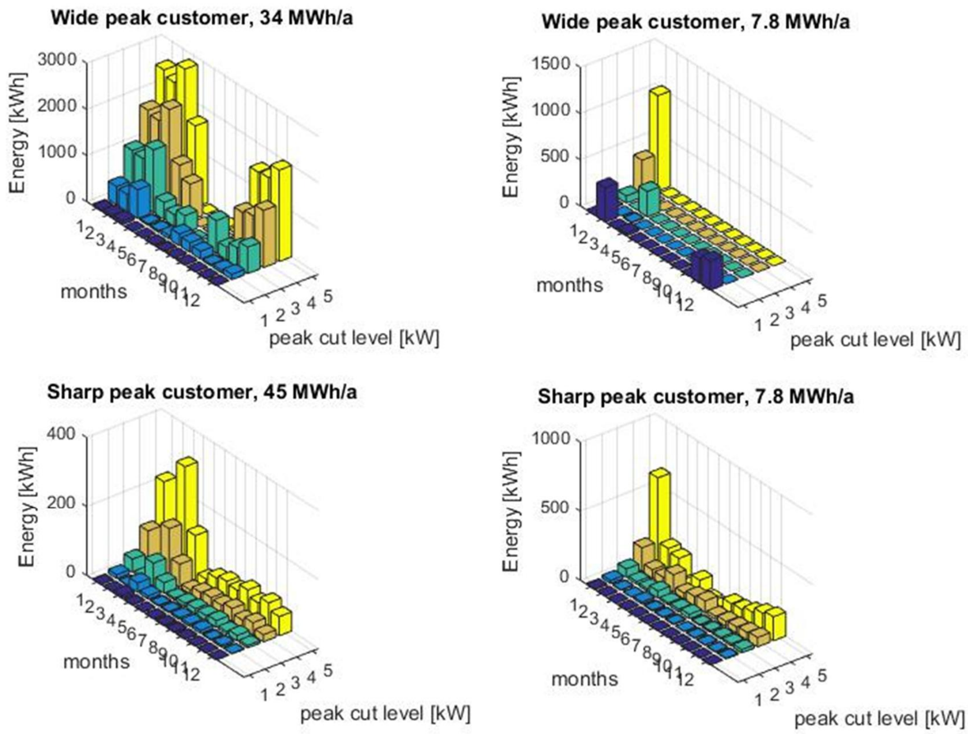

Figure 5.24. Monthly energy needed for various peak cut levels

The month-long period is taken as an example here. However, also the year- or week-based energy can be calculated by taking the same approach, which is an advantage of the developed methodology and this simulation tool.

Using the obtained results on the monthly energy, the peak cut level was calculated in each month that a BESS of a given size (2, 5, 10, and 20 kWh) can technically achieve for each customer. Using the obtained monthly peak cut levels, the savings can be calculated. Further, the energy stored in the BESS each month that is needed from the battery to achieve the peak cut level was calculated (Figure 5.25). This energy is then used in the calculation of the OPEX component.

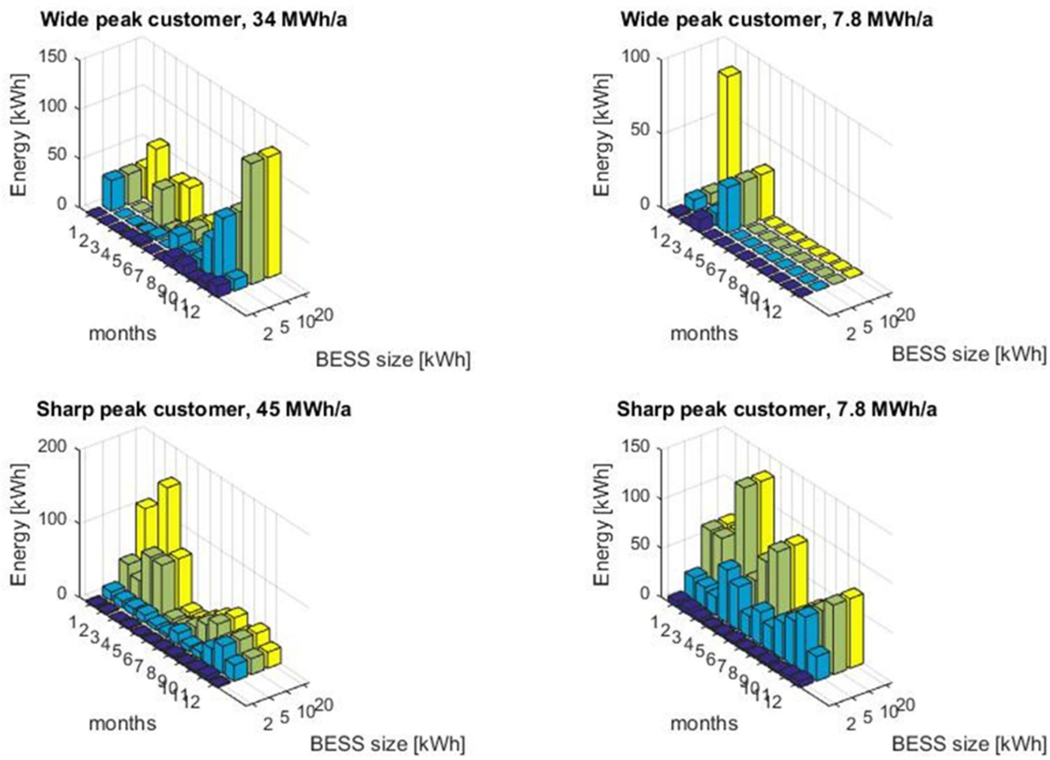

Figure 5.25. Monthly energy stored in a BESS to achieve the technically possible calculated peak cut level

As it was calculated earlier in Section 5.3.2, for the batteries of the sizes 2, 5, 10, and 20 kWh, the minimum annual energy was 950 kWh/a, 2375 kWh/a, 4750 kWh/a, and 9500 kWh/a, respectively. Comparing this with the results in Figure 5.25, one can conclude that the battery is underutilized when used only for the peak shaving task, and thus, there is no need for replacement before the calendar lifetime reaches the end. Therefore, the loss-related price of energy stored in a BESS will be used further in the profit calculations.

2) Profit calculation

For the profit calculation, the monthly savings and OPEX for each customer have to be defined as it was derived in (4.8) in Section 4.3.3.

The annual savings vary depending on the customer's load profile. It can be seen from Figure 5.26 that the customers with long peak operating times (wide peak customers) make significantly lower savings than the customers with the short peak operating times. The reason for this is the difference in the amount of energy required from the battery to cut the peaks. The same reason leads to the difference in the OPEX components, presented in Figure 5.27.

