RESIDENTIAL DEMAND RESPONSE BASED ON DYNAMIC ELECTRICITY PRICING: THEORY AND PRACTICE

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Voorwoord

Elke week maakt de klimaatverandering het nieuws. Ondanks deze steeds groeiende aandacht is een algehele economisch en politiek haalbare oplossing nog niet in zicht. Hoewel de grote transformatie uitblijft, bevinden we ons in een transitiefase. Stap voor stap komen deeloplossingen naar boven die fungeren als een minuscuul stukje uit een immense puzzel.

Ook in de elektriciteitssector heeft de klimaatverandering zijn weerslag. Slechts enkele decennia geleden zou een mens raar opkijken wanneer hij of zij in een huis terechtkwam met een Tesla voor de deur, zonnepanelen op het dak, een slimme meter in de kelder, een batterijpakket in de tuin, een robotstofzuiger en slimme witgoedtoestellen die reageren op de elektriciteitsprijs in de keuken en in-home displays en tablets met bijhorende informatie over elektriciteitsverbruik in de woonkamer. Vandaag beseffen we dat dit realiteit kan zijn. Ik ben benieuwd wat we binnen 10 jaar mogelijk achten. Ondanks dat het woord "dynamiek" traditioneel niet gelinkt wordt aan de elektriciteitssector, kunnen we deze stelling vandaag ontkrachten. De transitie komt op toerental, dynamiek is het codewoord. En ik heb het geluk om hiervan deel uit te mogen maken.

Met volgende quote van Bill Gates in het achterhoofd, wil ik mijn steentje bijdragen: "We always overestimate the change that will occur in the next two years and underestimate the change that will occur in the next ten. Don't let yourself be lulled into inaction." Laat ik met deze wijze woorden de thesis op gang trekken, en mijn uiterst minieme bijdrage leveren aan een ongekende nieuwe wereld.

Alvorens volledig van start te gaan, wil ik het niet nalaten om enkele personen te bedanken die rechtstreeks en onrechtstreeks een bijdrage leverden aan mijn werk.

Vooreerst wil ik mijn promotor, Professor Belmans bedanken om mij vertrouwen te geven en mij de kans te geven om een doctoraat te vervolledigen. Door zijn academische en industriële ervaring en zijn visie, creëert hij werk en mogelijkheden binnen en buiten ELECTA. Ik ben blij dat ik van deze optie gebruik gemaakt heb. Bovendien stond hij me toe om in alle vrijheid mijn weg te zoeken binnen de academische wereld en op de kritieke momenten bood hij de nodige stimulans om er nog eens tegenaan te gaan.

Ook wil ik Professor Driesen bedanken. Dankzij hem ben ik meegestapt in de KIC PhD school. Hij was mijn directe aanspreekpunt. Door de buitenlandse avonturen die volgden, ben ik gegroeid als academicus en persoon.

In this perspective, I also want to thank Professor Ramos for being my host at the Institute for Research and Technology at Comillas Pontifical University. During my stay, I was welcomed with open arms. This time proved to be very fruitful in the academic way. Special thanks also to Dr. Luis Olmos and Kristin Dietrich for the interesting talks about dynamic tariff design and the ROM-model. I also want to thank all colleagues and friends from the institute for the necessary distractions apart from work.

I also thank Ms. Kiliccote for being my host at the demand response research center at Lawrence Berkeley National Laboratory. Through her close connections with industry, I was able to get in contact with several demand response companies and get familiar with the North-American demand response market. Our weekly discussions proved to be a good exercise to check my academic results with reality.

Mijn economische achtergrond wou ik niet verloochenen. Daarom is een deeltje van dit doctoraat gebaseerd op economische en econometrische modellen. Hierbij wil ik Professor Pepermans bedanken. Door onze vele discussies, ben ik dieper in de materie gedoken en heb ik antwoorden gevonden op voordien niet gestelde vragen. Mede dankzij hem, is mijn werk beter in lijn met de economische theorie.

Professor D'haeseleer bedank ik voor zijn nuttige feedback op deze tekst. Bovendien heb ik gebruik kunnen maken van de rijke ervaring die bij TME rond unit-commitment modellen is opgebouwd. De feedback van Kenneth Bruninx en Dr. Erik Delarue werd ten zeerste geapprecieerd.

Mijn dank gaat ook uit naar Professor Adhemar Bultheel om de preliminaire en publieke verdediging voor te zitten.

Voorts wil ik heel ELECTA bedanken. In deze dynamische omgeving, heb ik de opportuniteit gehad om ervaring uit te bouwen op verschillende terreinen: academisch onderzoek, begeleiden van thesissen, projectwerk, nauwe samenwerkingen met industrie, werkpakketleiderschap, labo's geven, assistent van een vak, enz. Bovendien ben ik als newbie gestart op een topic genaamd "demand response" en heb ik ELECTA zien uitgroeien tot een gevestigde waarde in deze materie. De stappen die we de laatste jaren op dit en vele andere vlakken gezet hebben zijn onnavolgbaar. De elektriciteitssector is in volle dynamiek en we kunnen stellen dat ELECTA de boot niet gemist heeft. Het allerbelangrijkste is bovendien dat ik in tussentijd omringd was door de meest fantastische collega's. Aan de collegialiteit en amusementswaarde zullen weinige onderzoeksgroepen kunnen tippen. Ik zou elke collega 1 voor 1 kunnen bedanken. Al is het niet voor het pintje bier, de gezamenlijke (sport)activiteiten, dan wel om de gezellige babbel tussendoor. Omdat ik mijn voorwoord korter wil houden dan mijn tekst zelf, ga ik dit achterwegen laten. Daarom richt ik me specifiek aan de personen die een directe bijdrage aan dit werk hebben geleverd. Eerst en vooral wil ik Cedric bedanken voor de verhelderende discussies. Deze stonden me toe om alles eens op een rijtje te zetten en af te wijken van mijn eigen denkpatroon. Bedankt voor uw enthousiasme doorheen mijn hele doctoraat en voor het nalezen van de tekst. Ook Jeroen T. wil ik bedanken. Zijn wiskundig inzicht en Matlab skills hebben menig onderzoeker binnen ELECTA vooruit geholpen. Ik was daar één van. Vooral bij het optimaliseren van witgoed heeft onze samenwerking geloond. Ook Frederik R. bedank ik. Het gebruik van flexgrafieken kent geen geheimen voor hem. Zijn hulp bleek dan ook heel nuttig bij het schedulen van elektrische wagens op basis van de elektriciteitsprijs. Ook de samenwerking met Marijn wierp vruchten af en heeft bijgedragen tot het hoofdstuk omtrent modelleren van investeringsbeslissingen. Tot slot bedank ik ook de hele ondersteuning binnen ELECTA, met name het secretariaat en het IT- en labopersoneel. Zij vormen een onmisbare schakel binnen. Zij stonden altijd klaar voor mij. Bovendien kreeg de cover van dit boekje een heuse opwaardering dankzij de grafische kunsten van Nathalie.

Gedurende heel mijn doctoraat was ik nauw betrokken bij het LINEAR-project. Daarom dank ik de collega's uit ELECTA, VITO, en iMinds uit werkpakket 9 voor de fijne samenwerking. Speciale dank aan Pieter, Kristof en Heidi om de rol van werkpakketleider gedurende een groot deel van het project op jullie te nemen en aan Wouter voor het aanleveren van LINEAR-data.

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Tot slot bedank ik Paz, mijn steun en toeverlaat. Elke dag opnieuw staat zij voor mij klaar.

Een welgemeende dankuwel!

Benjamin

Abstract

The need for flexibility within power system operation is growing as more intermittent renewables with limited controllability are integrated. While traditionally this need is met by supply side resources, the demand side also has intrinsic flexibility available which could be tapped, often referred to as demand response. Although policy makers and industry recognize the value of demand response, its use and understanding remains limited. This is especially the case on the residential level.

This thesis aims at enhancing the understanding of demand response by addressing three knowledge gaps, ranging from designing dynamic tariff schemes to incentivize demand response, over quantifying the residential load modifications these cause, until determining the final benefits this brings for households and society as a whole.

First of all, the demand response incentive following from the current residential tariff designs is limited especially in view of more renewable energy resources. Moreover, these tariffs do not reflect the time-dependency of the underlying cost of electricity. In order to allow demand response and to reflect actual costs to the users, this thesis argues a balance has to be found between tariff principles related to costs and social acceptability on the one hand and its resulting demand response incentive on the other. This balance can be accomplished by proper tariff design. It is shown that the choice of the tariff design not only affects the demand response incentive, but also the resulting benefits.

Second, the magnitude to which residential users react to those tariff schemes remains largely unknown. This thesis shows that flexibility obtained from both wet appliances and battery electric vehicles is considerable. Moreover, automation adds to the level and predictability of demand response. Hereby, predictability can be reached by means of price elasticities.

Finally, the benefits residential demand response brings to power system operation are not properly identified. This thesis shows that demand response leads to operational benefits as costs of plant operation decrease, while enhancing system reliability. Moreover, demand response proves to be an efficient means to integrate intermittent renewable energy resources. On the investment side, demand response leads to a postponement and reduction of the need for additional generation capacity.

Samenvatting

De nood aan flexibiliteit voor de werking van het elektriciteitssysteem groeit naarmate meer intermitterende hernieuwbare energiebronnen met beperkte controleerbaarheid geïntegreerd worden. Hoewel deze nood traditiegetrouw door elektriciteitscentrales aan de aanbodzijde wordt opgevangen, beschikt de vraagzijde ook over intrinsieke flexibiliteit die kan ingezet worden. Hierbij wordt vaak verwezen naar vraagrespons. Hoewel beleidsmakers en industrie het nut van vraagrespons herkennen, blijft het gebruik en de kennis beperkt.

Deze thesis verrijkt de kennis omtrent residentiële vraagrespons door zich op drie hiaten te richten. Deze hiaten omvatten het ontwerp van elektriciteitstarieven die vraagrespons aanmoedigen, het inschatten van de huishoudelijke verbruiksaanpassingen, en het bepalen van de voordelen die dit oplevert voor huishoudens en voor de maatschappij als geheel.

Ten eerste moedigen de huidige elektriciteitstarieven vraagrespons nauwelijks aan, zeker met het oog op toenemende hernieuwbare elektriciteitsbronnen. Bovendien vatten deze tarieven de onderliggende tijdsafhankelijke kost van elektriciteit onvoldoende. Om vraagrespons toe te laten en de eigenlijke elektriciteitskost naar de eindgebruiker te reflecteren, toont deze thesis aan dat er een balans nodig is tussen tariefprincipes gerelateerd aan kosten en sociale aanvaardbaarheid enerzijds en de resulterende stimulus voor vraagrespons anderzijds. Deze balans wordt bereikt door een gepast tariefontwerp. De keuze van het ontwerp beïnvloedt niet alleen de stimulans voor vraagrespons, maar ook de voordelen die hieruit voortvloeien.

Ten tweede blijft de grootteorde waarmee residentiële gebruikers reageren op deze tarieven niet gekend. Deze thesis toont dat flexibiliteit afkomstig van zowel wasmachines, droogkasten, afwasmachines als van batterij-aangedreven elektrische voertuigen substantieel is. Zij geeft ook aan dat automatisatie bijdraagt tot de grootteorde en de voorspelbaarheid van vraagrespons. Deze voorspelbaarheid kan deels gevat worden door prijselasticiteiten.

Tot slot zijn de huishoudelijke en maatschappelijke voordelen van residentiële vraagrespons niet geïdentificeerd. Deze thesis toont aan dat vraagrespons resulteert in operationele voordelen aangezien de operationele productiekost van elektriciteitscentrales daalt en de betrouwbaarheid van het elektriciteitssysteem toeneemt. Bovendien leidt vraagrespons tot een efficiëntere integratie van hernieuwbare energiebronnen. Tenslotte resulteert vraagrespons in uitstel en vermindering van de nood aan additionele productiecapaciteit.

Abbreviations and symbols

List of abbreviations

ACER	Agency for the Cooperation of Energy Regulators
AIDS	Almost Ideal Demand System
BEV	Battery Electric Vehicle
CCGT	Combined Cycle Gas Turbines
CES	Constant Elasticity of Substitution
CHP	Combined Heat and Power
CPP	Critical Peak Pricing
DOE	Department Of Energy
DP	Dynamic Pricing
DR	Demand Response
DSM	Demand Side Management
DW	Dishwasher
DY	Dryer
DSO	Distribution System Operator
EC	European Commission
ENS	Energy Not Served
ENTSO-E	European Network of Transmission System Operators for Electricity
EU	European Union
GAI	Generalized AIDS
GAMS	General Algebraic Modeling System
GEP	Generation Expansion Planning
GL	Generalized Leontief
GM	Generalized McFadden
GT	Gas Turbines
IBP	Incentive-Based Program
ICE	Internal Combustion Engines
ICT	Information and Communication Technologies
IEA	International Energy Agency
ILP	Integer Linear Programming
IRP	Integrated Resource Planning
LA-AIDS	Linear Approximate Almost Ideal Demand System
LDC	Load Duration Curve
LDP	Locational Dynamic Pricing
LOLE	Loss Of Load Expectation
LP	Linear Programming
MILP	Mixed-Integer Linear Program
PtOP	Peak to Off-Peak
PWR	Pressurized Water Reactors
QUAIDS	Quadratic Almost Ideal Demand System
REN	Renewable tariff
RES	Renewable Energy Sources

RO	Real Options
RTP	Real-Time Pricing
SET	Strategic Energy Technology
SPP	Steam Power Plants
ToU	Time-of-Use
TSO	Transmission System Operator
TSP	Total Shifting Potential
VOLL	Value of Lost Load
VREG	Vlaamse Regulator voor Elektriciteit en Gas
WA	Wet Appliance
WM	Washing Machine

List of symbols

a	Type of appliance
e	Type of BEV
g	Generator
h	Pumped storage hydro plant
j	Appliance cycle
k	Stage within planning horizon
l	Linked appliance cycle
n	Number of hours shifted
p, p′	Hourly time period
q	Quarterly time period
s, s′	State of the BEV
t	Thermal plant
$\Omega_{x,d,\boldsymbol{u},\omega}$	State space
ω	Long-term uncertainty of the demand growth for electricity

c_k	Total costs in stage *k*	[€]
$\mathrm{C_{ajn}}$	Cost for cycle j of appliance a shifted with n-1 hours	[€]
ch_p^e	BEV *e* charging indicator in period *p*	{0,1}
D_p	Demand in period *p*	[MW]
d_p	Electricity demand in period *p*	[MW]
$\mathrm{DP_q}$	Dynamic price in quarter *q*	[€/MWh]
$ddo_{p,a}$	Downward demand variation for type of appliance *a* in period *p*	[MW]
$\mathrm{DDoMax_a}$	Maximum downward variation of demand of appliance *a*	[p.u.]
$drdef_p$	Downward reserve deficit in period *p*	[MW]
DResC	Downward reserve deficit cost	[€/MWh]

$dup_{p,a}$	Upward demand variation for type of appliance *a* in period *p*	[MW]
DUpMax_a	Maximum upward variation of demand of appliance *a*	[p.u.]
$ec_p^{e,s}$	Consumption of BEV *e* in state *s* in period *p*	[MW]
$ECMax_p^e$	Maximum power charged by BEV *e* in period *p*	[MW]
$\mathrm{EEfBtW^e}$	Battery-to-wheel efficiency for each type of BEV *e*	[p.u.]
$\mathrm{EEfGtB^e}$	Grid-to-battery efficiency for each type of BEV *e*	[p.u.]
EEMax	Maximum energy charged by BEV	[MWh]
EMax	Maximum battery energy content boundary	[kWh]
EMin	Minimum battery energy content boundary	[kWh]
$\mathrm{EP_p^{e,s}}$	Percentage of BEV of type *e* and in state *s* for each period *p*	[p.u.]
$\mathrm{EPT_p^{e,s,s'}}$	Percentage of BEVs of type *e* and in state *s'* that move to state *s* for each period *p*	[p.u.]
$\mathrm{ET_p^{e,s}}$	Battery energy used in transport of each type of BEV *e* in each state *s* for each period *p*	[MWh]
FC^t	Fixed cost for thermal unit *t*	[€/h]
f_T	Operational costs of the non-flexible period T_{NF} actualized to period *T*	[€]
$\mathrm{Flat_{Energy}}$	Average energy tariff component over the year	[€/MWh]
$\mathrm{Flat_{Distr}}$	Average distribution tariff component over the year	[€/MWh]
gc_p^h	Consumption of pumped storage hydro plant *h* in period *p*	[MW]
gp_p^g	Output of generator *g* in period *p*	[MW]
IC	Investment cost of a thermal plant	[€]
$\mathrm{IS_{a,j+1}}$	Initial cycle start of appliance *a* with cycle *j*	[h]
J_k	Minimum total expected costs in stage *k*	[€]
nse_p	Non-supplied power in period *p*	[MW]
NSEC	Non-supplied energy cost	[€/MWh]
oc	Minimum operational cost	[€]
ocf_{aj}	Optimal cycle finish for cycle *j* of appliance *a*	[h]
$ocs_{a,j}$	Optimal cycle start for cycle *j* of appliance *a*	[h]
$opcost$	Total operational cost	[€]
$power_\mathrm{q}$	Charging power in quarter *q*	[MW]
PowerMax	Maximum power charging capacity	[MW]
r	Discount factor	[p.u.]
rfe	Rescaling factor for energy component	
$RTP_{Distr,p}$	Hourly dynamic distribution tariff component in period *p*	[€/MWh]
$RTP_{Ener,p}$	Hourly dynamic energy tariff component in period *p*	[€/MWh]
SC^t	Start-up cost of thermal unit *t*	[€]
$\mathrm{SLP_p}$	Synthetic load profile in period *p*	[p.u.]
$soc_p^{e,s}$	State of charge of the battery of BEV *e* at the end of period *p* in each state *s*	[MWh]
st_p^t	Start-up thermal unit *t* in period *p*	{0,1}

T	Planning horizon	[Years]
$\mathrm{T_{NF}}$	Number of non-flexible periods after planning horizon	[Years]
$\mathrm{T_{max}}$	Last time interval of the simulation period	[h]
TSP	Total shifting potential	[h]
uc_p^t	Commitment of thermal unit *t* in period *p*	{0,1}
u_k	Investment decision in stage k	[MW]
$\mathrm{UncG_p}$	Power generation from uncontrollable capacity in period *p*	[MW]
$urdef_p$	Upward reserve deficit in period *p*	[MW]
UResC	Upward reserve deficit cost	[€/MWh]
$\mathrm{VC^t}$	Variable cost for thermal unit *t*	[€/MWh]
wc_p	Wind curtailment in period *p*	[MW]
$\mathrm{WP_p}$	Wholesale price in period *p*	[€/MWh]
x_k	Total installed capacity in stage *k*	[MW]
X_{ajn}	Shift of cycle j of appliance a with n-1 hours	{0,1}

Table of contents

0. Introduction

0.1 Context and motivation

Power system operation is on the verge of a major transition. Due to new challenges such as the integration of more intermittent renewable energy sources (RES), supply-side resources could be insufficient to keep the balance at all times. To reach this higher need for flexibility and to increase efficient power system operation, a paradigm shift is occurring as more and more flexibility is provided by demand side resources. While initially the intrinsic flexibility of the demand side was neglected, nowadays, demand is starting to take a more active role within power system operation. This is also referred to as demand response (DR).

Demand response can be triggered by providing more dynamic electricity tariffs reflecting the dynamic nature of the underlying cost of electricity. These tariffs are also referred to as dynamic pricing (DP). This way, the demand side is incentivized to modify its demand pattern in order to bring more efficient power system operation in which the operation of RES is integrated.

Although the inclusion of demand response and dynamic electricity tariffs is already described in the literature since the 80s, the use and understanding is still limited. Especially residential demand response is still neglected and no clear indication of the impact on both household and supply side level is available.

These gaps become apparent on three levels. First of all, current electricity tariff designs fall short on incentivizing DR, especially on the residential level. Second, no clear indication or quantification is available on how residential users react to more dynamic tariff schemes, leading to slower implementation. And finally, benefits resulting from DR are largely unknown, again leading to slower implementation.

To address these gaps in the literature and practice, this thesis aims to enhance the knowledge of residential DR and DP. In addition, it also desires to enable more informed decision making by policy makers, industry and residential users. In this perspective, this thesis intends to answer following questions:

- Q1: What are demand response and dynamic electricity pricing?
- Q2: How should dynamic electricity prices be designed?
- Q3: To which extent do residential users modify their power pattern as a reaction to DP?
- Q4: How can this modification be quantified and predicted?
- Q5: What benefits do such load modifications bring for the residential users and for power system operation and investments?

0.2 Outline

This thesis is divided into four parts. Each part contributes to the understanding of demand response based on dynamic pricing by answering the questions formulated in Section 0.1. An overview of the first three parts and the underlying chapters is visualized in Fig. 0.1. The final part covers the conclusions and recommendations following from this thesis. Each of these parts is discussed in what follows.

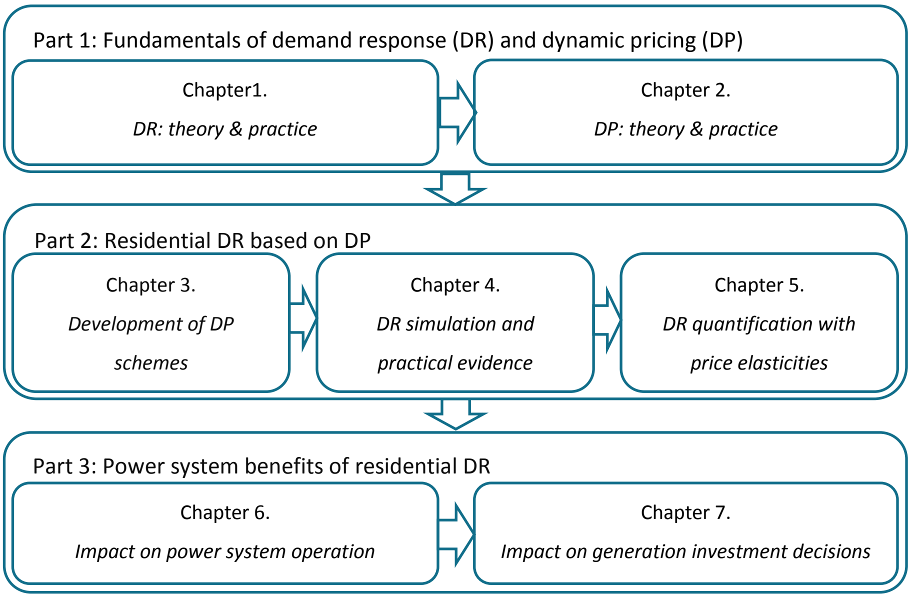


Fig. 0.1. Thesis overview.

0.2.1 Part I: Fundamentals of demand response and dynamic pricing

Chapter 1 presents the theory and practice of demand response. It creates the background of this thesis as it discusses different demand response types and programs, and various benefits they can bring forward. Moreover, it provides an overview of worldwide deployment of demand response.

This chapter is partly based on the following paper:

- B. Dupont, C. De Jonghe, K. Kessels and R. Belmans, "Short-term Consumer Benefits of Dynamic Pricing," in *IEEE, International Conference on the European Energy Market (EEM)*, Zagreb, Croatia, May 2011.

Chapter 2 focuses on one of the demand response programs, being dynamic pricing. More specifically, the focus is on locational dynamic pricing (LDP) schemes in which prices depend on both time and location. It provides a theoretical framework for LDP schemes accounting for general principles of tariff design related to costs and social acceptability. Also the impact of RES on this theoretical framework is assessed. Moreover, it describes how tariff design can trigger demand response. Backed by this framework, existing tariff schemes are assessed.

This chapter is based on the following paper:

- B. Dupont, C. De Jonghe, L. Olmos and R. Belmans, "Demand response with locational dynamic pricing to support the integration of renewables," *Energy Policy,* vol. 67, pp. 344-354, April 2014.

0.2.2 Part II: Residential demand response based on dynamic pricing

The second part simulates and quantifies residential demand response resulting from different dynamic pricing schemes. For each tariff scheme, demand modifications are analyzed and the resulting residential benefits are pointed out. It consists of 3 chapters covering from the development of DP up to the quantification of the resulting demand response.

Chapter 3 describes the development of different dynamic pricing schemes taking into account the principles discussed in Chapter 2. This results in various dynamic pricing schemes which reflect the dynamics in the underlying costs and the availability of RES to a different extent.

Chapter 3 is partly based on the following paper:

- B. Dupont, C. De Jonghe, K. Kessels and R. Belmans, „Short-term Consumer Benefits of Dynamic Pricing," in *IEEE, International Conference on the European Energy Market (EEM)*, Zagreb, Croatia, May 2011.

Chapter 4 describes residential demand response following the different dynamic pricing schemes from Chapter 3. Distinction is made between simulation and practical evidence. While demand response simulation allows setting benchmarks, practical evidence retrieved from a pilot project allows obtaining practical demand response results.

This chapter is partly based on the following papers and project deliverable within LINEAR:

- B. Dupont, J. Tant, and R. Belmans, "Automated Residential Demand Response Based on Dynamic Pricing," in *IEEE PES International Conference and Exhibition of Innovative Smart Grid Technologies (ISGT Europe)*, Berlin, Germany, October 14-17, 2012.
- B. Dupont, P. Vingerhoets, P. Tant, K. Vanthournout, W. Cardinaels, T. De Rybel, E. Peeters, and R. Belmans, "LINEAR

Breakthrough Project: Large-Scale Implementation of Smart Grid Technologies in Distribution Grids," in *Third IEEE PES Innovative Smart Grid Technologies (ISGT), Europe edition*, Berlin, Germany, October 14-17, 2012.

- B. Dupont, "LINEAR Deliverable 2.1: Portfolio management based on dynamic pricing," LINEAR, Belgium, November 2014.

Chapter 5 provides a quantification of residential demand based on results from the previous chapter. The quantification is obtained by means of price elasticities allowing to estimate demand response when sending a dynamic pricing scheme to residential users.

0.2.3 Part III: Power system benefits of residential demand response

While part II focuses on demand response at household level, part III describes the benefits on power system level following from residential demand response. Hereby, distinction is made between the impact of demand response on power system operation and generation investment decisions.

Chapter 6 provides an operational model that quantifies power system operation benefits of residential demand response and tests this model within a Belgian case study pointing out the impact of RES.

The chapter is based on the following paper:

- B. Dupont, K. Dietrich, C. De Jonghe, A. Ramos, and R. Belmans, "Impact of residential demand response on power system operation: A Belgian case study," *Applied Energy*, vol. 122, pp. 1-10, June 2014.

Chapter 7 provides an investment model quantifying generation investment benefits of residential demand response and tests this model within a Belgian case study. Again, the impact of RES is pointed out in this chapter.

This chapter is based on the following paper:

- B. Dupont, M. Maenhoudt, C. De Jonghe, K. Dietrich, A. Ramos, G. Deconinck, and R. Belmans, "Impact of short-term demand response with battery electric vehicles on generation investment decisions: A Belgian case study," submitted for *Energy Policy*.

0.2.4 Part IV: Conclusions and recommendations

Chapter 8 reviews the conclusions drawn throughout this thesis. Additionally, recommendations for further research are suggested.

PART I

Fundamentals of demand response and dynamic pricing

1. Demand response: theory and practice

1.1 Introduction

The European electricity system is facing three tremendous evolutions. First, the European Union aims to reduce greenhouse gas emissions by at least 80% below 1990 levels towards 2050 [1]. Therefore, they consider integration of renewable energy sources (RES) as a key instrument. Second, the European transmission and distribution grid is ageing and needs replacement as most of the infrastructure was invested during the seventies [2]. Finally, electricity demand will rise due to the electrification of energy services such as transport or heating and cooling of buildings and dwellings. Examples of this electrification are the integration of heat pumps and electric vehicles. These three evolutions trigger the need for more flexibility in order to ensure reliable power system operation in which electricity supply equals electricity demand at all times.

Traditional solutions to ensure the balance between demand and supply are found at the supply side. New generation, transmission, and distribution investments are made to cover the electrification of demand and ageing infrastructure. Moreover, variability of demand and generation from RES is covered by the remaining power generation capacity. Although these means of flexibility benefit reliability, only focusing on traditional solutions could be insufficient, expensive, and harmful for the environment.

Rather than only focusing on the supply side, the demand side itself can also bring flexibility into the system. This is also referred to as demand response (DR). By more active involvement of end-users which can change electric usage in response to power system conditions, operation of and investment in generation, transmission, and distribution can profit, also facilitating the integration of RES.

European interest, recognition and promotion of DR are rising within the last decade. This is reflected at the level of policy, regulation, standardization, and the electrical energy industry as such.

European policy recognizes that a further introduction of DR will benefit end-users, industries, and society as a whole [3]. In the Energy Efficiency Directive [4], the conditions are created for national policy makers, regulators, network operators, and the energy industry to integrate DR in the market in the near term. This is expressed by the following statements: "Member states shall ensure that national regulatory authorities encourage demand side resources, such as demand response, to participate alongside supply in wholesale and retail markets", and "Member states shall promote access to and participation of demand response in balancing, reserves, and other system services markets, inter alia by requiring national regulatory authorities […] in close cooperation with demand service providers and consumers, to define technical modalities for participation in these markets on the basis of the technical requirements of these markets and the capabilities of demand response."

The Agency for the Cooperation of Energy Regulators (ACER) also expresses its support to DR in its Framework Guidelines on Electricity Balancing: "These terms and conditions, including the underlying requirements, shall, in particular, be set in order to facilitate the participation of demand response, renewable and intermittent energy sources in the balancing markets [5]."

By the end of 2014 European standardization organizations are expected to develop a standard facilitating demand response and complementing the current smart grid standard under Mandate 490 [6].

The European industry also paves the way for DR. Among others, this can be seen in the European Electricity Grid Initiative issued by European transmission and distribution system operators [7]. Moreover, new energy businesses are created to enable more flexibility at the demand side and national and worldwide smart grid initiatives such as Smart Grid Flanders [8] and the Global Smart Grid Federation [9] foster DR knowledge.

Apart from increased interest from European stakeholders, other developments are also building momentum for DR. The integration of smart metering systems enhances accurate metering of demand and therefore stimulates active involvement of end-users. This integration is boosted by the European Commission (EC) in the Third Energy Package stating that by 2020 consumers are required to be equipped with intelligent metering systems subject to a cost-benefit analysis [10]. Advanced ICT and automation widen the possibility of stimulating DR without any loss of comfort or production efficiency for end-users. The importance is stipulated by a growing interest from industry not directly related to energy, e.g. data management companies, appliance manufacturers, telecom, technology providers.

This chapter is structured as follows. Section 1.2 provides deeper insight in DR and confusion with other terminology is clarified. Section 1.3 discusses the broad range of programs, user classes and load types involved in DR. Different benefits of DR are highlighted in Section 1.4. Section 1.5 discusses the deployment of DR and finally Section 1.6 concludes.

1.2 Definition of demand response

Various organizations around the globe provide a definition of demand response.

The first definition was given by the Department of Energy (DOE) in the U.S. [11] and was later on adopted by the US Federal Energy Regulatory Commission [12] and some academics [13]:

- "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized".

Within Europe the following definitions are formed:

- European Commission: "Demand response is to be understood as voluntary changes by end-consumers of their usual electricity use patterns - in response to market signals (such as time-variable electricity prices or incentive payments) or following the acceptance of consumers' bids (on their own or through aggregation) to sell in organized energy electricity markets their will to change their demand for electricity [3]."
- European University Institute: "Changes in electric usage implemented directly or indirectly by end-use customers/prosumers from their current/normal consumption/injection patterns in response to certain signals [14]." Hereby, only consumers acting voluntarily are concerned, excluding demand response that is mandatory or without any compensation. Moreover, stand-alone generators on distribution level are not considered.

The International Energy Agency (IEA) defines demand response in the following way:

- "Demand response programs are programs and activities designed to encourage consumers to change their electricity usage patterns, including timing and level of electricity demand, covering all load shape and customer objectives. Demand response includes time-of-use and dynamic rates or pricing, reliability programs such as direct load control of devices and instantaneous interruptible load, and other market options for demand changes, such as demand side bidding [15]."

In all definitions, DR entails a change in the electric usage pattern of end-users in response to signals such as dynamic electricity prices or incentive payments. Additionally, in Europe emphasis is put on the voluntary nature of DR programs and the definition is widened by also including changes in injection patterns. Also note that DR involves changes in power consumption, yet not necessarily in total energy usage.

Although the consistency in defining demand response, confusion with other terminology such as demand side management (DSM) exists. Within DSM programs a market party actively uses different options to modify electricity demand to increase customer satisfaction and coincidentally produce desired changes in the electric utility's load shape [16]. These programs were already created in the early 1980s in the U.S. in reaction to concerns on the dependency on fossil fuels and on the environmental impact of generation [17]. In this context, often is referred to integrated resource planning (IRP) [18], [19]. These planning models contrast to traditional electricity expansion planning as IRP includes both supply and demand side options in the planning process. The demand side options, also referred to as DSM, cover different load shape objectives distinguishing between energy [MWh] adjustments and power adjustments [MW] [20]. The most well-known objective is energy efficiency which focuses on permanent energy consumption [MWh] reductions. In contrast, objectives related to DR typically entail power adjustments. Examples are load shifing and valley filling. In other words, DSM is a wider concept than DR as it also captures energy adjustments such as energy efficiency.

1.3 Categorization of demand response

Different categories of demand response exist depending on the way it is encouraged and the purpose it is used for, the user classes it serves, and the load types targeted.

Demand response programs

Two groups of DR programs are distinguished: incentive- and price-based [11], [13]. This classification is made according to the techniques used for encouraging changes in the instantaneous electric power usage. While in price-based programs, end-users react to dynamic prices, incentive-based programs provide incentive payments independent from the electricity rate. Within each program, several subcategories exist (Fig. 1.1).

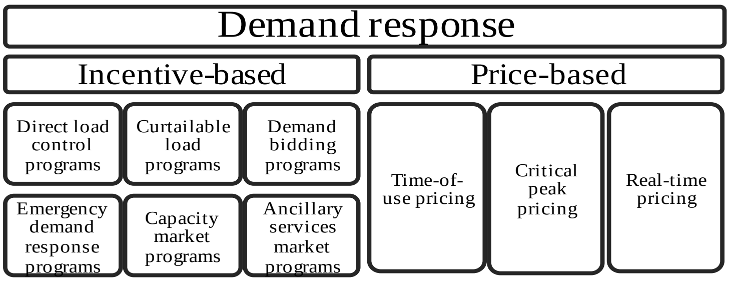


Fig. 1.1. Demand response programs distinguishing between incentive-based programs and price-based programs.

On the left hand of Fig. 1.1, *incentive-based programs* are depicted. In those programs, participating users receive payments for reducing their demand at critical times. Incentive-based programs include six subcategories: direct load control, curtailable load, demand bidding, emergency demand response, capacity and ancillary services markets programs. In *direct load control programs*, a third party is in control of some appliances at the end-user's premises (e.g. air conditioners, heat pumps). In the event of system stress, the third party can control those appliances directly in compensation for a previously known participation fee. Often these programs are also referred to as dispatchable. In *curtailable load programs* [21] end-users are in control of their own appliances. By enrolling into the program, the end-user makes the commitment to modify load when a request is received. The gain for the participants can take different forms as bill credits and participation fees. A penalty is given in case the user does not respond to the load signal. In *demand bidding programs* end-users make the commitment to modify load by bidding in the wholesale electricity market. If the bid is cleared, the end-user is obliged to reduce his load by the according amount. *Emergency demand response programs* are called upon times when system security is in danger. End-users get incentive payments for helping to resolve system stability. *Capacity market programs* use load reduction commitments [21], partly replacing traditional generation commitments on capacity reserve markets. Participating end-users receive an up-front reservation payment for offering the load capacity and an activation payment for calling the capacity in case of an event. In *ancillary services market programs* end-users bid load reduction commitments in ancillary markets as operating reserves [22]. When the bid is accepted, end-users receive an up-front payment reflecting the spot market price for being on stand-by. Once the load reduction is called for, end-users receive the additional spot market electricity price.

Price-based demand response programs are depicted on the right hand side of Fig. 1.1. In those programs, time-varying tariffs also referred to as dynamic tariffs, approximate the actual cost of energy. Those tariffs are offered to make end-users shift consumption from high to low price periods. Although many variants of price-based demand response programs exist, most can be classified in three subcategories according to their tariff design: time-of-use, critical peak and real-time pricing [23]. While all three are dynamic in nature and therefore more closely reflecting the underlying cost of energy, the frequency of updating predetermined prices differs. *Time-of-use tariffs* divide the day into different time blocks in which different electricity prices apply. These prices are fixed for a specific period (e.g. a month). Even though they reflect the average cost of energy during the time blocks, they fail to account for short-term variability in wholesale prices. This is partly resolved by *critical peak pricing*, which adds a component to time-of-use or flat tariffs. This component is only applied during critical peak hours for a limited number of hours a year. Typically the end-user receives the critical peak tariffs on short notice. As a refund, a price discount during non-critical peak hours applies. The variability of the electricity tariff is even greater with *real-time prices*, which typically reflect hourly wholesale and imbalance prices. Between a day-ahead and an hour-ahead, the end-user receives new hourly electricity prices. This pricing program allows a deeper reflection of the underlying cost of energy. A more extensive description of these tariff designs is provided in Chapter 2.

The main difference between incentive-based and price-based demand response programs is the level of end-user involvement in load modification. Incentive-based programs trigger load modification in the occasion of critical events based on contractual arrangements. In return the end-user receives an incentive payment. Although participation is voluntary, falling short on a specific demand response request brings penalties. In price-based programs, the end-user enrolls in a dynamic pricing scheme. Voluntary load modifications are based on the user's own economic and rational preferences. In such programs no penalties are incurred, although the user can be imposed to high electricity prices.

DR user classes and load types

Demand response programs target all user classes: residential, commercial, and industrial. For each user class, the load type and its accompanying end-use service differ. While the end-use service for residential and commercial users is closely related to comfort, industrial users are more concerned about the efficiency of production processes. Moreover, each user class is characterized by different types of loads which can be used for demand response purposes. A distinction can be made between storable, shiftable, and curtailable loads [14]. With storable loads, thermal inertia or batteries can be used to separate the moment of power consumption and the end-use service in time; examples are electric vehicles for residential users or air conditioning in commercial buildings. With shiftable loads power consumption can be shifted in time without loss of the end-use service. Usually this shifting involves planning which might affect comfort or production efficiency; examples of such loads are washing machines and dishwashers for residential users or production processes in industry which can be moved in time. With curtailable loads power consumption is forgone along with the end-use service. Therefore, this curtailment also involves a loss of comfort or production output; examples are household lighting or curtailment of industrial processes.

1.4 Benefits of demand response

Demand response brings about several benefits for participants and society as a whole [11], [13] (Fig. 1.2).

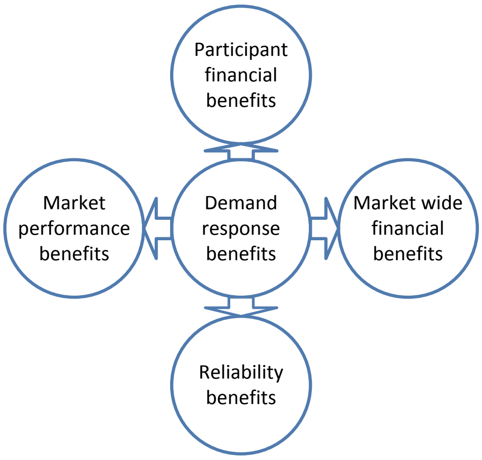


Fig. 1.2. Demand response benefits.

Benefits can be split up in four categories: participant financial benefits, market wide financial benefits, reliability benefits and market performance benefits. Participant financial benefits consist of short-term direct bill savings resulting from incentive payments or a decreased electricity bill. Market wide financial benefits are divided into short-term operational benefits and long-term investment benefits. Demand response can lead to operational benefits in the short run due to a reduced start-up cost of expensive peaking units. Moreover, demand can be aligned with the availability of generation from RES. This causes lower wholesale prices during peak periods or when generation from RES is abundant. In the long run, utilities avoid capacity, transmission and distribution investment costs [24], because the system can be tuned to a lower peak demand due to sustained demand response. Both short and long term benefits result in a lower electricity price for both participating and non-participating end-users due to more efficient power system operation. Demand response can also lead to reliability benefits [25], as additional system flexibility reduces the probability of a demand-supply imbalance [26]. Demand response can furthermore lead to market performance benefits [27]. End-user's ability to decrease electricity consumption during high price moments reduces generator's incentive to bid above marginal generation costs.

1.5 Deployment of demand response

Within Europe, the Nordic region and the United Kingdom are on the forefront when dealing with demand response [28]. Hereby, demand response resources contribute up to 30% of the total ancillary services market. Although the main part of these resources is attributable to large industrial users, an increasing amount is coming from medium and small users.