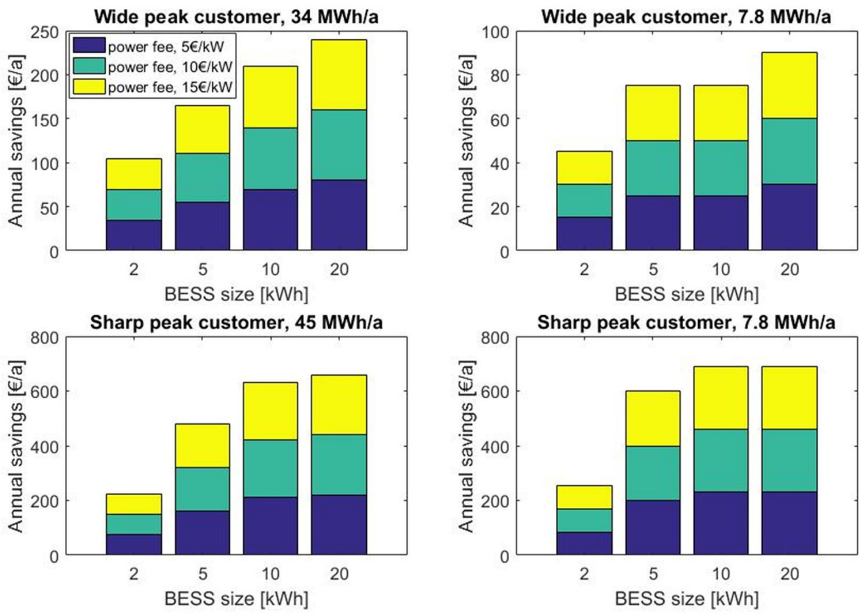

Figure 5.26. Annual savings from the peak shaving at various power fees

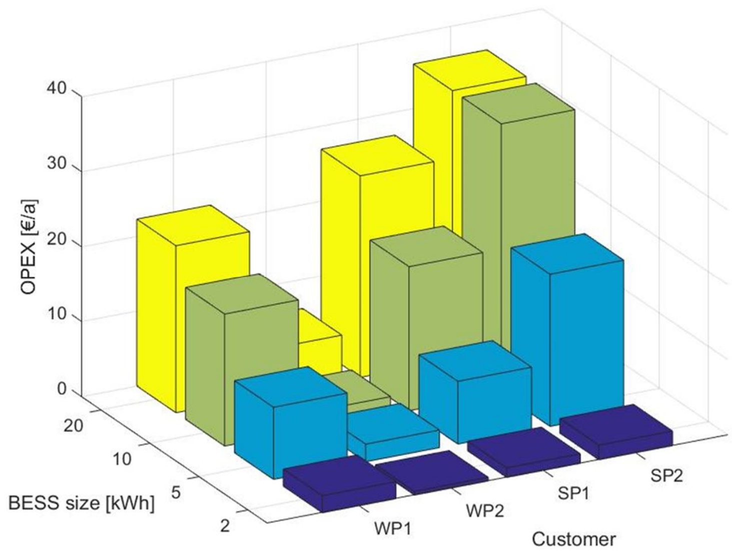

Figure 5.27. Annual OPEX for various BESS sizes and customer types

The annual profit can now be calculated as the difference between the savings and the operational expenses, and is illustrated in Figure 5.28.

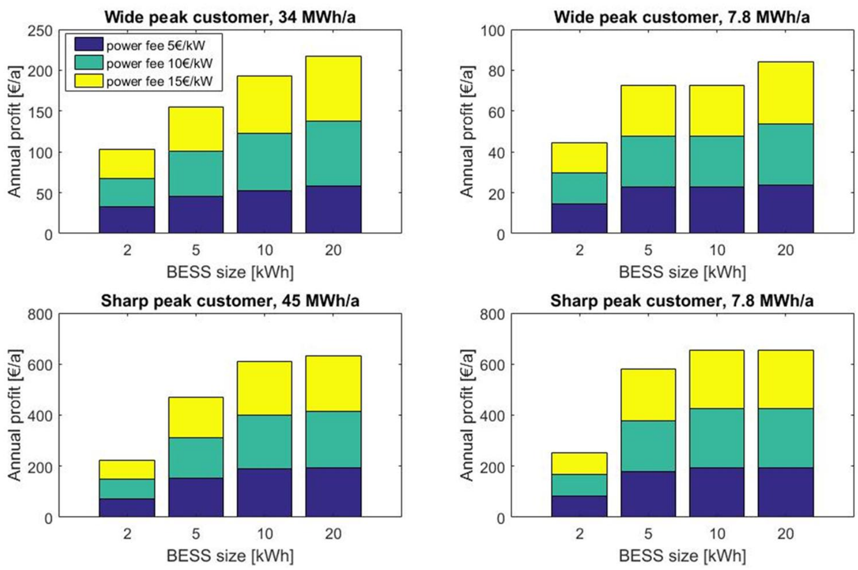

Figure 5.28. Annual profit for various power fees and customer types

The results show that the annual profit for the large residential customer with a short peak operating time is two to three times as high as for the large customer with a long peak operating time. The difference in profit for the smaller customers (right-hand figures) is even larger, five to eight times.

Next, the same results are extended to the group of 10 000 customers and shown in Figure 5.29, Figure 5.30, and Figure 5.31.

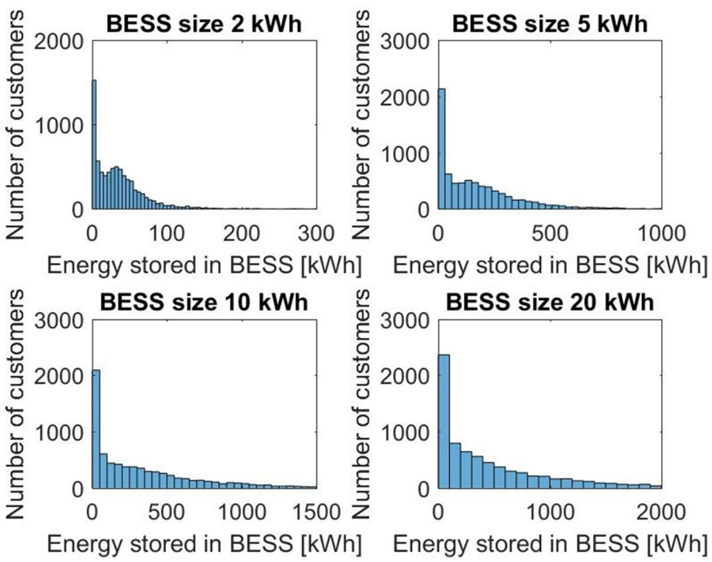

Figure 5.29. Annual energy required for the peak shaving task

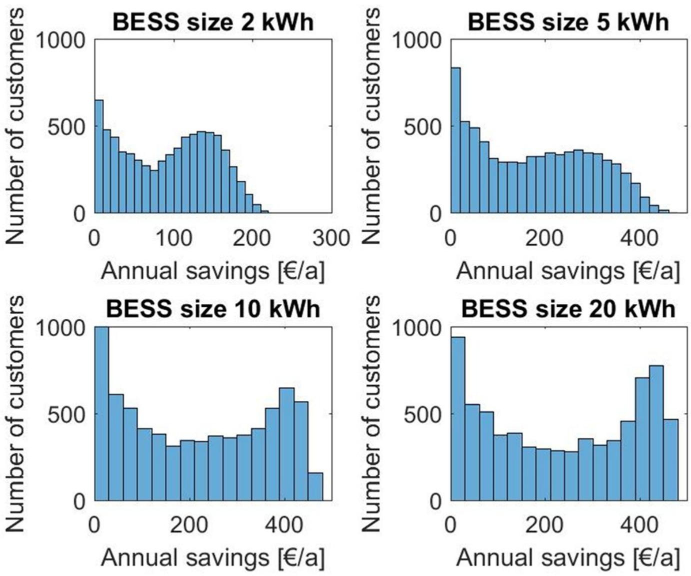

Figure 5.30. Annual savings from a peak shaving task, power fee 10 €/kW, month

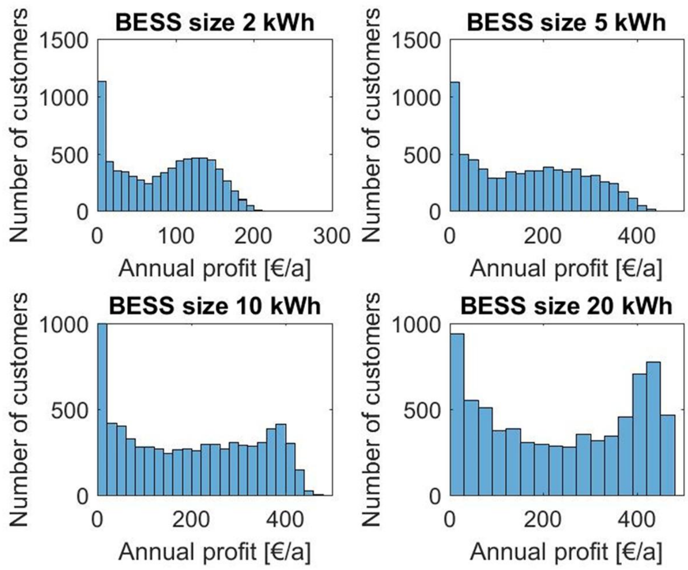

Figure 5.31. Annual profit from a peak shaving task, power fee 10 €/kW, month

The results show that for the majority of the customers the annual profit is much higher than the profit obtained from the energy-based markets. The profit varies depending on the size of the BESS and the type of customer.

5.5 Conclusions

This chapter aimed to find the most promising and attractive DR marketplaces for a single residential customer, following the methodology presented in Section 4.3. In the calculations, the AMR data from years 2015 and 2016 of 10 000 residential customers and prices in the Elspot, the balancing power, and the FCR-N hourly markets in years 2012–2017 were applied. The power-based tariff was based on the one-month peak hourly power value. Based on these input data, the results show that the most promising options for a single customer are the FCR-N hourly market and a power-based tariff. Instead, the energy arbitrage in the Elspot and balancing power markets did not yield an attractive return for the customer.

It was demonstrated that in each DR marketplace there are many variables that affect the annual reward obtained. Moreover, the level of profit varied considerably from market to market. Table 2 shows the profitability level in the individual DR marketplaces and the factors affecting it.

Table 2. Profitability and influencing factors in various DR marketplaces

DR marketplace		**Profit level (€/a/customer)**	**Influencing factors on profitability**
Elspot		0–5	price volatility, load profile
Balancing power market		0–30	price volatility, load profile
FCR-N hourly market	TCL	10–80	size of power bid
	BESS	200–2000	size of BESS, price bid in the market
Peak shaving		40–400	load profile, size of BESS, power fee

The results show that the profit in the Elspot and balancing power markets is low even without any constraints taken into account. The constraints, for instance, limited availability of loads for control (owing to the comfort of the end customer) and payback effect after the load control event, would decrease the profit even further. This means that these marketplaces will be left out of the further analysis in stage 2. Instead, the break-even analysis is an appropriate tool for the discussions on which price level and when the profitability on such a DR marketplace will be attractive for the end customers. Regardless of the DR marketplace, the break-even analysis in any of them involves the following questions:

1) With the present cost of flexibility resources at the end customer level, at which reward level (hourly prices, tariffs) is it profitable for a single customer to offer

their flexibility resources to the market? In other words, what should the level of price incentives be in energy- and power-based applications in order to deliver benefits to a single customer?

Figure 5.32 shows how much the market price volatility should be in the Elspot or balancing power market for each of the 10 000 case customers in order for them to gain 20 €, 50 €, and 100 € per year. The market price volatility is calculated as the average daily market price difference, or the difference between the maximum and minimum price of the day (24 hours). Only for a very few customers the price difference may stay under 100 €/MWh in order to gain 333the reward or annual profit of 100 €/a. For the majority of the customers, the necessary price difference is far above 50 €/MWh.

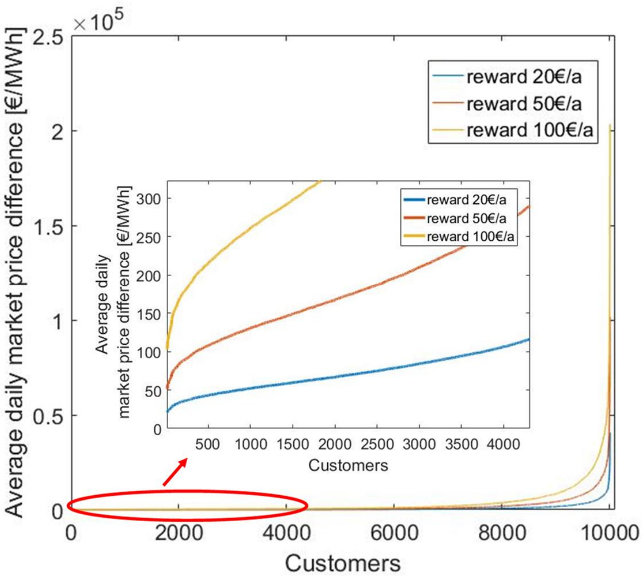

Figure 5.32. Average price level in the energy-based market at which the desired annual reward is achieved

On the other hand, Figure 5.33 and Figure 5.34 show that the average price difference in the Elspot and balancing power market in the year 2017 was 20–50 €/MWh, respectively.

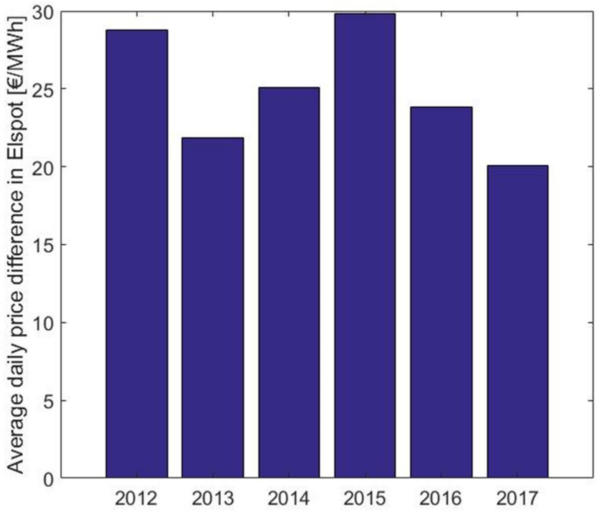

Figure 5.33. Average daily price difference in Elspot

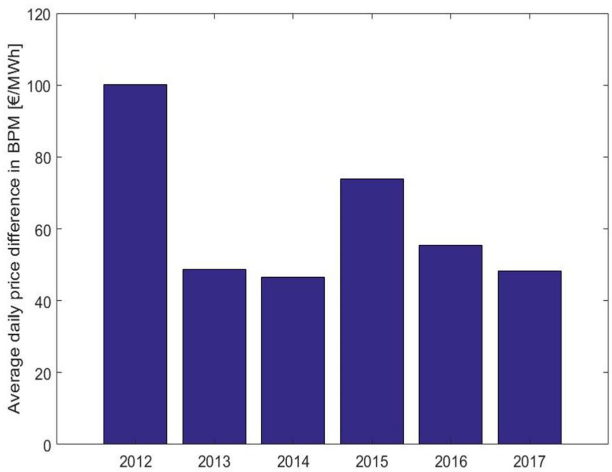

Figure 5.34. Average daily price difference in the balancing power market

The necessary price difference of far above 50 €/MWh and the present level of the price difference of 20–50 €/MWh shows that it is not profitable for a single customer to participate in the energy market-based load control.

2) With the present reward level in the DR marketplaces, what is the cost of technology installed on the customer's premises that makes it attractive for a customer to be involved in the markets at today's reward level?

The answers to these two questions together with the learning rate of technology and market price development give an answer to the question of when a break-even point will occur. Providing that the present cost of battery for residential customers is approximately 1275 €/kWh (equal to 1500 $/kWh (Schmidt 2017)), and assuming 5000 cycles and a 95 % round-trip efficiency, the price difference in the energy-based markets should be above (1275 €/kWh/(5000 cycles*0.95)) = 0.27 €/kWh, which is 270 €/MWh. This price difference is not realistic in the day-ahead market Elspot and is reached only rarely in the balancing power market.

Another conclusion of stage 1 of the methodology is that such DR marketplaces as frequency regulation in the FCR-N hourly market and peak shaving against the power-based distribution tariff are promising and attractive for single residential customers.

These applications are brought further to stage 2 of the methodology, where the methodology and the simulation tool will be developed to define an operating strategy that meets the interests of the end customer and the involved stakeholders (TSO and DSO).

6 Methodology to define the operating strategy in multiple DR applications (stage 2)

At this stage of the methodology, the operating strategy of the end customer's flexible resources in the promising DR applications is developed. These marketplaces were selected in stage 1 of the methodology. Further input data required in this stage are the customer's comfort preferences and the flexible resources that they possess.

The results of stage 1 show that the FCR-N hourly market and the power-based tariff are the two attractive marketplaces for the end customer. Therefore, this chapter will focus on developing the methodology to operate in these two applications. As such, the goal of the second stage is to provide a practical, understandable, and realistic/implementable solution to the problem of the control of flexibility resources in multiple DR marketplaces. Such a solution allows:

a) to show the relationship between DR marketplaces when a flexibility resource is operated simultaneously for multiple tasks,
b) to find the most and least influencing factors on the final decision,
c) to understand the interdependence between intermediate decisions, and
d) an opportunity to test and run numerous scenarios.

The rest of the chapter presents the framework and the content of the methodology.

6.1 Framework of the methodology

Now, the large complex multi-objective problem described in Chapter 0 is simplified to the definition of an optimal operating strategy in the two applications.

The different structures of the DR marketplaces make the decision-making procedure and operation in the two applications a complicated task. The major differences are:

1) Rules of participation in the two markets,

2) Type of resource needed: one is an energy-intensive, the other a power-intensive application, and

3) Target level of the SoC: a full battery for the peak shaving and a half-full battery for the frequency regulation.

It is important to note that the rules in both applications affect the strength of the conflict, the quantitative value of revenue loss and/or savings obtained from the market, and thereby, the selection of the priority order of the two applications.