While demand response is gaining importance in Europe, the United States are running ahead with up to 50% of peak resources provided by DR in some markets [28]. This 50% derives from the different user classes covering different DR programs (Fig. 1.3). The main part of demand response resources is retrieved from the commercial and industrial users and the wholesale market. This last one refers to demand response reported by wholesale providers which cannot be attributed to specific retail companies or user classes [12]. Another observation is that residential demand response is lagging and the main source of residential demand response comes from direct load control.

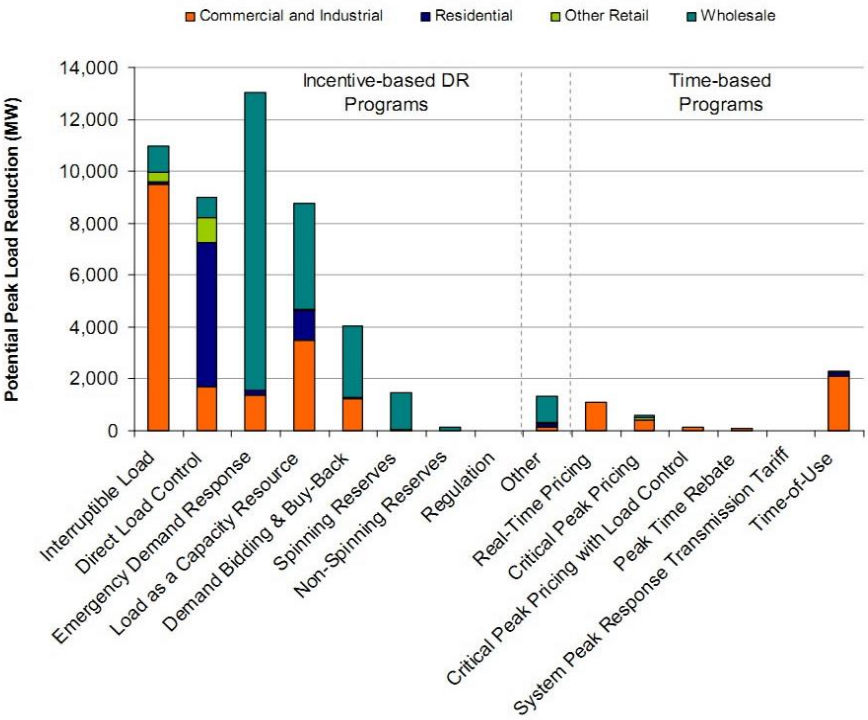


Fig. 1.3. Reported potential peak reduction for commercial and industrial, residential, wholesale and other users within incentive-based or time-based programs in 2010 in the US based on a FERC Survey [29].

Although worldwide implementation is still limited, the potential of residential demand response is considerable. Empirical evidence suggests that the potential economic benefits are substantial and residential users respond to dynamic pricing schemes [28]. Moreover, some residential loads such as water and space heaters are by nature controllable and can offer cost-effective opportunities. As the deployment of smart metering and enabling technologies is gaining speed, this residential potential starts to getting tapped.

1.6 Summary & Conclusions

The concept of demand response has been defined. A deeper description of different programs, user classes, and load types has been provided. Moreover, the rising interest of policy makers, regulators, standardization bodies, and industry has been pointed out. It has been shown that although benefits of demand response are known, DR within one user class is still lagging behind, being residential.

Over the past years, residential demand response seems to be on the verge of a breakthrough due to the deployment of smart metering, ICT, enabling technologies and smart appliances. How and when the majority of the demand response potential will be tapped is still unknown.

2. Locational dynamic pricing: theory and practice

2.1 Introduction

Departing from the general demand response (DR) description, this chapter further elaborates on one of the DR programs, being price-based programs. The focus is on residential users with a locational dynamic pricing (LDP) scheme. Within this scheme, the price depends on time and location. As LDP allows capturing the locational and time dependency of underlying costs [30], residential consumption and generation can be valued against their contribution to the whole electricity system. In turn, LDP can influence the location and time of consumption and generation [31]. Hereby, the amount of residential flexibility triggered depends on the tariff design of LDP.

In order to evaluate the potential of constructing an LDP scheme in view of incentivizing demand response, first the underlying costs of consuming and generating electricity need to be assessed. Therefore, a theoretical framework is built (Fig. 2.1). The framework starts from costs incurred at the generation, transmission and distribution (T&D), and retail level. These costs are translated into a tariff scheme according to some general principles. Depending on the potential for locational and time dependency of tariffs, traditional and locational dynamic pricing can be applied to charge for residential demand and generation. While typically traditional pricing leads to inflexible demand and generation, residential flexibility can be triggered by LDP.

In the literature, demand response is often neglected when constructing tariff schemes. The design is mainly based on principles related to cost and practicality [32], [33]. Other papers, primarily based on experimental projects, mainly focus on incentivizing demand while harming some of the cost related principles [34], [35]. In contrast, this chapter discusses the impact and relationship between costs and practicality on the one hand, and demand response on the other. This approach aims to provide a background for policy makers, industry and academics to assess existing tariff schemes and construct new ones.

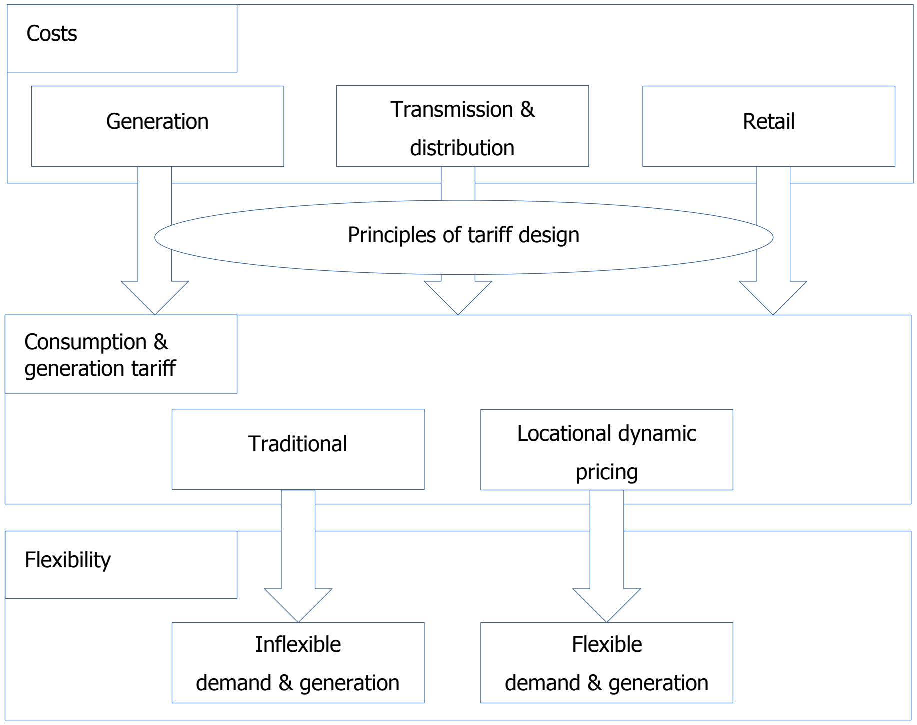


Fig. 2.1. Theoretical framework of locational dynamic pricing, translating costs into tariffs triggering flexibility.

In Section 2.2, general principles of tariff design are discussed and applied to traditional and LDP tariff schemes. Section 2.3 gives a more detailed perspective on LDP for consuming electricity by evaluating the potential of making each tariff component locational and time dependent. Hereby, the influence of renewable energy sources (RES) is pointed out. Section 2.4 elaborates on the potential of LDP for residential generation of electricity. Section 2.5 highlights some practical considerations to be taken into account. Section 2.6 assesses how tariff design of LDP can affect the incentive for demand response and how this relates to general principles of tariff design. To clarify the theoretical concepts discussed, Section 2.7 discusses some existing tariff designs and assesses four illustrative tariff schemes. Section 8 concludes.

2.2 Locational dynamic pricing based on general principles of tariff design

Principles of tariff design

In a liberalized electricity system, distinction is made between the regulated and competitive part of the system. Typically, the T&D networks are considered as regulated and operated by a transmission system operator (TSO) and a distribution system operator (DSO), respectively. Competition is introduced in generation and retail activities. Both regulated and competitive parties incur costs and convert them into tariffs taking into account general principles of tariff design.

In the literature, a wide variety of general principles of tariff design is provided. In Bonbright [36] general principles for public utility tariffs are discussed. In Berg and Tschirhart [37] the focus is on optimal pricing and tariff design for natural monopolies, while Pérez-Arriaga and Smeers [32] provide guidelines for grid tariff design. While most of these principles date from the era of vertically integrated utilities, they also apply in a context of an unbundled electricity system. In what follows, five general principles of tariff design are selected and discussed. A distinction is made between principles resulting from practical considerations and social acceptability, on the one hand, and cost related principles, on the other.

Three principles result from practical consideration and social acceptability.

- **Transparency**: a tariff design should be clear and understandable for the user;
- **Simplicity**: a tariff should be simple, aligning with the transparency principle;
- **Minimum volatility:** tariff fluctuations in the short and long term should be limited to protect the user.

While historically the lack of ICT, metering and automation did not allow for complex tariffs with high short-term volatility, technological breakthroughs have altered this. These breakthroughs make it feasible to send LDP schemes regularly, register consumption and generation on a shorter time frame, and automate consumption and generation at the residential level. Therefore, it becomes easier to meet the principles related to practicality in case of more complex or volatile tariffs.

Two principles are cost related:

- **Cost recovery**; all actors should be able to recover their costs. Although this principle arises from the regulated part of the electricity system, it is assumed that competitive actors also should recover their costs in order to remain profitable in the long run.

- **Cost causality**; consumers or generators should pay the costs they cause. In other words, costs should be assigned to whoever they belong to. This creates non-discrimination as consumers face the same price for electricity which causes the same costs. It also implies that cross-subsidization is avoided as costs are allocated to the beneficiary of the electricity, instead of being socialized. In other words, cost causality avoids the cross-subsidies between different customer groups as stated in Borenstein [38].

Traditional pricing in view of RES

Considering the large-scale introduction of RES and its accompanying operational and economic challenges, traditional tariff designs meet with the principles out of practical consideration and social acceptability, while conflicting with the cost related tariff principles.

Traditional pricing schemes align with simplicity, transparency and minimum volatility principles due to the intrinsic nature of flat or day-night tariff designs. Cost recovery is under stress as RES can bring additional costs for T&D which were initially not anticipated. Cost causality is harmed as well, as traditional tariffs do not reflect varying generation costs due to the intermittent nature of generation from RES. This leads to cross-subsidization in time as defined in Borenstein [38]. As the underlying cost of energy is variable, consumers who consume less when more generation from RES with zero marginal costs is available, subsidize the other consumers under traditional tariffs. Although variability of costs already existed before, it increased due to the integration of RES. Moreover, cross-subsidization in location occurs as every consumer pays the same price independent of the local availability of generation from RES and the local operational challenges it brings. As the cost causality principle is seriously harmed, especially in view of the introduction of RES, a new tariff design such as LDP is required.

Locational dynamic pricing

In contrast to traditional tariffs, dynamic pricing schemes allow for more variability in the price level and pattern over the course of the day. This adds to the cost related principles of tariff design as this tariff facilitates to pass on the costs to their beneficiaries and to avoid cross-subsidization over time. Next to the dynamics of this tariff scheme in time, a dynamic price can be made locational resulting in a locational dynamic price [30]. This allows allocating the costs to the beneficiary and avoids cross-subsidization over locations.

Besides the contribution to cost causality, LDP also allows attracting flexibility at the residential level [11]. This offers the demand side the potential to be part of the solution to the challenges RES brings. Historically, the focus at the demand side was on the flexibility consumption can bring. This was referred to as demand response. In the event of more dispatchable decentralized generation, flexibility of consumption should be complemented with flexibility of generation as discussed in Chapter 1. Therefore, residential demand response can refer to flexibility of both consumption and generation.

2.3 Residential consumption tariff

In this section, LDP for residential electricity consumption is assessed. It consists of a tariff for the withdrawal of electricity from the grid and for the investment in the electricity system associated with it. This tariff incorporates the costs of consumption without taking into account local generation facilities. In the next section, the injection tariff discusses the value a residential user gets for local injection of electricity.

Before the potential for demand response can be estimated, the potential for making a tariff dynamic and locational according to the cost causality principle needs to be assessed. It should be based on the underlying costs of the electricity. A distinction needs to be made between cost components, categories and drivers (Fig. 2.2).

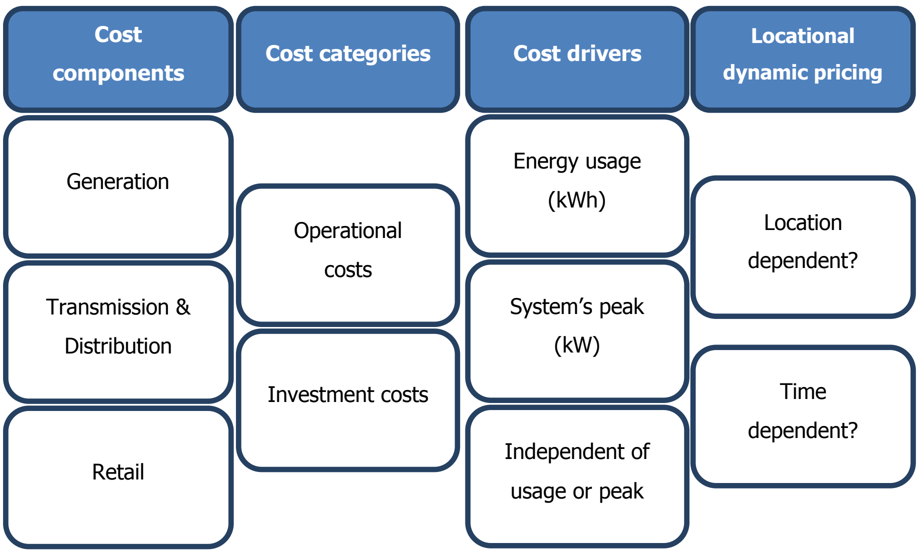


Fig. 2.2. Potential for locational dynamic pricing based on cost components, cost categories, and cost drivers.

Three cost components are distinguished: generation, T&D, and retail. All three should separately meet the five principles of tariff design as much as possible.

Cost categories reflect the different types of costs associated with the nature of the business underneath each cost component. The following cost categories are associated with generation, system operation, and retail business.

- Operational costs are variable costs that typically depend on operational decisions of the different actors in the system. Generation, T&D, and retail costs share some similar operational costs such as wages and office rents. However, most costs depend on the nature of the business (generation, T&D, retail).
- In contrast to operational costs, investment costs are made with a longer term perspective. Therefore, these costs also largely contribute to future electricity usage.

For all costs within a cost category, a distinction in cost drivers is made [33].

- Costs driven by energy usage expressed in kWh, such as the fuel costs.
- Costs driven by system's peak expressed in kW due to the balance between demand and generation. It refers to the net peak as both demand and generation are considered in the system. It can refer both to the local and global level, depending on the underlying cost component. An example is a distribution feeder investment partly driven by the net peak at the local level.
- Costs independent of energy usage or system's peak. In the literature, this cost is considered to be driven by the number of users [39]. An example is the metering cost partly driven by the number of users connected.

In the following, the time and locational dependency of costs are affected by the time and locational dependency of its cost drivers. As both energy usage and system's peak are variable over the course of the day, time dependency of tariffs is possible. Similarly, locational dependency of tariffs rests on the locational dependency of its cost drivers. If the cost driver is situated at the local or global geographical area, costs should be borne by the beneficiaries in that specific area.

The time and locational dependency of the underlying costs of each component are assessed based on the cost drivers of its underlying cost categories. The different cost categories of each component are evaluated against its time dependency. Locational dependency is discussed. This leads to insights in the potential for locational and time dependency of tariffs in view of demand response. The focus is on costs depending on the nature of the business. As operational costs such as wages and office rent are incurred by generation, T&D, and retail, these costs are omitted for simplicity. Costs are assigned to each of the different components based on who makes the initial costs, not on the market actor which bears the responsibility of the costs. The assignment of costs due to grid losses illustrates this. Even though the TSO is responsible for these costs and charges them to the consumers, costs are assigned to generators as they bear the operational costs of generating more.

Also note that several rate designs exist to recover costs: energy charging [c€/ kWh], demand charging [c€/ kWh] and fixed charging [c€] [39]. This is in line with the cost drivers as defined in Fig. 2.2. In what follows, the focus is on energy charging implying that all costs are translated in a price per kWh. According to Weston [39], energy charging is the preferred rate design for residential consumers as these promote energy efficiency. Moreover, energy based charging is widely adopted in Europe. Nevertheless, combining energy charging with demand or fixed charging and its impact on DR is subject to further research.

2.3.1 Generation component

Operational costs for generation are split up in generation costs, surplus generation costs, generation costs as a service to the TSO, and maintenance and repair costs (Table 2.1).

Table 2.1. Underlying costs of generation cost component.

Cost categories	Costs
Operational costs	Generation costs
	Surplus generation costs
	Generation costs as service to the TSO
	Maintenance and repair costs
Investment costs	Generation investment costs

Generation costs consist of fuel and environmental costs. The driver of these costs is typically energy usage expressed in kWh as energy usage typically affects the commitment of contributing generation plants. As the energy usage is affected by the variability and unpredictability of RES, the commitment of plants and their underlying operational costs are affected as well [31]. This adds to the dynamics of the underlying costs. The next costs are surplus generation costs driven by energy usage as they result from grid losses. Costs as a service to the TSO include ancillary services. Although compensation mechanisms exist to recover them from the TSO, initial costs are partly incurred by the generator. As stated in Parsons et al. [40], variability and unpredictability of RES add to the underlying costs of ancillary services. Finally, maintenance and repair costs complete the operational costs.

Investment costs mainly consist of investments in generation plants, including the RES. These investment decisions mainly depend on the expected future energy usage pattern on the one hand, and the expected unpredictability and uncontrollability of demand and generation on the other. It corresponds to the expected hours of generation plant commitment and availability. The latter is mainly applicable for flexibility purposes as this gains importance in view of a massive introduction of variable RES [41].

On the whole, most generation costs are attributable to present and future energy usage at system level. As electric power use is time dependent, the underlying cost is also time dependent making dynamic pricing (DP) a logical rate design. This contributes to cost causality and no excessive cross-subsidization. By allowing DP, consumers pay the generation cost they cause. Especially in view of more integration of RES, characterized by intermittency and limited predictability, importance grows.

Locational dependency of generation costs is applicable as well, as surplus generation costs or losses due to consuming electricity depend on the location of the consumption. If lines are congested, locational pricing is even more appropriate to reflect cost causality. In view of RES, locational dependency gains importance. An example is the electricity transport from areas with an excess of RES and limited demand to areas with excess demand [42]. It contributes to losses and increases the importance of locational pricing. The same applies at the distribution level if residential consumers are able to consume locally generated electricity, reducing losses. Next to losses and congestion costs, the remaining costs of the generation component are not dependent on the location of consumption.

2.3.2 Transmission and distribution component

Next to general operational costs like wages or office rent, the operational cost of T&D operation constitute mainly of grid maintenance and repair (Table 2.2). As the cost driver of these costs is typically locationally dependent, location can be reflected in the tariff.

Table 2.2. Underlying costs of T&D component.

Cost categories	**Costs**
Operational costs	Grid maintenance & repair
Investment costs	Expansion existing T&D grid
	New T&D assets
	Connection costs of demand and generation

A considerable amount of costs results from investments in T&D assets. A distinction can be made between expansion of the existing grid, investments in new assets, and connection costs of demand and generation. In general, three different kinds of investments are done: reliability, economic, and connection investments [43]. In what follows, each of them is evaluated against its costs driver after which its time and locational dependency are assessed.

Reliability investments arise when security and safety standards are exceeded, or when quality and continuity of supply are jeopardized. These problems typically lead to expansion of the existing grid or to investments in new assets. Most problems are driven by a system's peak expressed in kW leading to investments scaled to system peak. In this case, the system refers to the area where the reliability problem occurs making it locationally dependent. Other investments are caused by the energy usage pattern expressed in kWh. E.g., next to the system's peak, the usage pattern also affects the aging of transformers [44]. Both costs driven by energy usage and system peak are affected by the integration of RES, as RES can both hamper and benefit reliability [45], [46].

Economic investments are made to maximize the global surplus of network users within a specific geographical area. The cost driver is mainly the usage and peak of the relevant system. Again, costs need to be allocated to beneficiaries. Examples are investments to increase competition, to defer congestion or to decrease losses [47]. Again, RES impact the cost drivers and the accompanying economic investments, either magnifying or reducing investment costs [48], [49].

Connection costs, both of demand or generation, represent the cost of connecting to the grid. They are driven by energy usage and system peak. Connection costs directly attributable to a specific consumer or generator can be directly charged to this consumer or generator [50]. This part falls outside the LDP scheme as costs can be recovered directly. If the investment costs also bring benefits to other consumers or generators, they should contribute to recover the investment costs. It can be part of the LDP scheme.

Most T&D operation and investment costs are driven by both energy usage and system's peak. As the introduction of centralized and decentralized RES affects both elements, investments are also affected. Depending on the usage and peak pattern at the relevant system level, RES can both increase or decrease investment costs.

To follow the cost causality principle, consumers and generators causing this usage or peak, should pay for the corresponding costs. Therefore, a different tariff can be charged to consumers depending on their contribution to usage and peak. As discussed in Olmos and Pérez-Arriaga [51], in case T&D investment costs are already incurred, they should be recovered by a fixed charge over time. If not, the cost recovery can conflict with the system operation and lead to inefficiencies. This implies that investment costs already incurred should not be transformed in time dependent tariffs. By charging a fixed charge depending on the residential usage and peak pattern, cost causality is still met.

The driver of T&D costs can be assigned to consumers or generators within the specific geographical area where the reliability, economic or connection problems occur. As a result, T&D charges should be location dependent in order to reflect cost causality and defer cross-subsidization over location. Examples on how to transfer transmission costs in prices can be found in Green [52] and Shirmohammadi et al. [53]. In Brandstätt et al. [54], the transfer of distribution costs is discussed.

2.3.3 Retail component

The retail business mainly operates as an intermediary between generation and system operation business on the one hand, and users on the other. Basic retail activities consist of procurement, sales, and billing [55]. Several retail businesses are involved in marketing and user service activities. Underlying costs are typically driven by the number of users. These are independent of energy usage and peak pattern, leading to limited potential for transferring costs in locational dynamic pricing.

2.4 Residential injection tariff

Next to the role of consumers, residential users can take the role of generators when they install local generation facilities at their premises and inject electricity in the distribution grid. Following the cost recovery principle, installation costs made by the residential generator need to be recovered as well. A distinction is made between the direct costs at the household level itself and the indirect costs at the grid level.

Direct costs are for installing and operating its local generation facilities. Based on the costs they make, they should be compensated according to the cost causality principle. Although cost recovery is not guaranteed, local generators try to recover the two cost categories of Fig. 2.2. In other words, these costs should be regained through the generation component paid by the consumers. As this puts local generators on an equal footing with centralized generators, local electricity generation affects the overall costs of generation. Therefore, together with the costs of centralized generation, the direct costs of local generation can be translated in a locational dynamic tariff charged to consumers.

Next to the recovery of direct costs resulting from the installation and operation of local facilities, generation can also **indirectly** affect costs at the grid level. In contrast with direct costs made by the local generators themselves, indirect costs are initially borne by the TSO and DSO. As they are caused by local generators, they should be assigned to them following the cost causality principle. Again, these indirect costs are split according to Fig. 2.2. Consistent with Section 2.3.2, distinction is made between operational costs and investment costs.

Similar to withdrawal, injection of electricity at the residential level can lead to grid reliability problems triggering additional investments. These problems mainly occur at the distribution level as this network was only designed for consumption purposes. Following the cost causality principle, additional cost should be paid for by the local generators. In contrast, local generation can also avoid network problems, which reduces investment needs [31]. In this case local generation should be compensated. The second indirect investment cost is the economic investment costs due to global surplus maximization. Again, costs need to be allocated to the beneficiaries. The final indirect cost is the connection costs associated with the installation of the generation facility at the residential level. Similar to generation at a centralized level, costs should be borne by the user who causes them.

Following the same principles and reasoning as with consumption of electricity, these indirect costs made at grid level can be translated in a locational dynamic tariff charged to local electricity injection.

2.5 Practicability of locational dynamic pricing

Operational and investment costs, driven by energy usage or system's peak, can be transformed to LDP. This adds to the cost causality principle and defers cross-subsidization. Although this approach is viable from a theoretical point of view, some practicalities have to be taken into account.

Operational and investment costs should be exactly determined together with their beneficiaries in order to attain full cost causality. In practice, both calculation of costs and allocation to the beneficiaries are difficult to determine, as every node in the grid needs to be modelled in detail [51]. Moreover, T&D investments are based on predictions of energy usage and peak flows, which complicates exact cost determination and allocation. Indivisibilities of investments and strong increasing returns to scale are further complicating this exercise [32].

Social acceptability and practicality are at stake if full cost causality is applied. As cost causality implies largely varying electricity charges depending on time and location of consumption, electricity charges can differ from one time period and household to another. The integration of RES only strengthens this variation. This conflicts with the principles of tariff design of transparency, simplicity and minimum volatility.

To overcome these challenges, a balance has to be found between cost causality and its feasibility of cost and beneficiary determination on the one hand, and social acceptability and practicality on the other.

2.6 Tariff design incentivizing demand response

Apart from meeting the cost causality principle, LDP can influence decisions on the timing of electricity usage of residential consumers and generators. This way, the demand side becomes a flexible part of the electricity system reacting to changing system conditions. As both operational and investment costs are partly driven by residential users, it becomes relevant to defer these costs by influencing their behavior. Apart from consumption, LDP can also influence the decisions on the timing of dispatchable electricity generation at the residential level. In what follows the focus is on consumption, although the same reasoning can be applied for generation. Although in theory LDP can also influence the choice of residential users on the location of their consumption or generation in the network, only the influence of costs on the operation at their current location is discussed.

An LDP scheme can be sent to residential consumers in different forms, depending on the advance notice of sending the pricing scheme to consumers, the length of the price blocks, and the length of the price patterns (Fig. 2.3). More practical examples of tariff designs can be found in the literature. In Ortega et al. [56] and Bartusch et al. [57] a tariff design for distribution network costs is proposed, while in Dupont et al. [58], [59], the focus is mainly on tariff design for generation costs. Each of the theoretical concepts is assessed according to the principles of tariff design and the demand response incentive for consumers. Cost related tariff principles are balanced against principles related to practicality. The balance between both leads to a certain demand response incentive (Fig. 2.4).

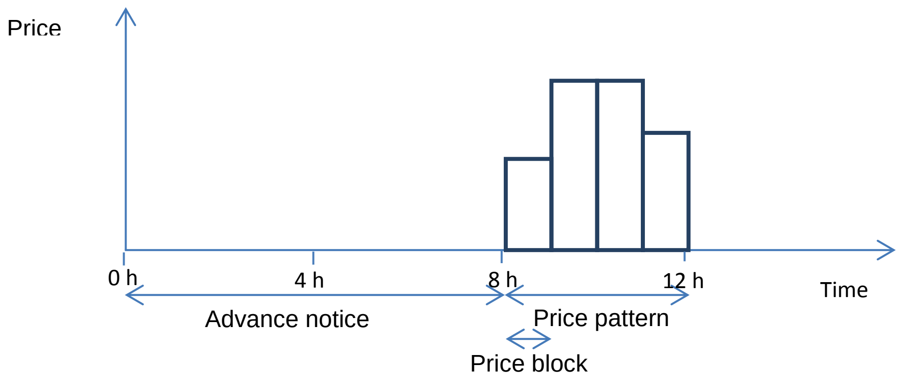


Fig. 2.3. Tariff design based on advance notice, and the length of price blocks and price patterns.

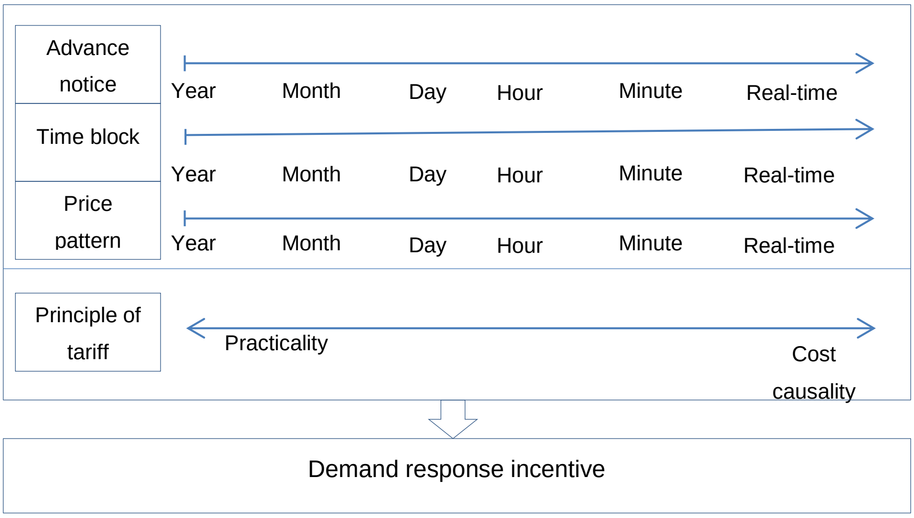


Fig. 2.4. Demand response incentive following from the design concepts of locational dynamic pricing: advance notice, price blocks, and price patterns.

2.6.1 Advance notice

Advance notice refers to the time period between the moment when the price is sent to the consumer and when it is applied [60]. In Fig. 2.3, the price for hour 8 is sent to the consumer at hour 0, resulting in an advance notice of 8 hours. Advance notice of DP tariffs gives residential consumers the possibility to react. The longer consumers know their tariffs in advance, the better they are able to adjust demand as this adds to the transparency and simplicity principles of tariff design.

This contrasts with the cost causality principle as advance notice assumes a prediction of costs. If prices are sent a year in advance, it's difficult to get the costs right, but easier for consumers to adapt consumption. The closer to real-time, more information becomes available making cost predictions more accurate. This contributes to the cost causality principle, although consumers experience more difficulties to adapt consumption at the last moment. Full cost causality can be achieved if prices are communicated at or after real-time. This decreases demand response benefits as demand is not able to react to the price signal anymore.

The contrast between the demand response incentive and the cost causality principle can be reduced in two ways.

A first way is by sending the predicted price pattern in advance to consumers. This serves as a trigger for demand response. When costs are known, the final price reflecting full costs causality can be sent and billed. The practical implementation depends on the accuracy of predicting costs and the willingness of consumers to take on the risk of an inaccurate prediction.

A second way is by using automation of residential appliances. In this case, appliances cycle whenever the price is lowest, without further consumer interaction. Only consumer preferences need to be set. Examples are the shifting potential for a washing cycle or the temperature set point for a heat pump. As consumer interaction is minimal, automation can protect consumers against complexity and volatility, overcoming the demand response demotivation of consumers.

In what follows, a more detailed view on advance notice is provided for each of the different components of Fig. 2.2:

Generation

A considerable part of generation costs is not affected by the daily consumption pattern of residential users. Examples are operational costs such as wages and office rent. As these costs are known in advance, the time of communicating them can occur beforehand as long as the cost recovery principle is satisfied.

Most generation plants are scheduled based on day-ahead predictions of electricity generation from RES, reserve requirements, and on day-ahead predictions of demand and demand response. This commitment of plants results in an expected cost of covering demand, leading to a price pattern which can be communicated to the users.

As the commitment of plants is based on predicted demand and demand response from consumers and generation from RES, prediction errors induce an intraday rescheduling of the generation plants. Following cost causality, this results in a new price pattern which can be communicated to the consumers. This process of rescheduling generation and communicating prices can continue until real-time. At the moment of consumption itself, the actual cost of generation is known (Fig. 2.5). In view of an optimal incentive for demand response, a balance should be found between following the cost related principles and the principles related to practicality and social acceptability.

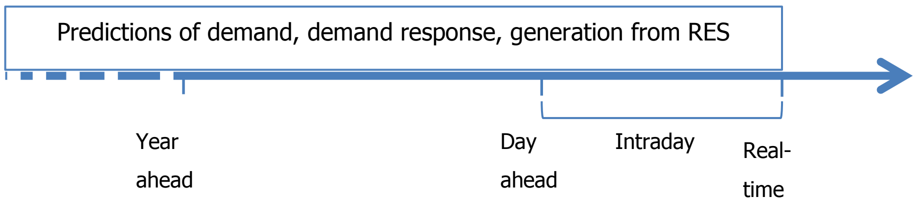


Fig. 2.5. Cost uncertainty over time.

Transmission and distribution

A considerable part of the T&D costs is not affected by the daily consumption pattern of residential consumers. Examples are investment costs such as meter installation and operational costs such as wages and office rent. As these costs are known in advance, the time of communicating these costs can occur beforehand as long as the cost recovery principle is satisfied.

Time dependency of T&D prices is less straightforward, because of possible conflicts with system operation. As this reasoning only applies when investment costs are already incurred, elaboration is needed when investments are not done yet. In this case, it is important to notice that reliability investments, economic investments and new connections are driven by the operation of consumers and generators. This implies that the operation of residential users can defer investments by using demand response [61]. Therefore, in some situations it can be more efficient to send locational dynamic prices and defer investments, instead of making the investments directly [54], [62]. To align with cost causality, a link should be found between forward looking network investment costs and prices sent to households [31]. Similar to the energy component, costs can be derived if demand and generation patterns of both centralized and decentralized RES are predicted. As this prediction is again covered by uncertainty, cost prediction gets more accurate closer to real-time.

2.6.2 Length of price blocks and price patterns

The length of price blocks refers to the time period in which the same price is applicable. As an example, the length of price blocks is one hour in Fig. 2.3. Dynamic pricing schemes charge a different price during different price blocks as costs fluctuate. Full cost causality would charge a different price every time costs change. The volatility of these costs depends on the underlying cost of power system operation. Similar to advance notice, a balance should be found between reaching the cost related tariff principles and the principles related to practicality, in order to optimally incentivize demand response [63].

Three examples of dynamic pricing schemes with a different length of price blocks are visualized in Fig. 2.6. The smaller the length of different price blocks, the better the principle of cost causality can be met. As a result of small price blocks, volatility is higher and the tariff could be more complicated or loose transparency. Moreover, consumption cycles such as washing machine cycles can last longer than the length of the price blocks, making the DR decision for the consumer more complex.

Full cost causality could discourage demand response as adjusting consumption to short price blocks is more difficult. If price blocks get longer, demand response for a residential consumer could become more convenient as tariffs become more transparent and simpler to react to. If the length of the price blocks becomes longer than the shifting potential of demand, the DR incentive decreases again. Moreover, it is more difficult for wider price blocks to reflect price spikes. If the price block lasts longer, the peak price level is flattened by averaging with shoulder periods. This leads to a lower opportunity for bill saving, resulting in a lower incentive for DR.

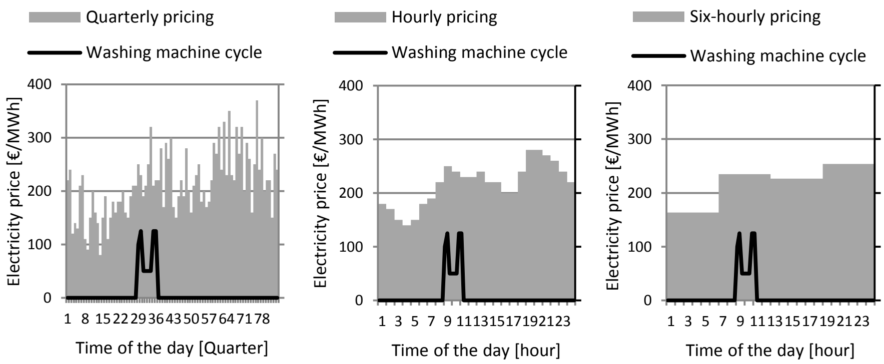


Fig. 2.6. Dynamic pricing scheme with quarterly (left), hourly (middle), and six-hourly (right) pricing blocks and consumption of washing machine cycle.

The price pattern consists of one or multiple price blocks. The length of the price pattern refers to the total time period covered by the pricing signal sent to the users constituting of the different price blocks, e.g. 4 hours in Fig. 2.3. Next to the length of individual price blocks, the length of the communicated price pattern also affects the cost related principles and the principles related with social acceptability, thereby affecting the demand response incentive.

The longer the communicated price pattern lasts, the more costs are based on predictions. This makes it more difficult to attain full cost causality, but adds to the principles of social acceptability as for example demand shifting can be planned in time. Therefore, adjusting demand based on this longer price pattern is easier.

2.7 Tariff designs in practice

2.7.1 Existing tariff designs

Around the world, different tariff designs are implemented. In line with Chapter 1, four main tariff designs are distinguished: flat, Time-of-Use (ToU), critical peak pricing (CPP), and real-time pricing (RTP) [12]. Each of these tariff designs aligns with a different extent with the cost related principles and the principles related to social acceptability and practicality. The specifics of each of these four tariff designs are given in Table 2.3.

Table 2.3. Tariff designs.

Tariff design	Advance notice	Price pattern	Price block
Flat	days	Year/season	Year/season
Time-of-use	days	Year/season	>1 block/day (e.g. day-night)
Critical peak pricing	< 1 day	Hours	Hours
Real-time pricing	< 1 day	1 hour	1 hour

Each tariff design differs in its period of advance notice, price blocks, and price pattern. Flat tariffs are the traditional design and apply a constant price over a longer time period such as a year or season. Therefore, the length of the price pattern and price block is equal. The price level is set based on long term cost predictions. ToU pricing also typically sends a pricing scheme which applies over a longer time period, although the length of the price blocks are shorter. ToU pricing distinguishes between different price blocks a day. A widespread example is day-night pricing in which a lower price applies during the night. During the 80s, this price design was introduced within Belgium following investments in nuclear capacity. This design aimed at avoiding nightly shut downs of nuclear plants. In the CPP scheme, a peak price is added on top of another pricing scheme during a limited number of hours per year. In general, the length of advance notice is less than a day, while the length of the price block covers several hours. This tariff design is mainly used in the US. Finally, in RTP the length of advance notice, price blocks, and price patterns decreases to close to real-time. Although deployment of these pricing schemes for residential users is limited, some examples can be given. In Illinois, US, an hourly RTP scheme is used which charges consumers based on hourly wholesale prices [64]. To overcome the principles of social acceptability, pricing schemes can be coupled with information and automation services. Moreover, predicted prices are sent to the users day-ahead, although afterwards they are charged based on actual prices. In Sweden, a day-ahead hourly RTP scheme is used [65]. This implies that residential users are noticed the previous day of a tariff pattern covering 24 hours divided in hourly price blocks and are billed on the same tariff pattern afterwards. This design reflects availability of generation from RES more closely and aims to compensate inflexibility resulting from RES integration with flexibility at the demand side. A residential tariff design with smaller price blocks attaining higher cost causality than the latter has not been found in the literature.

2.7.2 Assessment of illustrative tariff schemes

Based on the different tariff designs from the previous section and in accordance with the theoretical framework discussed, four examples of tariff schemes are constructed and assessed. This allows testing and clarifying the different theoretical concepts.

To construct these schemes, the underlying costs and their time and locational dependency need to be assessed first. A realistic quantification of the underlying costs is outside the scope. Nevertheless, in what follows simplified tariff schemes are built serving as an illustration. Three cost components are considered: generation, T&D, and retail. Components are assumed to be driven by energy usage and are accordingly translated in tariffs expressed in €/MWh. Only the generation component is assumed to be time dependent and only the T&D component is assumed to be locational dependent.

Based on the underlying costs characteristics, four different tariff schemes are obtained: Flat1, Flat2, ToU, and RTP (Table 2.4). Compared to the previous section, the CPP tariff design is left out for the purpose of simplicity, while two flat tariffs are presented to illustrate the effect of the way generation is remunerated. The first three tariff designs are implemented in Belgium [66], while the last aligns with the design from Illinois [64]. The price levels of the schemes are given. Locational dependency of costs is transferred in the Flat2, ToU, and RTP design. Time dependency of generation cost is only fully reflected in RTP. In other designs, generation costs are averaged over longer time periods. Flat1 differs from the other tariffs in the way generation is remunerated. While Flat1 remunerates generation based on the consumption tariff as a whole covering generation, T&D and retail, other tariff schemes only remunerate injection based on the generation component.

These tariff schemes are tested on two types of residential users with similar consumption pattern (Fig. 2.7). The first user (U1) is located in a city and does not possess any type of generation. The second user (U2) is situated in a rural area and has solar panels installed. Daily electricity generation in terms of energy of U2 equals his daily consumption. To integrate locational dependency in the example, it is assumed that distribution costs are higher for U2 compared to U1. Applying the tariff designs on the two users leads to seven tariff schemes (Fig. 2.8).

Table 2.4. Characteristics of theoretical tariff schemes.

Tariff	**Cost component**			**Cost dependency**		**Remuneration generation**
	Gen.	**T&D**	**Retail**	**Locational**	**Time**	
Flat1	Flat	Flat	Flat	No	No	Total tariff
Flat2	Flat	Flat	Flat	Yes	No	Generation component
ToU	Day-night	Flat	Flat	Yes	Yes	Generation component
RTP	Hourly	Flat	Flat	Yes	Yes	Generation component

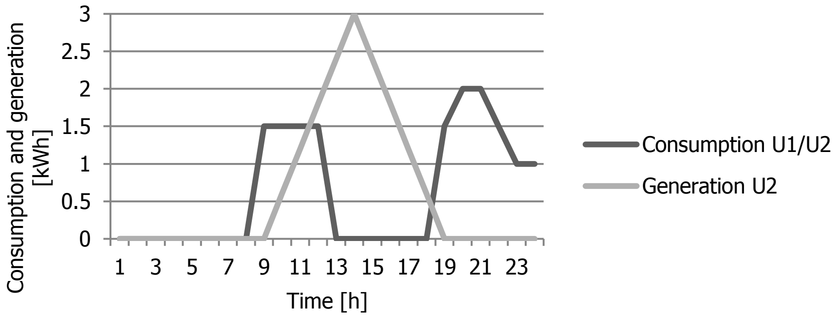


Fig. 2.7. Fictional consumption and generation patterns of the residential users.

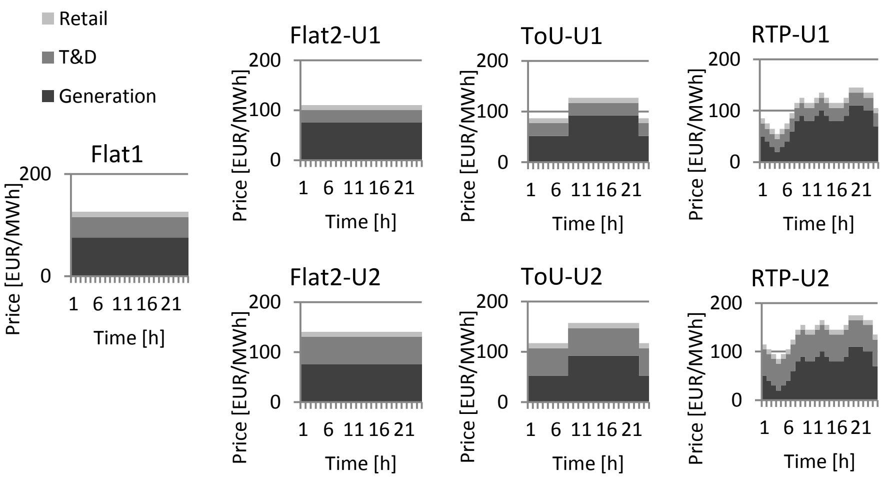


Fig. 2.8. Fictional tariff schemes for the residential users.

The cost related principles of tariff design are assessed by comparing daily electricity bills following from the different tariff schemes. The bills for the two users are depicted in Table 2.5. Distinction is made between the generation, T&D, and retail components. The RTP bill is assumed to be a perfect approximation of actual costs and serves as a reference to assess cost causality. Although the different bills result from a theoretical example, the comparison with the reference bill illustrates the concepts of cost related principles.

Table 2.5. Daily electricity bills for residential users following from different tariff schemes.

		Flat1 U1	**Flat1 U2**	**Flat2 U1**	**Flat2 U2**	**ToU U1**	**ToU U2**	**RTP U1**	**RTP U2**
Generation	[€]	1.13	0.00	1.13	0.00	1.30	-0.08	1.43	0.13
T&D	[€]	0.60	0.00	0.38	1.29	0.38	1.29	0.38	1.29
Retail	[€]	0.15	0.00	0.15	0.23	0.15	0.23	0.15	0.23
Total	[€]	1.88	0.00	1.66	1.52	1.83	1.44	1.96	1.65

In the Flat1 tariff, a discrepancy occurs between the total bill and the actual costs represented by the RTP bill. This illustrates that the Flat 1 tariff is not able to fully meet cost causality. This discrepancy is also present in the underlying components. For U1, only the retail component captures the actual costs. The discrepancy in the generation component leads to cross-subsidization in time, implying that users who consume during inexpensive periods subsidize the other users. The discrepancy in the T&D component leads to cross-subsidization in location, implying that users who live in an area with low T&D costs subsidize the other users. For U2, the total bill is zero. This follows from an equal daily consumption and generation, and from a generation remuneration based on the total tariff scheme. As U2 does not bear the costs he causes, this leads to cross-subsidization and to cost recovery problems. This illustrates that the impact of residential RES should be properly valuated. In the Flat2 tariff, the locational dependency is reflected and injection is only remunerated based on the generation component. This leads to an accurate T&D component for both users. As retail costs are not locational and time dependent, this component is accurately valuated as well. The time-dependency of generation costs is not reflected, as observed in the difference in generation costs between the Flat2 and RTP design. In the ToU tariff, time-dependency is included. Depending on the consumption and generation pattern of the users, the bill approximates the actual costs better or worse. This illustrates that an imperfect reflection of costs in time-depending tariffs designs can worsen the alignment with the cost causality principle for some users.

Although a quantification of demand response is not within the scope of this chapter, it can be noticed that the four tariff schemes affect the demand response incentive differently. Only Flat1 does not incentivize demand response. Flat2 incentivizes demand response in case generation capacity is installed, as shifting consumption can defer the T&D cost of injecting and withdrawing electricity. Time-varying tariff schemes such as ToU and RTP also incentivize demand response. As RTP is able to more accurately reflect the impact of RES, demand response based on this scheme contributes to RES integration.

2.8 Summary & Conclusions

Traditional tariff schemes are not able to reflect the challenges renewables integration brings. In contrast, locational dynamic pricing can capture these challenges by allowing price dependency on location and time.

To assess the potential of locational dynamic pricing and the residential flexibility it can trigger, this chapter provides a theoretical framework. First, it evaluates the underlying costs of electricity. This is essential as demand response is mainly triggered if a substantial part of the underlying costs is locational and time dependent. Costs of electricity are split in cost components and cost categories. In general, cost components constitute of generation, T&D, and retail. Cost categories consist of operational and investment costs. The locational and time dependency of these costs is assessed according to its cost drivers: energy usage, system's peak, and cost independent of usage or peak. It is shown that the different cost categories are highly affected by the integration of RES as this affects the cost drivers. As usage and peak typically depend on the time of the day, most costs driven by these drivers can be made time dependent. Moreover, locational dependency of costs relates to the locational dependency of its cost drivers. If costs are driven by usage or system's peak at local level, costs should be assigned to this local level. If costs are induced by usage or peak at the global level, costs should be shared among its beneficiaries at the global level.

When designing an LDP scheme, the principle of cost causality should be strived for, although some constraints need to be taken into account. Full cost causality is not always possible as cost determination and allocation is not straightforward. Meanwhile, general principles resulting from social acceptability and practical consideration should be considered. While cost causality allows for a non-discriminatory way of billing residential users as they pay for the cost they cause, the demand side is still considered as an inflexible part of the system. Therefore, additional principles of tariff design are needed to incentivize demand response in an efficient way. This leads to an LDP scheme which not only takes into account RES, but also helps RES integration as this scheme allows for more flexibility.

The demand response incentive is affected by three concepts related to tariff design: advance notice, length of price blocks and length of price pattern. These concepts in their turn affect the general tariff principles related to costs and social acceptability, often in a contrary way. Therefore, a balance has to be found between tariff principles related to costs and social acceptability on the one hand and its resulting demand response incentive on the other.

PART II

Residential demand response based on dynamic pricing

3. Development of dynamic pricing schemes

3.1 Introduction

Based on the theoretical framework previously discussed, different dynamic pricing schemes are constructed. The variety in resulting dynamic tariff schemes leads to a deeper understanding of the potential for incentivizing demand response. Moreover, this chapter forms the basis on which the following chapters build. Although the same methodology can be used for other countries, pricing schemes are based on Belgian cost structures. Locational pricing is not considered. Also note that in what follows the focus is on an energy based rate designs expressed in c€/kWh. Other types of rate designs are out of scope and subject to further research.

Section 3.2 starts by describing the price level of the different tariff components within Belgium. Based on the underlying costs and time-dependency, Section 3.3 describes a methodology to develop dynamic tariff schemes. The tariff schemes following from this analysis are discussed and compared in Section 3.4 and 3.5 respectively. Finally, Section 3.6 concludes.

3.2 Tariff components

A Belgian residential electricity tariff consists of several tariff components. Compared to the theoretical tariff components discussed in the previous chapter, in reality the structure and the content of the electricity tariff differs. Taxes and levies are added to the generation, transmission, distribution, and retail components. Belgian examples of levies are the financing of the connection of offshore wind farms, surcharges for green certificates, surcharges for public lighting, financing of promotion of rational energy use, etc. Other taxes and levies are mentioned separately on the residential bill. Rather than distinguishing between generation and retail, Belgian residential bills only account for an energy component summing both components.

The breakdown of a residential electricity tariff in Belgium is visualized in Fig. 3.1 based on an analysis of the Belgian federal regulator [67]. The tariff components are derived for a typical residential user connected to the low voltage grid with a yearly daytime and nighttime consumption of 1600 and 1900 kWh respectively [67]. The figure shows that the total tariff amounts to 20 c€/kWh of which 75% consists of the energy and distribution components. The remaining part is attributable to transmission and taxes and levies. Only those taxes and levies not included in the energy, transmission, and distribution components are visualized.

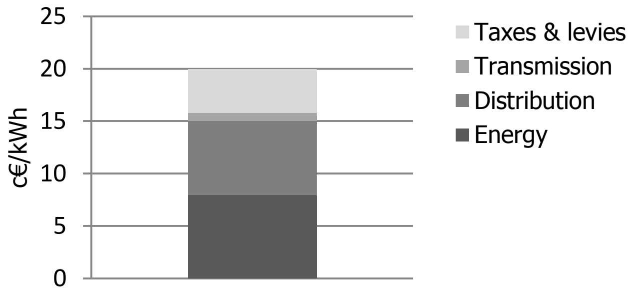


Fig. 3.1. Breakdown of the electricity tariff for a typical Belgian residential user.

3.3 Dynamic tariff scheme development

This section describes a methodology for developing dynamic pricing schemes based on the different tariff components and applied to the Belgian case. Based on available cost information, the time dependency of underlying costs of each component is assessed. Afterwards, these costs are translated in a dynamic tariff component. This approach is followed for each tariff component, being a simplification aiming at providing insights, rather than reflecting full cost causality.

Energy tariff component

As generation and retail are competitive in Belgium, no further insights in the underlying cost structure of the energy component are publicly available. Nevertheless, the main part of the energy tariff component is related to electricity generation costs which can be approximated by the price on the Belgian day-ahead wholesale market, later on referred to as the Belpex-price [68]. Within this market, hourly variation of power generation costs is reflected.

As the Belpex-price accounts for only part of the total energy component, rescaling is needed for generators and retailers to recover their costs. In addition, revenue for the generators and retailers should be the same under flat pricing than under dynamic pricing if the residential users do not change their consumption pattern. This is also referred to as revenue neutrality [69].

A valid rescaling factor *rfe* is derived from:

$$\sum_{p=1}^{8760} \left[\left[\mathrm{SLP_p} \cdot \mathrm{WP_p} \right] \cdot rfe \right] = \mathrm{Flat_{Energy}} \tag{3.1}$$

with:

$\mathrm{SLP_p}$: Synthetic load profile during hour p [% of yearly consumption],

$\mathrm{WP_p}$: Wholesale price during hour p [c€/kWh],

rfe: Rescaling factor for energy component,
$\mathrm{Flat}_{\mathrm{Energy}}$: Average energy tariff component over year [c€/kWh].

The wholesale price is based on hourly day-ahead Belpex-prices of 2011 [68]. Hourly electricity use of residential users is derived from synthetic load profiles of 2011 [70], while the average energy tariff is based on [67] as discussed in Section 3.2.

Based on the rescaling factor and the Belpex-prices, the hourly dynamic energy tariff component $RTP_{Energy,i}$ is:

$$RTP_{Energy,p} = rfe \cdot \mathrm{WP_p}. \qquad (3.2)$$

The resulting dynamic energy tariff component for a random day in October is depicted in Fig. 3.2. The tariff varies considerably during the day between 6.26 c€/kWh and 18.35 c€/kWh. Two measures define the variability. First, the peak to off-peak (PtOP) ratio describes the ratio between the maximum and minimum price level during the day. Often this measure is used to describe the incentive for users to react to the pricing signal. For October 20th, the PtOP ratio is 2.93. Second, also the hourly variance within a day captures the DR incentive. This is the average of squared differences from the mean. The higher the variance, the further hourly prices deviate from the daily mean, in this case 7.51.

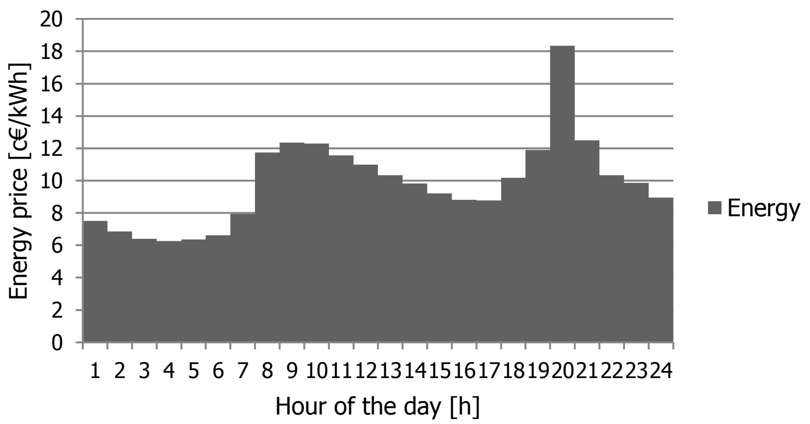


Fig. 3.2. Dynamic energy tariff component for Thursday October 20th.

Transmission and distribution tariff component

Belgian transmission and distribution is regulated as future costs need to be approved by regulators in advance. To attain perfect cost causality in time as discussed in the previous chapter, a quantification of the underlying costs and the time dependency of the cost drivers is required. As this is outside the scope of this thesis, a simplified approach is taken in view of demonstrating tariff development and its implications. Therefore, transmission costs and its resulting tariff are assumed flat over the year, while distribution costs are assumed to vary with the level of electricity usage of residential users. In this perspective and after discussions within a residential pilot project named LINEAR [71], the dynamic distribution tariff component $RTP_{Distr,p}$ becomes:

$$RTP_{Distr,p} = \frac{\mathrm{SLP_p}}{\sum_{\mathrm{p=1}}^{8760} \mathrm{SLP_p}^2} \cdot \mathrm{Flat_{Distr}} \tag{3.3}$$

with:

$RTP_{Distr,p}$: Dynamic distribution tariff component [c€/kWh],

$\mathrm{Flat_{Distr}}$: Average distribution tariff component over the year [c€/kWh].

Hereby, $RTP_{Distr,p}$ is determined based on the ratio between the hourly usage and its weighted average over the year. This results in a higher distribution tariff when the hourly electricity usage of residential users is above the weighted average. Moreover, the formula ensures revenue neutrality and cost recovery.

The resulting dynamic distribution and flat transmission tariff components for October 20th are depicted in Fig. 3.3. The distribution tariff varies widely during the day between 3.86 c€/kWh and 9.00 c€/kWh. Therefore, the PtOP-ratio amounts to 2.33 and the variance is 2.30.

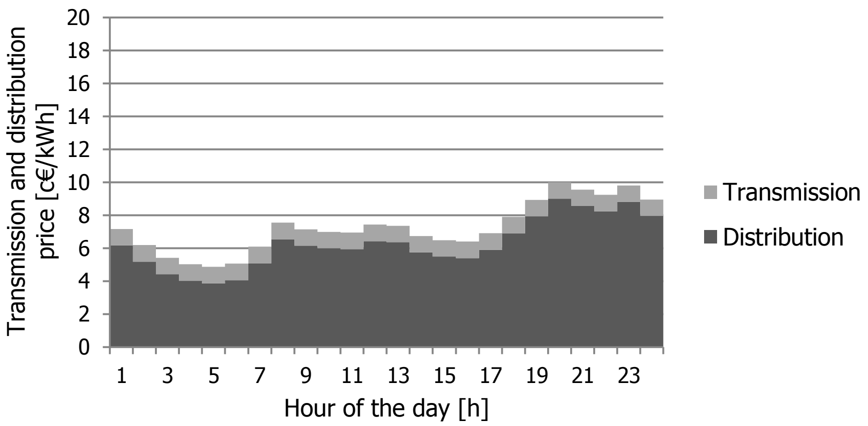


Fig. 3.3. Dynamic distribution tariff component and flat transmission component for Thursday October 20th.

Taxes & levies tariff component

Finally, although taxes and levies are partly variable in time, they are also assumed flat during the day (Fig. 3.4).

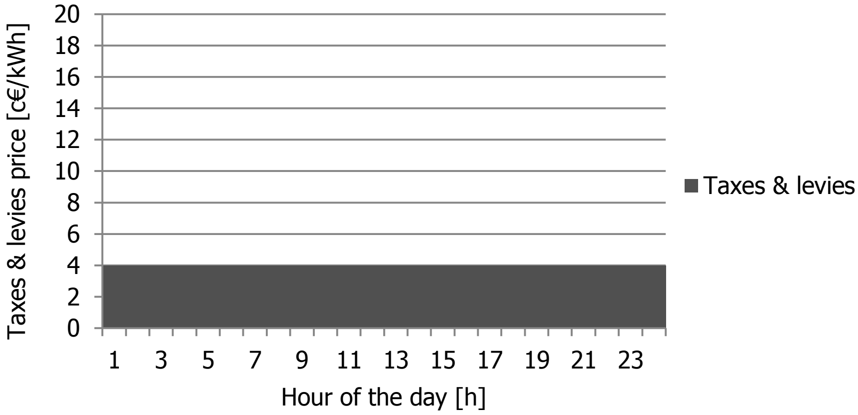


Fig. 3.4. Flat taxes & levies tariff component for Thursday October 20th.

Total dynamic tariff

Once all dynamic components are known, first the dynamic tariff design needs to be decided upon by determining advance notice, the length of the price blocks, and the length of the price pattern. Then, the price level of each type of price block is set by calculating the weighted average of all hourly prices of the same type. Finally, by summing the resulting dynamic tariff components, the final dynamic pricing scheme is obtained.

3.4 Tariff schemes

Based on the tariff development methodology and on different tariff design characteristics, four different dynamic tariff schemes are constructed. They are summarized in Table 3.1, along with the flat pricing scheme. In what follows, each tariff scheme is briefly discussed.

Table 3.1. Design characteristics of considered tariff schemes.

	Advance notice	Price pattern	Price Blocks
Flat pricing	Year-ahead	1 year	1 year
Time-of-use pricing	Year-ahead	1 year	Peak, off-peak
Critical peak pricing	Basis: Year-ahead	Basis: 1 year	Basis: Peak, off-peak
	CPP: Day-ahead	CPP: 1 hour	CPP: 10 peaks of 1 hour
Real-time pricing	Day-ahead	24 hours	1 hour
Renewable pricing	Day-ahead	24 hours	0h-7h, 7h-10h, 10h-13h, 13h-17h, 17h-20h, 20h-24h

3.4.1 Flat pricing

The flat pricing scheme is widespread in Belgium [72]. Although the price with flat pricing schemes in Belgium can be adapted over the different seasons, it is assumed that it remains flat over the entire year. Assuming that the contract with the residential user spans a year, the period of advance notice covers up to a year-ahead.

An example of the flat tariff scheme for a day in October is provided in Fig. 3.5, distinguishing between the different tariff components.

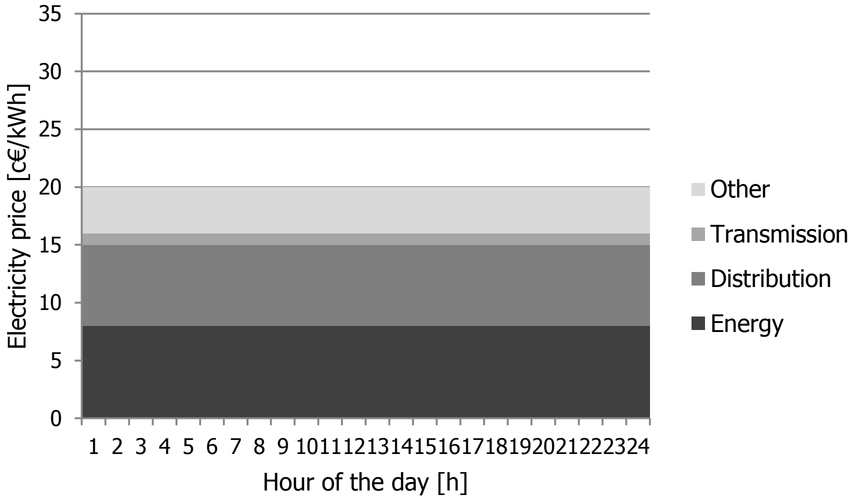


Fig. 3.5. Flat tariff scheme for Thursday October 20th.

3.4.2 Time-of-use pricing

Together with flat pricing, time-of-use pricing is the main tariff scheme in Belgium. As shown in Table 3.1, two price blocks are distinguished within this tariff scheme. Depending on the geographic area within Belgium, the peak tariff covers the daytime block from 7h to 22h during weekdays, while the off-peak period covers all hours during weekends and the nighttime block from 22h to 7h during weekdays. Similar to flat pricing the price patterns spans a full year.

An example of the ToU tariff scheme for Thursday October 20th is provided in Fig. 3.6, distinguishing between the different tariff components. The peak tariff amounts to 21.58 c€/kWh, while the off-peak tariff sums to 18.60 c€/kWh. This leads to a price difference of 2.98 c€/kWh and a peak to off-peak (PtOP) ratio of 1.16. The variance sums up to 2.17 for this day.

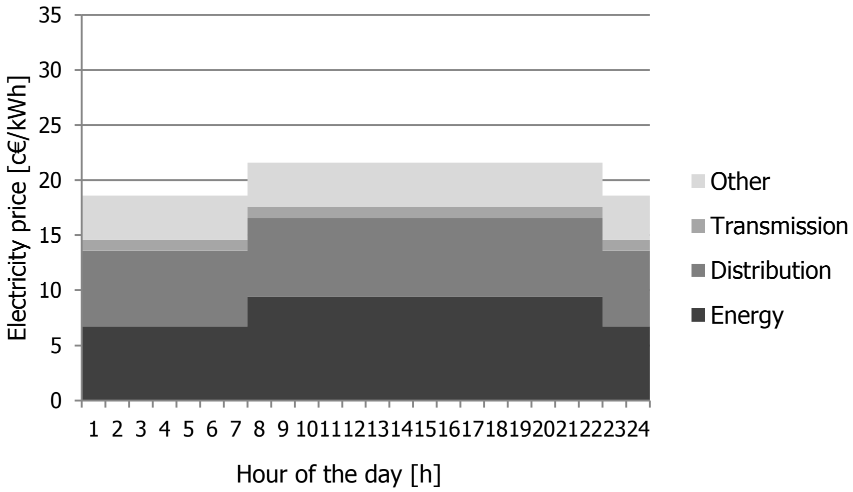


Fig. 3.6. ToU tariff scheme for Thursday October 20th.

3.4.3 Critical peak pricing

A dynamic tariff scheme, which is currently not available in Belgium for residential users, is Critical Peak Pricing (CPP). This tariff scheme covers the ToU scheme which is overruled when an hourly price spike is sent on a day-ahead basis. The occurrence of this event is limited to 10 times a year. The purpose of this tariff scheme is to reduce consumption during these critical events.

To attain the level of the price spikes, the energy component of the ToU price is lowered by 0.5 c€/kWh for all periods and the resulting revenue loss is recovered by charging a higher price level during the critical peak hours. These critical hours were chosen to be the ones with the highest Belpex-price. This leads to a price of 162.55 c€/kWh on top of ToU price.

Note that contrary to prices within other dynamic tariff schemes, the critical peak price is not based on the principle of cost causality and therefore does not reflect the underlying costs. Instead, the critical peak price is sent to assure demand response to be triggered and therefore to avoid the critical event.

An example of the CPP tariff scheme for Thursday October 20th is provided in Fig. 3.7. During this day a critical peak price is called. The peak tariff amounts to 183.83 c€/kWh, while the off-peak tariff sums to 18.30 c€/kWh. This leads to a price difference of 165.53 c€/kWh and a PtOP-ratio of 10.04. The variance adds up to 1118.89.

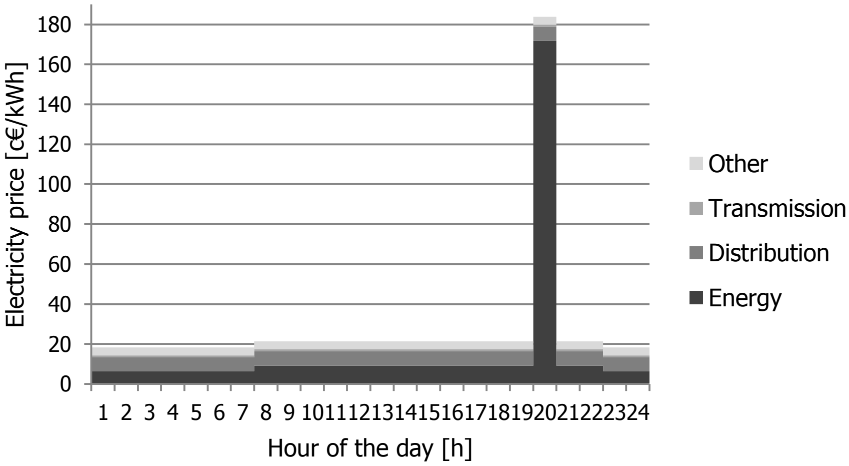


Fig. 3.7. CPP tariff scheme for Thursday October 20th.

3.4.4 Real-time pricing

A second dynamic tariff scheme, currently not available in Belgium for residential users, is real-time pricing (RTP). In this thesis, day-ahead RTP is assumed covering 24 price blocks a day. This allows a closer reflection of the underlying costs compared to the flat, ToU, and CPP tariff scheme.

An example of the RTP tariff scheme for Thursday October 20th is provided in Fig. 3.8, distinguishing between the different components. The peak tariff amounts to 32.34 c€/kWh, the off-peak to 15.21 c€/kWh. This leads to a price difference of 17.13 c€/kWh and a PtOP-ratio of 2.13. Variance adds up to 15.81.

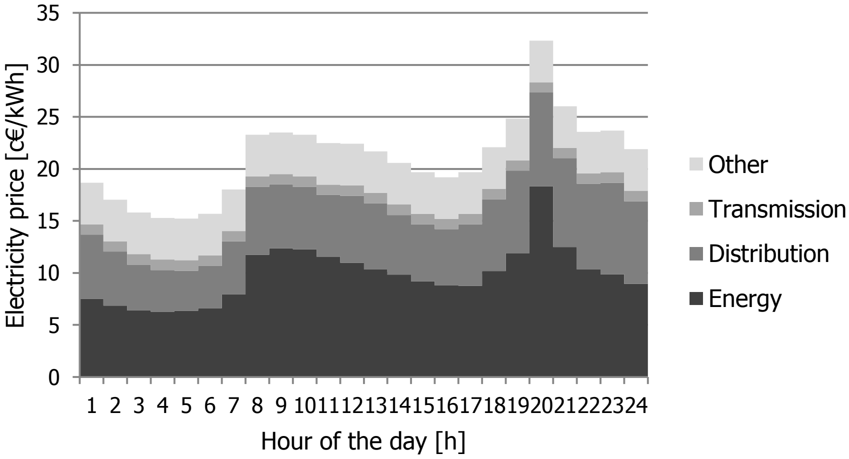


Fig. 3.8. RTP tariff scheme for Thursday October 20th.

As the energy and distribution tariff patterns vary over the day, it could happen that these two patterns of the underlying tariff components incentivize opposing demand response directions. From the point of view of DSOs and retailers, these opposing signals have to be avoided. The direction of the DR incentive of each component is determined by the deviation of the hourly price from its daily average. For example, an hourly price of the energy component above its daily average incentivizes a demand reduction, while an hourly distribution price during the same hour below its daily average incentivizes a demand increase. This implies an opposing demand response incentive triggered by the energy and distribution component. This decreases the impact of the demand response incentive resulting from each individual component. In what follows, this effect is referred to as opposing dynamic components. Within the RTP scheme, this effect is present in 2724 hours or 31.10% of the hours within a year. In the remaining 68.10% of the time, the demand response incentive is enlarged due to coincident variability of the energy and distribution pattern. Hereby, any size of opposing effects is considered however small. When neglecting smaller effects, this picture changes. When a deviation of the hourly price from the daily average of less than 0.25 c€/kWh is not considered, the opposing effect only takes place in 13.82% of the time. When deviations of less than 0.5, 1, 1.5 and 2 c€/kWh are neglected, this further reduces to 8.79, 1.84, 0.29 and 0.01% of the time respectively. Therefore, it can be concluded that during the main part of the hours in which the price deviation is high, the demand response incentive is enlarged due to coincident dynamic components.

3.4.5 Renewable pricing

A final dynamic pricing scheme is referred to as renewable pricing (REN). The purpose of this tariff scheme is to align consumption with power generation from renewable energy sources. It is used within a Flemish pilot project, named LINEAR [58]. As shown in Table 3.1, this pricing scheme sends the price pattern day-ahead similarly to RTP. Nevertheless, renewable pricing differs from RTP in two ways.

The price pattern is divided in 6 price blocks instead of 24. The width of each time block is chosen based on similarity between the price levels in adjacent hours [58]. The purpose of the wider blocks is to allow residential users to react more easily.

The impact of power generation from wind farms and solar panels on the wholesale price and energy component is enlarged, as the share of RES increases [73]. Therefore, wholesale prices are adjusted according to the RES capacity [74]. Wholesale price adjustment is based on market resiliency analysis. This analysis states the wholesale price sensitivity due to an increase in offer or demand on the market. Based on [68], an hour with 100 MW renewable energy generation above average leads to a 0.332 €/MWh decrease of the hourly wholesale price. This resiliency factor is applied to annual hourly generation profiles of solar and wind plants, derived from public data [75], [76]. Hereby, the resiliency factor is applied to the hourly power deviation from the average power. Moreover, this impact is increased with a factor 5 in order to stimulate consumption during moments of power generation from RES. The hourly price adjustments over the whole year are shown in Fig. 3.9 and Fig. 3.10 for power generation from solar and wind plants respectively. Only short-term effects are considered, while the long-term effect due to the impact on generation investments is not. The adjusted wholesale prices are depicted in Fig. 3.11 and compared to the initial wholesale price within a price duration curve. This curve ranks the hourly price levels within a year from high to low. The price adjustment leads to a higher spread of prices even extending to negative prices. The final residential energy price component is obtained by multiplying the wholesale price with a rescaling factor similarly to rescaling in Section 3.3. As the price blocks cover multiple hours and after adding distribution, transmission, and other components, the total REN-tariff becomes positive during all hours of the year.

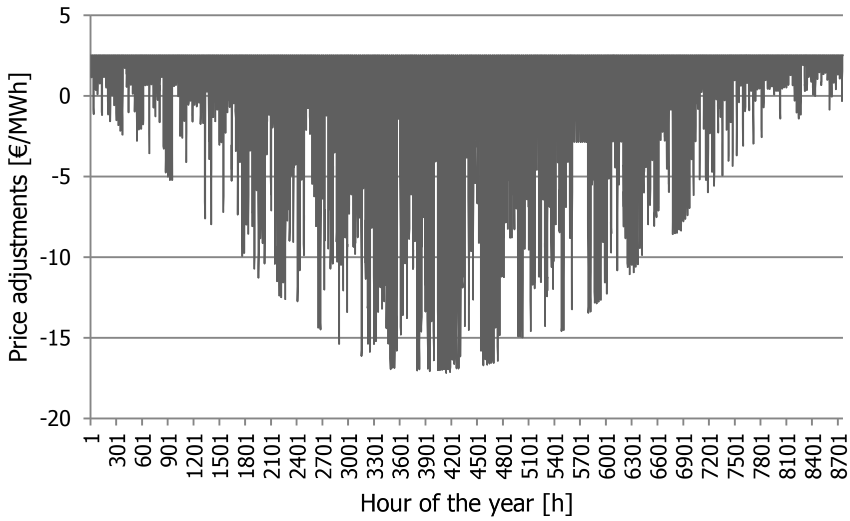


Fig. 3.9. Wholesale price adjustment due to power generation from solar panels.

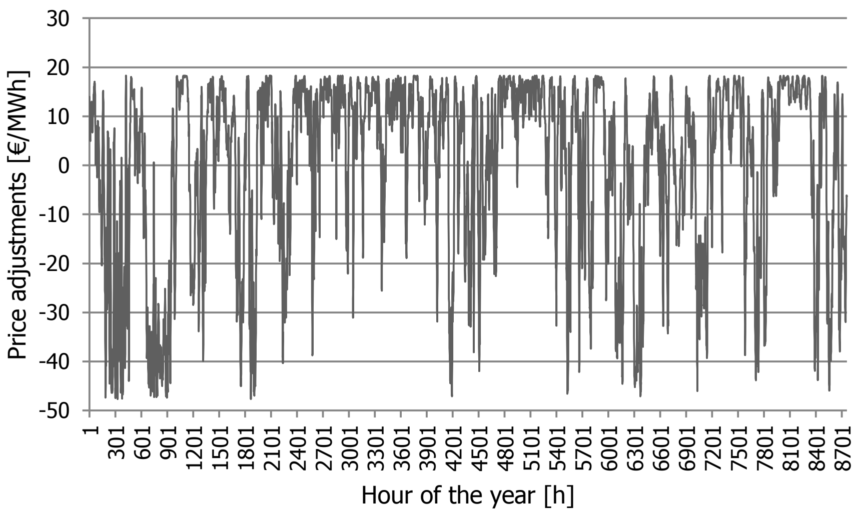


Fig. 3.10. Wholesale price adjustment due to power generation from wind mills.

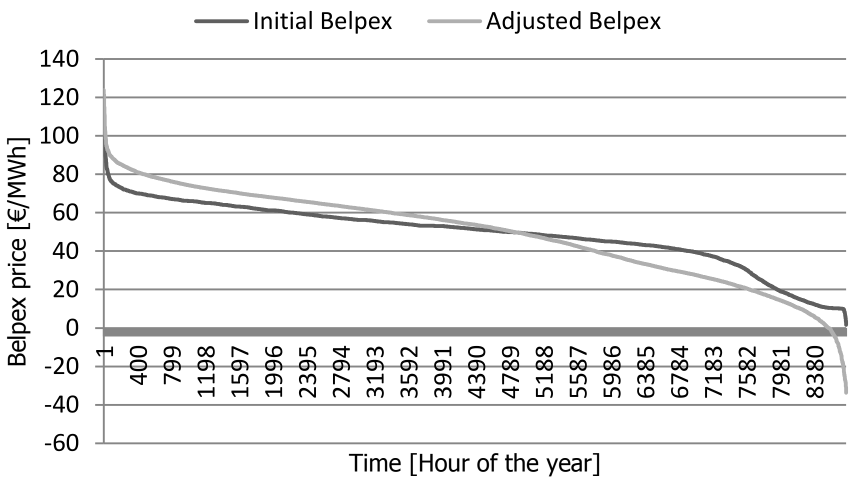


Fig. 3.11. Initial and adjusted wholesale price.

An example of the REN tariff scheme for Thursday October 20th is provided in Fig. 3.12, distinguishing between the different components. The peak tariff amounts to 23.48 c€/kWh, while the off-peak tariff sums to 16.20 c€/kWh. This leads to a price difference of 7.28 c€/kWh and a PtOP-ratio of 1.44. Variance adds up to 5.76.

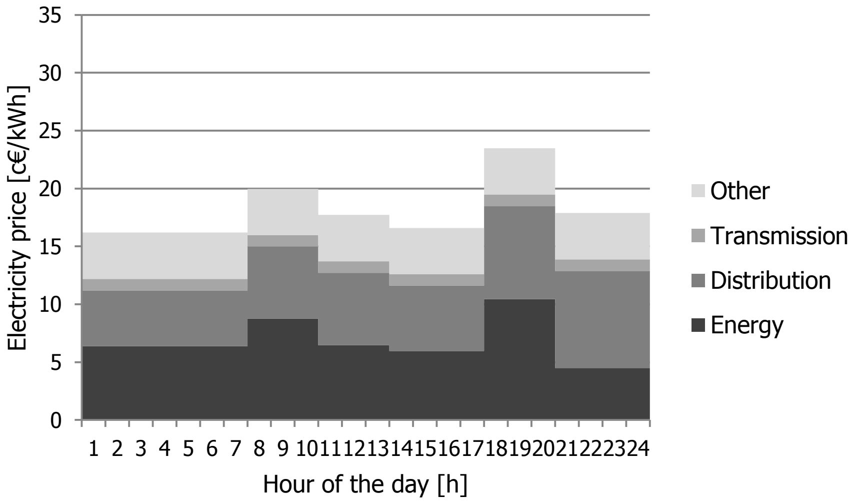


Fig. 3.12. Renewable tariff scheme for Thursday October 20th.

3.5 Tariff comparison

To gain insights in the similarities and differences between schemes, tariffs are compared based on the price patterns within a single day and on price curves and statistics for a full year.

The different tariff schemes within a single day are depicted in Fig. 3.13. They result from the methodology as previously described and all meet the cost recovery and revenue neutrality principle. The CPP tariff scheme is omitted for clarity reasons. The flat price positions between the peak and off-peak price of the ToU tariff. This follows from the calculation method of both pricing schemes and from the cost recovery and neutrality principle. By comparing the flat and ToU tariff scheme, it can be seen that averaging over multiple periods reduces the peak tariff and enlarges the off-peak period. Therefore, the PtOP-ratio and the demand response incentive get smaller. The same principle applies for the RTP and REN tariff schemes. The RTP is higher than the flat or ToU price during the main part of the day, when consumption is higher. This implies that apart from daily variations, flat pricing is not able to account for seasonal variation. As in general Belgian wholesale prices are higher during winter compared to summer, flat and ToU pricing are undervalued during winter while overvalued during summer. Finally, the REN tariff scheme is lower than the RTP scheme. This implies that power generation from RES during this day was higher than average, lowering prices.

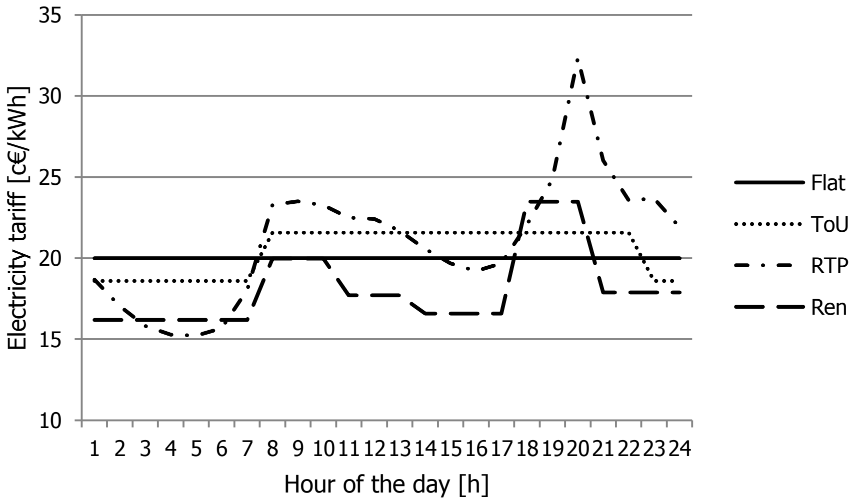


Fig. 3.13. Comparison of tariff schemes for Thursday October 20st.

Next to the insights following from an individual day, some general observations for a full year can be derived by analyzing the price duration curve (Fig. 3.14) and the statistics of each tariff scheme. The price duration curve ranks the hourly price levels within a year from high to low. The CPP tariff scheme is left out for clarity reasons. Comparison between the remaining schemes shows that similarly to the previous figure, flat pricing lays between the peak and off-peak price of ToU. Peak prices within ToU only occur in less than 50% of the times as no peak prices are present in weekends. The RTP and REN tariff schemes illustrate that these tariff schemes increase the variability around the flat tariff. Comparing the RTP and REN tariff schemes shows that for the main part of the year, the REN further deviates from the flat tariff. This follows from the inclusion of a higher price impact of power generation from RES, increasing price variability. Although Fig. 3.14 illustrates the hourly price spread for the entire year, it does not allow capturing the demand response incentive as short-term demand response results from the proportion between the different price blocks within the short-term, such as a day.