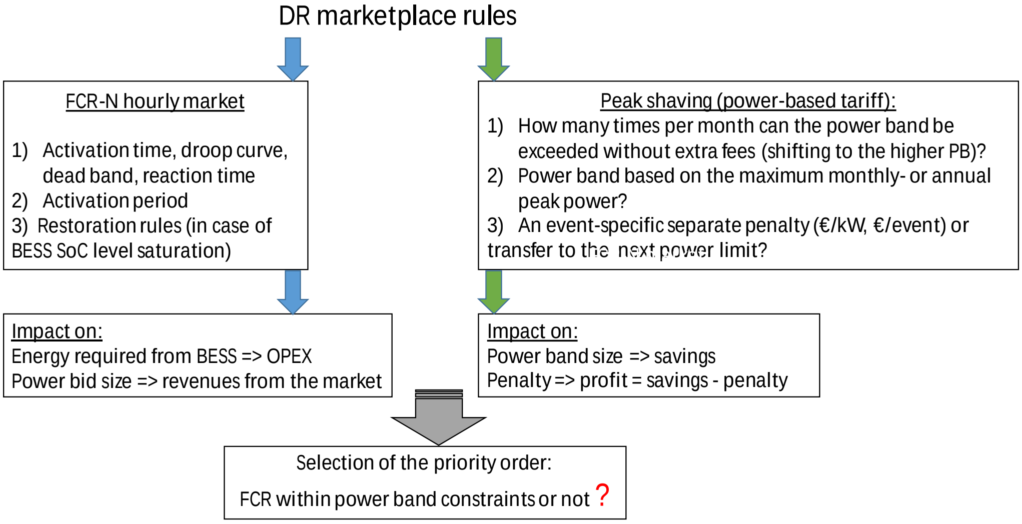

Figure 6.1. Impact of the DR marketplace rules on the selection of the optimal priority order of the tasks

Furthermore, the FCR-N hourly market has an hourly price, whereas the power band tariff is a monthly or annual one. This means that in the case of a monthly power tariff, the optimal priority order should be defined for each month.

The limitations of the methodology are the following:

1) The studies focus on finding the theoretical earning potential using historical load and price data. The simulation of the real-time bidding process and definition of the operating strategy in real time are left for future research.

2) Uncertainty of the control signal is not taken into account. This means that the forecast error of the peak power is neglected and the load forecast is assumed to be perfect. The historical load measurement data are used in the analyses.

3) The cost of SOC (state of charge) corrective measures of the BESS are not taken into account.

4) The optimal operating strategy is defined based on the rewards over a specific period of time (in this case, one year).

5) Hourly resolution load data were used in the analyses. However, the use of second-resolution data may yield different results, which can lead to even opposite decisions regarding the optimal operating strategy.

6.2 Defining the operating strategy for the two applications

The two promising applications, frequency regulation and peak shaving, yield two main strategies (see Figure 6.2).

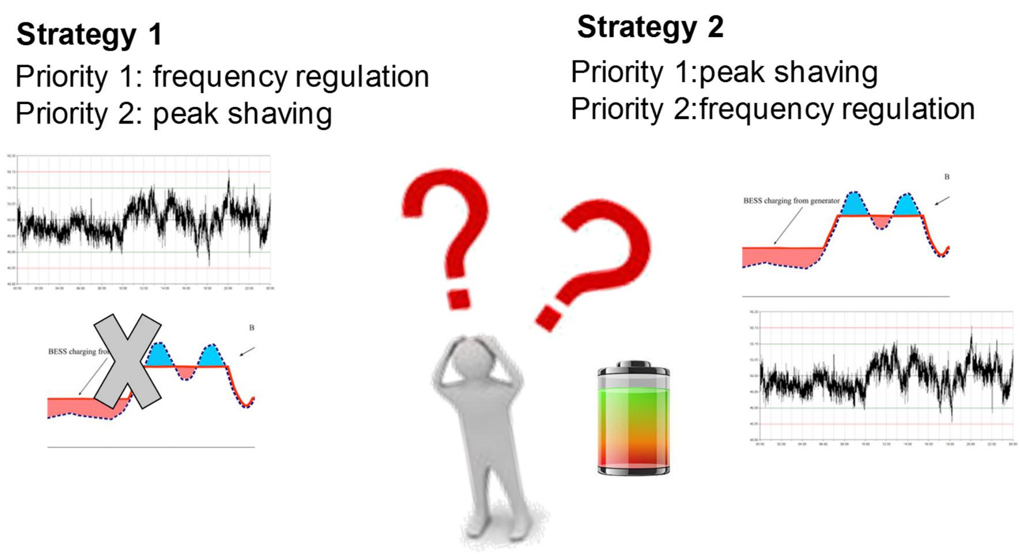

Figure 6.2. Challenge of selecting the optimal strategy

The difference between the strategies lies in the priority order of the applications. In the first strategy, the customer has an objective to maximize the profit in the FCR-N hourly market by maximizing the power bid to the market. The power band constraints are not followed in this strategy. Therefore, the frequency regulation is prioritized over the peak shaving. In the second strategy, the customer has an objective to stay within the power band and at the same time maximize the profit obtained from the FCR-N hourly market. Therefore, the peak shaving task is prioritized over the frequency regulation.

Next, the end customer poses a question: which strategy is the most profitable for him/her? In order to answer this question, the strategies are mathematically formulated and simulated in Matlab. Here, the assumption is that the customer will choose the strategy that delivers the maximum profit (see Figure 3.5). The mathematical description of the strategies presented here is adapted from (Belonogova 2018).

Strategy 1: A BESS is operated for the FCR-N hourly market without power band constraints.

The assumption is that a small customer can participate in the FCR-N market through an aggregator. The power bid to the FCR-N hourly market is defined according to the energy capacity available in the battery, which can be estimated according to the SoC level in the battery as the minimum of the discharging and charging energies:

$$Eavailable(t) = \min[SoC_{MAX} - SoC(t); SoC(t) - SoC_{MIN}] * Etotal \tag{6.1}$$

where

$Eavailable(t)$	energy capacity available in the battery in hour t [kWh]
$SoC(t)$	estimated state of charge level during hour t [%]
SoC_{MAX}	maximum allowed SoC level [%]
SoC_{MIN}	minimum allowed SoC level [%]
$Etotal$	total usable energy capacity of the battery [kWh]

After the available energy capacity has been estimated, the power bid can be defined:

$$PowerBid_{FCR}(t) = Eavailable(t) * \beta * C_{rate} \tag{6.2}$$

where

$PowerBid_{FCR}(t)$	power bid to the FCR-N hourly market [kW]
β	activation period [1/h]
C_{rate}	battery charge/discharge rate relative to its capacity [p.u.]

In this study, the activation period β was assumed to be 30 min. However, in the further research there is a need to check the sensitivity of the results to this parameter. First, there are discussions going on about reducing the activation period to 15 min (European Union Electricity Market Glossary 2018) and secondly, for instance, the studies (Hollinger 2017) show that the impact of the activation period may be significant on the charging and discharging corrective energy. In addition, the shorter activation period means that more capacity is left available for the other applications, and thus, the technical conflict between the two applications is weaker.

Finally, the objective function is derived:

$$Profit(k) = max \sum_{tstart}^{tend} Profit_{FCR}(t) + Profit_{PS}(k) \tag{6.3}$$

$$Profit_{FCR}(t) = Revenues_{FCR}(t) - Cost_{FCR}(t) = PowerBid_{FCR}(t) * Price_{FCR}(t) - Energy(t) * price_{kWh} \tag{6.4}$$

where

$tstart, tend$	start and end of the time period
$Profit_{FCR}(t)$	profit from the FCR-N hourly market [€] in hour t
$Price_{FCR}(t)$	hourly price in the FCR-N hourly market [€/MW]
$Energy(t)$	energy stored in the BESS during the frequency regulation task [kWh/h]

The profit from the peak shaving task $Profit_{PS}(k)$ is calculated as in (4.8).

Strategy 2: A BESS is operated for the FCR-N hourly market within the power band constraints. It is assumed that the peak shaving and frequency regulation tasks cannot be executed simultaneously during the same hour. This means that the BESS capacity is bid to the FCR-N hourly market only in the hours when the load is estimated to be below the power band.

The objective function remains the same, but the power band constraint is added to the definition of the power bid:

$$PowerBid_{FCR-PB}(t) = \min[PowerBid_{FCR}(t); (PB(k) - Load(t))] \tag{6.5}$$

where

$PB(k)$	power band over time period k [kW]
$Load(t)$	end customer's power consumption [kW] in hour t

The algorithm to define the operating strategy of the battery is presented in Figure 6.3. Regardless of the strategy, the whole procedure is divided into three steps: 1) an SOC correction during the previous hour, 2) an operation during the delivery hour, and 3) profit calculation and decision on the optimal strategy. This algorithm allows to calculate the theoretical earning potential as it does not take into account uncertainty.