In order to capture the demand response incentive, different statistics for each tariff scheme are provided in Table 3.2. A distinction is made between the daily PtOP-ratio and the daily variance. For each day within each tariff scheme, these characteristic are calculated after which the yearly minimum, median, and maximum of these daily values are derived (Table 3.2). As no price variability is present within the flat pricing scheme, the PtOP-ratio is 1.00 while the variance amounts 0.00. For the ToU tariff scheme the minimum PtOP-ratio and variance remain the same as ToU prices are flat during weekends. During weekdays values go up arriving at a variance of 2.17. The minimum and median values are similar for the CPP tariff schemes as both tariff schemes are parallel during the main part of the year. During the days including the critical peak prices, both PtOP and variance boom reaching values of 10.04 and 1118.89 respectively. For the RTP scheme, the minimum PtOP and variance values are 1.40 and 2.42, exceeding the maximum values of the ToU scheme and the median value of the CPP. It implies higher price variability within the day of the RTP scheme during the main part of the year. The same applies for the REN scheme, although the latter has lower minimum and median PtOP ratios and variances. This results from longer price blocks, which average peak or off-peak periods with shoulder periods decreasing the price spike and price drop. The maximum characteristics are higher in the case of the REN tariff scheme due to the impact of power generation from RES leading to more price extremes.

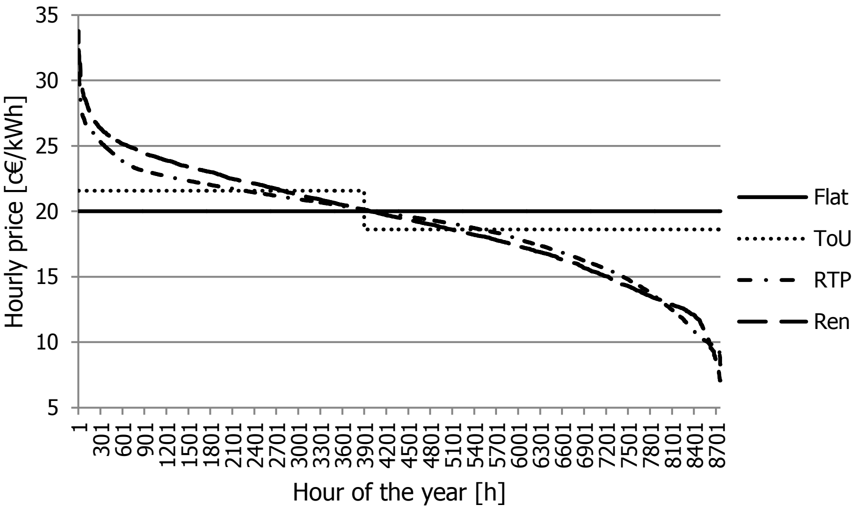


Fig. 3.14. Yearly price duration curves for the different tariff schemes.

Table 3.2. Statistics of different pricing schemes.

	Peak to off-peak ratio			Variance		
	Min.	Median	Max.	Min.	Median	Max.
Flat	1.00	1.00	1.00	0,00	0.00	0.00
ToU	1.00	1.16	1.16	0,00	2.17	2.17
CPP	1.00	1.16	10.04	0,00	2.17	1118.89
RTP	1.40	1.88	2.51	2.42	9.71	25.60
REN	1.12	1.44	3.03	0.44	6.93	39.03

3.6 Summary & Conclusions

This chapter discusses the development of different dynamic tariff schemes and the implication the choice of a particular tariff scheme has on tariff characteristics and demand response incentives. Based on a distinction in the length of advance notice, the length of the price blocks, and the length of the price pattern, five tariff schemes are discussed: flat, ToU, CPP, RTP, and REN.

Three types of tariff schemes can be distinguished based on their objectives: meeting cost causality, decreasing demand during critical events, and aligning consumption with power generation from RES. The first tariff type covers the flat, ToU, and RTP tariff schemes. While the flat scheme allows meeting cost causality over the year, it does not meet cost causality over a shorter time horizon. The ToU tariff scheme goes one step further by allowing cost causality over the peak and off-peak periods within the year. Moreover, it stimulates short-term demand response due to the difference between peak and off-peak prices. The RTP tariff scheme meets cost causality on an hourly basis reflecting the hourly underlying costs and therefore incentivizing demand response. In the second type of tariff schemes, cost causality is not the main objective, but the focus is on reducing demand during critical events. The example used is CPP. This tariff scheme is typically used within a capacity constrained power system that is not able to meet demand during every hour of the year. Therefore, a previously agreed price spike is sent during these critical events aiming to reduce demand. As such events occur rarely, this tariff scheme is not suited to cover the intermittency in a power generation portfolio based on RES. Moreover, this tariff scheme only aims at securing a power generation shortage while a power generation excess is not covered. The third type of tariff schemes aims at a more efficient integration of intermittent RES by aligning demand with the available power generation from RES. An example is the REN tariff scheme which increases the impact of power generation from RES on the electricity price.

To assess the quantity of short-term demand response following from a tariff scheme, two characteristics often used are the daily PtOP-ratio and the daily variance. Apart from critical peak days within the CPP scheme, the RTP scheme shows the highest daily PtOP and variance during the main part of the year. Although yearly variability is higher, daily PtOP and variance are lower for the REN tariff as peak and off-peak periods are averaged with shoulder periods due to wider price blocks. Another effect that can limit the daily PtOP and variance values, is the opposing dynamic components effect. Although existing, it should be noted that this effect only occurs in 0.29% of the time when only price deviations larger than 1.5 c€/kWh are accounted for. Nevertheless, in reality further optimization and prioritization of these opposing signals seems interesting.

4. Demand response simulation and practical evidence

4.1 Introduction

This chapter discusses residential demand response (DR) as a reaction to dynamic pricing. To achieve a comprehensive insight in demand response under it various forms, distinction is made between demand response following from the different dynamic pricing schemes developed in the previous chapter, DR simulation and practical evidence, and DR with different underlying residential load types.

In Section 4.2, DR with different residential load types is simulated based on the various dynamic tariff schemes developed in Chapter 3. After this theoretical demand response description, practical evidence of residential demand response is highlighted in Section 4.3 based on results from a residential pilot project. Finally, Section 4.4 summarizes and concludes.

4.2 Demand response simulation under various tariff schemes

A theoretical approach is taken by simulating demand response following from dynamic tariff schemes. Hereby, it is assumed that power consumption of different load types is shifted towards the lowest price period while accounting for user preferences. This simulation serves as a benchmark against which results from real-world pilots can be compared allowing to consider different load types and tariff schemes. It can also be seen as the case in which loads automatically shift towards the lowest price period with a minimum level of interaction with residential users, also referred to as automated demand response. The assumption is that prices are binding once communicated. Therefore, demand shifts do not affect prices communicated to the households. Note however that this is an approximation, especially if the amount of DR becomes substantial. In the ideal case, the dynamic pricing scheme sent to the residential users already accounts for the resulting demand shifts. Nevertheless, this is subject to further research.

To attain deeper insights in this simulation, first the optimization model for the different load types is discussed. The focus is on wet appliances (WAs) and on battery electric vehicles (BEVs). Afterwards results of DR are discussed in a descriptive analysis, comparing DR with different load types under different dynamic tariff schemes. Finally, household benefits of demand response are described.

4.2.1 Wet appliance scheduler

Starting from the dynamic pricing schemes, a WA scheduler shifts consumption cycles of appliances towards the lowest price period. Several load control algorithms are discussed in the literature [77], [78], [79], and [80]. Most studies optimize the appliance schedule for one day, given a theoretical time window in which the predefined power consumption profile can be shifted [78], [79], and [80]. Adding to these studies, this section applies a WA scheduler to measured consumption data of residential consumers. These realistic consumption profiles call for a different approach as the power profile and timing of each appliance cycle differ day by day. Moreover, the scheduler requires the integration of user preferences to ensure a more realistic outcome. Therefore, a WA scheduler based on Integer Linear Programming (ILP) is developed.

Data & Assumptions

Within the context of the LINEAR project [71], consumption profiles of over 200 Belgian households are measured since 2012. Out of these 200 profiles, 30 profiles were selected based on quality and completeness of data. For each of the households a three-month period is considered covering January till March 2013. Hereby, distinction is made between total and flexible consumption. Total consumption covers all consumption within the household, while flexible consumption only covers consumption due to the use of WAs. These WAs cover washing machines, dishwashers, and dryers. Each WA is submetered separately.

The average consumption profile for WAs within a household is visualized in Fig. 4.1 and Fig. 4.2 for an average week and weekend day respectively. Generally daytime consumption during weekends is higher than during weeks. The difference in consumption profiles during weeks and weekends has two main reasons. In weekends more consumers are at home during daytime. Some of the households are registered for a day-night tariff scheme, implying a lower price during weekends and during the nighttime of weeks. Therefore, some of the WA cycles are already shifted towards the evening of weekdays and towards weekends. Also the profile of WAs differs. During weeks, consumption of dishwashers typically peaks at the end of the day. Consumption of washing machines typically peaks between 9h00 and 12h00, while the dryer peaks between 12h00 and 13h00. This illustrates the link between washing machine and dryer. The dryer runs behind on the washing machine. This can also be seen by the delayed rise in the consumption profile of the dryer in the morning. During weekends, peaks in consumption profiles of washing machines and dryers fall later during the day. Nevertheless the link between both appliances remains.

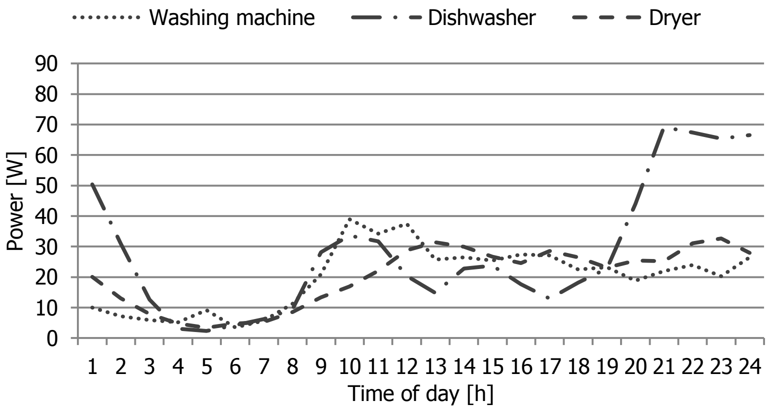


Fig. 4.1. Average household power profiles of WAs during an average weekday.

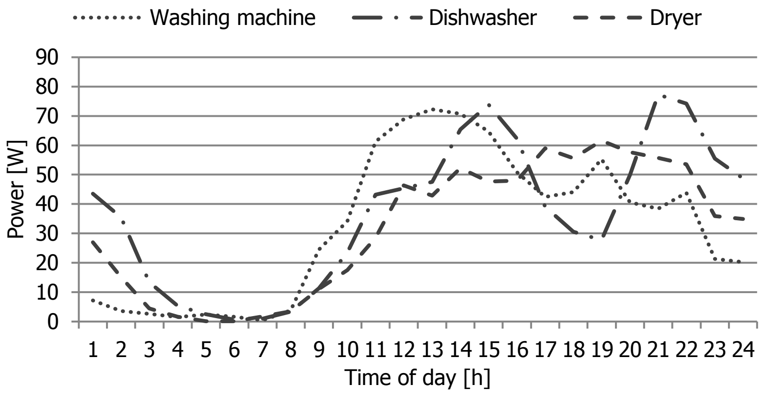


Fig. 4.2. Average household power profiles of WAs during an average weekend day.

As WAs are considered to be flexible, they can be shifted in time. Therefore, two WA consumption profiles are distinguished: the unscheduled measured and the scheduled profile with DR. The unscheduled flexibility profile equals the historical profile and results in the averaged measured profiles of Fig. 4.1 and Fig. 4.2. The scheduled profile with DR is obtained after running the WA scheduler. Hereby, it is assumed that consumers do not change the loading behavior of their appliances under dynamic pricing schemes. This implies that residential users load and initialize their WAs at the same time as in the unscheduled case. Afterwards they set the shifting potential (TSP) with a timer, stating by when the cycle needs to be finished. Within this period, the appliance cycle is optimally scheduled based upon the dynamic pricing scheme. Only a shift of the full cycle is considered, as the wet appliances are assumed uninterruptible.

Before the model for scheduling WAs is discussed, an overview of the spread of total and flexible consumption of households for the three-month period is visualized by means of a boxplot (Fig. 4.3). Hereby, the upper and lower box each covers a spread of 40% or 12 out of 30 households. The border between both represents the household with median consumption level, while the wickers represent households with minimum and maximum consumption levels. This illustrates that the amount of flexibility originating from WAs is limited compared to the total consumption. Moreover, the relative spread of both total and flexible consumption is high. Therefore, total and flexible consumption depends on the household itself, as the frequency of use and number of appliances vary. While flexible consumption accounts for less than 80 kWh per 3 months in some households, other households have over 270 kWh available for flexibility purposes during the three-month period. Although not visualized, also appliance ownership differs amongst households. While 23 households possess all three wet appliances, 7 households only possess two.

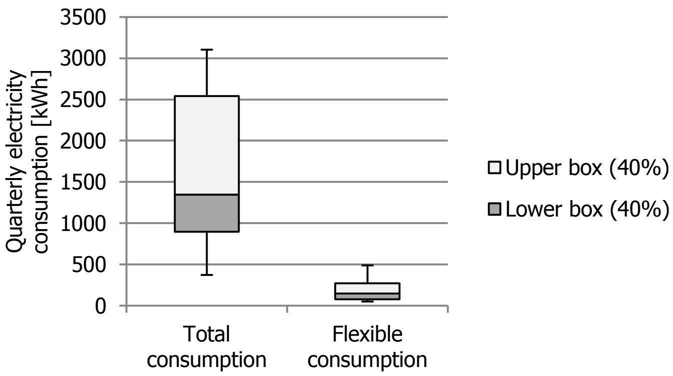


Fig. 4.3. Spread of total and flexible consumption of 30 households for a three-month period with the upper and lower box each representing 40% of the observations and the wickers representing the minimum and maximum consumption levels.

Integer Linear Program (ILP)

Objective Function

The objective of the scheduler is to minimize electricity costs by shifting WAs to the lowest price periods. The objective function is:

$$\sum_{ajn} \mathrm{C}_{ajn} * X_{ajn}, \tag{4.1}$$

where C_{ajn} reflects the cost for cycle *j* of appliance *a* (1 = washing machine, 2 = dryer, 3 = dishwasher) shifted with *n* - 1 hours, where $n \in \{1, \dots, \text{shifting potential}\}$. X_{ajn} represents a binary auxiliary decision variable. If X_{ajn}= 1, cycle *j* of appliance *a* is shifted for *n* - 1 hours. Values of C_{ajn} are calculated before solving the ILP. This allows easily adding constraints integrating user preferences into the model.

Constraints

Cycle *j* of appliance *a* needs to be executed once within the shifting interval:

$$\sum_{\mathrm{n}} X_{ajn} = 1 \qquad \forall\, a, j. \tag{4.2}$$

An appliance cycle needs to be finished within its total shifting potential (TSP):

$$ocf_{a,j} \le \mathrm{IS}_{\mathrm{a,j}} + \mathrm{TSP} \qquad \forall\, a, j, \tag{4.3}$$

where $ocf_{a,j}$ is the optimal cycle finish and $\mathrm{IS}_{\mathrm{a,j}}$ is the initial cycle start of cycle *j* of appliance *a.*

An appliance cycle needs to be finished before the initial start of the next cycle of the same appliance:

$$ocf_{a,j} \le \mathrm{IS}_{\mathrm{a,j+1}} \qquad \forall\, a, j. \tag{4.4}$$

The last cycle of the time horizon needs to be finished before the horizon ends:

$$ocf_{a,j} \le \mathrm{T_{Max}} \qquad \forall\, a, j, \tag{4.5}$$

where $\mathrm{T_{Max}}$ represents the last time interval of the simulation period.

In most cases, a direct link exists between the cycle of the washing machine and dryer as washed load is put in the dryer after finishing. Therefore, the washing machine needs to finish before the dryer cycle is initialized:

$$ocf_{1j} \le \mathrm{IS}_{2l} \qquad \forall\, j, \tag{4.6}$$

where ocf_{1j} represents the optimal cycle finish of cycle *j* of the washing machine and IS_{2l} stands for the initial cycle start of the linked dryer cycle *l*.

Scheduler Example

Fig. 4.4 illustrates the change in consumption pattern after solving the ILP. Hereby, the total shifting potential (TSP) is set to 8 hours in line with results from the LINEAR project [71]. The example depicts the flexible consumption pattern of one household under RTP for two random weekdays in February. Hourly prices are represented at the top. Underneath, the unscheduled and scheduled consumption patterns of the washing machine and dryer are depicted. For reasons of clarity, non-flexible consumption and consumption from dishwasher cycles are omitted. Clearly, washing machine and dryer cycles are shifted towards the lowest cost periods given an 8 hour shifting potential. Moreover, the figure illustrates that the washing machine cycle needs to be finished before the start of the associated dryer cycle.

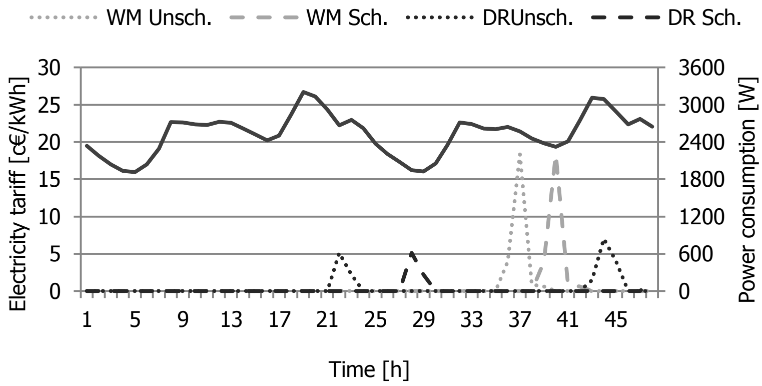


Fig. 4.4. Hourly price pattern, and unscheduled & scheduled consumption patterns of washing machine (WM) and dryer (DR) during two random weekdays of February for one household.

4.2.2 BEV scheduler

Starting from the dynamic pricing schemes, a BEV scheduler shifts battery charging of BEVs to the lowest price period in order to minimize total electricity costs. To ensure a realistic outcome, the scheduler requires the integration of driving behavior and technical characteristics of vehicles. Therefore, a BEV scheduler based on Linear Programming (LP) is developed and discussed.

Data & Assumptions

To determine the optimal charging profile, data are needed on both the driving patterns of BEVs and on vehicle characteristics.

The driving patterns are derived from results of the 3rd Flemish Mobility Study (OVG3) [81]. In this study transportation behavior of 8800 drivers was analyzed from September 2007 till 2008. Over this period, the status of the vehicles is listed, distinguishing between driving and standing still. Moreover, standing still is split in 'at home' and 'other'. In Van Roy et al. [82], the energy consumption of each driving cycle is determined based on these driving patterns and the vehicle sizes.

From the analysis of OVG3 [81] and Van Roy et al. [82], 100 representative BEVs with a full year of data on minute basis were selected and driving patterns and energy consumption were obtained. The average status of all vehicles during a week and weekend day is visualized in Fig. 4.5 and Fig. 4.6, distinguishing between driving, at home, and at another location. Both during weeks and weekends the main share of vehicles is standing still at home or another location. On average weekend days, the share of vehicles driving never exceeds 10% while the share during weekdays is a bit higher.

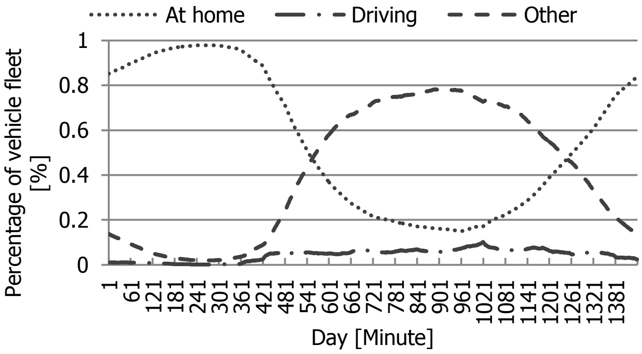


Fig. 4.5. Average number of vehicles driving, at home and at another location during weeks.

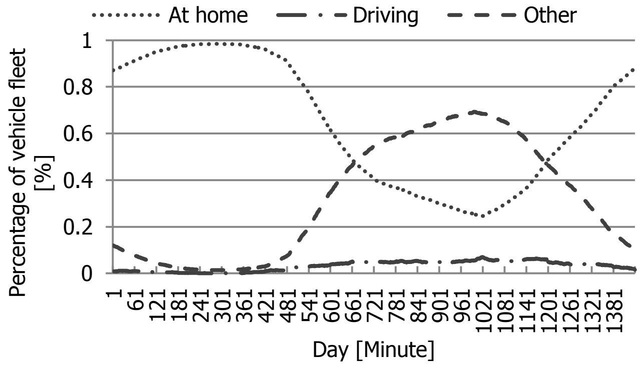


Fig. 4.6. Average number of vehicles driving, at home and at another location during weekends.

Table 4.1. Technical characteristics of BEVs.

	Subcompact BEV	Midsize BEV	Large BEV	Reference
Specific consumption [kWh/km]	0.16	0.19	0.25	[81]
Battery capacity [kWh]	20.8	31.2	41.6	[81]
Grid-to-battery efficiency [%]	90	90	90	[81]
Battery-to-wheel efficiency [%]	90	90	90	[81]
Maximum state of charge [% of battery capacity]	95	95	95	[82]
Maximum charging power [kW]	4	4	4	[83]

Three types of vehicles are considered: subcompact, midsize, and large, accounting for 26%, 67%, and 7% of the total fleet respectively. Each type has its own technical battery characteristics (Table 4.1). Effects such as aging of the battery and depreciation are not considered.

Two charging scenarios are considered. Within the unscheduled scenario, BEV batteries start charging as soon as they are plugged in. BEVs are only assumed to be plugged in at home. This scenario serves as reference. Within the scheduled scenario, timing and quantity of charging is optimized over the period when the BEV is at home. Hereby, it is assumed that residential users do not change their driving behavior under dynamic pricing schemes: they arrive and depart at the same time as in the unscheduled case. In both charging scenarios batteries charge until they reach the maximum state of charge or until the BEV departs.

The spread in consumption due to BEV charging, also referred to as flexible consumption, is visualized in Fig. 4.7 by means of a boxplot. Apart from flexible consumption, inflexible household consumption without BEVs is also visualized based on data retrieved in the scope of the LINEAR-project [71]. The upper and lower box in both boxplots each covers the spread of 40% or 40 out of 100 households. The border between both represents the median consumption level, while the wickers represent minimum and maximum consumption levels. This illustrates that the amount of flexibility from BEVs is substantial compared to inflexible consumption. Moreover, the spread of both inflexible and flexible consumption is high. Consequently, inflexible and flexible consumption depends on the household or BEV itself, as the use of appliances and BEVs varies. While consumption due to BEV charging accounts for less than 2000 kWh in some households, others have over 4500 kWh available for flexibility purposes over the year. For inflexible consumption, spread is even higher covering consumption from over 300 kWh up to almost 13000 kWh. Nevertheless, these high inflexible consumption values typically result from electric heating. Although considered as inflexible within this dissertation, this is not necessarily the case in practice.

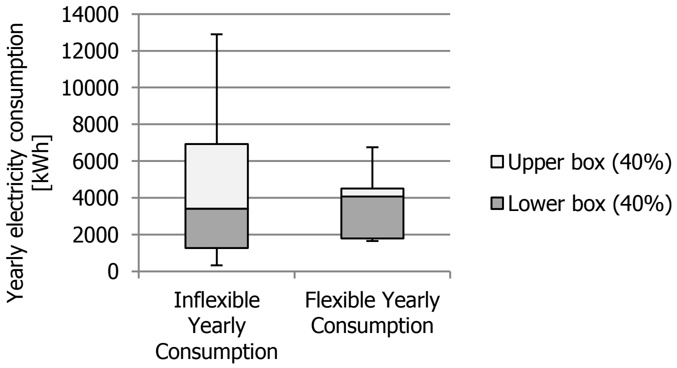


Fig. 4.7. Spread of inflexible consumption and flexible consumption from BEVS of 100 households for a year with the upper and lower boxes each representing 40% of the observations and the wickers representing the minimum and maximum consumption levels.

Linear Program (LP)

Before the BEV scheduler is used, available data is preprocessed. Therefore, a minimum and maximum boundary between which cumulative energy should lay is determined. An example of the minimum and maximum energy boundaries of one BEV on October 20th is given in Fig. 4.8. The minimum boundary (EMin) is obtained by a strategy that postpones charging as much as possible. The maximum boundary (EMax) results from charging as soon as the BEV arrives home until the battery is fully charged or the vehicle departs again, aligning with the unscheduled charging scenario. If the BEV is not fully charged during standstill, the minimum and maximum boundaries overlap and no charging flexibility is available. As the area between minimum and maximum boundary grows, more charging flexibility becomes available which can be used for demand response purposes. Once the boundaries are found, the optimal charging path can be determined between these boundaries resulting from a Linear Programming (LP) approach.

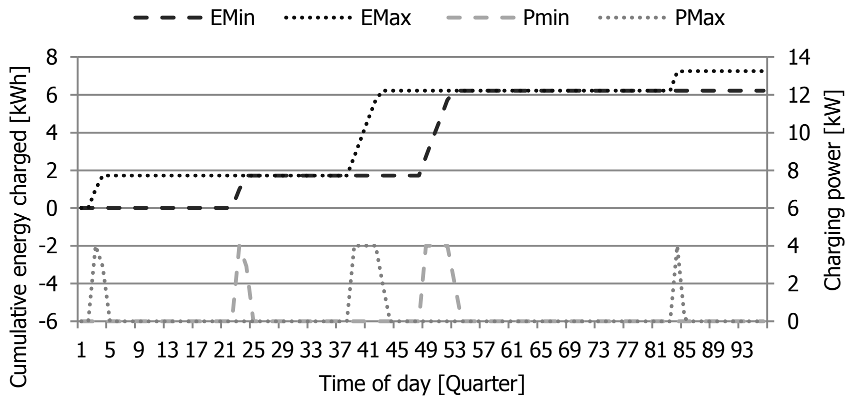


Fig. 4.8. Minimum (dashed, black) and maximum energy boundaries (dotted, black), and minimum (dashed, gray) and maximum power patterns (dotted, gray) for October 20th for a random BEV.

Objective Function

The objective of the BEV scheduler is to minimize the yearly electricity cost by charging the BEVs during the lowest price periods, reflected by the objective function:

$$Min. \sum_{\mathrm{q}} \mathrm{DP_q} * power_q, \quad (4.7)$$

where $\mathrm{DP_q}$ reflects the dynamic pricing scheme in quarter *q*, while $power_q$ represents the charging power in quarter *q.* Time steps cover 15 minutes, contrary to the hourly time steps in the WA case.

Constraints

The charging power is limited by the maximum power charging capacity $\mathrm{PowerMax}$:

$$power_{\mathrm{q}} \leq \mathrm{PowerMax} \qquad \forall \text{ q}. \tag{4.8}$$

Discharging of BEVs is not considered:

$$power_{q} \geq 0 \qquad \forall \text{ q}. \tag{4.9}$$

The cumulative energy content needs to be within the minimum and maximum energy boundaries:

$$\sum_{j=1}^{q} power_{q} \leq \mathrm{EMax}_{q} \qquad \forall \text{ q}, \tag{4.10}$$

$$\sum_{j=1}^{q} power_{q} \geq \mathrm{EMin}_{q} \qquad \forall \text{ q}. \tag{4.11}$$

The charging pattern of each BEV is separately optimized for each week of the year.

Scheduler Example

Fig. 4.9 illustrates the change in the charging pattern after solving the LP. The example depicts the charging pattern of a random BEV for October 20th. Hourly prices or the RTP tariff design are shown together with unscheduled and scheduled charging patterns. Clearly, the scheduled charging pattern of the BEV is shifted towards the lowest price periods given minimum and maximum energy boundaries of Fig. 4.8. The last unscheduled charging cycle is shifted towards the next day and is not shown in the figure.

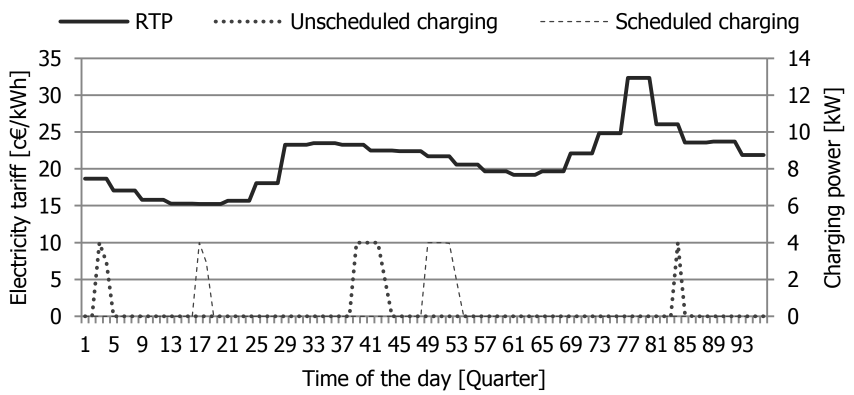


Fig. 4.9. Electricity tariff and unscheduled charging patterns (dotted) and scheduled charging patterns (dashed) of a random BEV during October 20th.

4.2.3 Descriptive analysis

In this section, the effect of simulated demand response is outlined in a descriptive analysis. First, the change in consumption pattern of WAs and BEVs due to demand response based on RTP is discussed. Distinction is made between flexible consumption only and total household consumption. Afterwards, a similar analysis is performed for other dynamic tariff schemes.

Effect on residential consumption pattern

To get an overall view on the flexible consumption pattern change due to WA consumption or charging of BEVs, Fig. 4.10 and Fig. 4.11 show the average unscheduled and scheduled consumption patterns for one particular day under RTP. These patterns result from the WA and BEV scheduler respectively and are the average pattern over all households considered.

For WAs, results show that flexible consumption is shifted towards the early morning and the afternoon. Thereby new peaks of flexible consumption arise, while noon and evening peaks disappear. Considering total consumption, no new peaks arise due to WA scheduling. Instead, valleys are filled in the night and afternoon. Nevertheless, total peak impact is limited due to limited use of WAs in the unscheduled case.

For BEV charging, results show that charging power increases towards the evening and night without DR, resulting from the arrival of vehicles at home during the evening time (Fig. 4.5). In case of total unscheduled consumption this leads to a peak in consumption just before midnight. Scheduling of vehicles evokes a renewed average charging pattern, peaking during nighttime while being low during daytime. The evening peak of flexible consumption reduces, while the average night peak nearly triples and is shifted towards 5h00.

New peaks created by BEV charging based on dynamic electricity pricing often are said to be harmful for the normal functioning of distribution grids [84], [85], [86], and [87]. Although technical implications of BEV charging are out of scope of this dissertation, some remarks in this perspective are made. The impact of BEV charging based on DP is often assessed within weak distribution grids. In such a grid, the problem is not the charging based on DP itself, but rather the addition of load: also unscheduled charging brings about technical issues. Nevertheless, scheduled charging can increase these. Simulations often assume all BEVs are scheduled based on the same DP. This is not necessarily the case when households have different contracts with different retailers. Hereby, lowest price periods can differ. Moreover, not necessarily all households participate in DP. Simulations often assume that all households in distribution grids possess a BEV. Although this might be true in the long run, in the short run this is unlikely. If all households possess BEVs, dynamic pricing patterns change shape as considerable load is added. This again can influence the number of participants in DP schemes. Several methods exist to avoid load peaks. An example is to spread load over the lowest price block, instead of all starting to charge in the beginning of the price block. Nevertheless, this method is only applicable if price blocks are long enough. Another example is the use of local voltage droop control [85]. In this case, scheduling based on prices can be performed within the technical boundaries of the distribution grid.

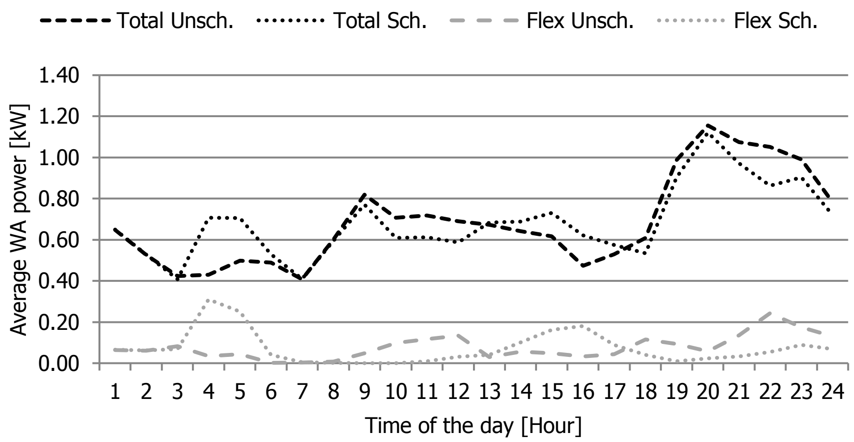


Fig. 4.10. Total unscheduled (dashed, black) and scheduled power patterns (dotted, black), and unscheduled (dashed, gray) and scheduled (dotted, gray) power patterns of WAs under RTP for a random weekday in February.

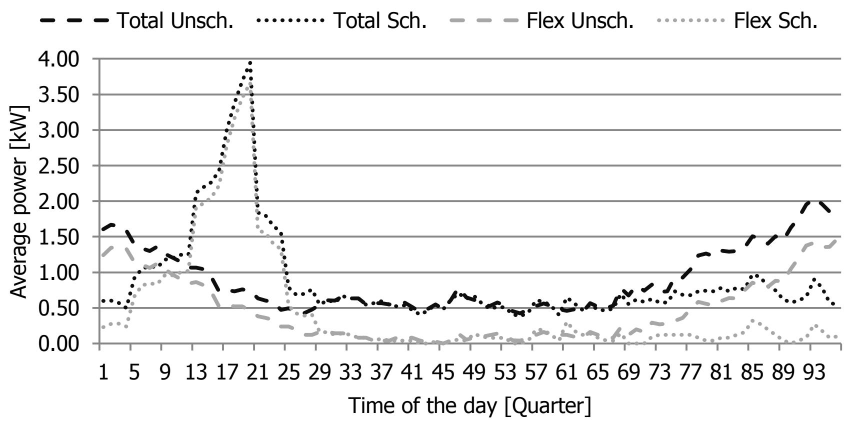


Fig. 4.11. Total unscheduled (dashed, black) and scheduled power patterns (dotted, black), and unscheduled (dashed, gray) and scheduled (dotted, gray) power patterns of BEVs under RTP during October 20th.

Demand response under different tariff schemes

Apart from the change in consumption pattern due to DR with RTP within a specific day, this subsection discusses the average flexible consumption pattern during week and weekend days due to various dynamic pricing schemes, allowing to assess the impact of various DP schemes.

The average demand modifications due to WA scheduling under different dynamic pricing schemes are shown in Fig. 4.12 and Fig. 4.13 for week and weekend days respectively. Shifting under all dynamic pricing schemes is visualized except for CPP which is omitted for clarity reasons. The average power pattern under CPP closely follows the pattern under ToU. During week days, scheduling of WAs under ToU shifts flexible consumption away towards the late evening and early morning. Consequently only evening peaks are reduced while noon peaks remain unaffected through ToU implementation. During weekends power profiles almost align for Flat and ToU pricing schemes. Only in the early morning, the patterns differ resulting from a shift of Friday evening to Saturday morning. Within the REN and RTP case, consumption is shifted. Both for REN and RTP, consumption is shifted away from noon and evening periods. It contrasts with the ToU tariff case in which consumption was only shifted away from evening periods. Nevertheless, REN and RTP tariff schemes cause different power patterns to evolve. Typically, new peaks occur later when RTP is applied as consumption is postponed longer for some WAs. As REN averages longer periods, typically the cheapest time blocks start earlier in case of REN. Therefore, new peaks are created in shoulder periods. This illustrates that the effect of a shift in consumption depends on the underlying tariff scheme and that due to averaging of prices over longer periods, new flexible peaks do not necessarily end up in the preferred hour.

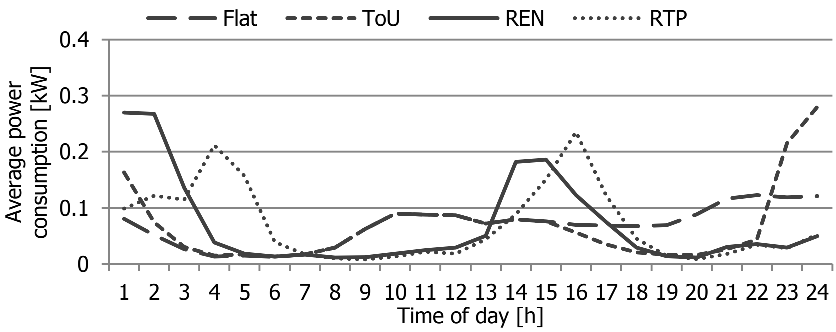


Fig. 4.12. Average power patterns of WAs during weekdays under different pricing schemes: flat (long dashed line), ToU (short dashed line), REN (solid line) and RTP (dotted line).

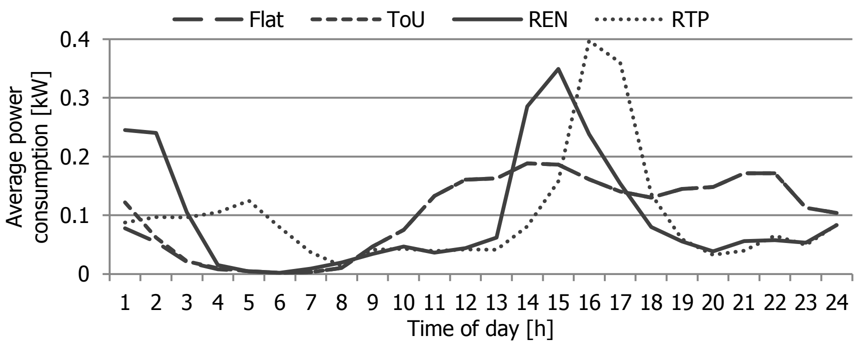


Fig. 4.13. Average power patterns of WAs during weekend days under different pricing schemes: flat (long dashed line), ToU (short dashed line), REN (solid line) and RTP (dotted line).

Average demand shifts due to BEV scheduling under different dynamic pricing schemes are visualized in Fig. 4.14 and Fig. 4.15 for weeks and weekends respectively. In line with WAs, scheduling under CPP is not visualized for clarity reasons. In ToU pricing, a clear difference between week and weekend days can be noticed. During weekdays a new peak arises in the evening, while the pattern under Flat and ToU pricing almost aligns during weekends. Also for REN and RTP pricing the evening peak diminishes. Hereby, consumption is shifted deeper into the night. For REN pricing, a new peak arises at 00h00 at the start of the new price block. Small peaks during the day also arise at the start of other price blocks. Nevertheless, these peaks could be spread over the whole price blocks flattening peaks. For RTP, charging is postponed longer until the lowest price block is obtained. Although on average these new peaks are smaller than in the REN case, this is not necessarily true for individual days.

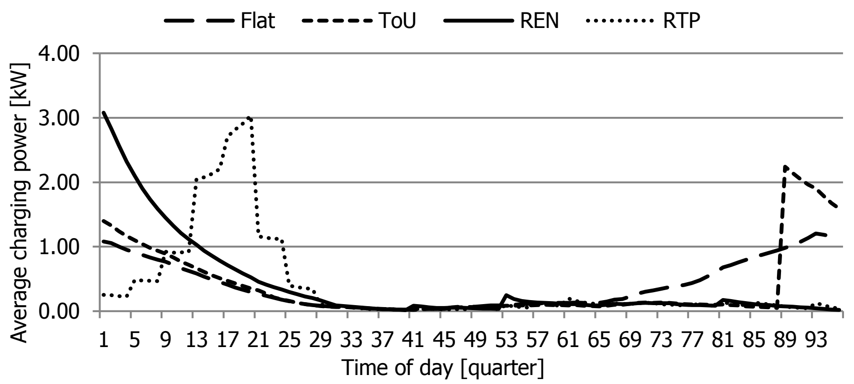


Fig. 4.14. Average power patterns of BEVs during weekdays under different pricing schemes: flat (long dashed line), ToU (short dashed line), REN (solid line) and RTP (dotted line).

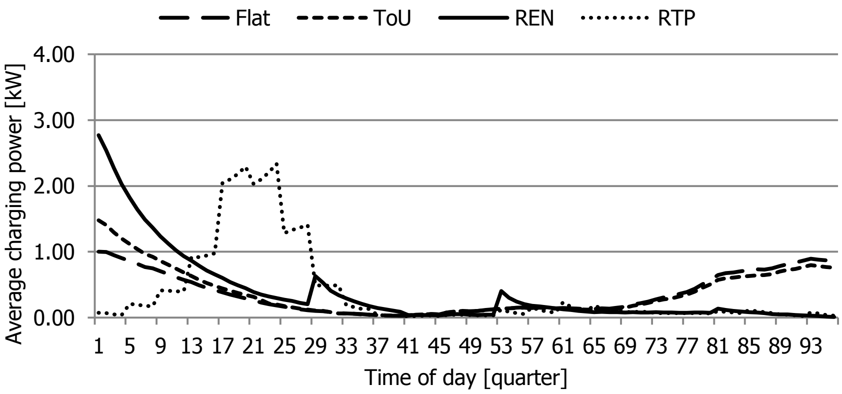


Fig. 4.15. Average power patterns of BEVs during weekends under different pricing schemes: flat (long dashed line), ToU (short dashed line), REN (solid line) and RTP (dotted line).

4.2.4 Household savings

Monetary savings obtained from residential DR are outlined. First, average annual household savings under the different tariff schemes are discussed, distinguishing between DR with WAs and BEVs. Apart from the averages, distribution of savings over all households is discussed afterwards.

Table 4.2 gives average costs for consumption from WAs and BEVs under different tariff schemes. Consequently, only costs due to flexible consumption are included. Distinction is made between average costs within the unscheduled and scheduled scenario. Difference between both is the average saving also expressed as a percentage of unscheduled costs. While savings for BEVs are based on yearly simulations, savings for WAs are extrapolated towards a year.

The annual average unscheduled costs vary among different tariff schemes. Typically, unscheduled costs are higher for more dynamic tariff schemes in case of WAs as unscheduled consumption from WAs partly falls in shoulder and peak periods. For BEVs the opposite is true as BEV charging largely falls during nighttime. This implies that even without DR, savings can be obtained from switching to another tariff design. Although not treated in this thesis, this effect also occurs for non-flexible consumption as described by Borenstein [88].

The table shows that the use of DR has the biggest monetary effect under RTP. In general, higher variability of the tariff scheme leads to higher savings. On average, savings under RTP are 6 to 7 times higher than under ToU, both for WAs and BEVs, although lowest costs for WAs are reached under REN.

Finally, both average annual costs and absolute savings are higher with BEVs. For BEVs average yearly savings of €144 are obtained under RTP while for WAs this is limited to €18. This follows from higher consumption with BEVs. Also in relative terms, savings for BEVs are higher. This follows from a longer shifting potential into the night and from uninterruptability of WA cycles.

Table 4.2. Impact of demand response on average annual electricity costs due to wet appliance consumption and charging of battery electric vehicles under different tariff schemes.

	Wet appliances			Battery electric vehicles		
	Unscheduled cost [€]	Scheduled cost [€]	Savings [€]	Unscheduled cost [€]	Scheduled cost [€]	Savings [€]
Flat	132	x	x	683	x	x
ToU	132	129	3 (2%)	663	643	20 (3%)
CPP	131	127	4 (3%)	659	634	25 (4%)
RTP	146	128	18 (12%)	652	508	144 (22%)
REN	137	123	14 (10%)	662	566	96 (15%)

Apart from average savings, individual household savings provide deeper insight into the usefulness of DR as practical implementation of DR not necessarily focuses on all households. Rather implementation could focus on one household type. Therefore, Fig. 4.16 and Fig. 4.17 depict boxplots with the spread of cost savings resulting from DR with WAs and BEVs respectively, each box representing 40% of households.

These figures illustrate large spread of cost savings for each tariff scheme. This is especially true for more dynamic schemes. Moreover, the figure also shows that savings due to BEV scheduling is a multitude of savings due to WA scheduling.

For WA scheduling, cost savings under ToU and CPP remain below €10 for over 90% of households. For RTP and REN, this picture changes as cost savings can top 30 and even €40 for some households. For BEV scheduling, cost savings under ToU and CPP are lowest. Nevertheless, most households save more than €20 annually, even extending to around €50. In more dynamic tariff schemes such as RTP and REN, all households save over €50. For RTP more than 90% of households save over €100.

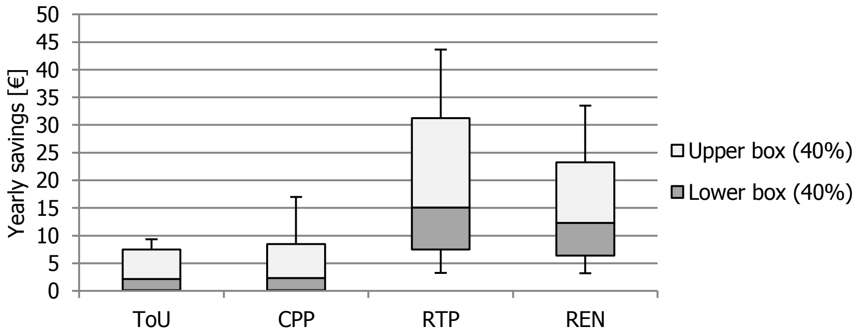


Fig. 4.16. Spread of cost savings due to DR with WAs under different tariff schemes: ToU, CPP, RTP and REN. The upper and lower boxes represent 40% of the observations and the wickers represent the minimum and maximum yearly savings.

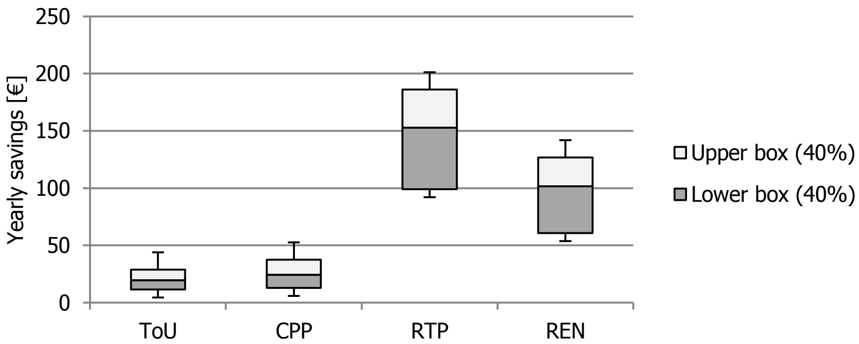


Fig. 4.17. Spread of cost savings due to DR with BEVs under different tariff schemes: ToU, CPP, RTP and REN. The upper and lower boxes represent 40% of the observations and the wickers represent the minimum and maximum yearly savings.

4.3 Practical evidence of demand response: the LINEAR field test

In contrast to the previous section, this section discusses more practical results of residential demand response following from dynamic pricing. In this perspective, results from a Flemish residential demand response project called LINEAR are highlighted.

The general set-up of this project is discussed and specific measurements used are highlighted. A descriptive analysis points out the main impact from dynamic pricing on household consumption patterns within the field test. Finally, household savings obtained within LINEAR are described.

4.3.1 Set-up LINEAR

General project scope

LINEAR is a large-scale research and demonstration project focused on the introduction of smart grids, and more specifically on demand response strategies, at residential premises in the Flanders region in Belgium. The LINEAR project aims at a technological as well as an implementation breakthrough of DR. Its focus is twofold. On the one hand, the project deals with research and development efforts required to deploy DR technologies. On the other hand, it aims at implementing these technologies in a field test, by setting up a pilot in which 245 households participate.

The project started in May 2009 and receives partial funding from the Flemish government for the academia and research institutes (KU Leuven, VITO and IMEC, embedded in EnergyVille, and iMinds). Furthermore, several industrial partners, including Belgacom, Eandis, EDF-Luminus, Fifthplay, Infrax, Laborelec, Miele, Siemens, Telenet and Viessman, invest and actively participate in the project. Finally, the Flemish regulator for the electricity and gas market (VREG), as well as industry and government interest groups (Agoria, EWI, VOKA) take part in the project.

As demand response can serve many purposes, the following four cases are selected and addressed within the field test of LINEAR: portfolio management, wind balancing, transformer ageing, and line voltage management. The portfolio management case investigates how residential DR helps optimizing the generation portfolio by reacting to day-ahead market prices. The wind balancing case assesses the impact of DR on the imbalance of a balancing responsible party due to errors in wind predictions. The transformer ageing case investigates whether DR can avoid accelerated ageing of distribution transformers. Line voltage management assesses the usefulness of DR for avoiding voltage deviations in distribution grids. In what follows the focus is only on the first case as this is the topic of this dissertation.

To gain insight in consumer behavior and acceptance towards DR, two different consumer interaction models are tested, referred to as manual and automated demand response. In the manual DR interaction model, 60 households participate. They receive dynamic electricity tariff schemes day-ahead and are supported with home energy management systems and displays showing current and historic tariff schemes and consumption profiles. Consequently, households can manually shift consumption in order to align consumption with cheaper price periods. Within the automated demand response interaction model, 185 households participate. They do not receive price signals, yet appliances are steered automatically towards dynamic prices through the LINEAR project while satisfying comfort requirements.

Two different appliance types are considered for automation purposes: shiftable and storable. Over 440 shiftable appliances such as washing machines, dryers, dishwashers, are deployed within LINEAR. When they are configured, household consumers are requested to set a deadline for the end of the appliance cycle, also referred to as the shifting potential. Within the time window between configuration time and deadline, the appliance is started by LINEAR. Regarding storable appliances, 15 hot water buffers are deployed. For these appliances, no user interaction is required as LINEAR operates them within the household's comfort zone.

Substantial difference exists in the way DR is remunerated. For manual demand response, it is based on the underlying dynamic electricity price. Hereby LINEAR opted for renewable pricing, as described in Section 3.4.5. This tariff scheme is day-ahead based on day-ahead wholesale prices and predicted generation from renewables, distinguishing between 6 time blocks a day. For portfolio management with automated DR, again consumption is optimized based on this renewable tariff scheme. Nevertheless, remuneration is based on the shifting potential configured for the shiftable appliances. Hereby, each hour of shifting potential is remunerated against an incentive payment of €0.025 per hour per appliance, implying a remuneration of €1 for every 40 hours of shifting potential configured with an appliance.

Measurement data

In order to assess the impact of DR based on dynamic electricity pricing, measurement data from LINEAR are analyzed. In this perspective, a distinction is made between a reference period during which no DR incentive is sent to the households and a field test period during which a DR incentive is provided, for both manual and automated DR. In both cases, comparison between reference and field test periods allows assessing the impact of DR. The same months for both reference and field test periods are selected.

For manual DR, measurement data considered in this dissertation cover 16 households for a four-month period for both reference and field test period. This period runs from March 1st till June 30th in 2013 and 2014 respectively. During the reference period around 81% of households were enrolled in a day-night tariff scheme in which prices are lower during nighttime and weekends.

For automated DR, measurement data considered in this dissertation cover 48 households for a two-month period for both reference and field test period. This period runs from September 16th till November 17th for 2012 and 2013 respectively. Around 70% of households were enrolled in a day-night tariff scheme during the reference period. Also important to note is that within these 48 households, 123 appliances were automated covering 43 washing machines, 43 dryers, 34 dishwashers and 3 hot water boilers.

4.3.2 Descriptive analysis

Manual DR results

A first difference between consumption during reference and field test period consists of the total consumption during both periods. While consumption during the reference period was 39515 kWh for the 16 households over the four-month period, consumption during the field test over the similar period the following year only was 35937 kWh, aligning with a consumption drop of 9%. To investigate whether this drop does not originate from a couple of households only, the spread of the difference between the reference and field test consumption over the various households is visualized by means of a boxplot, each box representing 40% of housholds (Fig. 4.18). Positive values indicate a higher reference than field test consumption. Negative values indicate higher field test consumption. Overall, consumption during the reference period is higher than during the field test. The median difference between consumption during reference and field test periods amounts to 149 kWh over the four-month period.

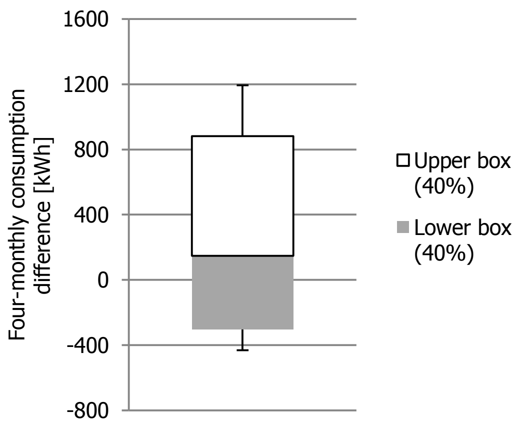


Fig. 4.18. Spread of the difference in household consumption between the four months of the reference and field test period. The upper and lower boxes represent 40% of the observations and the wickers represent the minimum and maximum consumption difference.

Energy conservation can originate from several factors. Within LINEAR consumers are stimulated to take an active role in adapting consumption in order to perform better compared to the reference period. Hereby, a comparison between consumption in reference and field test periods is sent to the consumers. Submetering of appliances helps to detect energy intensive appliances and act accordingly. Moreover, households receive a different renewable electricity price on a daily basis. This also keeps them actively involved to modify their consumption. These results align with the literature which states that feedback results in energy conservation [89]. Nevertheless, a second factor which could explain conservation is formed by climatologic circumstances as 2013 was colder than 2014. To check this, consumption of a control group over the same period was analyzed, consisting of 31 household. The group was measured on a quarterly hour basis and faced no interaction with LINEAR or other projects. Analysis shows that also within this control group, consumption drops with 6%. Therefore, it can be concluded that external factors outside control of LINEAR influence total consumption. Whether LINEAR triggered additional energy conservation remains subject to further research.

This drop in consumption is also shown in Fig. 4.19 visualizing average LINEAR-household consumption patterns during both reference and field test periods for week and weekend days. During week days consumption drops mainly occur during peak periods such as between 7h and 13h and between 20h and 24h. During shoulder periods consumption drops are less apparent. During weekends consumption again mainly drops during the late evening and in the morning from 10h to 13h.

Although energy conservation is quite apparent, distinction should be made between conservation on the one hand and consumption shifts or DR as discussed in this dissertation on the other. To obtain more insights in the latter, Fig. 4.20 visualizes the average daily consumption pattern relative to total daily consumption. In other words, each pattern sums up to one, making consumption shifts more clearly visible better illustrating the DR incentive. Nevertheless, note that this is an approximation.

During the field test relative consumption decreases during the late evening period both during week and weekend days. It has two main reasons. The average price block from 20h to 24h is the highest over the day, incentivizing consumers to shift consumption away. Around 81% of consumers had a day-night tariff scheme during the reference period, implying a lower price starting from 21h or 22h. Therefore, reference consumption during this period is higher. From the reference to the field test, this consumption is shifted backwards to the early evening resulting in a consumption increase in the period 17h to 20h. Another rise in consumption following from the field test is found in the off-peak period from 13h to 17h. For both week and weekend days the increase is most profound at the start of the off-peak period. This suggests that households wait for their appliances to start until this period begins. Finally, during the night period, no demand increase is observed. Therefore, it can be concluded that on average consumers do not shift consumption past midnight.

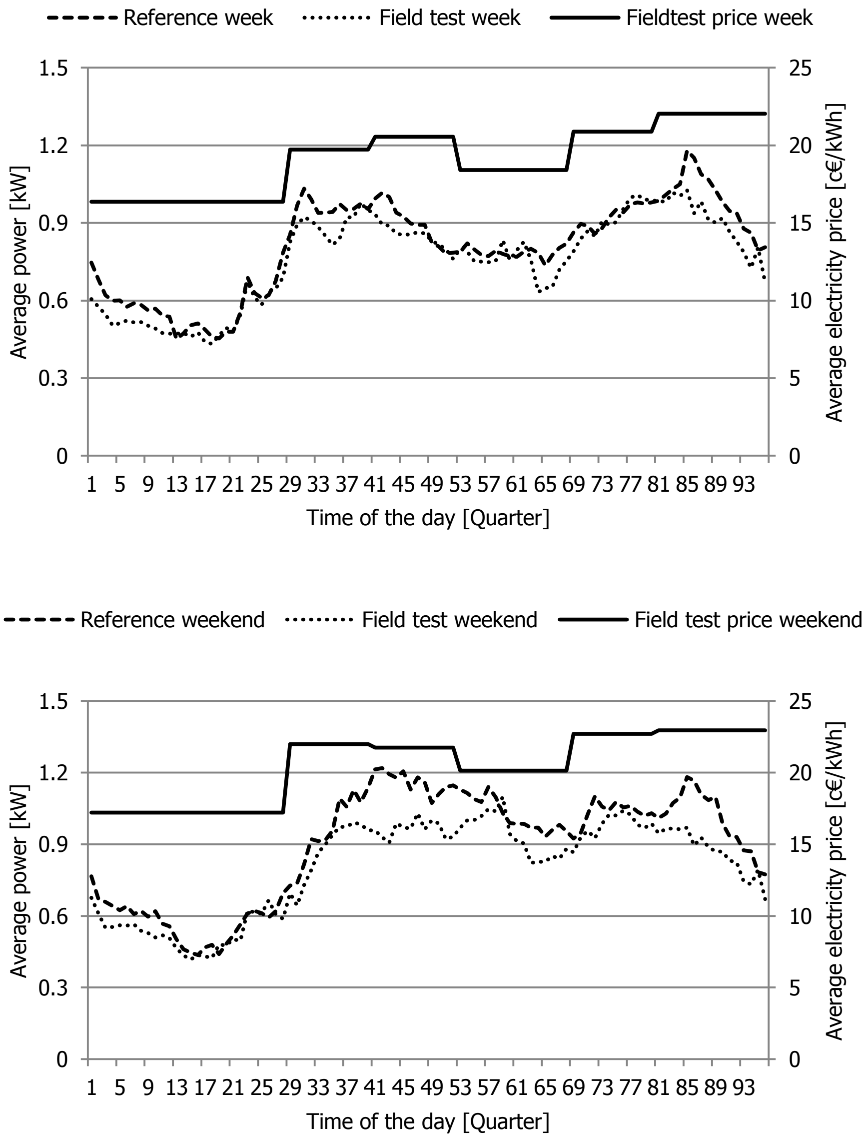
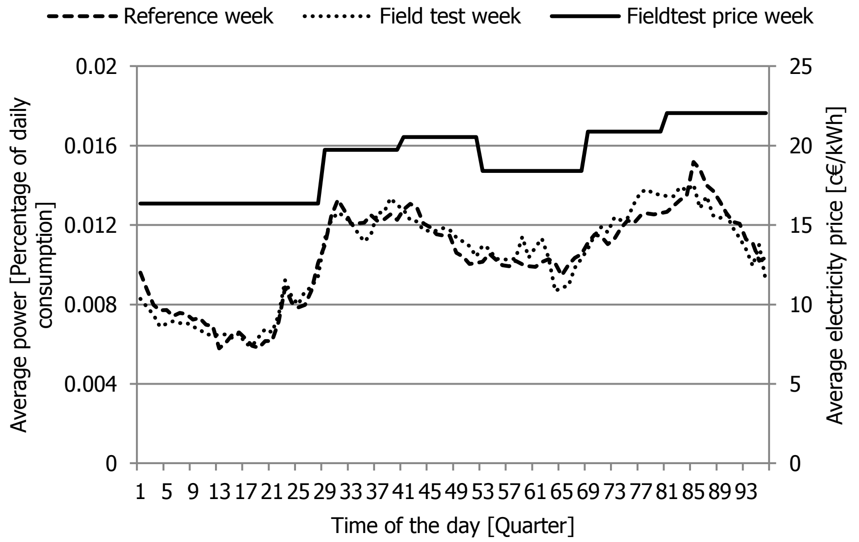


Fig. 4.19. Impact of manual demand response based on renewable pricing on the average power pattern of households during week (top) and weekend days (bottom) expressed in kW, distinguishing between reference (dashed lines) and field test (dotted lines) consumption.



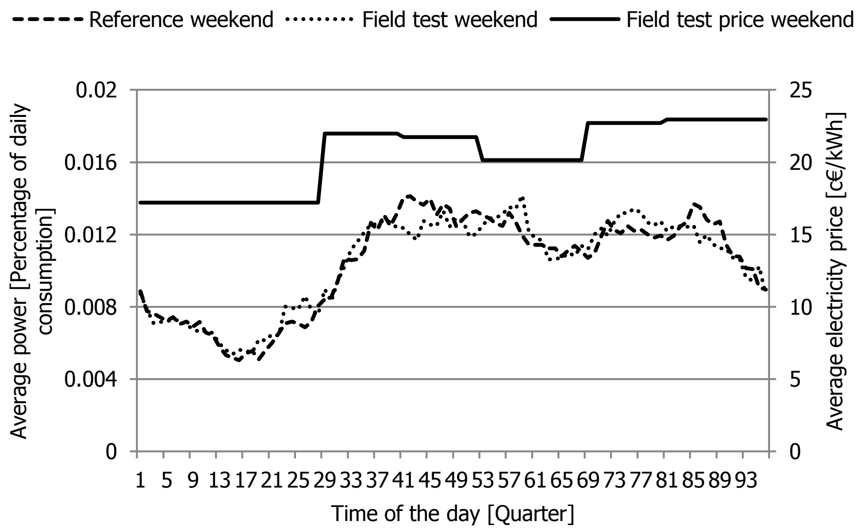


Fig. 4.20. Impact of manual demand response based on renewable pricing on the average power pattern of households during week (top) and weekend days (bottom) expressed as percentage of average daily consumption, distinguishing between reference (dashed lines) and field test (dotted lines) consumption.

To further distinguish between energy conservation and demand response, Fig. 4.21 visualizes the difference-in-differences for relative average power within each time block. Therefore, the difference between relative average power during reference and field test periods for the control group is subtracted from the difference of relative average power for the LINEAR group. This partly ranges out the climatological factors in play for both the control and LINEAR group. Therefore, the impact of LINEAR is more properly visualized. Values close to zero imply that there is no substantial difference. The impact of LINEAR within these periods is limited. The further away from zero, the higher the LINEAR impact. During night and noon periods in week days the impact is limited compared to the morning and evening periods (Fig. 4.21). This implies that the shift of consumption from the late evening towards the early evening can be attributed to LINEAR as previously discussed. Moreover, LINEAR induces a larger average reduction in consumption during the morning. During weekends, the same pattern occurs although the impact during noon from 10h to 13h and during the night is bigger compared to weeks.

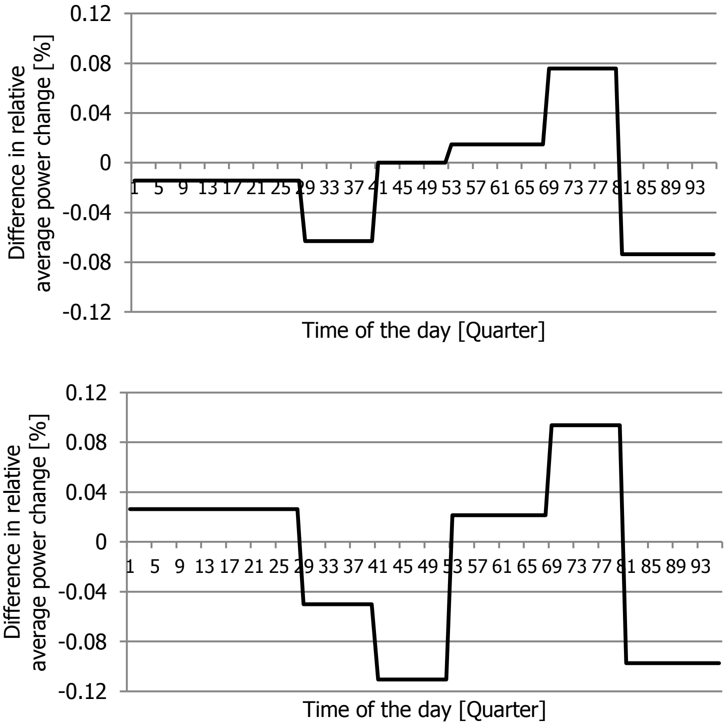


Fig. 4.21. Difference in change of relative average power within each time block towards the field test period between the LINEAR and control group for week (top) and weekend (bottom) days.

Although previous figures help visualizing whether consumers react to electricity prices in general, less insight is provided in the amount of energy shifted, following from the averaging of patterns over all considered week or weekend days. In this perspective, Fig. 4.22 visualizes the average power pattern over all considered households during one random Thursday in March. Consistent with previous results, in general consumption during the field test drops. Moreover, the drop is clearest in the late evening from 20h till 24h. Hereby, power goes down by up to 750 W. Nevertheless, no clear patterns of demand shifting can be noticed during the rest of the day. This implies that control and predictability of demand shifts are limited under manual demand response as implemented within LINEAR.

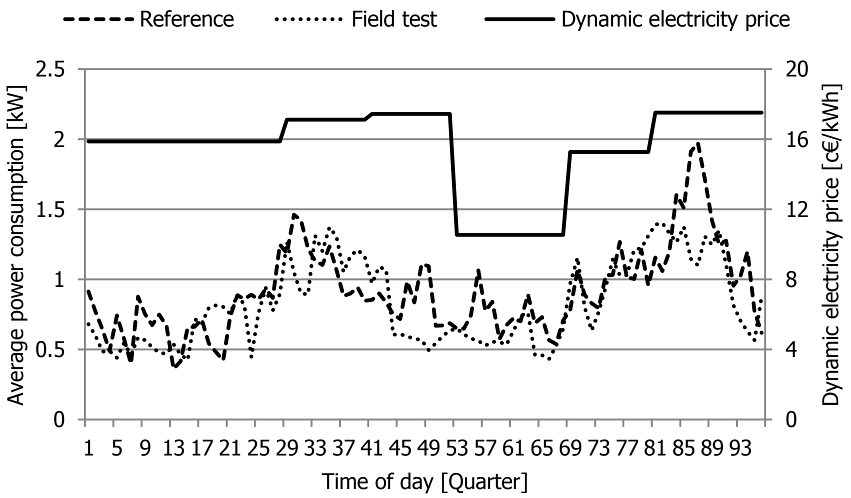


Fig. 4.22. Impact of manual demand response based on renewable pricing on the average power pattern of households during a random Thursday in March, distinguishing between reference (dashed lines) and field test (dotted lines) consumption.

Automated DR results

Total consumption during the reference and field test period amounts to 42619 and 42337 kWh respectively, implying an energy conservation of 0.7%. This consumption covers 48 households over the two-month period. Compared to manual DR the conservation effect is limited. This can be explained by the fact that less feedback is provided. Also the interaction with households is different compared to manual DR. The main action of households under automated DR is setting the shifting potential of their shiftable appliances, without considering prices or comparing current with reference consumption. Moreover, climatological circumstances between both reference and field test periods were not considerably different. Therefore, the impact on total consumption differences between reference and field test period is limited.

Fig. 4.23 visualizes the impact of renewable pricing on the average consumption patterns for week and weekend days expressed in kW. For reasons of consistency with manual DR, the same patterns are repeated in Fig. 4.24 yet expressed as a percentage of the average daily consumption. Due to data availability, a control group could not be added for automated DR.

At the starts of lower price periods small consumption peaks occur during the field test, as seen after midnight and after 13h during week days and after 13h and 20h during weekend days. Figures show practical evidence that in general consumption during lower price periods increases while consumption during high price periods decreases. Examples are a decrease in consumption during the morning period from 7h till 13h and the evening from 17h till 24h. Increases in consumption are found during the night and afternoon. This is in contrast to results of manual DR where almost no shift towards the night was observed. Therefore it illustrates that automation helps shifting consumption deeper in the night. These results are consistent with results from simulated demand response discussed in Section 4.2.

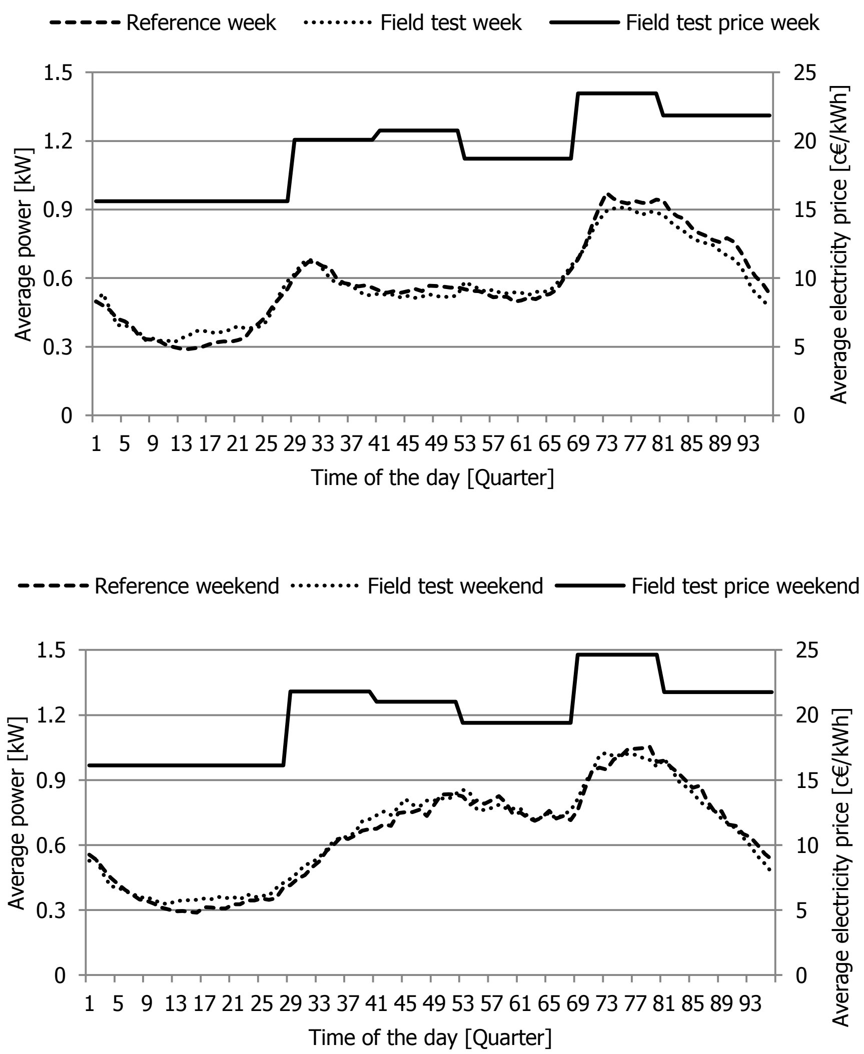
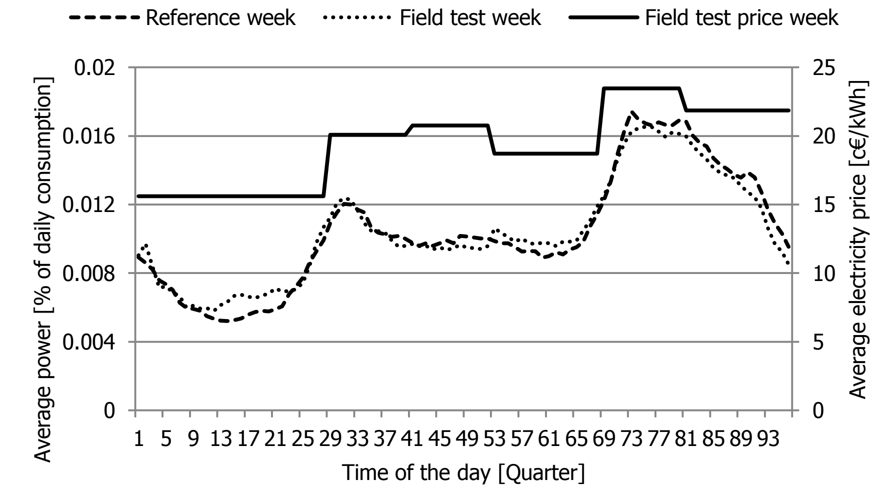


Fig. 4.23. Impact of automated demand response based on renewable pricing on the average power pattern of households during week (top) and weekend days (bottom) expressed in kW, distinguishing between reference (dashed lines) and field test (dotted lines) consumption.



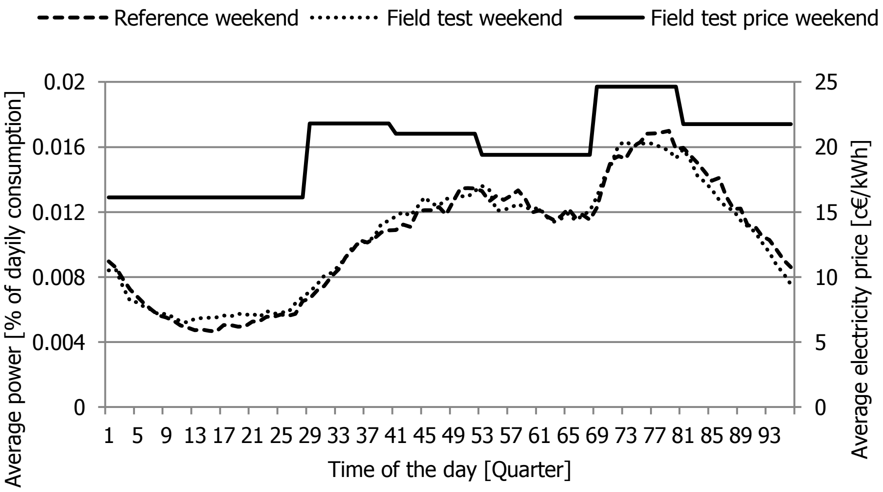


Fig. 4.24. Impact of automated demand response based on renewable pricing on the average power pattern of households during week (top) and weekend days (bottom), expressed as percentage of average daily consumption and distinguishing between reference (dashed lines) and field test (dotted lines) consumption.

Consistent with manual DR, visualizing demand shifts for one random day helps gaining insights in the amount of shifting. Therefore, Fig. 4.24 depicts the power profiles during a random Thursday in October for reference and field test period. Clear demand shifts over different price periods are noticed. This implies that automation adds more controllability and predictability of demand shifts compared to manual demand response. Next, average increases and decreases of 250 W can be noticed. This amount is in line with simulated DR with white appliances as described in Section 4.2. As previously mentioned, also the moment towards which demand is shifted aligns: the night and the late afternoon. In other words, practical results from the LINEAR field test partly confirm results from theoretical simulations.

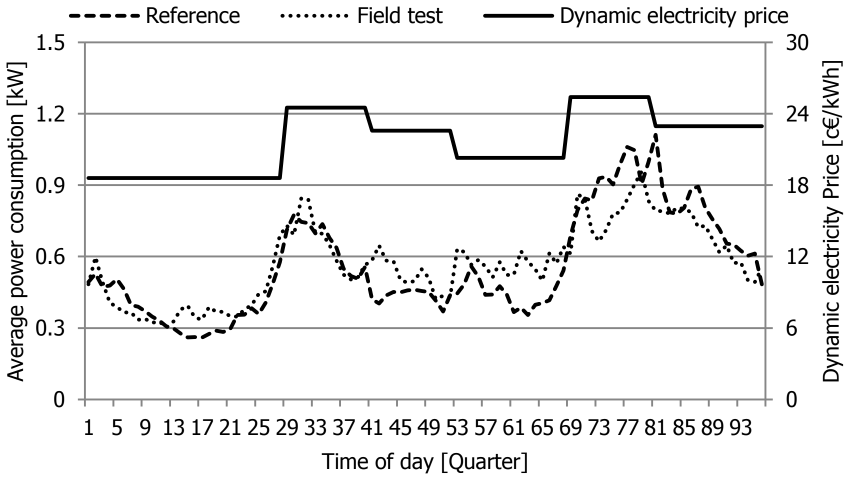


Fig. 4.24. Impact of automated demand response based on renewable pricing on the average power pattern of households during a random Thursday in October distinguishing between reference (dashed lines) and field test (dotted lines) consumption.

4.3.3 Household savings

Monetary savings obtained from residential DR within LINEAR are outlined. Again distinction is made between manual and automated DR. First, average annual household savings under manual and automated DR are discussed. Apart from the averages, the distribution of savings over all households is discussed.

Table 4.3 depicts average household savings under manual and automated DR within LINEAR. Consequently, total household consumption is included covering both flexible and non-flexible consumption. Savings are calculated based on the difference between costs during the reference and the field test period. As only 4 and 2 months were considered in the reference and field test period of manual and automated DR respectively, savings were extrapolated to obtain annual savings.

Table 4.3 shows that annual household savings for manual DR amount to €135. This is a multitude of results from simulated demand response. Although these average savings are substantial, this result should be interpreted with care. These savings mainly result from energy conservation rather than from a demand shift. Only 16 households were considered for manual DR. Apart from manual DR, the average result of automated DR closely approximates results from simulation. For the average household, savings amount to €14.

Table 4.3. Impact of manual and automated demand response based on renewable pricing on average annual electricity savings within the LINEAR project.

	Average annual household savings [€]
Manual demand response	135
Automated demand response	14

Apart from average savings, individual household savings provide deeper insight into usefulness of DR. Therefore, Fig. 4.25 depicts a boxplot with the spread of cost savings resulting from manual and automated DR, each box representing 40% of housholds.

This figure illustrates a large spread of cost savings for both manual and automated DR. For some households, even negative savings are observed. This implies a higher bill during the field test compared to the reference period. Although not visualized in the figure, this mainly results from an increase in consumption. Nevertheless, most households have positive savings even extending to around 700 and €400 for manual and automated DR respectively. At the median, households save 100 and €26 for manual and automated DR respectively.

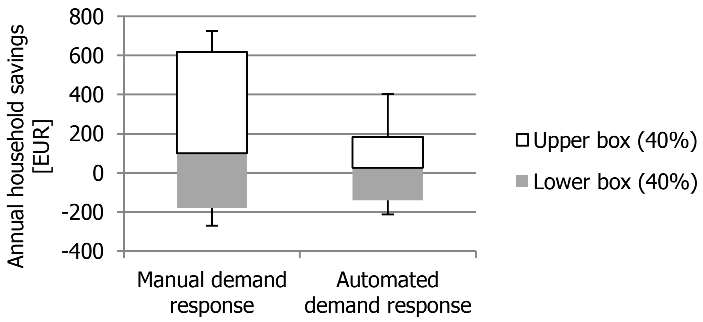


Fig. 4.25. Spread of cost savings due to manual and automated demand response based on renewable pricing with the upper and lower boxes representing 40% of the observations and the wickers representing the minimum and maximum savings.

4.4 Summary & Conclusions

Residential demand response as a reaction to dynamic pricing is discussed. To attain a thorough understanding, both theoretical and practical set-ups are highlighted. Within the theoretical set-up residential demand response is simulated. The benefit of these simulations is that DR under different dynamic pricing schemes can be analyzed and that the impact of different load types such as WAs and BEVs can be assessed. Within the practical set-up, impact of DR is described based on the LINEAR field test. Hereby, two consumer interaction models are tested, automated and manual DR. While under manual DR households modify their consumption based on a REN tariff received in day-ahead, LINEAR steers consumption of shiftable and storable loads itself under automated DR. Note that the impact of DR on the underlying cost and price is not accounted for. This is subject for further research.

Simulations of WAs show that RTP shifts consumption away from noon and late evening periods towards the afternoon and night respectively. On appliance consumption level, this leads to the rise of new peaks during the day. Nevertheless, considering total household consumption no new peaks are created as shifted consumption fills the valleys. Hereby, it should be noted that the impact on peaks in total household consumption is limited as the initial number of WAs in operation during peak periods is limited.

While consumption of WAs is limited, consumption of BEVs is considerable. Adding them to the reference household consumption profile creates new peaks even if DR is not in use. This new peak arises just before midnight as most vehicles have returned home and started charging during this period. Applying DR based on RTP, this new peak is shifted towards the night. On average, this new peak is almost double of the reference consumption peak. Whether this peak increase leads to grid stability problems partly depends on the number of BEVs scheduled towards prices, on the underlying pricing scheme, and on the approach to optimize these BEVs.

Assessing the impact of DR under different tariff schemes, simulations show that DR based on ToU pricing mainly affects evening peaks during weeks while noon peaks remain almost unaffected. Moreover, during weekends power profiles during weekends align between ToU and Flat pricing. Adding more dynamics to pricing schemes, also leads to more variation in consumption profiles, illustrated under REN and RTP simulations. REN peaks start earlier as prices are averaged over a longer period. The drawback is that consumption is not always shifted to the most advantageous period leading to new peaks during initial shoulder periods.

Apart from the impact of different dynamic tariffs with different appliances on consumption patterns, also the amount of household savings is affected. More dynamics in a tariff scheme leads to higher savings. For instance, savings under RTP are 6 to 7 times higher than under ToU. Significant differences in the amount of savings occur between WAs and BEVs. Hereby, savings with BEVs are a multitude of those with WAs. This mainly results from the amount of energy both consume. Although average annual savings for WAs amount to less than €20, the spread over different households shows that for some households savings are almost double.