The algorithm works as follows. In each previous hour t-1, it is checked whether the price bid for the hour t is accepted by comparing it with the hourly price in the FCR-N hourly market. If the price bid is accepted, the next condition of whether there is a need to cut the peak power is checked (condition Load(t)>PB). Four possible cases can develop: 1) both FCR and peak shaving, 2) FCR and no peak shaving, 3) no FCR and peak shaving, and 4) no FCR and no peak shaving. According to each case and strategy type, the SOC level is corrected to the target level (100 % for the peak shaving and 50 % for the peak shaving).

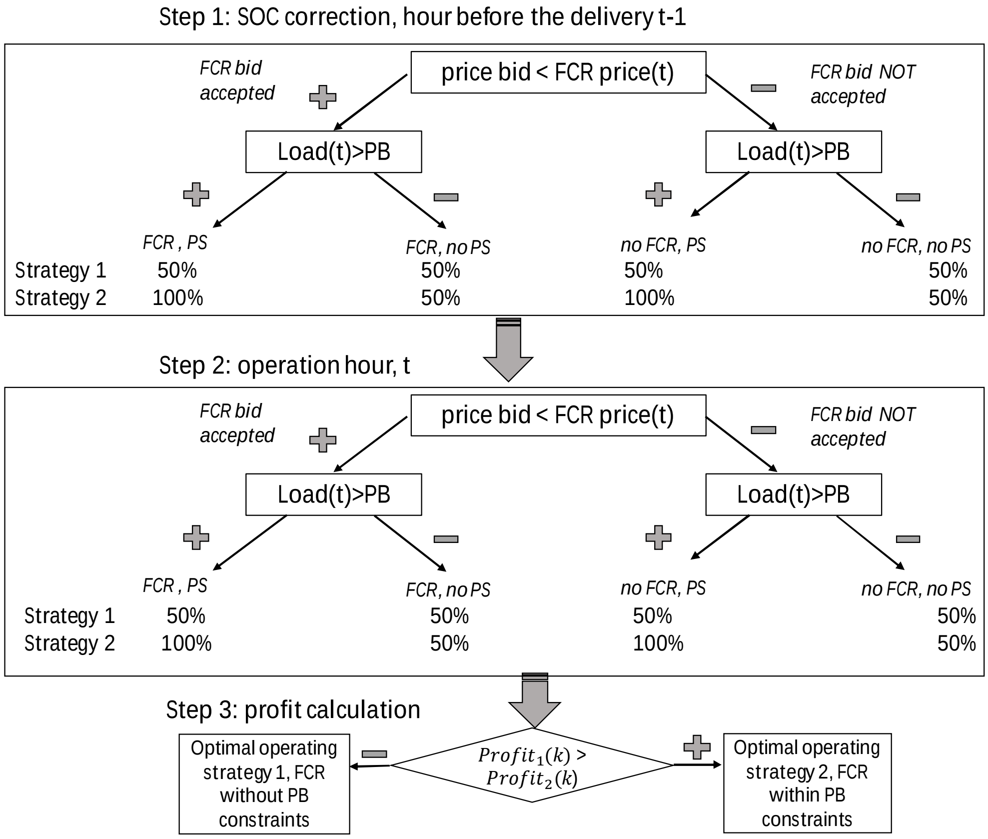

Figure 6.3. Algorithm to define the optimal operating strategy in period k (PB: power band)

Although the methodology is developed and implemented on two specific applications (energy-based and power-based), its advantage is that the same approach is suitable for other combinations of applications, for instance two energy-based or two power-based applications. The algorithm to define the optimal operating strategy for other applications can contain the same elements as presented here: specifying the rules of the DR marketplaces, defining the technical and economic conflicts of objectives, and estimating the profit obtained from the operating strategies with different priority orders and making an appropriate decision to select a strategy. In the next chapter, the proposed methodology is implemented on four example customers.

7 Results of operating strategy definition in multiple applications (stage 2)

This chapter presents the results of the simulation tool that was built by applying the methodology developed in the previous chapter.

The same four customers as illustrated in Figure 5.22 Section 5.4 are used in the simulations of stage 2. The reason that the simulation of stage 2 was run only for four customers is twofold. First, running the developed algorithm for a single customer participating in peak shaving and frequency regulation is computationally exhaustive owing to the need to go down from the hour- to the second-resolution level of analysing the data. Besides, varying the influencing factors such as the size of the BESS and the power fee further increase the required memory capacity. However, this simulation can be extended to the rest of the 10 000 customers by using for instance the remote computer resources of the CSC-IT Center for Science (CSC 2018).

The second reason for not running the simulation for the rest of the customers is because the focus of the calculations was on identifying the influencing factors and analysing with the help of the simulation tool to which extent these factors affect the results. However, the goal was not to obtain any absolute results. Therefore, the simulation was narrowed to only four representative customers.

There are two customers with a wide shape of peak power (WP1, annual consumption 34 MWh/a and WP2 7.8 MWh/a) and two customers with a sharp shape of peak power (SP1, 45 MWh/a and SP2, 7.8 MWh/a).

7.1 Conflict of objectives: case study

The simulated results show that there are both technical and economic conflicts of objectives between the two applications. A technical conflict can be seen in both strategies, and the load profile of the customer has a significant impact on it.

1) In strategy 1, the BESS operation in the FCR-N hourly market significantly increases the monthly peak powers for the customers with long peak operating times (WP1 and WP2), whereas for customers SP1 and SP2 such an effect can be seen only with large sizes of BESS. This is due to the fact that customers with short peak operating times have more capacity within the peak power level, which allows the battery to charge and discharge against the frequency deviation without significantly exceeding the peak power level. The effect is opposite for the customers with long operating peak times. Figure 7.1 shows that the BESS size of 10 kWh produces higher peak powers for customers SP1 and SP1 only in some months, whereas for customers WP1 and WP2, it creates even two times as high peak powers as the original peak power in some months.

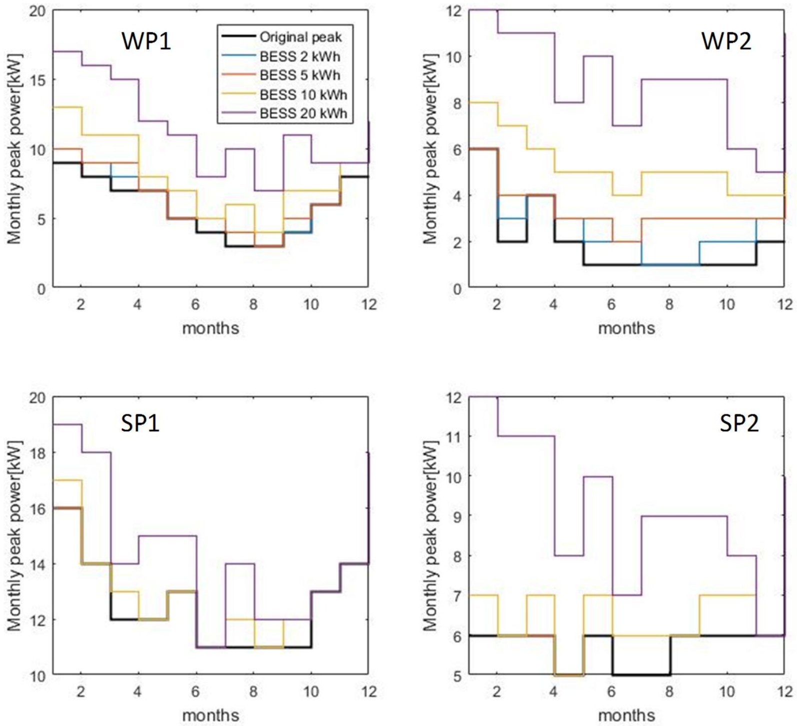

Figure 7.1.Technical conflict between the applications when frequency regulation is prioritized over power constraints (strategy 1)

2) In strategy 2, the BESS is not available for the FCR-N hourly market during the hours when the load exceeds the power band level. This can happen for instance when the electricity consumption is higher than forecasted on the previous day, for instance if the outdoor temperatures are lower than expected. If the power bid is accepted for that specific hour, the customer will be penalized for not providing the promised power available. According to the present rules, the penalty is equal to the hourly price in the market. The risk related to the increase in monthly power fees and the opportunity of earning in the FCR-N hourly market have to be estimated before making the decision of whether to participate in the frequency regulation task. In this case, the rules of both applications have a strong impact on the decision-making process: what is the penalty of exceeding the power level during 1,2,3…x hours per month and correspondingly, the penalty of not providing the resource during those hours?