Practical results from the LINEAR field test partly confirm results from theoretical simulations. This is mainly true for automated DR. Also in this case a consumption shift from noon and evening to the afternoon and night is observed. Moreover, the amount of load shifted approximates the simulation results.

While results for automated DR align with results from simulation, results from manual DR differ. Apart from DR also energy conservation is observed. While this conservation mainly follows from climatological circumstances, the impact of LINEAR could not be completely ruled out and is subject to further research. Provision of dynamic tariff schemes to households also leads to shifts in demand. Nevertheless, these shifts are less profound than with automated or simulated DR. The amount of shifting is more limited under manual DR and no shifting towards the night occurs. Automation overcomes these hurdles.

5. Demand response quantification: price elasticities based on renewable pricing

5.1 Introduction

Several parameters exist to quantify the level of demand response following dynamic pricing schemes. DR can be measured as a peak demand reduction. Generally, this parameter gives the percentage drop in demand during peak periods. Although this gives an indication of the peak reduction potential, no information is given on the aggregated load modification and its sensitivity to electricity price levels. The second way of expressing DR is by means of the price elasticity of demand. Price elasticity represents the responsiveness of user demand to electricity price changes [89]. This measure provides a more exact quantification of DR, allowing to predict the demand level after implementing a dynamic pricing scheme.

Section 5.2 describes the concept of price elasticities based on consumer demand theory. Moreover, different categories of price elasticities are listed and empirical evidence of price elasticities is discussed in a literature review. Section 5.3 describes the statistical model used to estimate price elasticities. Section 5.4 applies this model to simulated DR and practical evidence from the LINEAR-project as discussed in the previous chapter. Based on the obtained price elasticities, Section 5.5 predicts demand patterns following from dynamic prices and Section 5.6 concludes.

5.2 Literature review

5.2.1 Consumer demand theory

Before an indication of DR following from dynamic electricity prices can be derived, an economic model of consumer demand is needed. Such a model allows studying consumer behavior and preferences and eventually leads to their mathematical quantification. In this perspective, a functional form is needed which relates several variables determining consumer behavior. This functional form should fulfill two conditions. The functional form should be consistent with restrictions on demand functions implied in economic theory. Moreover, it should allow sufficient flexibility in order not to restrict the estimated parameters.

Economic theory assumes that an individual consumes goods in order to maximize utility subject to budget constraints [91]. Typically, the utility of an individual is a function of the consumed goods, also referred to as a direct utility function.

Optimization of the utility function while accounting for the budget constraint results in a demand function, expressing the quantity of demand of a good as a function of its price, prices of other goods, income, and additional factors of importance. Hereby, distinction is made between a Marshallian and Hicksian demand function referred to as an uncompensated and compensated demand function respectively [91]. In a Marshallian demand function income or budget is assumed to be constant across the demand curve, while in a Hicksian one utility is assumed constant. Translating this towards electricity demand as discussed in this thesis, Hicksian demand mainly assumes shifting of electricity demand from one period to another. Hereby, utility remains constant and comfort is unaffected. Apart from the substitution effect, Marshallian demand additionally assumes an income effect. This implies that next to shifting electricity also the total amount of electricity consumption changes due to a change in the total budget for electricity.

Apart from using a direct utility function, demand functions can be derived from indirect utility and expenditure functions. Often, these functions are preferred in empirical work. While an indirect utility function expresses utility in function of prices and income, an expenditure function expresses expenditures in function of prices and income.

5.2.2 Categories of price elasticities

Based on the functional form and the demand function, consumer behavior is derived by estimating price elasticities. As previously discussed, this consumer behavior is also referred to as DR in case of dynamic electricity pricing.

Several categories of price elasticities are distinguished in order to quantify DR. The three main categories are own, cross, and substitution price elasticities. The mathematical expressions are:

own elasticity: $$\varepsilon_i = \left[\frac{\partial q_i}{q_i}\right] / \left[\frac{\partial p_i}{p_i}\right], \tag{5.1}$$

cross elasticity: $$\varepsilon_{i,j} = \left[\frac{\partial q_i}{q_i}\right] / \left[\frac{\partial p_j}{p_j}\right] \qquad for\ i \neq j, \tag{5.2}$$

substitution elasticity: $$\sigma_{i,j} = \frac{\partial(q_j/q_i)/(q_j/q_i)}{\partial(p_i/p_j)/(p_i/p_j)} \quad for\ i \neq j, \tag{5.3}$$

with:

q_i: electricity demand in period *i*,

q_j: electricity demand in period *j*,

p_i: electricity price in period *i*,

p_j: electricity price in period *j*.

Own price elasticity refers to the relative change in demand in response to a change in the electricity price in the same period. These elasticities are typically negative as a price increase incentivizes a decrease in demand. While own price elasticity captures the relative change in demand within the same period, cross price elasticity refers to the relative change in demand due to a change of the electricity price in another period. Hereby, electricity demand in different periods are considered as different products. Positive cross-elasticities reflect a demand increase when the price in another period goes up. Therefore, demand in these periods are substitutes. Negative elasticities also occur, implying that a price increase in one period will lead to a demand decrease in another. Therefore, demand in these periods are complements. Finally, substitution elasticity defines the change in relative demand of electricity between two periods in response to a change in the relative electricity price between them. Typically, substitution elasticities are negative implying a relative demand decrease over two periods when the price ratio over those two periods increases.

5.2.3 Functional forms

To determine price elasticities of electricity demand with dynamic pricing, several functional forms are used in the literature. In what follows different functional forms are listed and their main advantages and disadvantages are discussed in line with Table 5.1. Although most common functional forms are included, this list is not exclusive. To enhance readability, the mathematical specifications are not discussed in detail. Nevertheless, references are provided in which the specifications can be found. The specification for the functional form used in this dissertation is discussed in Section 5.3.

Table 5.1. Overview of different functional forms used for determining the price elasticity of electricity demand.

Functional form	Consistency with demand theory?	Flexible form?	Price elasticities	Sources
Double logarithmic	No	No	Own & Cross	[92], [93]
Constant elasticity of substitution	Yes	No	Substitution	[94], [95], [96], [97], [98], [99], [100], [101]
Almost ideal demand system	Yes	Yes	Own & Cross	[102], [103], [104], [105], [106]
Generalized Leontief	Yes	Yes	Substitution	[95], [107]
Generalized McFadden	Yes	Yes	Own & Cross	[108], [109]

Double logarithmic

The double logarithmic functional form expresses the logarithm of electricity demand as a linear combination of the logarithm of prices. Usually, household and time dummies are added in order to increase predictive power of the functional form.

Its advantage is the ease of interpretation and estimation. Price elasticities can simply be derived from the coefficients of the price variables yielding own and cross price elasticities. Estimation can be performed by ordinary least squares. The main disadvantage of this functional form is that it leads to ad hoc estimates. This implies that own and cross price elasticities are assumed constant across several price levels. In other words, the resulting elasticities do not depend on the price levels itself and therefore usability during periods with different prices is limited. The double logarithmic functional form is not strictly consistent with economic theory as it cannot be derived from the process of utility maximization. Often estimation of this functional form leads to inconsistent and biased estimates due to problems of serial correlation.

While Angevine and D. Hrytzak-Lieffers [92] apply the double logarithmic functional form for estimating price elasticities, the use of this functional form is often discouraged due to its disadvantages. Variants of the double logarithmic functional form are the single logarithmic and quadratic functional form. The former expresses the logarithm of demand as a function of prices and is applied in Horowitz [93]. The quadratic form expresses demand as a function of prices and the square of prices [98].

Constant elasticity of substitution

The constant elasticity of substitution or CES functional form expresses the ratio between peak and off-peak electricity demand as a function of an intercept, the ratio between peak and off-peak prices and some additional variables. Typically, substitution elasticities are derived from this functional form as the variables refer to the ratios of demand and price. Hereby, a two-stage budgeting process of residential consumers is assumed to align with economic theory [110]. The budget is assigned between electricity and other products. Hereby, homothetic separability of utility functions is assumed. This implies that the input demand and elasticities can be derived from subfunctions alone, without knowledge related to other products [111]. The electricity budget is assigned over the different periods of the day. Demand during these periods is considered as different products.

The first advantage is that it is consistent with economic theory as it is derived from the maximization of a utility function. The model and the resulting price elasticities can easily be estimated as the model is highly structured. The main disadvantage is that the functional form is not flexible. This implies that the substitution elasticity is independent of the price levels itself. The functional form does not allow estimating cross elasticities which can capture the price effect in a given hour on quantity in another. Therefore, it cannot be determined whether demand in a given hour is a substitute or a complement.

The CES functional form is frequently applied in the literature [94], [95], [96], [97], [98]. Often it is used when the applicable dynamic pricing scheme only distinguishes between peak and off-peak periods. An exception is [97], in which the functional form is applied to a real-time pricing pilot. Also variants of CES functional forms are often applied, the most common variant being the nested CES functional form [99], [100], [101]. In this functional form shifting demand between days is also considered next to shifting within days.

Almost ideal demand system

The almost ideal demand system (AIDS) expresses budget shares of electricity demand as a function of the logarithms of prices and the logarithm of real total daily expenditures [103], [112]. Typically, own and cross elasticities can be derived from this form. Similar to the CES functional form, AIDS assumes a two-stage budgeting process in which the total budget is first divided between electricity and other products and afterwards between the different electricity demand periods during the day. Moreover, homothetic separability is also assumed.

The main advantage of the AIDS model is that it’s relatively simple to estimate while estimated price elasticities depend on the price level itself. The model provides a first-order flexible functional form in which the complementarity or substitutability of different demand periods can be addressed. Moreover, distinction can be made between Marshallian and Hicksian price elasticities. Finally, the flexible functional form is derived from economic demand theory of utility maximization while restrictions of homogeneity and symmetry are easily imposed. Nevertheless, other functional forms exists which are theoretically superior.

For deriving the price elasticity of electricity demand, AIDS is applied in Filippini [102] and Matsukawa [104]. Moreover, several variants of AIDS exist: Linear Approximate AIDS (LA-AIDS) model, Generalized AIDS (GAI) model and Quadratic AIDS (QUAIDS) model. While the GAI model was applied to derive the price elasticity of electricity demand in Navigant [105] and Bigerna and Bollino [106], no examples were found for the LA-AIDS and QUAIDS model.

Generalized Leontief

The generalized Leontief (GL) functional form expresses utility as a function of the squared roots of demand. In turn, the derived demand function expresses the logarithms of demand ratios as a function of the ratios of the square root of prices. Typically, from this demand function substitution elasticities are derived. Consistent with previous functional forms, a two-stage budgeting process and homothetic separability are assumed.

The main advantage of this functional form is its consistency with economic demand theory. The form is also flexible as the elasticity of substitution can vary between different pairs of inputs as well as with different input prices. Finally, it is also suited for estimating small price elasticities. Its main disadvantage is that demand in all periods is assumed substitutable, neglecting complementarity. Moreover, estimation is complex.

The generalized Leontief functional form is applied to demand under dynamic electricity pricing within Braithwait [95] and Boisvert et al. [107]. Within Braithwait [95], estimated results from the GL and CES functional form are compared.

Generalized McFadden

The generalized McFadden (GM) functional form uses a variable cost function to derive demand functions from which own and cross elasticities can be found [113]. The flexible functional form satisfies consumer demand theory. Consistent with previously discussed flexible forms, it assumes a two stage budgeting process.

Its main advantage is that it is theoretically superior to other functional forms. The flexible functional form is second-order flexible while being able to capture small positive and negative elasticities. Its main disadvantage is that it is complex to estimate.

For deriving the price elasticity of electricity demand, the GM functional form is applied for industrial demand in Taylor et al. [108] and Patrick and Wolak [109].

5.2.4 Evidence of residential price elasticities

Based on various residential pilot projects, several own, cross, and substitution elasticities are found in the literature (Table 5.2). The main part of these studies entail ToU or CPP tariff structures. RTP was only tested in the US, although a hybrid form of RTP and ToU was studied in the EdF Tempo tariff in France [114]. It can be seen that substitution elasticities range between -0.05 and -0.41, while own elasticities range between 0.00 and -2.42. Cross elasticities range from -0.12 to 1.42.

Apart from residential elasticities, elasticities from larger consumers are also found in the literature. They typically include medium-to-large commercial, industrial, and governmental demand [92], [99], [108], [109]. For these consumers, own price elasticities following from RTP range between 0.00 and -0.27.

Table 5.2. Overview of substitution, own and cross price elasticities based on various residential pilot projects with distinct tariff schemes. Results based on the literature.

Pilot or Company Name	Source	Location	Year	Enabling technologies	Tariff scheme	Functional Form	Elasticity		
							Subst.	Own	Cross
Energy Australia	[115]	AU	2006		ToU	Not available		-0.30 to -0.38	-0.04 to -0.12
Swiss utilities	[102]	CH	1987-1990		ToU	AIDS		-1.29 to -2.42	0.48 to 1.42
Midwest Power Systems of Iowa	[116]	US	1991-1992		ToU	CES	-0.12 to -0.17		
PG&E	[117]	US	1983-1984		ToU	CES	-0.37		
Carolina Power and light	[110]	US	1970-1980		ToU	CES	-0.05 to -0.25		
Connecticut Light & Power	[118]	US	2009	x	ToU/ CPP	CES	-0.05 to -0.08		
GPU pilot	[96]	US	1997	x	ToU/ CPP	CES	-0.06 to -0.41		
California Statewide Pricing Pilot	[98] [119] [120] [121] [121]	US	2003-2004		ToU/ CPP	CES	-0.09 to -0.15		
BGE experiment	[94]	US	2008-2009	x	CPP	CES	-0.10 to -0.23		
EdF Tempo Tariff	[114]		1989-1991		RTP/ ToU	Variant on GL		-0.18 to -0.79	
ComEd RTP pilot	[122] [123]	US	2003-2006		RTP	Double Log		-0.04 to -0.08	
ComEd RTP pilot	[93]	US	2005		RTP	Double Log		No sign. results	

Variation in elasticity estimates over different residential pilot projects, results from several factors. Underlying tariff structures differ. Although the general tariff design itself can be similar, the price levels and price blocks differ leading to different estimates. Residential demand differs as a result of different geographic conditions or climate zones. This leads to different degrees of air conditioning or heat pump ownership affecting demand and therefore demand response. Some pilot projects offer enabling technology. Examples are in-home displays, energy orbs, air conditioning switches or smart thermostats. Typically, they lead to a higher demand response incentive and therefore a higher elasticity. Finally, elasticity estimates resulting from the application of different functional forms can lead to different results. This follows from the fact that all functional forms are approximations of an underlying, but unknown functional form.

Several aspects are still missing in the estimation of elasticities resulting from pilot studies. Evidence from residential pilots with RTP is still missing. Hourly day-ahead RTP was only tested in the ComEd pilot, while the EdF pilot included some hybrid form of RTP and ToU. Moreover, the role of automation is untested in most pilots. The focus is on demand response with no automation or on switching of air conditioning, while automation of wet appliances or new loads such as electric vehicles is not investigated yet.

5.3 Almost ideal demand system

A more in-depth discussion of the selected functional form in this thesis is provided, being the almost ideal demand system (AIDS). This functional form is selected because of its advantages such as flexibility, relative easiness of estimation, and alignment with consumer demand theory. In what follows, the AIDS model is expressed mathematically together with its applicable restrictions. The mathematical description of price elasticities derived from AIDS is provided. Finally, the estimation method used for solving the AIDS model and deriving its price elasticities is given.

As previously discussed, the almost ideal demand system expresses daily budget shares of electricity demand as a function of the logarithms of prices and real total expenditures [112]. The mathematical expression is:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log \frac{x}{P} \tag{5.1}$$

with:

w_i:	budget share from electricity demand in period i [%],
p_j:	electricity price in period j [€/MWh],
x:	total daily expenditure [€],
P:	price index,
α_i, γ_{ij} and β_i:	parameters to be estimated.

This demand system can be estimated for every period within the day.

The budget share w_i is obtained by multiplying prices and demand in each period i and dividing it by the total daily budget. The price index P is defined by:

$$\log P = \alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2} \sum_j \sum_k \gamma_{kj} \log p_k \log p_j \tag{5.2}$$

To align with consumer demand theory, several restrictions on the parameters are imposed, namely adding up, homogeneity of degree zero in prices and daily expenditures, and Slutsky symmetry [112]. Adding up implies that total expenditure shares should sum to one. Homogeneity of degree zero in prices and daily expenditures implies that a proportional change in these variables does not affect budget shares. Slutsky symmetry implies that the substitution effect of an increase in electricity price in period j on the budget share in period i is equal to the substitution effect of an increase in electricity price in period i on the budget share in period j.

The restrictions are imposed as follows:

Adding up: $\sum_{i=1}^{n} \alpha_i = 1$, $\sum_{i=1}^{n} \beta_i = 0$, and $\sum_{i=1}^{n} \gamma_{ij} = 0 \; \forall \, j$ (5.3)

Homogeneity: $\sum_{j} \gamma_{ij} = 0 \; \forall \, i$ (5.4)

Symmetry: $\gamma_{ij} = \gamma_{ji}$ (5.5)

A full derivation of the AIDS model is provided in Deaton and Muellbauer [111].

Once the parameters of the AIDS model are estimated, Marshallian and Hicksian price elasticities are determined according to:

Marshallian: $\eta_{ij} = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} - \frac{\beta_i \alpha_j}{w_i} - \frac{\beta_i}{w_i} \sum_k \gamma_{kj} \log P_k$ (5.6)

Hicksian: $\eta_{ij}^{*} = \eta_{ij} + w_j (1 + \frac{\beta_i}{w_i})$ (5.7)

with:

η_{ij}: Marshallian price elasticity of electricity demand,

η_{ij}^{*}: Hicksian price elasticity of electricity demand,

δ_{ij}: Kronecker delta ($\delta_{ij} = 1 \text{ for } i = j, \delta_{ij} = 1 \text{ for } i \neq j$).

Elasticities depend on the budget shares w illustrating that the applied functional form is flexible.

To estimate the proposed demand system, a statistical software package called STATA 12 is used in what follows [124]. This package provides commands such as QUAIDS to estimate the almost ideal demand system. Additional information is given in [125] and [126].

5.4 Price elasticities for simulated demand response and within LINEAR

This section builds further on the descriptive analysis of demand response discussed in Chapter 4 and quantifies demand response by means of price elasticities. Again distinction is made between simulated demand response with WAs and BEVs on the one hand and practical evidence from LINEAR with manual and automated DR on the other.

The notion behind price elasticity differs between the simulated and LINEAR cases. This follows from the underlying assumptions of demand behavior (Table 5.3). For the simulated cases, optimal elasticities based on renewable pricing (REN) are obtained. This naming is chosen as these elasticities follow from optimized demand profiles. Hereby demand is always shifted to the lowest price period independent of price differences between periods. Therefore, these elasticities align with a best case scenario as households are extremely price sensitive within the boundaries of their comfort zone. Note that as a consequence, price elasticities also depend on the pricing scheme itself as the same demand shifting applies whether relative price differences are small or large. Therefore, 'based on renewable pricing' is explicitly added to the naming of the optimal elasticities. While elasticities following from simulation serve as benchmarks, price elasticities under the LINEAR cases are based on real behavior of households. In the manual DR case, households receive renewable pricing schemes and can react accordingly. This reaction can take the form of shifting demand, but also of a conservation or growth in demand. Remuneration is based on the pricing scheme itself. Elasticities derived from manual DR align with price elasticities as defined within economic theory as they represent the genuine response of households towards price changes. In the automated DR case, households set a shifting potential for their appliances based on which they receive a bonus. During this shifting potential, the appliance is automatically cycled by LINEAR. While these households do not see the renewable pricing scheme, their consumption is shifted based on it. Therefore, elasticities in this case are useful to estimate the relationship between prices and demand, yet do not align with elasticities as defined in economic theory. Consequently, these elasticities are referred to as automated elasticities based on renewable pricing. Although the reasoning behind elasticities from this case aligns with optimal elasticities from the simulated cases, automated elasticities follow from practice. Therefore, also other demand behavior apart from shifting can occur.

Table 5.3. Underlying characteristics of simulated and practical demand response cases and its resulting elasticities and interpretation.

Cases		Customer involvement	Demand behavior	Remuneration	Elasticities
Simulation	WAs	None, optimization starting from historic profiles	Shifting	Based on DP	Optimal price elasticities based on REN
	BEVs	None, optimization starting from historic profiles	Shifting	Based on DP	Optimal price elasticities based on REN
LINEAR	Manual DR	Reaction to DP	Shifting, conservation, growth, etc.	Based on DP	Price elasticities as defined within economic theory
	Automated DR	Set shifting potential	Mainly shifting, yet also other types of behavior possible	Based on shifting potential	Automated price elasticities based on REN

Based on the almost ideal demand system, elasticities are estimated for the four cases. As the focus is on demand shifting within the comfort settings of the household rather than other demand behavior, demand is assumed to be Hicksian. This shifting behavior is especially valid in the simulated cases and in the automated DR case. Based on LINEAR inquiries, the main DR behavior for manual DR is also shifting. So Hicksian elasticities are derived approximating this substitution effect.

This model is run twice for every case, once for week days and once for weekend days. In each model run, all available week or weekend days are included. This distinction between week and weekend is made because of differences between demand patterns. Therefore, price elasticities are also expected to be different. Nevertheless, no substitution between week and weekend days is considered. This forms a limitation of the current model. Next, a day within the model is considered to cover the period from hour 8 until hour 7 the next calendar day instead of the usual calendar day from hour 1 until hour 24. The reasoning behind this is that demand shifts towards the night period are mainly based on comparison of night prices with previous prices rather than with following prices. Moreover, flexibility of appliances available during the evening spans two calendar days as it often runs into the night. Therefore, the night block is linked to price blocks of the previous calendar day rather than the following ones.

The datasets used for calculating price elasticities cover both a non-treatment and treatment period. Distinction between both periods allows accounting for the effect on the demand pattern from going from traditional towards renewable pricing. The non-treatment period aligns with the unscheduled and reference period for the simulated and LINEAR cases respectively. The treatment period aligns with the scheduled and field test period for the simulated and LINEAR cases respectively.

Elasticity matrices following from the different cases are discussed. Before assessing the resulting elasticity matrices for each case, an example is provided in Fig. 5.1 in order to understand their structure. The matrix depicts the influence of all price blocks within the renewable pricing scheme, on demand in all periods during the day. Hereby, rows represent demand blocks, columns price blocks. The first period considered within the matrix is the block from hour 8 until hour 10 as this is the first period within the AIDS model. Every cell of the matrix contains an elasticity which describes the effect of price in a certain period on demand in another or the same period for cross and own price elasticities respectively. Own price elasticities lay on the diagonal, while cross elasticities are found alongside the diagonal.

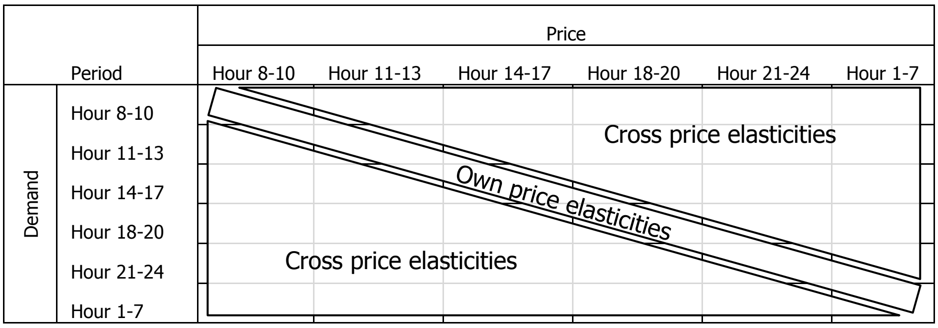


Fig. 5.1. Example of price elasticity matrix, distinguishing between different time periods resulting in own and cross price elasticities.

5.4.1 Wet appliances

In line with Chapter 4, optimal price elasticities following from demand shifting with wet appliances are based on simulated shifting of WAs within 30 households covering a period from January till March. Hereby, simulation starts from realistic demand measurements.

As price elasticities determined by the almost ideal demand system are flexible, price elasticities vary from day to day. Fig. 5.2.A provides optimal elasticities for one random Thursday in February. Based on the estimated parameters from the model run for all weekdays and the characteristics of the random Thursday, price elasticties are obtained. This day partly aligns with the day visualized in Section 4.2.1, yet also covers the hours of the first price block of the next calendar day. Also note that these elasticities do not align with economic theory as previously discussed. These elasticities merely serve as a benchmark of what optimally could be attained under REN pricing. To illustrate this point, optimal elasticities based on other pricing schemes are provided in Appendix A.

A. WAs		Price					
	Period	Hour 8-10	Hour 11-13	Hour 14-17	Hour 18-20	Hour 21-24	Hour 1-7
Demand	Hour 8-10	-0.195**	-0.037	0.182**	0.132*	-0.179**	0.098**
	Hour 11-13	-0.041	-0.311*	0.493***	-0.137	0.122	-0.125**
	Hour 14-17	0.167**	0.410***	-0.606***	-0.020	0.308***	-0.258***
	Hour 18-20	0.106*	-0.100	-0.018	-0.270***	0.109	0.173***
	Hour 21-24	-0.121**	0.075	0.227***	0.092	-0.423***	0.151***
	Hour 1-7	0.089**	-0.102**	-0.254***	0.193***	0.202***	-0.128**

B. BEVs		Price					
	Period	Hour 8-10	Hour 11-13	Hour 14-17	Hour 18-20	Hour 21-24	Hour 1-7
Demand	Hour 8-10	-0.662***	0.148***	-0.096***	0.095***	0.502***	0.013
	Hour 11-13	0.242***	-0.652***	-0.037	0.143***	0.382***	-0.078***
	Hour 14-17	-0.234***	-0.056	-0.459***	-0.304***	1.362***	-0.309***
	Hour 18-20	0.120***	0.112***	-0.158***	0.045	-0.737***	0.617***
	Hour 21-24	0.387***	0.180***	0.430***	-0.446***	-1.763***	1.212***
	Hour 1-7	0.020	-0.070***	-0.184***	0.708***	2.294***	-2.768***

C. Manual DR		Price					
	Period	Hour 8-10	Hour 11-13	Hour 14-17	Hour 18-20	Hour 21-24	Hour 1-7
Demand	Hour 8-10	-0.133**	0.067	-0.094*	-0.005	0.077	0.087**
	Hour 11-13	0.075	-0.556***	-0.021	-0.086	0.475***	0.112**
	Hour 14-17	-0.092*	-0.018	0.184**	0.057	-0.071	-0.060
	Hour 18-20	-0.003	-0.057	0.043	-0.023	-0.027	0.068**
	Hour 21-24	0.040	0.219***	-0.037	-0.019	-0.177***	-0.027
	Hour 1-7	0.071**	0.082**	-0.049	0.074**	-0.042	-0.135***

D. Automated DR		Price					
	Period	Hour 8-10	Hour 11-13	Hour 14-17	Hour 18-20	Hour 21-24	Hour 1-7
Demand	Hour 8-10	0.190**	-0.175***	-0.183***	-0.251***	0.301***	0.119**
	Hour 11-13	-0.196***	-0.154	0.081	-0.035	0.135	0.169***
	Hour 14-17	-0.180***	0.071	-0.123	0.074	0.222***	-0.064
	Hour 18-20	-0.187***	-0.023	0.056	0.471***	-0.408***	0.091**
	Hour 21-24	0.156***	0.062	0.117***	-0.283***	-0.087*	0.035
	Hour 1-7	0.097**	0.123***	-0.053	0.100**	0.055	-0.323***

Legend:	(dark grey)	Significant negative price elasticity
	(light grey)	Significant positive price elasticity
Note:	*** p<0.01,	** p<0.05, * p<0.1

Fig. 5.2. Optimal price elasticities, automated price elasticities, and price elasticities as defined within economic theory based on REN pricing for one random Thursday based on simulation with WAs (A) and BEVs (B) and on practical experience from manual (C) and automated (D) DR within LINEAR, stating the significance level of each price elasticity.

The elasticity matrix shows that the own optimal price elasticities based on renewable pricing along the diagonal are all significant: the price during a price block has a significant impact on demand during the same period. Moreover, all own price elasticities are negative. This implies a demand decrease when prices go up. Nevertheless, own price elasticities vary over the time of the day. Also note that the significance level of elasticities is shown by the number of asterisks. One asterisk aligns with a p-value of less than 0.1 implying that results are significantly different from zero. More asterisks increase significance. Cross elasticities are visualized alongside the diagonal. Although the main part of cross elasticities is significant, demand during some periods is not affected by prices in others. Most significant cross elasticities are positive. This implies that demand within one period rises when price in another period goes up. Demands during those periods are considered as substitutes. Also some negative cross elasticities are found. This is the case for demand in the period from hour 1 till hour 7 which is complementary with hours 11 to 13 and 14 to 17. The sign of significant values are symmetric within the matrix although values differ. Therefore complementarity and substitutability between specific periods matches, yet the impact of prices differs in quantity.

The lowest negative own price elasticities are found in hours 14 to 17 and hours 21 to 24 with a value of -0.606 and -0.423 respectively. This implies that when prices rise by 10% in one of these periods, demand decrease with 6.1% and 4.2% respectively. The highest cross price elasticity is found between the price in hours 14 to 17 and demand in hours 11 to 13 with a value of 0.493. Therefore, if the price in hours 14 to 17 rises by 10%, demand in the previous period goes up with 4.9%. These effects align with results from the descriptive analysis of Chapter 4, yet price elasticities allow proper quantification.

5.4.2 BEVs

In line with Chapter 4, optimal price elasticities based on renewable pricing following from demand shifting with BEVs are based on simulated shifting of the vehicles of 100 households covering a full year. Hereby, simulation starts from realistic driving patterns while distinguishing between different types of vehicles.

Fig. 5.2.B visualizes an example of the optimal price elasticity matrix based on REN pricing for one particular Thursday in October in line with Section 4.2.2. The elasticity matrix shows that 5 out of 6 own elasticities along the diagonal are significant. Only for hours 18 till 20, the price does not have a significant effect on demand within the same period. Significant own price elasticities are negative illustrating a demand decrease when prices go up. Most cross elasticities alongside the diagonal are significant, implying that a price change in one period also influences demand in other blocks. In most cases, these cross elasticities are positive implying

substitutability between products. In line with the elasticity matrix following from shifting WAs, signs of significant elasticities within the elasticity are symmetric yet values differ. Also note that these elasticities do not align with economic theory, as previously discussed. These elasticities merely serve as a benchmark of what optimally could be attained under REN pricing. A more accurate quantification of demand response is subject to further research.

The highest absolute own and cross price elasticities is present in hours 21 to 24 and 1 to 7. Hereby, own price elasticities amount -1.763 and -2.768 respectively, while cross price elasticity between price in hours 21 to 24 and demand in hours 1 to 7 amounts to 2.294. This illustrates that demand in the night period is highly sensitive to prices in the late evening. The level of those elasticities can be explained by the high level of electricity demand of BEVs compared to WAs. Moreover, optimal elasticities are listed representing a best case scenario.

5.4.3 Manual DR

Apart from optimal price elasticity matrices based on renewable pricing following from simulated DR with WAs and BEVs, practical evidence from the LINEAR project allows deriving genuine price elasticities based on consumer interaction. The first interaction model tested within LINEAR is manual DR. To derive the price elasticity matrix, the same data are used as in Section 4.3 covering 16 households measured during both a reference and field test period from March till the end of June. As noted in the previous chapter, total household demand decreased significantly towards the field test. Therefore, also a control group covering 31 households is added to establish a true cause-and-effect relationship between prices and demand by controlling for parameters which changed from the non-treatment towards the treatment period. As previously discussed, climatological circumstances played a substantial role in case of manual DR.

Fig. 5.2.C visualizes an example of an elasticity matrix for a random Thursday in March. This day is in line with the day chosen in Section 4.3.2. The number of significant values within the matrix is considerably less than with previous optimal results from simulation. This illustrates that manual DR cannot reach the level of response compared to benchmark results and therefore the impact of price on demand is more limited. Along the diagonal five significant own price elasticities are present. Four of them are negative while the elasticity in hours 14 to 17 is positive. This implies an increase in demand when prices increase.

The highest negative own price elasticity is -0.556 and occurs in hours 11 to 13. The highest cross price elasticity is found in the hours 21 to 24. Hereby, a price increase in these hours, increases demand in the hours 11 to 13, reflecting substitutability.

5.4.4 Automated DR

Finally, also automated DR is tested within the LINEAR project leading the automated price elasticity matrix based on renewable pricing. To this end, the same data are used as in Section 4.3 covering 47 households measured during both a reference and field test period from mid-September till mid-November.

Fig. 5.2.D visualizes an example of an elasticity matrix for a random Thursday in October. More elasticities are significant compared to manual DR. Therefore, automation leads to additional DR. Nevertheless, the number of significant values is still smaller than in the simulated cases. This follows from the fact that in the simulated cases flexibility is given for each household and every time an appliance is set. Response from households within LINEAR varies to a larger extent between households and appliance types, as measurement results and inquiries filled in by participants pointed out. Nevertheless, commercial implementation of automated DR can approximate optimal results more closely as the focus of LINEAR was on a technical breakthrough of DR. Four own price elasticities are significant along the diagonal of which two are negative. These negative price elasticities occur during hours 21 to 24 and 1 to 7. As described in the previous chapter, demand typically goes up when prices are low in these periods. The negative own price elasticities confirm this. Several positive and negative cross price elasticities occur alongside the diagonal. Therefore, both substitutability and complementarity are present. Also note that these are automated elasticities under REN pricing and therefore do not align with economic theory, as previously discussed. A more accurate quantification of demand response is subject to further research.

The lowest negative own price elasticity occurs in hours 1 to 7 with a value of -0.323. The highest positive cross price elasticity is found for prices in hours 21 to 24 and demand in hours 8 to 10, with a value of 0.301. Hereby, a price rise of 10% in hours 21 to 24 increases demand with over 3% in hours 8 to 10.

5.5 Prediction of demand patterns based on renewable pricing

Although quantification of demand response by means of optimal and automated price elasticities and price elasticity consistent with economic theory helps gaining insight in general DR behavior, these price elasticities also help predicting aggregate demand patterns in case dynamic pricing schemes are sent to households. This is useful for system operators, generators and retailers in order to know the impact of dynamic price profiles.

Predictions on the daily demand patterns are made based on the above obtained elasticities. A predicted demand pattern results from the difference between reference and field test prices, the reference demand, and price elasticities. Similarly to previous sections, the same days for each of these cases are analyzed.

Fig. 5.3 shows how closely predicted average demand approximates average demand under renewable pricing. Again distinction is made between simulated DR with WAs and BEVs on the one hand and manual and automated DR within LINEAR on the other. For simulated DR, distinction is made between unscheduled, scheduled, and predicted demand. For DR within LINEAR, distinction is made between demand during the reference and field test period and predicted demand. The day represented in the figure does not align with a calendar day, but rather with the day used within the AIDS model. Therefore, the graphs start at 7h00.

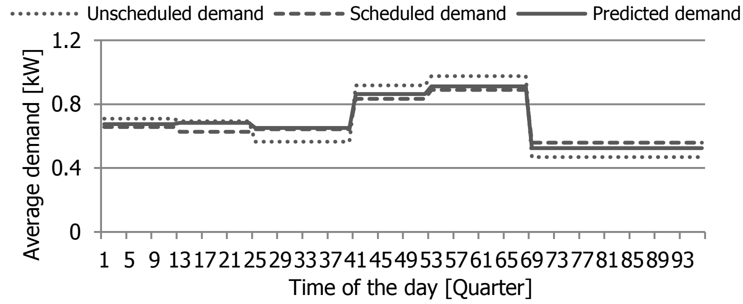
Predicted demand approximates demand after WA scheduling quite closely (Fig. 5.3.A). Nevertheless, a perfect approximation is not obtained as not all parameters are accounted for within the AIDS model. For example, no distinction is made between elasticities during different days of the week or during different months.

Fig. 5.3.B visualizes demand predictions based on optimal elasticities following from simulations with BEVs. As expected due to the high number of significant optimal elasticities, predicted demand again approximates scheduled demand quite closely. For closer approximations, again finer granularity has to be added to the model.

Fig. 5.3.C visualizes predictions for manual DR within LINEAR. Predicted demand does not approximate field test demand. This could be expected as prediction builds further on the reference measurements. Therefore, differences between pre- and post-treatment outside the control of LINEAR are not accounted for: prediction by means of elasticities should start from a classical prediction model which includes parameters such as time, season, weather, etc. Hereby, price elasticities can be included in the prediction model. This mainly results from the limited number of significant price elasticities, implying a limited effect of prices. Nevertheless, this is out of scope in this dissertation.

Fig. 5.3.D visualizes predictions for automated DR within LINEAR. Although better compared to the manual DR case, predictions still fail to approximate the field test demand pattern closely. This follows from the same main reason as for the manual case.

A.



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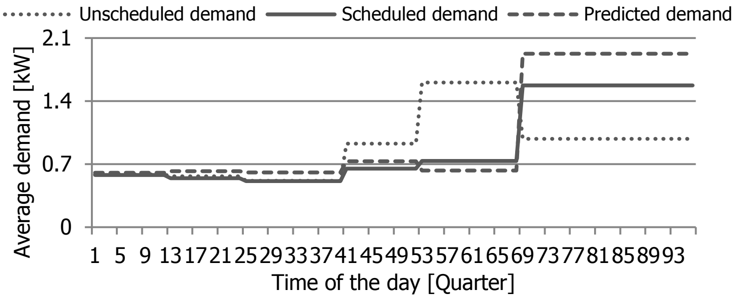

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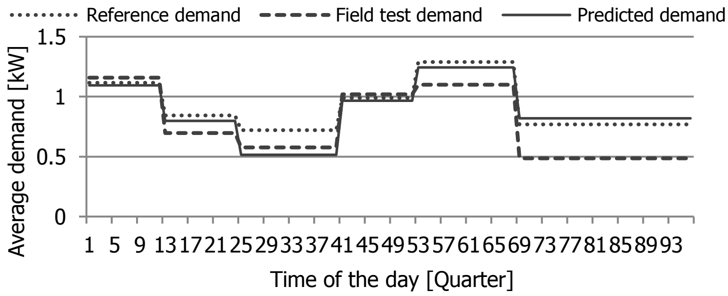

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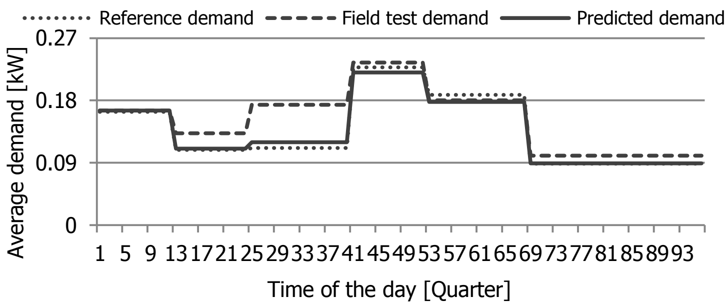

Fig. 5.3. Predicted demand based on elasticities following from simulation with WAs (A) and BEVs (B) and from manual (C) and automated (D) DR results within LINEAR, distinguishing between reference demand (dotted), field test demand (dashed) and predicted demand (solid).

5.6 Summary & Conclusions

This chapter provides a quantification of demand response by means of price elasticities. Price elasticities capture the responsiveness of user demand to electricity price changes. Several categories of price elasticities exist covering own, cross, and substitution price elasticities.

To derive elasticity estimates several functional forms can be used to approximate the true underlying preferences of households. These functional forms relate several variables determining consumer behavior. Often these functional forms are derived from consumer demand theory and align with restrictions on demand functions. This is the case for the constant elasticity of substitution model, the almost ideal demand system, the generalized Leontief model, and the generalized McFadden model. Some functional forms also provide flexibility in order not to restrict the estimated parameters. Examples of the latter are the almost ideal demand system, the generalized Leontief and the generalized McFadden model.

In a literature review, practical evidence of price elasticities in various residential pilot projects is highlighted. Nevertheless, no consistency is found in the elasticity estimates. This is due to differences in geographic conditions, implementation designs, but also to the choice of the functional form. Moreover, the literature review shows that price elasticities following from more dynamic pricing schemes such as RTP and REN are still lacking. Additionally, the impact of automation and the introduction of new loads such as BEVs is not investigated thoroughly.

To overcome the above literature gaps, this chapter estimates price elasticities for four different cases. Two cases cover simulated demand response based on WA and BEV scheduling under REN pricing. The other two cases cover practical evidence from manual and automated DR within LINEAR again under REN pricing. For each case, elasticity matrices are derived by means of the almost ideal demand system. This system is chosen as it provides a relatively simple estimation while preserving flexibility of the elasticities and consistency with economic theory.