The economic conflict takes a different shape depending on the type of customer, the size of the BESS, and the power tariff options. The results shown in Figure 7.2 indicate that in most of the cases, operating in the FCR-N hourly market without any power constraints (blue bar, strategy 1) is more profitable than operating in the market within the power limits (yellow bar, strategy 2), according to the annual profit calculated for both strategies at the monthly power fee of 10 €/kW. Moreover, the smaller is the size of a BESS unit, the less is the difference between the two strategies in the profit obtained. This is because the small size of a battery does not significantly affect the peak power levels. However, it can be clearly seen that for the customers with short peak operating times (SP1 and SP2), the two strategies are competing with each other if the BESS size is below 10 kWh.

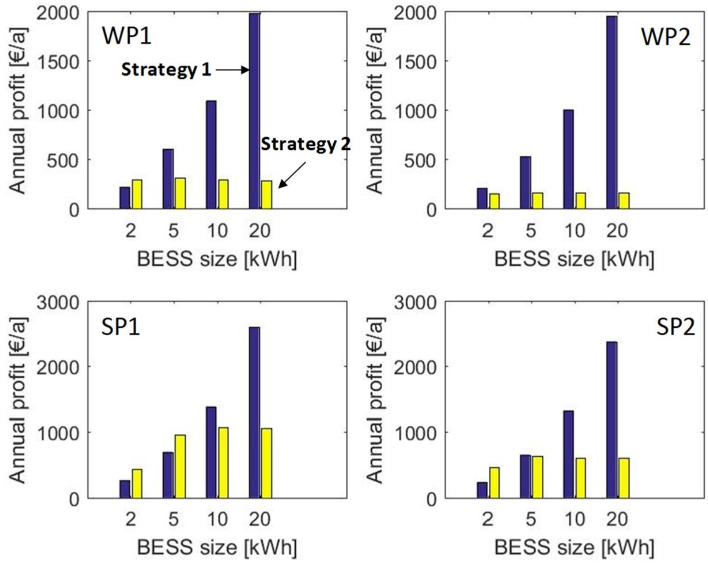

Figure 7.2. Annual profit for various BESS sizes and customers (monthly power fee 10 €/kW)

The conclusion is that customers with short peak operating times may consider operating their batteries within the power band limits. Instead, customers with long peak operating times will likely operate their batteries for frequency regulation without any power constraints, thereby significantly increasing their peak powers.

A further question is at which size of the monthly power fee the customers would stay within the power levels, in other words, the profitability of strategy 2 is higher than that of strategy 1. This is done by increasing the monthly power fees to 20 and 30 €/kW. The results are presented in Figure 7.3 and Figure 7.4. The results demonstrate that increasing of the power fee is a powerful approach for the customer to make the decision to operate in the FCR-N hourly market within the power constraints. The higher power fees not only increase the savings (strategy 2, yellow bar) achieved by staying under the power limit but also decrease the profit obtained from the FCR-N hourly market (strategy 1, blue bar) as a result of the increased cost of the higher power band. Thus, the annual profit of strategy 2 increases whereas the profit of strategy 1 decreases, meeting at the break-even point.

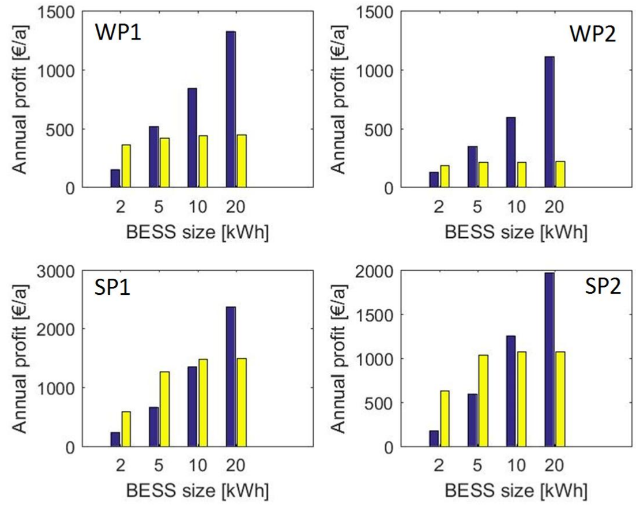

Figure 7.3. Annual profit for various BESS sizes and customers (monthly power fee 20 €/kW)

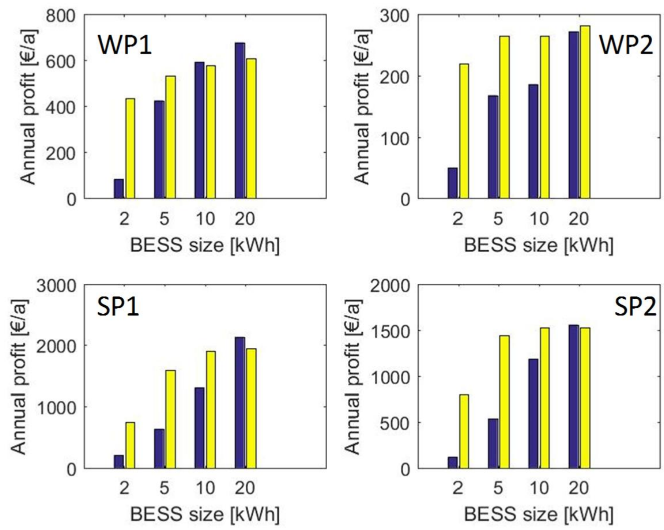

Figure 7.4. Annual profit for various BESS sizes and customers (monthly power fee 30 €/kW)

Provided that a single customer can participate in the FCR-N hourly market only through an aggregator, the customer will get only part of the revenues from the market. The other part will be left to the aggregator to cover its operational, risk-related, and other costs. Therefore, the last simulation run includes the parameter of an aggregator's margin, which has been excluded from the simulations so far. The assumption is that the aggregator takes 20 % of the hourly revenues and the customer gets the remaining 80 %. The objective of the simulations is to find out whether such a business case affects the decision-making process of the customer between two strategies, and to which extent.

The results are presented for the power fee of 15 €/kW, both with and without the aggregator's charge in Figure 7.5 and Figure 7.6, respectively. Among the customers under study, a shift from strategy 1 to strategy 2 could have been made only in one case, for customer SP1, who has a BESS of 10 kWh. In the other cases, the blue bar (strategy 1) decreased only slightly and did not significantly affect the results.

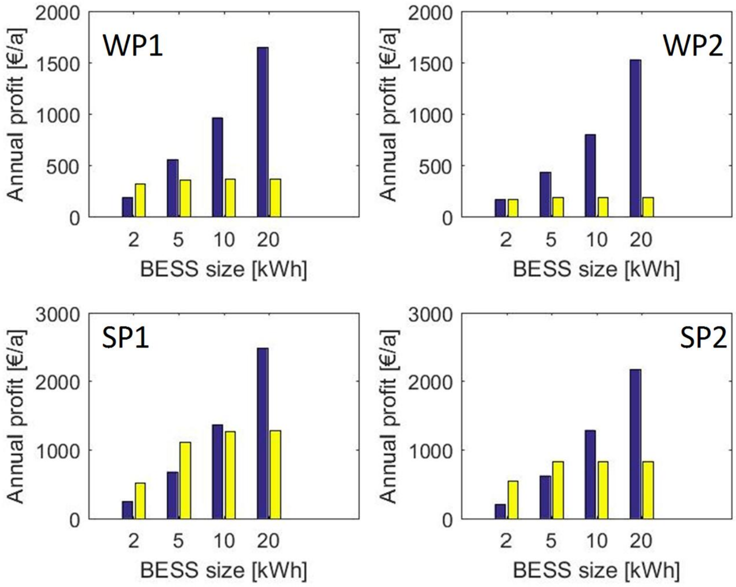

Figure 7.5. Annual profit for various BESS sizes and customers (monthly power fee 15 €/kW)