Results show that most elasticities within the elasticity matrix are significant in the simulation cases. These elasticities are optimal based on renewable pricing and represent a best case scenario. Therefore, these do not align with economic theory, yet they provide a quantification of demand response. Note however, that more accurate ways to quantify demand response are subject to further research. The high number of significant values follows from the fact that households are assumed to be extremely price sensitive within the boundaries of their comfort zone. Especially in the BEV simulation optimal elasticities are significant due to the high level of electricity demand by BEVs. The high sensitivity of BEV demand towards pricing can also be seen in the level of optimal elasticity coefficients as these are a multitude of optimal elasticities with WA scheduling. Compared to the simulated cases, practical evidence from LINEAR leads to less clear results, although significant elasticities are also found. This follows from the fact that not all households actively participated in LINEAR. Nevertheless, it is clearly shown that automation leads to more significant levels of demand response.

Apart from using price elasticities to gain insights in DR behavior, this chapter also uses price elasticity matrices to predict aggregated demand profiles. This is useful for system operators, generators, and retailers in order to know the impact of dynamic pricing. Predicted demand approximates scheduled demand quite closely for the simulated cases. Therefore, it can be concluded that the AIDS model provides a thorough demand response quantification. Demand predictions based on elasticities following from LINEAR didn't approximate field test demand closely. Nevertheless, this is logical as the prediction starts from demand during the reference period. Therefore, other circumstances not related to price and changing towards the field test are not accounted for within the LINEAR cases. Therefore, the true value of prediction based on price elasticities can only be assessed when it is included in a classical prediction model which also accounts for additional variables. Yet this is outside the scope of this dissertation.

PART IV

Power system benefits of residential demand response

6. Impact of residential demand response on power system operation

6.1 Introduction

Power system operation around the world is facing challenges due to the integration of renewable energy resources (RES) and the electrification of energy services. To safeguard the demand-supply balance and to cover increased peak demand, demand response (DR) can be addressed.

The use of DR in systems with a high integration of renewables is investigated in literature. In Dietrich et al. [127], power system operation with high wind penetration is modeled by means of unit commitment modeling. This allows including the effect of wind variability. Results show that DR can level out variations in wind power, leading to cost and emission reductions. These reductions are accomplished by load shifting and peak reduction [16]. In De Jonghe et al. [128], it is shown by means of unit commitment modeling that DR brings a reduction in wind power curtailment. Also in Sioshansi and Short [129], the impact of DR programs in a high wind penetration scenario is tested. A day-ahead unit commitment model is combined with a real-time dispatch model. Next to the variability, this allows to account for the wind prediction error. Results show that less wind power is curtailed due to DR. In Moura and Almeida [130], the role of residential, commercial, and industrial demand side management for integrating wind power in the system is assessed. Results show that peak reduction mitigates operational problems caused by the variability of wind power generation.

The impact of the electrification by means of battery electric vehicles (BEVs) is investigated in the literature. In Wang et al. [131], the impact of plug-in hybrid electric vehicles on power system operation is investigated using a detailed unit commitment model. It is shown that total operating costs can be reduced up to 13%. In Bañez et al. [132], different possible charging strategies are tested in a unit commitment and daily economic dispatch model. The latter allows accounting for the prediction errors associated with power generation from RES. Finally, in Madzharov et al. [133], a detailed unit commitment model is used to determine the effect of different electric vehicle penetration levels on the total operating costs. Results show that for every 10% of additional electric vehicle penetration, total generation costs increase by approximately 1%.

A further refinement of the inclusion of DR in system operation modeling is needed. At the generation side, technical characteristics of generation plants such as ramping rates, minimum output, and minimum up and down time are neglected in Wang et al. [131]. In Dietrich et al. [127] and De Jonghe et al. [128], a day-ahead unit-commitment model is performed, ignoring real-time operation. Therefore, prediction errors associated with power generation from RES are not considered. At the demand side, shiftable demand is often determined as a percentage of peak demand without accounting for the underlying consumption patterns of specific appliances [128], [131]. A more detailed approach is needed to reach a realistic quantification of operational benefits. The same applies for BEVs as realistic driving patterns and BEV characteristics contribute to a more realistic outcome. Next to including realistic demand and supply characteristics, the analysis needs to be performed on a broad period of data. Otherwise, the implications of single events are overestimated.

This chapter assesses the impact of an introduction of DR on system operation, focusing on plant operation, system reliability, emissions, and costs. A detailed modeling approach of both supply and demand side is taken, allowing to obtain a realistic quantification of DR benefits and to assess the potential of introducing demand response. The approach is applied on a full year of data. The focus is on residential DR, including scheduling of wet appliances (WAs) and BEVs. Wet appliances include washing machines, dishwashers and dryers. BEVs only include residential light-duty vehicles. Electric heating is not considered as this requires the integration of weather conditions [134]. Note that the program to address the demand side is not discussed in this chapter as this is a potential study. Therefore, the demand response programs can be both price-based and incentive-based in line with Chapter 1.

Section 6.2 clarifies the operational model used to optimize system operation with DR. Section 6.3 elaborates on the data and assumptions for demand, DR, and generation. Results are highlighted in Section 6.4 and Section 6.5 concludes.

6.2 Model

The impact of DR with WAs and BEVs on system operation is evaluated with the reliability and operation model for renewable energy sources (ROM-model). This model approximates real-life power system operation by combining two sequential stages: an optimization stage in day-ahead and an hourly simulation stage updating the economic dispatch in real-time. Each stage is documented below (Fig. 6.1). The model is solved in GAMS 24.0.1 using CPLEX 12.2 as a mixed integer problem solver.

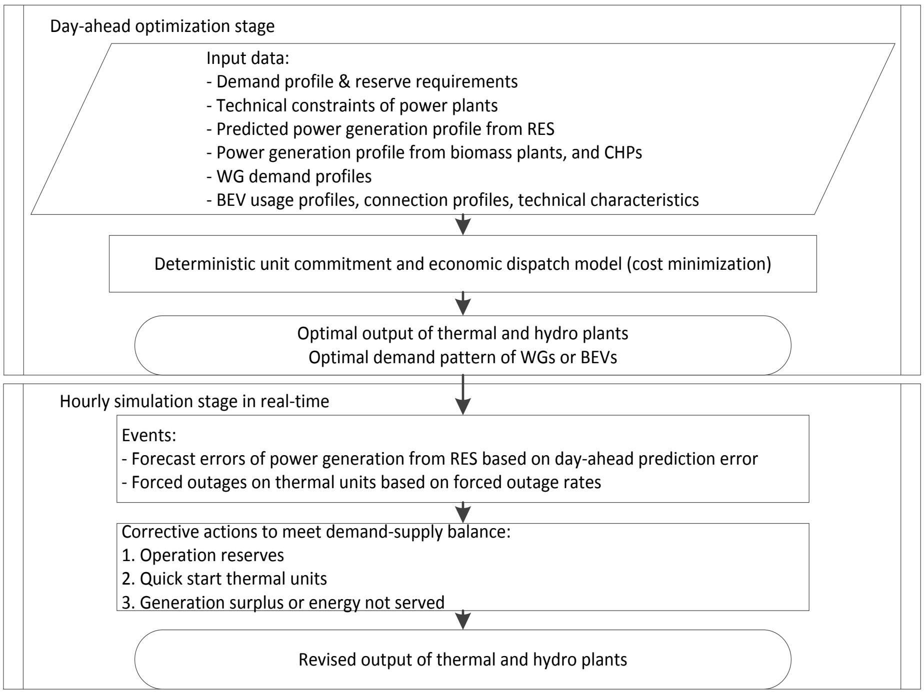

Fig. 6.1. Flowchart of the ROM-model, covering a day-ahead simulation stage and hourly simulation stage in real-time.

6.2.1 Day-ahead optimization stage

Basic model description

In the optimization stage, a deterministic unit commitment and economic dispatch model are used to determine optimal output of thermal and hydro plants for the next day. This model contrasts with stochastic unit commitment models in which uncertainty is considered [135], [136]. The specific mathematical formulation of the model used is extensively described in Dietrich et al. [127]. The model minimizes daily operational costs while meeting demand-supply balance and reserve requirements. Technical constraints for thermal units are considered. They include minimum and maximum output, maintenance, and ramping rates. Technical constraints for pumped storage units include bounds on the hydro reservoir and minimum and maximum output. The demand profile and predicted power generation profile from RES are considered as an input. Also power generation from biomass plants and combined heat and power plants (CHPs) are modeled as an input, as generation from these plants is considered as uncontrollable or not-dispatchable from system operator point of view.

Inclusion of residential demand response

Within the day-ahead optimization stage, DR with WAs and BEVs is introduced. Contrary to the use of price elasticities [137], [138], [139], this is done by optimizing the consumption patterns of the appliances themselves. Hereby, scheduling of appliances is modeled as a centralized decision making process.

For WAs, the model allows to integrate DR with different types of appliances, such as washing machines or dryers. The hourly load pattern of each appliance type can be shifted in time according to its shifting potential. The load pattern shift for each type must be balanced within one day. A detailed model description of the inclusion of WAs is provided in Dietrich et al. [127]. The main mathematical formulation is provided in Appendix B.

For BEVs, the model allows to integrate different types of cars with different types of usage and connection profiles. Several technical characteristics of BEVs and their batteries are considered: specific energy consumption when driving, battery capacities, grid-to-battery and battery-to-wheel efficiencies, maximum state of charge, and maximum charging power. When BEVs are scheduled, the energy requirements related to the mobility patterns must be satisfied. The inclusion of DR with BEVs is extensively described in Bañez et al. [132] and Ramos et al. [140]. The main mathematical formulation is added in Appendix B.

6.2.2 Hourly simulation in real-time

In the hourly simulation stage, two events are introduced which require corrective actions in order to meet the demand-supply balance. First, forecast errors of power generation from RES are integrated based on the difference between day-ahead predicted and real-time power generation. Second, forced outages on thermal units are simulated based on forced outage rates of power plants. Three main actions can be performed to restore the demand-supply balance. First, operation reserves kept available from the optimization stage are assigned. Secondly, quick start thermal units are deployed. As a last resort, generation surplus or energy not served is triggered. This leads to a revised output of thermal and hydro plants.

6.3 Data & assumptions

The impact of DR with WAs and BEVs on system operation is assessed within two alternative power generation portfolios for a one year period. The first portfolio contains the Belgian power generation portfolio of 2012, while the second portfolio consists of the projected Belgian portfolio in 2025. In what follows, data and assumptions on both the demand and supply side are discussed.

6.3.1 Demand

Demand in Belgium is based on hourly load data from 2012, provided by the European network of transmission system operators for electricity (ENTSO-E) [141]. Yearly demand sums to 84.59 TWh. Average, maximum, and minimum hourly demand amounts 9.63 GWh/h, 14.19 GWh/h, and 6.24 GWh/h respectively. Demand in 2012 and 2025 are assumed identical.

Wet appliances

Residential demand partly arises from consumption with WAs, split up in washing machines (WMs), dryers (DYs), and dishwashers (DWs). Average load patterns for all Belgian wet appliances are depicted in Fig. 6.2. These patterns are deducted from total demand and modeled separately. In order to derive Belgian load patterns for each appliance, the following parameters are used: number of times appliances are cycled, starting times of cycles, and consumption profiles of cycles. Based on [142] and statistics from the federal public service [143], over 9 million WAs are present in Belgium and the number of cycles a day amounts to 2.51, 1.30, and 1.85 million WMs, DRs, and DWs respectively. Starting times of appliances are derived from [144]. Consumption cycles are obtained from measured profiles from a pilot project named LINEAR [71]. This leads to a total yearly consumption of 1.93 TWh of which 0.53, 0.60, and 0.80 is attributable to WMs, DYs and DWs respectively. This exceeds 2% of total yearly electricity demand. It is assumed that all WA cycles can be used for load shifting purposes. While this is an overestimation, it allows results to be comparable with BEV scheduling. A shifting potential of 4 hours both forward and backward is assumed [145].

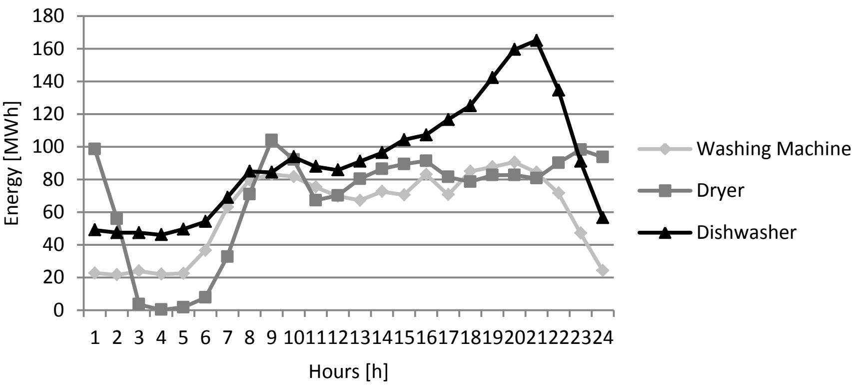

Fig. 6.2. Average daily load patterns of unscheduled Belgian wet appliances: washing machine, dryer and dishwasher.

Battery electric vehicles

As the current Belgian demand does not include a significant number of BEVs, their power consumption has to be added to demand representing the electrification of transportation. In both the 2012 and 2025 scenario, the number of Belgian light-duty vehicles is assumed to be 5.41 million based on federal public service statistics [146], of which 8% or over 430 000 vehicles are BEVs [147]. In line with Section 4.2.2 (Table 4.1), three types of vehicles with their own technical battery characteristics are considered: subcompact, midsize, and large vehicles. 200 representative BEVs and their accompanying driving patterns are considered. Total Belgian yearly power consumption of BEVs sums to 1.78 TWh. This exceeds 2% of total yearly electricity demand. The average load pattern in the unscheduled BEV charging scenario is depicted in Fig. 6.3. Hereby, it is assumed that BEVs are plugged in at each location when they are not driving. As soon as a BEV is plugged in, it starts charging until the battery reaches maximum state of charge or until the BEV departs again. With scheduled charging the timing and quantity of charging is optimized over the period when the BEV is not driving.

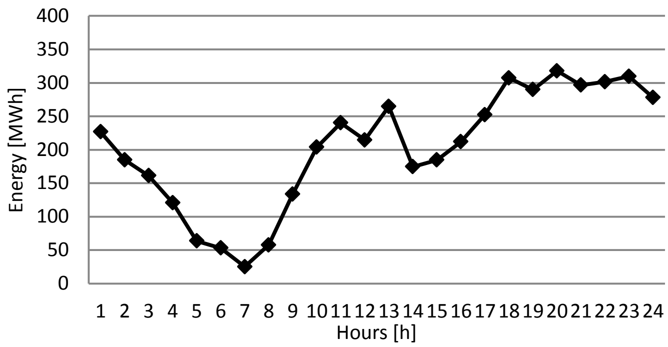

Fig. 6.3. Average daily load pattern of unscheduled charging of BEVs.

6.3.2 Power generation portfolio

Installed capacity

Current and future installed capacity in Belgium is based on data from ENTSO-E [148] and the Belgian TSO [149]. These capacity data are adjusted in several ways. Current and future installed wind, solar power capacity is revised according to estimations from Belgian regulators [150], [151] and the Belgian TSO [152]. A full nuclear phase out is assumed by 2025 [152]. Coal capacity is also phased out while additional gas capacity is integrated by 2025 [152]. Apart from covering demand, both current and future power generation portfolios need to provide reserves. An approximation of reserve requirements is based on ENTSO-E and amounts to 870 MW and 970 MW for 2012 and 2025 respectively [148]. Interconnection capacity and cross-border flows are not included in the analysis. The transmission grid is considered to be a copper plate with no internal congestions.

Total installed capacity in 2012 and 2025 amounts to 20.30 GW and 22.25 GW respectively. As depicted in Fig. 6.4, the 2012 portfolio is characterized by plants operating on a mix of primary energy sources. Gas and nuclear capacity make up the main part. This is complemented with solar, wind, hydro, biomass, coal, and oil capacity. Biomass capacity also includes waste and wood pellets. Oil is typically used in smaller turbojets. Towards 2025, nuclear, coal, and oil are phased out. Installed capacity of gas power plants rises due to an increase in combined cycle gas turbines and combined heat and power plants (CHPs). Moreover, renewable integration becomes even more significant as more wind, solar, and biomass capacity is installed. Renewables make up almost 50% of total installed capacity.

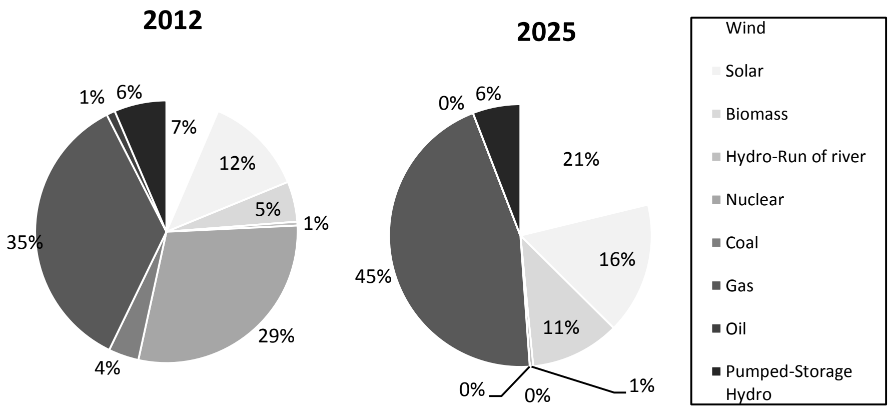

Fig. 6.4. Installed capacity in Belgium in 2012 and 2025.

Technical characteristics

Over 50 different thermal plants using different fuel types are present in Belgium. Capacities and fuel types of these plants are provided by the Belgian TSO [153]. Based on the capacities, the technical characteristics of plants are derived (Table 6.1). Five different technologies are considered: pressurized water reactors (PWRs), steam power plants (SPPs), combined cycle gas turbines (CCGTs), gas turbines (GTs), and internal combustion engines (ICEs). Except for start-up costs, probability of maintenance and forced outage rate, all technical characteristics of the first four technologies are based on [154] and consistent with [155]. For PWRs, efficiency is set to 100% as their fuel costs is expressed in €/MWh$_{electric,}$ as later on discussed. Start-up costs are based on [156], except for PWRs for which this characteristic is retrieved from [154]. The probability of maintenance and the forced outage rate are based on [157] for PWRs and on historic data from the Belgian TSO [158] for the other technologies. Technical characteristics of ICEs are retrieved from [156].

Table 6.1. Technical characteristics of power plants.

Technology	*Min. Output [% of P_{max}]*	Max. Output *[% of P_{max}]*	*Efficiency at Min. Load [%]*	*Efficiency at Max. Load [%]*	Up & Down Ramp *[% of P_{max}/h]*	Start-up costs *[€/MW]*	Maintenance *[% of hours]*	Forced Outage Rate *[% of hours]*
PWR	40	100	100	100	40	15	13	1
SPP	30	100	33	40	40	34	2	6
CCGT	45	100	53	60	100	73	7	2
GT	20	100	25	32	100	10	9	5
ICE	60	100	40	42	100	10	9	5

Power generation from run-of-river plants is assumed to be stable at 50% of capacity. Pumped storage units are assumed to produce at an efficiency of 80% [159]. The reservoir level allows power generation at full capacity for 5 to 6 hours.

Power generation data for solar, wind, biomass, and CHP plants are based on data from the Belgian TSO [149]. For wind power, both day-ahead predictions and real-time power generation data are included to account for the prediction error. Power generation from biomass is included based on historical output data, while CHPs are considered as must-run plants with an unavailability rate of 14% in consistency with GTs. Towards 2025, all uncontrollable power generation data is scaled towards its respective installed capacity.

Fuel cost and carbon content

Fuel costs and the carbon content of fuels are listed in Table 6.2. Fuel costs are expressed in €/MWh$_{thermal}$, except for uranium which is given in €/MWh$_{electric}$. Emission costs are set at 15 €/tCO_2 [155].

Table 6.2. Fuel prices and carbon content.

Fuel	Fuel costs [€/MWh]	Carbon Content [tCO_2/MWh]	References
Crude oil	48	0.63	[156], [160]
Coal	10	0.85	[156], [161]
Natural Gas	23	0.34	[154], [156]
UO_2	7	0.00	[162]

6.4 Results

This section describes results obtained from the Belgian case study for a whole year. As DR is the driver of operational benefits, scheduling of WAs and BEVs is addressed first. Afterwards, the impact of scheduling on power system operation is evaluated.

6.4.1 Residential demand response

Scheduled WA consumption patterns

To be able to assess the impact of residential DR on yearly power system operation, firstly the unscheduled and scheduled consumption patterns of WAs for 2012 are discussed. While on average 15% of the total WA consumption volume is reduced during peak moments, daily shifting patterns widely vary over the year. Fig. 6.5 compares the unscheduled WA consumption pattern and the spread of scheduled WA consumption. To obtain the spread of scheduled consumption, all daily consumption patterns are bundled. Afterwards, a distribution is made for each specific hour over all days. Hourly median values of scheduled consumption are represented by the white line. The intervals around the median capture a percentage of the total amount of observations and visualize the spread of the hourly wet appliance consumption. For example, the 0-10% interval shows the spread of the 10% lowest consumption values for each specific hour. It can be seen that WA consumption shows a large day-to-day variation, as demand and uncontrollable generation patterns differ between days. Therefore, cost minimization leads to different WA consumption patterns. In general, appliances are often shifted from the morning and the evening towards the late afternoon and the night. This leads to demand reductions of up to 150 MWh/h. Although shifting often leads to new peaks in total wet appliance consumption, shifted demand typically fills valleys when total demand is considered. Although not visualized, average shifting patterns in 2025 are similar to those in 2012. Nevertheless, variability of shifting patterns is higher in 2025 due to wind and solar power variability.

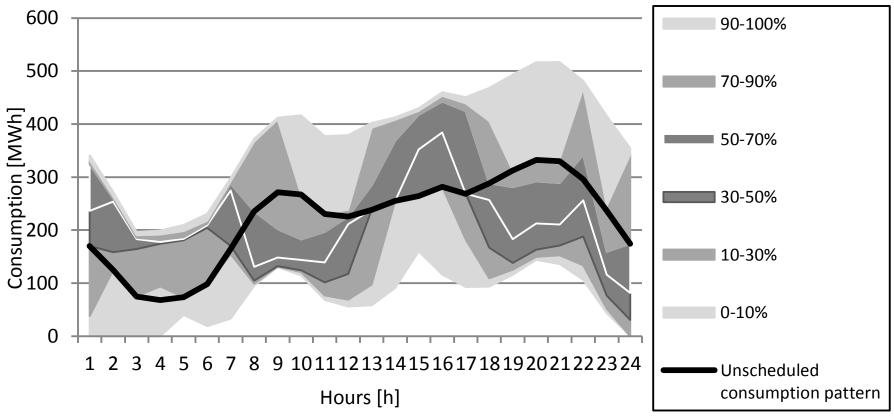

Fig. 6.5. Distribution of daily wet appliance consumption in 2012. The hourly median values of scheduled consumption are represented by the white line. The intervals capture a percentage of the total amount of observations in each hour.

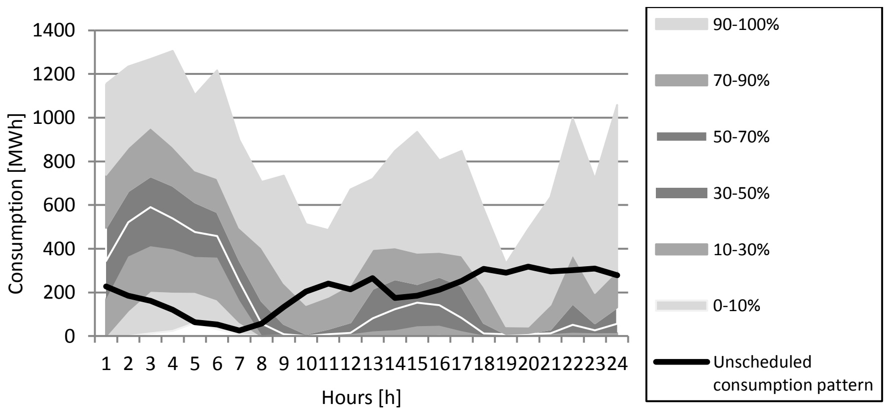

Fig. 6.6. Distribution of BEV charging patterns in 2012. The hourly median values of scheduled consumption are represented by the white line. The intervals capture a percentage of the total amount of observations in each hour.

Scheduled BEV consumption patterns

On average, 50% of the total BEV consumption volume in 2012 is reduced during peak moments. While unscheduled charging mainly takes place during daytime, scheduled charging shifts cycles towards the night (Fig. 6.6). Therefore, scheduled charging mainly occurs at home. Charging is mainly reduced during peak moments at noon and in the evening. Then total BEV consumption is often reduced to 0. This can amount to a 300 MWh/h reduction. Similarly to WA scheduling, scheduled charging creates new peaks on the level of BEV consumption. As these new peaks occur mainly during nighttime, shifted consumption fills valleys when total demand is considered. Compared to scheduled charging in 2012, shifts in the average BEV consumption pattern are less profound in 2025. Moreover, the variability of shifting patterns is higher. This results from more variability due to wind and solar capacity.

6.4.2 Impact of residential demand response on power system operation

Power plant operation

Demand response influences power plant operation within the current and future Belgian portfolio. To assess the influence, first power plant operation within two reference scenarios is evaluated. These reference scenarios consist of the 2012 and 2025 power generation portfolio in which no DR is present. Afterwards, the impact of DR is discussed. Distinction is made between WA and BEV scheduling as the impact is assessed in separate simulations.

The share of yearly power generation from different primary energy sources within the two reference scenarios is visualized in Fig. 6.7. For clarity reasons, power generation from oil and run-of-river hydro plants is omitted. These account for less than 1% of power generation. In 2012, 52% of demand is covered by power generation from nuclear plants, while 28% is produced from gas plants. Wind mills, solar panels, and biomass plants contribute 14% of power generation. The remaining part results from coal and hydro. In 2025, significant changes in power generation shares occur. Nuclear and coal plants are phased out, while power generation from gas plants increases substantially due to an increase in CCGTs and CHP plants. Also power generation from wind mills, solar panels, and biomass more than doubles. As power generation from wind mills and solar capacity increases, hourly ramping also increases. Comparing both power generation portfolios, the increase in uncontrollable power generation is noteworthy. While in 2012 uncontrollable power generation amounts 24%, this increases to 54% in 2025.

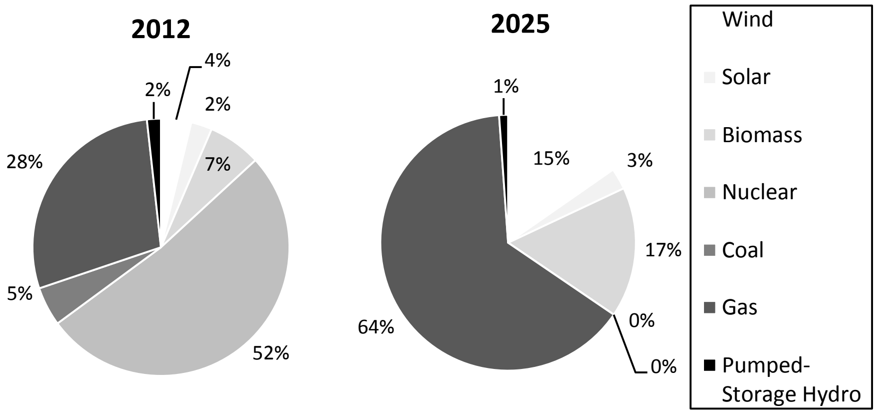

Fig. 6.7. Share of yearly power generation from different primary energy sources in Belgium in 2012 and 2025.

When looking at power plant operation of different technologies, PWRs and SPPs are typically used as base load units, CCGTs as mid-peak plants, while GTs, ICEs, and pumped storage units are used during peaks.

Residential DR affects annual power generation of different power plants. In what follows, the focus is on CCGTs, GTs, and pumped storage units, as DR influences these mid-peak and peak units most (Fig. 6.8). Hereby, annual generation of technologies within each scenario is compared with its reference scenario. Three main observations can be derived. WA scheduling decreases annual generation from mid-peak and peak units. BEV introduction increases the loading of those units. An exception is the decrease of GT loading in 2012, although largely outset by an increased CCGT loading. Finally, the increased loading due to BEV introduction is reduced by scheduling BEVs. In other words, the scheduling of BEVs decreases the impact of a BEV introduction.

Similar effects occur during the peak moments of the year. In Fig. 6.9, load duration curves of CCGTs and GTs are visualized. They depict the highest 300 hours of loading for each technology, covering different power plants. Due to decreased controllable generation capacity, mid-peak and peak plants run longer at full load in 2025 compared to 2012. Demand response, both with WAs and BEVs, decreases the hours mid-peak and peak technologies operate at full capacity. Moreover, in 2012 maximum GT loading is never attained under the scheduled BEV scenario.

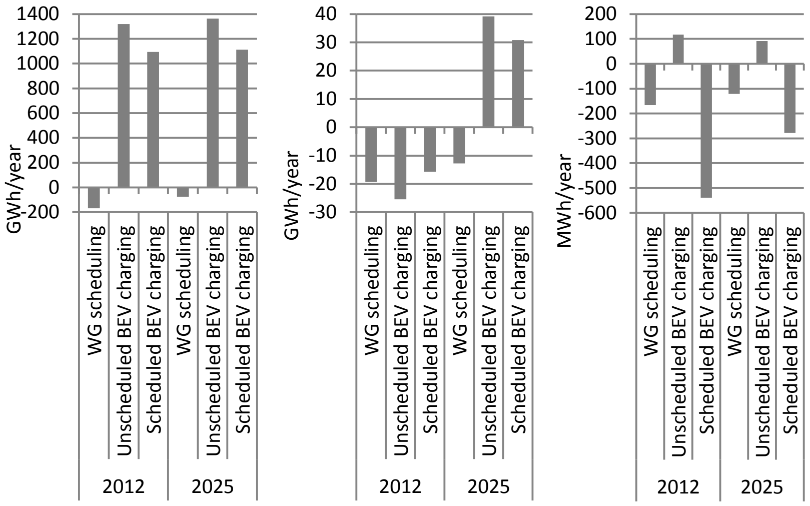

Fig. 6.8. Annual generation difference of CCGTs (left), GTs (middle), and pumped storage plants (right) compared to the 2012 and 2025 reference scenarios.

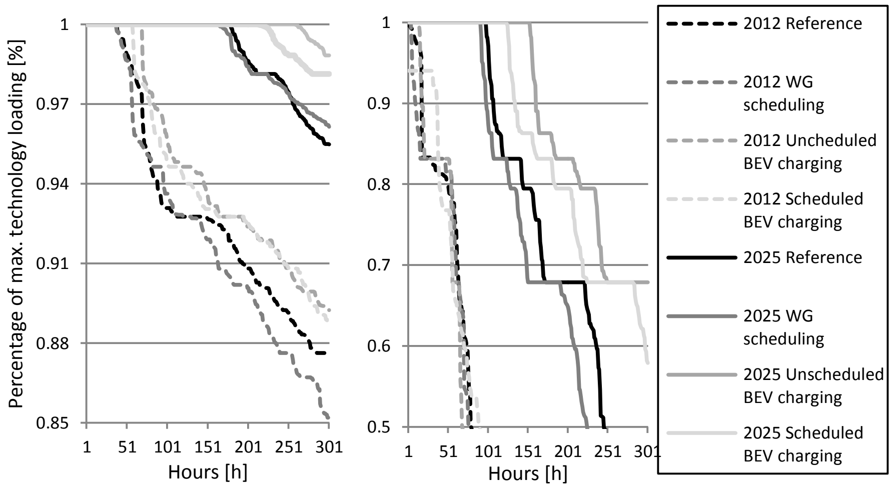

Fig. 6.9. Load duration curve of CCGTs (left) and GTs (right) for the top 300 hours of the year in different scenarios for 2012 (dashed lines) and 2025 (solid lines).

DR also influences the frequency of starting up mid-peak and peak plants within a year (Fig. 6.10). In both 2012 and 2025, the number of start-ups of CCGTs and GTs decreases when WAs are scheduled. This decrease can go up to 180 start-ups of CCGTs in 2012, corresponding to 15% of the reference start-ups. When unscheduled BEV charging is introduced, the number of start-ups goes up. This increase is reduced when BEVs are scheduled. For example, in 2012 the number of start-ups with CCGTs decreases with 437 or 33% compared to the unscheduled BEV scenario.

Except for base load technologies, similar reductions in start-ups are found for other technologies. This illustrates that although the amount of flexible residential demand is limited compared to total demand, residential DR influences the number of start-ups to a large extent.

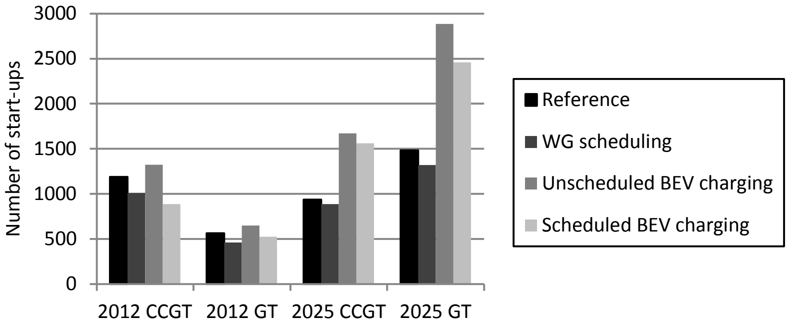

Fig. 6.10. Number of start-ups of CCGTs and GTs in different scenarios.

Reliability

As plant operation is modified by DR, power system reliability is also affected. This impact is visualized in the first two rows of Table 6.3. Reliability is expressed by energy not served (ENS) and loss of load expectation (LOLE). While ENS describes the total amount of electricity demand which could not be delivered, LOLE defines the number of hours in which it is expected that demand cannot be met. As interconnection capacity is not considered, ENS and LOLE should be interpreted with care. While these parameters provide insights in system reliability, actual reliability will be higher as interconnection capacity is available.

Results show that ENS and LOLE are a lot higher in 2025 compared to 2012. This results from the underlying generation portfolio and reserve requirements in both years. In 2012, controllable capacity and reserve requirements are high enough to cover variations in RES, CHPs, and demand. ENS only occurs during forced outages of multiple large power plants. In 2025, demand cannot be met during 200 hours. Although this number is distorted due to the exclusion of cross-border flows, it illustrates that the increase in wind, solar, biomass, CHP, and CCGT capacity and the limited increase in reserve requirements are not sufficient to fully cover the phase out of nuclear and coal capacity. Moreover, it indicates the need for sufficient interconnection capacity as controllable capacity within the capacity constrained portfolio is not always able to cover demand peaks. Together with limited predictability of wind power, this is the main reason of ENS.

Table 6.3. Reliability, emissions, and costs in different portfolios.

	2012 power generation portfolio				2025 power generation portfolio			
	Reference	WA scheduling	Unscheduled BEV charging	Scheduled BEV charging	Reference	WA scheduling	Unscheduled BEV charging	Scheduled BEV charging
ENS [GWh]	6.49	7.07	7.99	8.02	144.90	143.50	199.29	186.04
LOLE [h/year]	25	30	37	37	200	202	266	245
Renewable Surplus [GWh]	0.00	0.02	0.00	0.01	774.15	700.33	630.04	374.55
Emissions [MtCO_2]	8.94	8.92	9.62	9.62	10.37	10.33	11.00	10.86
Total Costs [M€]	1207	1200	1290	1278	1697	1686	1887	1842
Thermal Costs [M€]	1206	1199	1279	1271	1389	1381	1463	1445

ENS not necessarily decreases when DR is introduced. This is a consequence of two counteracting effects. On the one hand DR contributes to peak shaving, reducing ENS when total capacity is constrained, such as in 2025. In this case, DR with wet appliance decreases ENS with 1% compared to the reference case. Scheduling of BEVs also reduces ENS by 7% or 13.25 GWh compared to unscheduled charging. On the other hand, DR results in a decreased number of committed power plants in the day-ahead optimization stage. This can result in a decrease of flexibility from committed plants on top of the reserve requirements as plants are running closer to their capacity limits, yielding more ENS in the real-time simulation stage. Although the impact is small, this effect leads to an ENS increase within the 2012 power generation portfolio.

Environment

Scheduling of WAs and BEVs impacts the environment due to a change in power plant operation. In what follows, this impact is expressed by the amount of renewable surplus or spillage and CO_2-emissions as depicted in the third and fourth row of Table 6.3.

Results show that renewable surplus is zero in 2012 when no DR is used. Towards 2025 renewable surplus increases to 774 GWh due to limited controllability and the variability of wind and solar power generation. This equals almost 1% of annual demand. By scheduling WAs, surplus is reduced by 10%. By scheduling BEVs, the decrease is even higher and amounts to 41% or 255.49 GWh compared to the unscheduled scenario.

Also CO_2-emissions are affected by the underlying generation portfolio and the presence of DR. In 2012, CO_2-emissions amount to 8.94 million ton CO_2 in the reference scenario. Towards 2025, CO_2-emissions increase with 16% due to the nuclear phase out and its replacement by gas. By scheduling WAs, CO_2-emissions decrease to a minor extent. Although WA scheduling decreases the loading of polluting ICE in 2012, this effect is counteracted by an increased loading of coal plants. In 2025, only the loading and the number of start-ups of gas plants are reduced. This has a limited effect on emissions. The introduction of BEVs increases CO_2-emissions from the power system significantly due to increased power generation. Emissions increase with 8% in 2012 and 6% in 2025. Although the effect is limited, the scheduling of BEVs reduces CO_2-emissions compared to the scheduled case. It should be noted that the decrease in emissions due to the electrification of transport is not accounted for.

Cost

Demand response influences annual operational costs. This impact is visualized in the last two rows of Table 6.3. Hereby, only the controllable part of the generation portfolio is considered. Operational costs and subsidies of RES and CHPs are not included. Cost results are split into costs and thermal costs. While thermal costs only account for operational costs, total costs also include costs for not being able to meet demand or reserve requirements.

Results show that costs are higher in 2025. In 2025, total and thermal costs increase with 41% and 15% respectively. The increase in thermal costs is mainly due to the nuclear phase out, which increases the run-time of more expensive thermal plants. Moreover, thermal costs and total costs are of the same order in 2012, while in 2025 total costs are significantly higher. This results from increased violations of demand and reserve requirements, as discussed previously. By introducing DR with WAs, a yearly total cost reduction of 7 and 12 M€ is accomplished for 2012 and 2025 respectively. The cost reduction for 2025 is larger as more ENS is avoided. The thermal cost reduction mainly follows from a reduced use of other sources of flexibility, such as GTs and pumped storage hydro units. When BEVs are introduced, total costs rise substantially. The cost increase is higher in 2025, as future power generation capacity does not allow for a further increase in demand. If BEVs are introduced with scheduled charging, both total and thermal costs decrease with 10-25% compared with unscheduled charging. This ranges from 12 to 45 M€ of total yearly cost reduction and 8 to 18 M€ of thermal yearly cost reduction. This cost decrease is higher in 2025 as more ENS is reduced and less renewable surplus occurs.

6.5 Summary & Conclusions

This chapter studies the impact of demand response on power system operation by scheduling wet appliance and battery electric vehicles. A two-stage modeling approach is used on an hourly data set covering a full year. This allows taking into account both the variability and limited predictability of power generation from RES. Moreover, it provides a detailed representation of flexibility at the demand side. This benefits a realistic outcome allowing to assess a potential introduction of DR.

Results show that in general DR decreases the loading of mid-peak and peak plants over the year and during peak moments. This is also reflected in the reduced number of start-ups of those plants. Renewed plant operation impacts reliability, environment and costs of power system operation. While reliability is affected to a limited extent, DR provides an efficient means to integrate RES and avoid surplus. By shifting only 2% of total consumption towards moments with an excess of generation from RES, up to 41% of renewable surplus can be avoided. Finally, DR decreases thermal costs as less peaking plants need to be operated. This chapter shows that the impact of DR depends on the underlying power generation portfolio. The highest benefits of DR are accrued in a portfolio with a high amount of uncontrollable and renewable capacity.

Looking at the demand side, shifting WA cycles and BEV charging in time contributes to peak shaving. Up to 150 MWh/h and 300 MWh/h of the peak is reduced by WA and BEV scheduling respectively. BEV consumption is mainly shifted towards nighttime, while WA cycles are mainly shifted towards the night and the afternoon. Aside from these general observations, this chapter shows that a large variety in shifting patterns exists. While only 8% of light-duty vehicles or 432 000 BEVs are assumed to contribute to DR, compared to 100% or over 9 million of WAs, system benefits are higher in case of BEVs. This justifies an increased attention for DR with BEVs. While an introduction of unscheduled BEV charging impedes system operation, scheduling facilitates the integration extensively.