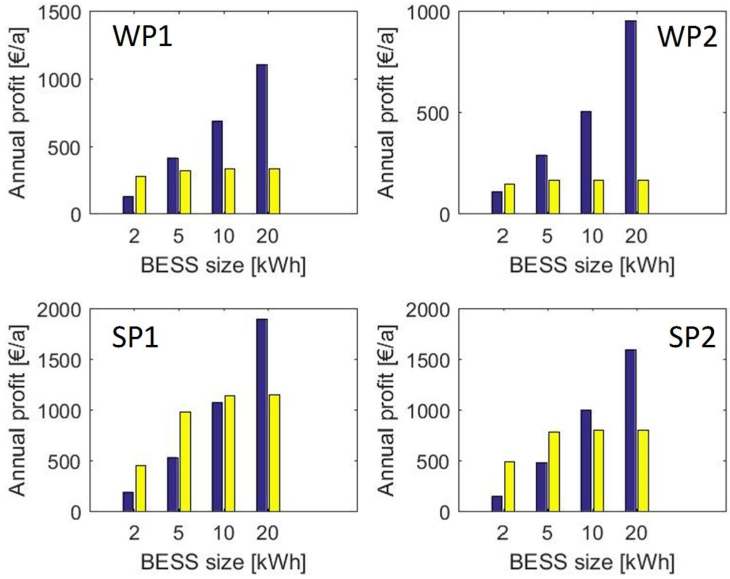

Figure 7.6. Annual profit for various BESS sizes and customers (monthly power fee 15 €/kW + the aggregator gets 20 % of the hourly revenues)

7.2 Implications of the results

The methodology applied to a single customer in the Nordic electricity market revealed that with the given reward levels in the applications, the most profitable strategy for a customer with a short peak operating time would be operation in the FCR-N hourly market while following the power constraints. On the other hand, for a customer with a long peak operating time, keeping the consumption under the power constraints does not bring significant savings, whereas operation of the flexible resources in the FCR-N market without any power constraints delivers the maximum benefit to the end customer.

However, free operation in the FCR-N market without power constraints is not a desirable strategy for the energy system for several reasons:

1) As frequency is a system parameter and it is the same in every part of the power system, the simultaneous operation of a large amount of flexibility resources against frequency deviation may cause undesired and unpredicted effects to the LV network grid, for instance voltage and power quality and overloading (Haakana 2016). On the other hand, such a consequence is rather theoretical. This is due to the small size of the FCR-N hourly market, and thus, it is unlikely that the activation of flexibility resources in a small market will have a large-scale

impact on the distribution grid, regardless of the fact that the frequency control signal is a system parameter and the same everywhere in the grid.

2) There is a high probability of resource and price saturation in the FCR-N hourly market as the number of participants increases and the cost of flexibility resources decreases. Already at the time of writing this dissertation (2018), the size of the FCR-N hourly market is small. Although it is beneficial for the energy system to have inexpensive and available resources to regulate the frequency, the earning potential may decrease to a level where the customers do not have interest in entering such a market anymore.

Meanwhile, the price level in the FCR-N hourly market has been decreasing in the past few years. At the same time, the value and cost of capacity in the distribution grid is likely to increase in the coming years. On one side, tightening requirements have arisen in the past decade regarding the reliability, quality, and security of supply of electricity, concerning especially the distribution grids. The requirements come from society, policymakers, and technology improvements. On the other side, the increasing amount of intermittent renewables in the LV network, low-carbon technologies on the end customer premises, and electrification of transport make the value of flexibility, in other words, the available capacity, more important than ever. This brings us to the conclusion that the cost of capacity and thereby the power fee of the power-based distribution tariffs for the end customers will probably increase in the coming few years.

The further outcome of the price development trends is that the priority order of the two applications may become just the opposite of what it is today. In other words, the customer will probably make a decision to choose strategy 2 and operate the BESS in the FCR-N hourly market within the power constraint. In the author's opinion, this strategy may be the most beneficial one for all stakeholders involved, which are the end customer, the TSO, and the DSO. For the end customers, such a strategy provides an additional revenue stream in the FCR market while keeping the electricity bill at a reasonable level. For the DSO, this strategy means cost-efficient, secure, and predictable operation of the distribution power system because the end customers stay within the pre-defined power level. Another benefit of such customer behaviour for the DSO is that the capacity utilization rate of the end customer connection point is improved in a case when the customer carries out various demand response activities (both power and energy based) within the power band.

For the TSO, the strategy 2 means that cheap and sustainable resources are available for the frequency regulation, and for example, there is no need to invest in large-scale BESS units. Moreover, the batteries are ideally suitable for the fast frequency response. This market is gaining attention in several countries already.

Furthermore, it is important to identify the possible risks related to participation in the markets. The risks are related to increasing peak powers, which may result in strategy 1. As the customers start to operate according to strategy 1 on a large scale, the risk is the increased peak powers and power fees, and increasing power fees not only for the customers involved in the demand response but also for the other ones. This, in turn, may create further risks of grid defection of customers equipped with solar PV and BESS, which is not a desirable consequence for the DSO’s business.

For the TSO, the risk that may occur especially in strategy 2, is the unavailability of the frequency regulation resources due to power constraints on the end customer level. This case reflects the conflict of objectives between the TSO and the end customer.

However, as it was mentioned above, the size of the FCR is small already today (2018), and thus, it is unlikely that strategy 1 will have large-scale impacts.

Table 3 presents the risks and opportunities related to the flexibility resource operation in the two DR marketplaces for the two strategies from the perspectives of all the stakeholders involved: a TSO, a DSO, an aggregator and a single customer.

Table 3. Risks and opportunities

DR marketplaces		**Risks**	**Opportunities**
Strategy 1 Higher peak powers, free operation in the FCR-N	DSO	impact on the distribution grid: power and voltage quality, overloading; Additional investments in integrated low-carbon technologies in the residential sector; grid defection;	End customer's flexible resources such as solar PV, EV, BESS, TCL can be used also for the DSO needs (RPC, VC);
	TSO		sufficient amount of frequency regulation resources; stable and reliable grid; cost-efficient resources;
	end customer	market saturation and decrease in prices, deteriorating business potential; possible conflict with the customer's local applications;	profit gain with the resources already available; new marketplaces, new revenue streams;
Strategy 2 peak power limited; modest operation in the FCR-N	DSO		peak load management in the distribution grid; investment deferral; efficient utilization of capacity; same as in strategy 1;
	TSO	Unavailability of the resources due to power limitations on the end customer's premises	same as in strategy 1
	end customer	higher electricity bill;	savings in the electricity bill, improved reliability of supply

To sum up, in order to mitigate the risks and maximize the opportunities that the marketplaces offer for the end customer and the stakeholder, the coordination between the involved stakeholders, in this case a TSO and a DSO, must be transparent and clear. A significant number of studies have recently focused on this issue, for instance (Gerard 2018).

8 Conclusions and further research

In the final chapter, conclusions of the doctoral dissertation are derived and further research questions are listed.

The main objective of the dissertation was to develop a methodology to solve a complex decision-making problem of the active residential customer in a flexible energy system. The starting point in the process of writing was to clarify the motivation for studying this topic. The changes, opportunities, and challenges associated with a single customer's behaviour along with the changes in the operating environment were identified and analysed. Next, the decision-making problem was mathematically formulated, which further revealed its complex, stochastic, and uncertain nature. After that, the next objective of the study was to find a way to solve such a problem in an understandable and practical manner so that the outcome could provide recommendations and suggestions for regulators, political decision-makers, and energy authorities on how to engage the residential customer in demand response activities in a socio-economic way. This means that the customer behaviour is such that it not only meets the customer's interests but also those of all stakeholders involved, and eventually, is beneficial for the whole flexible energy system. The main contribution of the work is the methodology built to solve such a problem.

The following sections describe the results in more detail, along with the contributions of the doctoral dissertation and further research needs.

8.1 Discussion on the results

The key advantage of the established methodology is its generic form, which makes it applicable to any operating environment. This means that no matter in which operating environment the end customer is located, the complex problem can be divided into two stages. In the first stage, the theoretical earning potential in each DR marketplace is estimated. At this stage, the constraints are not taken into account. The DR marketplace can be energy based or power based, in the form of a wholesale or a retail market. In the energy-based market, the earning potential of energy arbitrage is estimated without considering the constraints. The constraints can be related to the comfort of the customer (load availability) and uncertainty of the market price and electricity consumption. The energy-based market can be in the day-ahead, intra-day, or real-time market. In the power-based marketplace, the earning potential depends on the power capacity available on the end customer's premises and the reward level in the market. Again, the constraints are not taken into account at this stage.

In the second stage of the methodology, only those DR marketplaces are brought into consideration that were identified as promising for the end customer in the first stage. The challenge of the second stage is that it cannot be made generic, because in different operating environments the reward level in different markets is different, and thus, the attractive markets may be different for the end customer. Despite this, the tendency is that the reward level in the energy-based markets is decreasing whereas the reward level in the power-based markets is rising. This happens mainly due to the increasing amount of intermittent renewable energy resources in the power system. The case-specific results in the dissertation also showed that the energy-based applications are losing their priority in comparison with the power-based applications.

Although the results of stage 1 showed that there are two promising DR marketplaces in the Nordic electricity market environment, and therefore, the present methodology was developed for the two applications, there may be more than two promising markets in other operating environments. In that case, the methodology should be extended to deal with multiple marketplaces. Still, the elements of the methodology in stage 2 remain the same: generating possible operating strategies, identifying the technical and economic conflicts of objectives in each strategy, calculating the profit of each strategy, and defining the priority order of the applications.

The simulations demonstrated that already today (2018) the operation of batteries in multiple marketplaces is profitable. The most promising DR applications are frequency regulation in the FCR-N and peak shaving against the power-based tariff. Thus, the stakeholders involved are the end-customer, the DSO, and the TSO, whose interests and objectives may be conflicting with each other depending on multiple factors.

The objective of the DSO is to maintain the security, reliability, and quality of electricity supply to the end customers in a cost-efficient and sustainable way. At the same time, in the operating environment with increasing penetration rates of such low-carbon solutions as solar PV, EVs, BESS, and sustainable heating solutions on the end customer's premises, the value of capacity and flexible consumption will be growing.

New mechanisms will arise, such as power-based tariffs, which provide incentives to the end customers to remain under the pre-defined power constraint. Such mechanisms trigger further changes in the customer behaviour and operating environment, in a way that not only affects the customer and the DSO, but also creates opportunities and business cases for the other stakeholders. For instance, in the nearest future, the batteries and solar PV in the residential sector could also provide other services for which there is no market or reward mechanism available yet, for instance reactive power compensation and voltage control in the LV grid. This, in turn, may trigger a need for establishing a new marketplace.

8.2 Contributions of the study

The main contributions of the doctoral dissertation are

1. A generic methodology was built to solve the decision-making problem of an active customer in a flexible energy system. The methodology is not fixed to any specific environment and is thus suitable for any type of customer and DR marketplace. Another advantage of the methodology is that it can be easily

implemented not only for a single customer but also scaled up for any type of community containing flexibility resources, for instance a neighborhood, a village, or a local energy community. A further advantage of the methodology is that it is applicable for any number of DR marketplaces.

2. A simulation tool created in Matlab is made flexible for numerous input parameters. Thus, it allows to run a sensitivity and risk analysis, which provides important information and tools for the regulatory and decision-making entities regarding the framework for residential demand response.

3. The results obtained from the simulation tool indicate that the most profitable operating strategy for a single customer may not always be the most beneficial one for the whole energy system and multiple energy stakeholders involved. However, the changing reward level of the DR applications during the coming years may guide the behaviour of the active customer in a desired way for the social wellbeing.

8.3 Future research questions

The challenge of independent participation of the end customers in demand response applications is its unpredictable nature. It means that the impact on the electricity network and market is also unpredictable, which causes a need to direct such a behaviour in a structured manner. This can be done by means of a regulatory framework for residential demand response (see Figure 8.1).

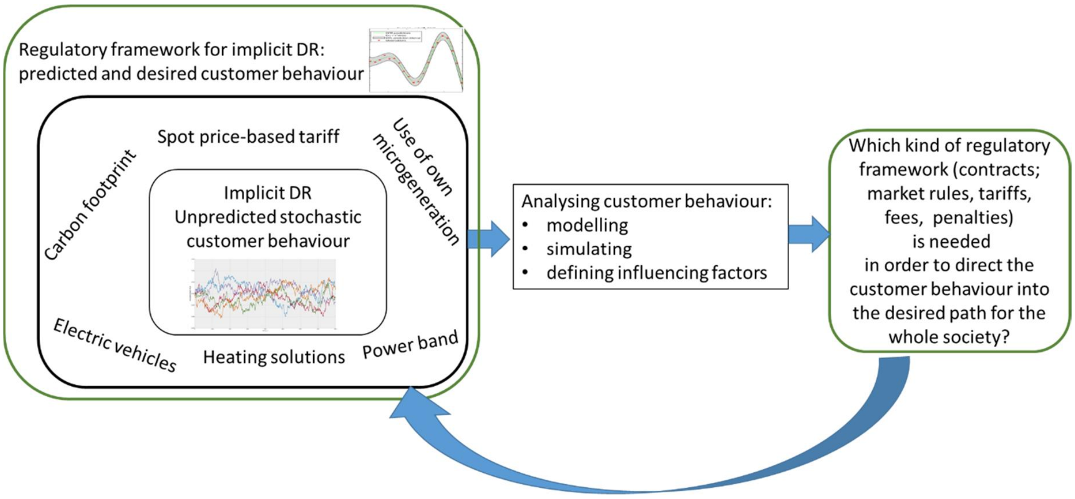

Figure 8.1. From stochastic to predictable customer behaviour

However, the regulatory framework for residential demand response cannot be built without first knowing the technical and economic potential of residential flexibility, attractive applications for the end customer, and the possible risks and threats that arise as a result of the end customer participation in the multiple applications.

Future research questions are:

1. Definition of the value of customer behaviour to electricity market players and distribution system companies in the short, mid, and long term.
2. Estimation of the impact of a single customer's/aggregated customers' demand response on the prices in the spot/balancing power market (volatility, price level) in the short, mid, and long term.
3. Analysis of a suitable electricity market model and the regulatory framework for the integration of a single customer's flexibility services: market bidding rules, the remuneration scheme for a residential customer, tariff options, and contract schemes.
4. Competitiveness of a single customer's flexibility resources in the operating environment in terms of the impact on the other generation units (peak load power plants, spinning and non-spinning reserves). What will happen with the peak load power plants if their peak operating time decreases as a result of an increase in the residential demand response? Will a single customer get remuneration for the contribution to the CO_2 emissions reduction?
5. Roadmap for residential customers from the present towards a sustainable decarbonized energy system.
6. Quantification of the environmental impact by estimating the decrease in CO_2 emissions: if we know how many kW/h (MW/h) can be avoided in the residential sector by applying a market-based demand response program, how much generation can be avoided by coal, oil, nuclear, or gas power plants?

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Appendix A

The table presents the literature review on allocation of various residential flexibility resources to different DR applications complemented by the optimization algorithm used to control the resources.

#	Publication	Flexibility resources	Control incentive	Optimization algorithm
1	(Abushnaf 2015)	Household appliances	TOU+demand limits; RTP + IBR tariffs	min(Energy;cost;discomfort)
	(Mathieu 2015)	air conditioners	Intraday market arbitrage	
2	(Alimohammadisagvand 2016)	thermal energy storage	day-ahead prices	backwards-looking, predictive control algorithms
3	(Ma 2016)	household appliances	day-ahead prices	minimization of cost and discomfort
4	(Vlot 2013)	wet and cold appliances	day-ahead, balancing	
5	(Ikegami 2010)	heat pump water heater, battery, hot water storage tank	marginal fuel costs	mixed integer linear programmins
6	(Tindemans 2015)	refrigerators	frequency regulation	
7	(Pengwei Du and Ning Lu 2011)	EWH	day-ahead market	
8	(Gomes 2004)	EWH+AC	power constraints	evolutionary algorithm

9	(Anvari-Moghaddam 2015)	residential smart house	dynamic tariffs (RTP, flat rate and TOU)	mixed-integer non-linear problem
10	(Moradzadeh and Tomsovic 2013)	different types of residential houses	day-ahead + real-time price penalties + network constraints	
11	(Adika and Lingfeng Wang 2014)	flexible load of a household	day-ahead + power constraints	
12	(Logenthiran 2012)	various loads	day-ahead	heuristic optimization
13	(Safdarian 2016)		power constraints	
14	(Dahl Knudsen and Petersen 2016)	space heating	CO_2 emissions vs day-ahead energy cost	model predictive control (minimization of weighted sum)
15	(Brivio 2016)	BESS	FCR+energy arbitrage	
16	(Trovato, Tindemans 2016)	TCL (refrigerators)	FCR (4 services) + energy arbitrage	linear programming linprog in MATLAB
17	(Schwerdfeger 2015)	EV	FCR + DSO constraints	
18	(Trovato, Teng 2016)	individual TCL	FCR + carbon emissions	MILP annual base
19	(Heleno 2016)	aggregated TCL	FCR	
20	(Weckx 2015)	aggregated residential demand	primary and secondary frequency support	

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ISBN 978-952-335-306-0
ISBN 978-952-335-307-7 (PDF)
ISSN-L 1456-4491
ISSN 1456-4491
Lappeenranta 2018