While this chapter provides insights into the impact of DR, some limitations are present in the modeling of the power system and DR. In the modeling of the power system interconnection capacity, transmission capacity, market behavior, demand uncertainty, and uncertainty in power generation from solar plants is neglected. Moreover, no stochasticity is included in the day-ahead optimization stage. In the modeling of DR, the willingness of households to provide flexibility and the cost it brings is not included. Furthermore, individual WA characteristics per household are not considered. Integrating this would further benefit a realistic outcome. Other paths for future research are the inclusion of a sensitivity analysis on reserve requirements, residential controllable generation technologies, the provision of reserves by means of DR and vehicle-to-grid charging.

7. Impact of residential demand response on generation investment decisions

7.1 Introduction

In the event of more power generation from renewables and the electrification of energy services, power system operation is challenged as shown in the previous chapter. Traditionally, these operational challenges in turn increase investments in additional generation capacity. As short-term demand response (DR) also helps overcoming these operational challenges, it can also affect generation investment needs.

In the literature, the calculation of the impact of demand response on generation investments is often simplified [163], [164]. Hereby, DR investment benefits are assessed based on a load duration curve (LDC). This curve ranks hourly demand from high to low for a full year of data. Afterwards, the calculation method of investment benefits states that a peak demand reduction during a limited percentage of hours, decreases generation capacity investments with the according level of peak load reduction. To illustrate the reasoning, an example is provided based on the load duration curve for Belgium for 2012 (Fig. 7.1) [141]. The reasoning implies a decrease in generation capacity with 15% when demand can be reduced during 5% of the hours of the year. By multiplying the capacity decrease with the cost of peak generation, the investment benefits of demand response are obtained.

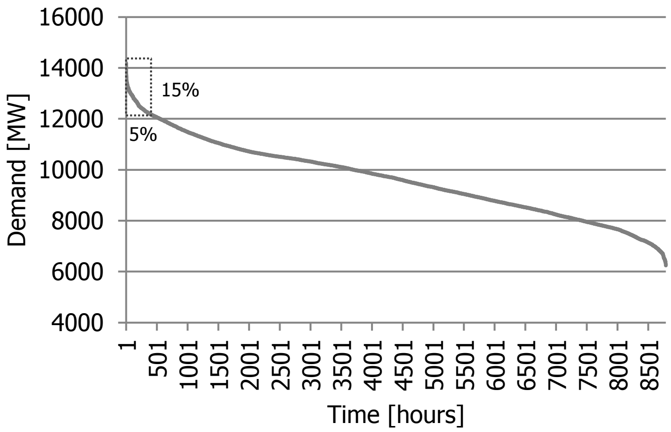

Fig. 7.1. Belgian load duration curve in 2012.

Although determination of the impact of DR on generation investments based on LDC is straightforward, several flaws arise due to neglecting chronology in power generation and demand. First of all, the LDC method does not account for temporal and intertemporal aspects of the operation of dispatchable power plants. Examples are outages or ramping constraints. Next, the impact of variability, limited predictability and limited controllability of generation from RES is not accounted for. Finally, the availability of demand response in time and quantity is not considered. For these reasons, a quantification of investment benefits based on the LDC method leads to unrealistic results and should be avoided. Therefore, detailed short-term power operation should be included when assessing the impact of demand response on generation investment decisions.

Apart from the influence of short-term power system operation, generation investment decisions are also influenced by long-term uncertainty. Although evidence of electrification is rising due to the integration of battery electric vehicles (BEVs) and heat pumps, the long-term evolution is covered by uncertainty influencing generation investment decisions. Also future use of DR with BEVs or wet appliances (WAs) remains uncertain.

To quantify the impact of short-term DR on generation investment decisions, the short-term operational characteristics of both RES and DR should be accounted for together with the long-term uncertainty in demand and demand response. Therefore, these aspects should be integrated in generation expansion planning (GEP) models [165]. These models allow determining the optimal generation investment decision. In general, GEP models consist of a long-term investment model and a short-term operational model. A higher level of detail and sophistication in both models allows a more realistic quantification of the impact of DR.

Within long-term investment models, a distinction is made between static and dynamic investment models on the one hand, and deterministic and stochastic models on the other. In static models an optimal generation portfolio is determined for one specific year, while in dynamic ones multiple decision stages are considered over the planning horizon [166]. In deterministic investment models no uncertainty in variables is considered, while in stochastic ones uncertainty is accounted for. An example is the uncertainty of demand over the planning horizon. To allow for multiple decision stages in which the gradual release of information due to uncertainty is reflected, a stochastic dynamic investment model is needed. Stochastic dynamic programming (SDP) determines the mathematical background of real options (RO) theory, often employed to evaluate financial options [167]. RO was introduced into investment projects in the power system to deal with long-term uncertainties by Dixit and Pindyck [168]. In contrast to the discounted cash flow approach which momentarily decides whether to invest in a project, the real options theory also evaluates whether a postponement of the investment is beneficial.

Hereby the reduction of uncertainty when waiting is accounted for [169]. Consequently the real options theory is mostly referred to as the ”wait and see” approach, while the discounted cash flow resembles the ”now or never” approach [170].

Next to the long-term investment model, the short-term power system operation model of GEP can include different degrees of detail. A widespread approach to capture some operational elements is the screening curve method in which technologies are assigned based on the LDC [171]. As mentioned before, this method neglects the chronology of power system operation. A more sophisticated approach is linear programming, first presented by Massé and Gibrat [172]. This approach optimizes the generation portfolio under a cost minimization objective, taking into account technical constraints of different power generation technologies. Recently these models are updated to determine the optimal generation portfolio under a large share of RES [173], [174].

Although a wide range of GEP models exist in the literature, DR is only considered rarely in these models. In De Jonghe et al. [175], a static single-year optimization approach is used to evaluate DR. Although a detailed operational model is used to reflect RES characteristics, appropriate DR characteristics are neglected. Moreover, the investment model does not account for uncertainty and investment decisions over the different years as the model is static. In Botterud et al. [176], the impact of DR on investments is assessed using a stochastic dynamic programming approach which accounts for uncertainty and for several investment decision stages. Although this leads to a detailed investment model, the representation of operational characteristics of DR and the power generation portfolio can be improved. In Choi and Thomas [177], the impact of DR is assessed in a case study using a deterministic dynamic approach. While a detailed operational model is used, several power plant and demand characteristics are neglected. Finally, Samadi et al. [178] assesses the effect of demand response with a simplified operational model without taking into account uncertainty.

This chapter assesses the impact of short-term DR with WAs and BEVs on generation investment decisions by combining real options theory with a detailed short-term operational model. It allows accounting for short-term operational characteristics and long-term uncertainty in demand or DR growth. Moreover, it allows policy makers to assess the feasibility of DR to help realizing policy targets such as the integration of renewables or a phase out of conventional generation capacity. The focus is on residential DR with WAs and BEVs. This approach contributes to the state-of-the-art in two domains:

- existing GEP models are complemented by an accurate representation of DR and an accurate short-term operational model, and
- this approach is applied to the Belgian case to draw relevant conclusions.

Note that the program to address the demand side is not discussed in this chapter as this is a potential study. Therefore, the demand response programs can be both price-based and incentive-based in line with Chapter 1.

Section 7.2 describes the GEP model used to optimize generation investment decisions. Section 7.3 elaborates on the data and assumptions for demand, DR, and generation. Results are highlighted in Section 7.4 and Section 7.5 concludes.

7.2 Model

The subsequent levels of the GEP model are depicted in Fig. 7.2. A discrete state space is created to represent the various compositions of the future power system. This state space covers all potential investment decisions and demand fluctuations over the planning horizon. A detailed two-step operational model is applied to calculate operational costs for each state in the state space. RO-theory is used by means of a stochastic dynamic programming model, leading to an investment decision in the first stage based on the calculated operational costs. Finally, an investment simulator assesses the optimal investment paths throughout the long-term planning horizon. Each level is described in detail.

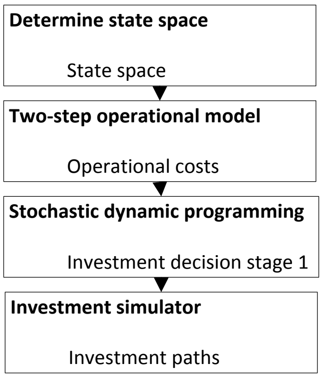

Fig. 7.2. Subsequent levels in generation expansion model.

7.2.1 Determination of state space

The discrete state space contains a finite number of possible states where the power system can end up in during the planning horizon. Typically, a state of the power system is defined by the power generation portfolio and the demand. The power generation portfolio within each state depends on the current power generation portfolio, planned investment and phase out decisions, and on new investment decisions. The latter leads to a decision tree over the considered planning horizon. A visualization of the different states over the different stages is depicted in Fig. 7.3. An increase in the number of possible investment decisions within one state enlarges the decision tree and therefore the state space. Demand and DR growth within each year depends on external factors such as the electrification of energy services and the willingness of users to offer DR resources. The variation in demand and DR growth is covered by uncertainty, leading to an uncertainty tree over the considered planning horizon. In this tree each path between two states is characterized by a probability of occurrence. An example of an uncertainty tree with two possible demand growth scenarios each characterized by a probability of occurrence (P_{up} and P_{down}) is visualized in Fig. 7.4. A similar uncertainty tree can be constructed for DR growth. A combination of the decision and uncertainty tree results in the total state space. After the planning horizon, a non-flexible period is added in which the states are equal to the respective state in the last stage. This period allows investments made in the last investment stages to be earned back.

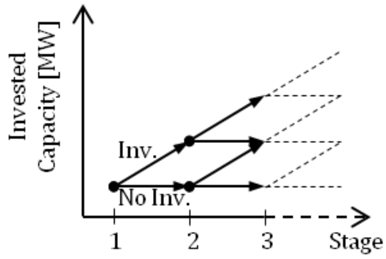

Fig. 7.3. Decision tree characterized by different states in different stages.

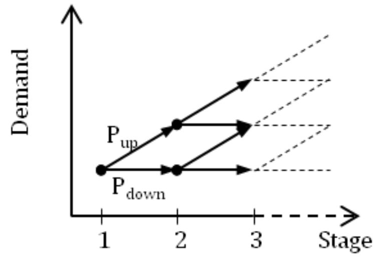

Fig. 7.4. Uncertainty tree characterized by different states in different stages.

7.2.2 Two-step operational model

A detailed two-step operational model is applied on each state of the state space. This model aligns with the operational model as described in Section 6.2. This model accounts for demand response and approximates real-life power system operation by combining two sequential steps: an optimization in day-ahead by means of a deterministic unit commitment and economic dispatch model, and an hourly simulation updating the economic dispatch in real-time. Based on this model, the operational costs for each state of the state space are obtained.

7.2.3 Stochastic dynamic investment model

Once all annual generation costs for each state are calculated, the investment model determines the expected total cost for the entire planning horizon based on RO-theory. The mathematical description of this model is:

$$J_1(\boldsymbol{x_1}, d_1) \;=\; \min_{\boldsymbol{u}_1,\dots,\boldsymbol{u}_{T-1}} \underset{\omega}{\mathrm{E}} \left\{ \sum_{k=1}^{\mathrm{T}-1} \left[\frac{1}{(1+r)^{k-1}} \cdot c_k(\boldsymbol{x_k}, d_k, \boldsymbol{u_k}) \right] + \frac{1}{(1+\mathrm{r})^{\mathrm{T}}} \cdot f_T(\boldsymbol{x_T}, d_T) \right\} \tag{7.1}$$

$$\boldsymbol{x_{k+1}} = \boldsymbol{x_k} + \boldsymbol{u_k} \tag{7.2}$$

$$d_{k+1} = d_k + \omega_k \tag{7.3}$$

$$c_k(\boldsymbol{x_k}, d_k, \boldsymbol{u_k}) = oc(\boldsymbol{x_k}, d_k) + \boldsymbol{u_k} \cdot \mathrm{ic} \tag{7.4}$$

$$f_T(\boldsymbol{x}_T, d_T) = c_T(\boldsymbol{x}_T, d_T | \boldsymbol{u}_T = 0) \cdot \frac{1-(1+r)^{-\mathrm{T_{NF}}}}{r} \tag{7.5}$$

$$\boldsymbol{x_k} \in \Omega_{\boldsymbol{x},k},\; d_\mathrm{k} \in \Omega_{d,k},\;\; \boldsymbol{u_k} \in \Omega_{\boldsymbol{u},k},\;\; \omega_k \in \Omega_{\omega,\mathrm{k}} \tag{7.6}$$

where,

$c_k(\boldsymbol{x_k}, d_k, \boldsymbol{u_k})$ = cost in period k to fulfill demand d_k with a given generation portfolio [€],

$f_T(\boldsymbol{x_T}, d_T)$ = operational cost of non-flexible periods T_{NF} actualized to period T [€],

$J_1(\boldsymbol{x_1}, d_1)$ = minimum total expected costs [€],

d_k = electricity demand in period k [MW],

$oc(\boldsymbol{x_k}, d_k)$ = minimum operational costs obtained from operational model [€],

$\boldsymbol{u_k}$ = investment decision in period k [MW],

$\boldsymbol{x_k}$ = total installed capacity in period k [MW],

ω = long-term uncertainty of demand growth for electricity,

ic = investment cost for thermal plants [€],

r = discount factor [%],

T = planning horizon [periods],

$\mathrm{T_{NF}}$ = number of non-flexible periods after the planning horizon in which the variables stay constant [periods],

$\Omega_{x,d,\boldsymbol{u},\omega}$ = state space.

This description only accounts for demand growth, but the description for demand response growth is similar.

The RO-model is solved by SDP and is based on previous work of Botterud et al. [176] and Mo et al. [166]. Equation (7.1) shows that the total expected actualized cost is minimized taking into account the uncertainty in demand growth ω. The current investment decision $\boldsymbol{u_k}$ determines the total installed capacity in the next stage $\boldsymbol{x_{k+1}}$ according to (7.2). This equation shows an investment decision is only effective in the next stage. Equation (7.3) shows that uncertainty in demand growth ω_k defines the demand level in stage k+1 given a probability distribution. As indicated in (7.4), total costs c_k consist of the operational and the investment costs. Apart from the planning horizon, a non-flexible period T_{NF} is added after the planning horizon. The costs of this period are actualized to the last stage of the planning horizon by (7.5). Finally, equation (7.6) defines the state space of the variables.

To obtain the expected total actualized cost for the entire planning horizon, the model starts its procedure in the last stage of the planning horizon T and iterates back until the first stage. The backward iteration is based on:

$$J_k(x_k, d_k) \; = \; \min_{\boldsymbol{u_k} \in \, \Omega_{u,k}} \left\{ c_k(\boldsymbol{x_k}, d_k, \boldsymbol{u_k}) + \frac{1}{(1+r)} \; \cdot \; \underset{\omega}{\mathrm{E}} \left[J_{k+1}(\boldsymbol{x_k}, d_k, \boldsymbol{u_k}) \right] \right\}. \qquad 7.7$$

Once the expected costs in the states of stage k+1 are known, the optimal paths to the states in stage k are determined, leading to an investment decision $\mathrm{u_k}$ with minimum total expected costs for each state. This procedure is repeated until the first stage is reached leading to the optimal investment decision in this period.

7.2.4 Investment simulator

Although the RO-model derives the optimal investment decision for the first stage, it does not provide insight in investment decisions over the entire planning horizon. Therefore, a simulator is created to determine the optimal investment paths while accounting for the gradual release of information over the years. The simulator starts from the optimal investment decision in the first stage based on the RO-model. Afterwards, the simulator randomly draws a demand growth based on given probabilities in the state space, as elaborated on in subsection 7.2.1. In the second stage, the RO-model is rerun subject to the investment decision and realized demand growth from the previous stage. This results in a new investment decision for stage 2. This process is repeated until the complete investment horizon is covered and the investment paths over the different stages are known. The simulation is repeated multiple times to cover various demand evolutions in order to determine the probability of each investment path.

7.3 Data & assumptions

The impact of DR on generation investment decisions is assessed within a Belgian case study (Fig. 7.5). Two alternative cases are considered. In the first one, the impact of DR with wet appliances (WAs) is evaluated; in the second the impact of DR with battery electric vehicles (BEVs) is assessed. These cases are referred to as the WA and BEV cases respectively. In both cases the impact of demand response is assessed by comparing a scenario without and with demand response, referred to as the unscheduled and scheduled scenario respectively. Both scenarios of each case are solved separately with a GEP model. Within each case and scenario, uncertainty is integrated in different ways. For the WA case, no uncertainty is assumed in the unscheduled scenario while uncertainty in demand response growth is included in the scheduled scenario. For the BEV case, uncertainty in the integration of BEVs is assumed in the unscheduled scenario. In the scheduled scenario this uncertainty comes along with the uncertainty in demand response growth. In what follows, data and assumptions for both cases and scenarios are further discussed for each of the subsequent levels of the generation expansion model.

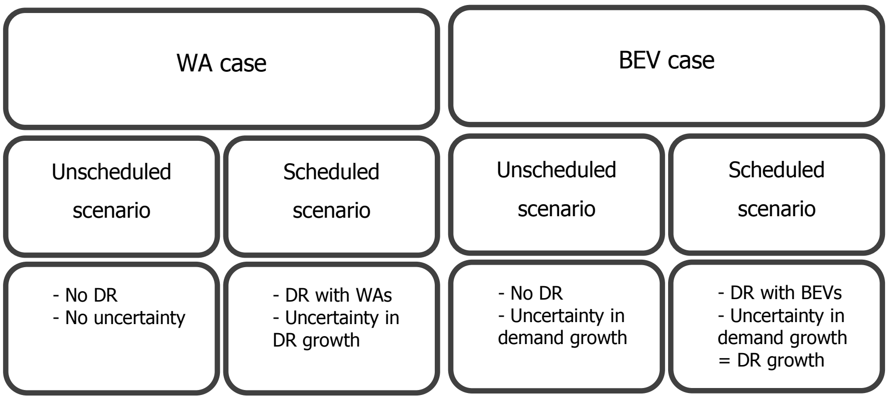

Fig. 7.5. Overview of cases and scenarios tested with the GEP model.

7.3.1 State space

The planning horizon of the complete state space covers 14 years, from 2013 until 2026. The horizon is split in 7 stages of two years each. Each state is defined by the power generation portfolio and its accompanying decision tree, and the demand and its accompanying uncertainty tree.

The initial installed Belgian power generation portfolio is in line with the one from Section 6.3.2. Nevertheless, internal combustion engines (ICEs) are neglected to limit calculation time. Moreover, the state space accounts for the gradual evolution of installed capacity, considering different primary energy sources such as nuclear, coal, gas, wind, solar, biomass, and hydro capacity (Fig. 7.6).

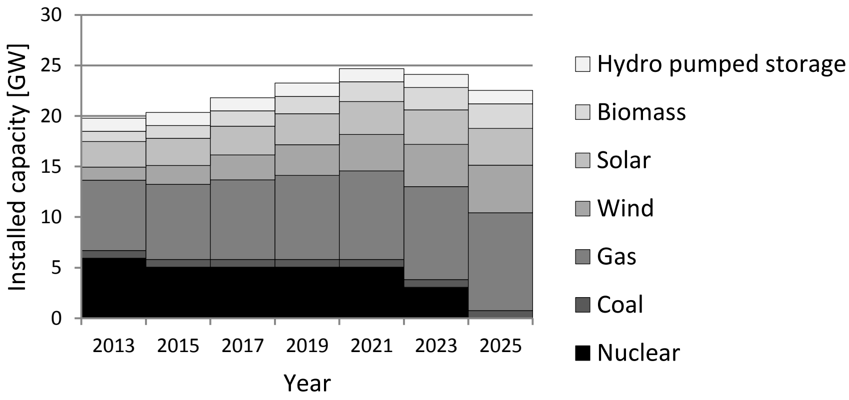

Fig. 7.6. Installed capacity of different primary energy sources over the planning horizon in Belgium.

On top of the planned capacity evolution, new capacity can be added based on an investment decision tree. Except for the final stage, in every stage an investment decision is taken. This decision entails the construction of two combined cycle gas turbines (CCGTs) with a capacity of 300 MW each. Plants are online after 2 years.

Next to the power generation portfolio, the state space is determined by demand. Demand in Belgium is obtained from hourly load data of the first 6 months of 2012, as provided by ENTSO-E [179]. This 6 months period is long enough to enable representativeness while limiting calculation time. Total demand in this period adds up to 43.77 TWh. The average, maximum, and minimum hourly demand amounts to 9.97, 14.2, and 6.50 GWh respectively. In view of comparability, the historic demand pattern is assumed to be equal in the different stages of the considered planning horizon. Based on the uncertainty trees of the WA and BEV cases, the demand pattern is adapted. Note that no industrial DR participation is assumed.

In the WA case, uncertainty in DR growth is assumed while the number of wet appliances remains constant. From one stage to the next demand response with WAs stays equal or increases. This stepwise increase between stages amounts to 20% of all Belgian wet appliances. The chance of this stepwise increase is assumed to be equal to the chance that the amount of DR remains the same, namely 50%. In the final stage, this leads to a maximum and minimum level of DR with WAs of 100% and 0% respectively. Consequently, the expected share of DR with WAs at the end of the planning horizon equals 60% of all WAs.

In the BEV case, uncertainty in DR is assumed due to the integration of BEVs. From one stage to the next either demand stays equal or increases due to power consumption from BEVs. The stepwise increase in BEV share between two stages amounts to 10% of all Belgian light-duty vehicles [180]. The chance that the amount of BEVs increases between two stages is assumed to be equal to the chance that no increase occurs, being 50%. In the final stage, this leads to a maximum and minimum BEV penetration level of 60% and 0% respectively. Consequently, the expected share of BEVs at the end of the planning horizon equals 30% of all Belgian light-duty vehicles.

A combination of the decision tree on the power generation side with the uncertainty tree on the demand side leads to 1 or 1*1 state in the first stage and 49 or 7*7 states in the final stage. In total, 140 distinctive states determine the state space. Besides the stages within the planning horizon, the non-flexible period T_{NF} considered after the planning horizon counts 25 years.

7.3.2 Operational problem

For each state of the state space, the daily operational model is executed for 6 months of hourly data. In this model, technical characteristics of power generation plants, WAs, and BEVs are integrated according to Section 6.3.

Within the WA case, the expected amount of consumption available for DR purposes at the end of the planning horizon amounts to 0.58 TWh or 1.32% of total demand. Within the BEV case, the expected number of BEVs at the end of the planning horizon corresponds to an additional power consumption level of 3.85 TWh, or 8% of the total envisioned historic demand.

As mentioned before, two scenarios are considered for both the WA and BEV case. These scenarios are included in the operational model as follows. Within the unscheduled scenario of the WA case, no DR is assumed. Therefore, power consumption of WAs aligns with historic power consumption. For the scheduled scenario of the WA case, power consumption from WAs is optimized according to Section 6.3.1. For the unscheduled scenario of the BEV case, the charging of BEVs cannot be scheduled in time and is modeled as an input. This assumes that BEVs start charging as soon as the vehicle is not driving until the maximum state of charge of the battery is reached or the vehicle departs again. For the scheduled scenario of the BEV case, the timing and quantity of power consumption from charging of BEVs is optimized. Comparison between the unscheduled and scheduled scenario within both the WA and BEV case allows assessing the impact of demand response.

7.3.3 Investment problem

Once the operational costs for every state are determined, the investment costs are defined and integrated in the real options model. Based on reference [181], the investment cost of CCGT capacity amounts to 727 €/kW$_e$. As the real option model determines the investment decision in the first stage, operational and investment costs need to be discounted. The discount rate is set to 10% [181].

7.4 Results

7.4.1 Operational costs

The annual operational costs of all feasible paths in the scheduled scenarios of the WA and BEV case are visualized in Fig. 7.7. Although each path is not clearly distinguishable, the figure illustrates the cost spread resulting from DR growth, demand growth and investment decisions over the planning horizon. For clarity reasons, annual costs higher than 2500 M€ are not visualized. The cost spread is larger in the BEV case. This illustrates that demand growth with BEVs increases costs substantially. The cost spread increases towards the end of the planning horizon which reveals a close link with the underlying generation portfolio. After 2013 costs tend to increase as nuclear capacity is phased out. The following years, the integration of RES leads to a cost decrease while in 2023 and 2025 cost rise again due to the completion of the nuclear phase out. In these years, the integration of BEVs and the installed capacity of CCGTs largely impact operational costs illustrated by the large cost spread. Although not visualized in the figure, annual costs in the BEV case can go up to 6759 M€. This aligns with the situation in which no investments are made while the number of BEVs constantly increases. Moreover, the unscheduled scenario for the BEV case has an even higher spread as the annual costs reach 7376 M€.

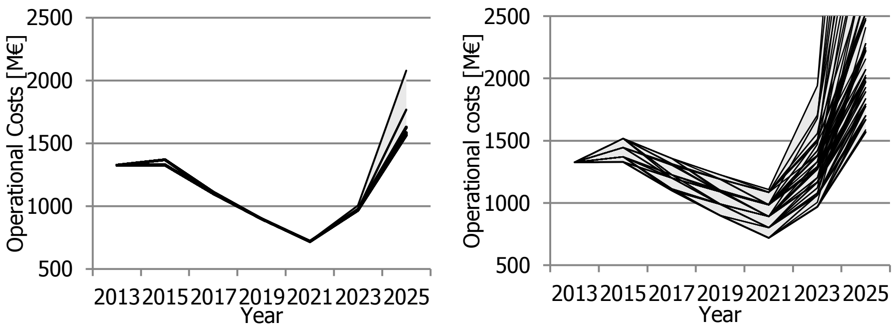

Fig. 7.7. Feasible operational cost paths over the planning horizon in the scheduled scenario of the WA case (left) and the BEV case (right).

7.4.2 Investment decision stage 1

The cost results for investment decisions in stage 1 are depicted in Table 7.1 for both the unscheduled and scheduled scenarios in the WA and BEV case. Distinction is made between operational and investment costs in stage 1, and actualized future operational and investment costs. Operational costs in stage 1 are based on extrapolation from 6 months to a year and covers both operational costs in this year and actualized operational costs of next year. These costs are equal in the different scenarios as no DR with WAs or BEVs is integrated yet and the investment decision only results in functioning power plants from stage 2 onwards. For actualized future costs, they depend on the case, the scenario and the investment decision.

Table 7.1. Cost results for investment decisions in stage 1 for the unscheduled and scheduled scenario of the WA and BEV cases.

Case	Scenario	Investment Decision	Operational costs [M€]	Investment costs [M€]	Actualized future costs [M€]	Total costs [M€]
WAs	Unscheduled	Do not invest	2.533	0	11.555	14.086
		Invest	2.533	436	11.269	14.237
	Scheduled	Do not invest	2.533	0	11.529	14.060
		Invest	2.533	436	11.243	14.211
BEV	Unscheduled	Do not invest	2.533	0	14.039	16.572
		Invest	2.533	436	13.609	16.578
	Scheduled	Do not invest	2.533	0	13.816	16.349
		Invest	2.533	436	13.405	16.373

In the WA case, investment in CCGTs decreases future costs in both scenarios. This cost decrease is lower than the investment costs itself. Therefore, it is optimal in both scenarios to postpone investment in CCGTs. Comparing both scenarios, costs are lower when DR is used. Scheduling of WAs leads to an actualized cost reduction of 26 M€.

In the BEV case, the actualized future cost decrease due to investment is again lower than the investment cost itself. Therefore, not investing in the first stage is optimal. Moreover, scheduling BEVs brings an actualized cost reduction of 223 M€ compared to the unscheduled scenario, i.e. 1.3% of total costs.

Comparing both cases, actualized total costs increase significantly when BEVs are integrated. For the unscheduled scenarios, integration of BEVs leads to a cost increase of 2486 M€ or 18% of total costs in the WA case. Moreover, this cost increase is significantly lower in the scheduled scenario. Comparing the impact of DR with WAs and BEVs, the impact of WA scheduling on total costs is minor due to two main reasons. First, the generation portfolio operates closer to its limits in the BEV case due to demand growth. This increases the influence of DR. Second, the amount of energy usable for DR is higher in the BEV case. The 10% increase in BEVs between two stages aligns with 0.64 TWh, while 20% of WAs only aligns with 0.20 TWh.

7.4.3 Investment paths

The different optimal investment paths over the different simulations for the WA and BEV case are depicted in Fig. 7.8. Hereby, distinction is made between the scheduled and unscheduled scenarios. Each optimal investment path is represented by a line which increases when investments are made and remains horizontal otherwise. The optimal investment paths largely differ between the WA and BEV case. Both the unscheduled and scheduled scenario of the WA case only count two investment increases while the BEV case counts three or four. This illustrates the demand growth due to integration of BEVs influences generation investment decisions. The WA case only depicts one optimal investment path while the BEV case has several. This illustrates that DR with wet appliances has no influence on generation investment decisions, while demand growth and DR with BEVs influences investment decisions in several ways due to its uncertainty.

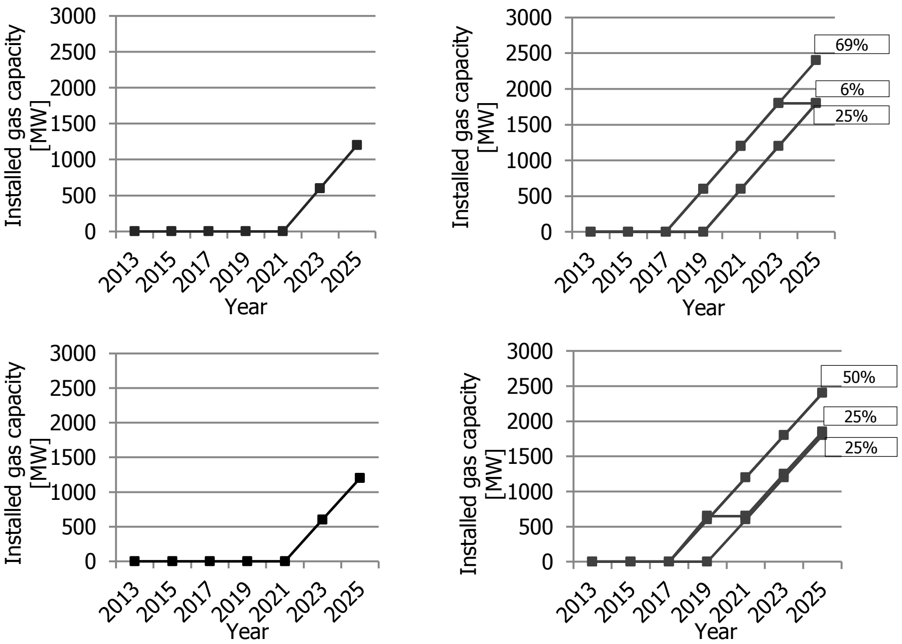

Fig. 7.8. Optimal investment paths over the planning horizon for the unscheduled (top) and scheduled (bottom) scenario in the WA case (left) and BEV case (right).

Focusing on the WA case, it can be noticed that investments are only needed towards the end of the planning horizon. Driven by the nuclear phase out, additional capacity is installed towards 2023 and 2025. This is independent of the inclusion of DR with WAs. Therefore, DR with WAs does not affect generation investments.

Focusing on the BEV case, three optimal investment paths exist for both unscheduled and unscheduled scenario. Within each scenario, the optimal paths differ due to distinctive demand growth resulting from the uncertainty tree. For each path, its occurrence in percentage is listed. In the beginning of the planning horizon, no capacity is installed in both scenarios. Based on an investment decision in 2017, installed capacity goes up towards 2019 in 75% of the cases for both scenarios. When no BEVs are integrated towards 2017, the investment decision is postponed. Otherwise, an investment is made. Starting from 2021, a difference occurs between the investment paths in both scenarios. While installed capacity always increases in the unscheduled, capacity remains equal in 25% of the cases in the scheduled scenario. This aligns with the case in which the BEV share amounts to 10% and an investment in CCGTs was already made in the past. This illustrates that DR can defer investment decisions depending on the number of BEVs integrated. The impact of DR is also observed towards the end of the planning horizon. While in the unscheduled scenario total installed capacity is 2400 MW in 69% of cases, this amounts to 50% in the scheduled scenario.

7.4.4 Power system operation paths

The optimal investment paths, resulting from minimizing the expected total costs, affect power system operation over the planning horizon. In this subsection, power system operation is assessed based on three parameters: operational costs, energy not served (ENS), and renewable surplus. This allows evaluating to which extent DR helps reaching current Belgian policy targets.

The evolution of power system operation is visualized in Fig. 7.9. Each of the three parameters is extrapolated to cover a full year. Distinction is made between the WA and BEV case. Different optimal paths over the planning horizon exist for both cases depending on previous investment decisions, DR and demand growth. In each subfigure, distinction is made between an area covering the unscheduled and one covering the scheduled scenario. The borders of the areas represent the minimum and maximum optimal paths. Due to limited impact of DR with WAs on power system operation, these areas almost coincide for operational costs and ENS. On the contrary, Fig. 7.9 shows clearly distinguishable areas in the BEV case. Next to the areas, median paths are represented in white. They result from the probability distribution of DR with WAs or BEVs. For clarity reasons the different optimal paths within the BEV case are only visualized for the scenario covering the smallest area. In case of operational costs and ENS, this area entails the scheduled scenario, while for renewable surplus it entails the unscheduled.

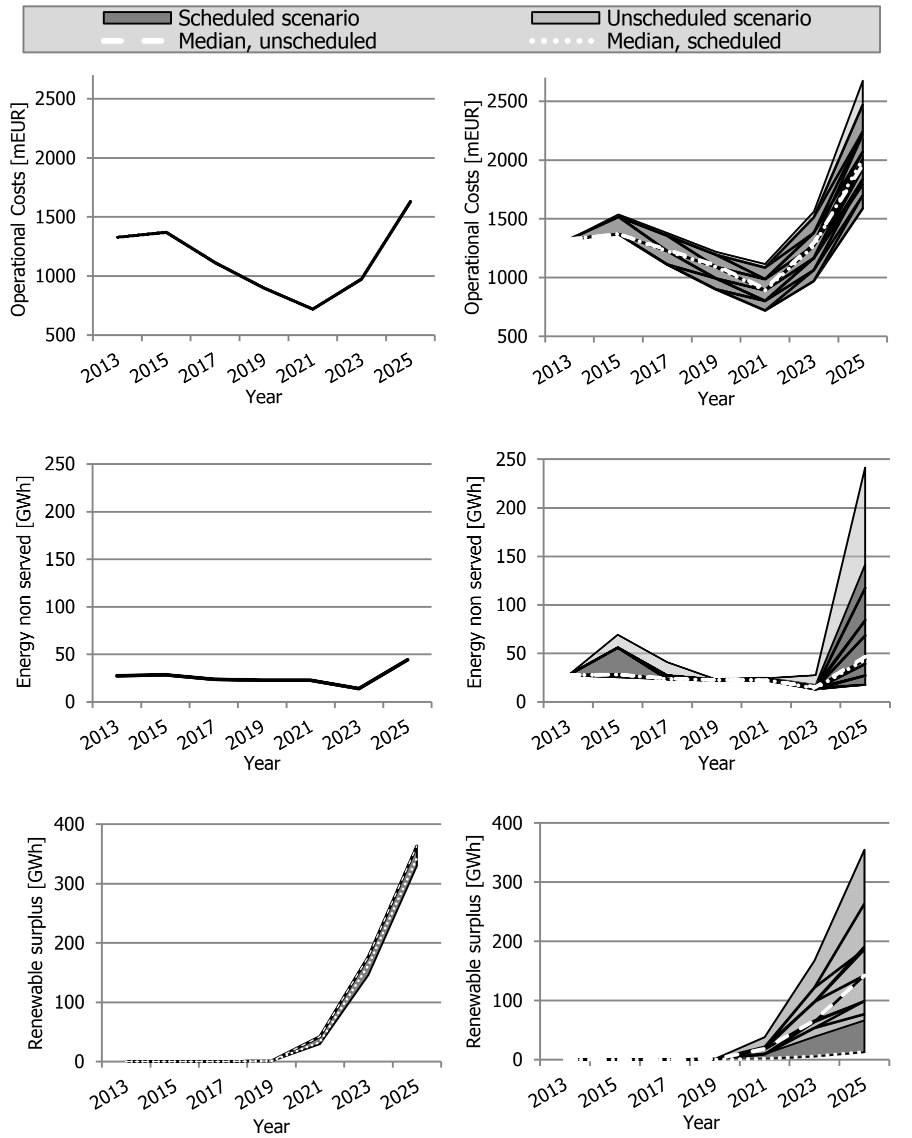

Fig. 7.9. Operational cost paths (top), energy non served paths (middle) and renewable surplus paths (bottom) in the WA (left) and BEV (right) cases corresponding to the optimal investment decisions. The median unscheduled pattern are represented in dashed white lines while the median scheduled patterns are represented in dotted white lines.

While the top figures of Fig. 7.7 depict the operational costs of all feasible investment paths, Fig. 7.9 only accounts for operational costs associated with the optimal. In the latter costs also go up towards the end of the planning horizon. Compared to Fig. 7.7, this cost increase is limited as investments are made in several stages. While in Fig. 7.7 operational cost go up to over 2000 and 6500 M€ for the WA and BEV case respectively, costs are now limited to 1600 and 2700 M€ for both cases. While in the BEV case the minimum and maximum optimal paths are clearly distinct, the minimum and maximum cost paths almost align in the WA case, due to the limited impact of DR with WAs on operational costs. In the final stage the difference between operational costs is limited to a maximum of 9 M€. In the BEV case, the minimum cost path is the same in both scenarios and aligns with the case when no BEVs are integrated. Comparing the median of the optimal cost paths between scenarios, illustrates that operational costs do not necessarily go down when DR is used. Although the effect is minor, this is related to the deferral of investments. The reduction in investment cost by using DR outperforms the higher operational costs.

The middle figures of Fig. 7.9 show the energy not served over the planning horizon. This parameter covers the amount of electricity which could not be delivered to the consumers. Although ENS is always present, ENS goes up towards 2025 in the WA case. It results from the full nuclear phase out. Hereby, the impact of DR with WAs remains negligible as no significant difference in the ENS paths is found. Nevertheless, larger spread is observed for the BEV case. Hereby, ENS increases towards 2015. This follows from a combination of the decommissioning of a nuclear plant and the integration of BEVs. This illustrates that current installed controllable generation capacity is limited. Towards 2025, the amount of ENS increases with more than 100% in several optimal paths of the BEV case. This follows from the full nuclear phase out and BEV integration. Comparing both scenarios, the minimum optimal path is the same while the maximum path is higher if no DR is used. Therefore, BEV scheduling limits the increase of ENS when thermal capacity is phased out. As interconnection capacity is not considered, ENS should be interpreted with care. While this parameter provides insights in system reliability, actual reliability is also influenced by interconnection and transmission capacity.

Finally, the bottom figures of Fig. 7.9 show the renewable surplus over the planning horizon. This covers the part of power generation from wind farms which is curtailed. For both the WA and BEV case, no power generation from RES is curtailed in the first stages, while in later stages surplus cannot be avoided due to the RES increase. While the spread in the final stages is again larger for the BEV case, DR with WAs also has a considerable impact on renewable surplus. Hereby, scheduling WAs decreases renewable surplus. Nevertheless, impact is larger for BEVs. Comparing between the unscheduled and scheduled scenario, the maximum optimal path align for both, while the minimum and median paths differ. DR largely reduces the renewable surplus. In more than 50% of cases, surplus remains below 20 GWh if DR is used. Therefore, DR with BEVs contributes to renewables integration.

7.5 Summary & Conclusions

This chapter investigates the impact of demand response on generation investments by means of a GEP model which accounts for detailed power system operation and uncertainty in demand or demand response growth over the planning horizon. This approach allows evaluating investment decisions over multiple stages within the planning horizon and to quantify the cost reduction demand response brings. It can be used by policy makers to assess the feasibility of promoting demand response and to understand how demand response helps accomplishing policy targets such as the integration of RES or the phase out of nuclear power plants.

This model is applied to the Belgian power system in which nuclear capacity is phased out and more RES are integrated towards 2026, while demand response and the integration of BEVs is subject to uncertainty. As shown in this chapter, alignment with the Belgian renewable and nuclear phase out targets leads to a considerable increase in operational costs if only the planned power generation investments are completed. To maintain cost-effective system operation an additional capacity of 1.2 GW is required. In case BEVs are integrated, the required capacity even reaches between 1.8 and 2.4 GW. Nevertheless, demand response can limit this investment need in quantity and time.

Scheduling BEVs leads to a reduction of invested capacity of 600 MW in 19% of the cases. Moreover, during the planning horizon investments can be postponed in time decreasing actualized costs. Overall, an actualized cost reduction of 223 M€ or 1.3% of total costs is reached by BEV scheduling. Given that no BEVs are integrated yet and that future power consumption of BEVs is limited compared to total demand, this cost decrease is substantial and calls for the inclusion of demand response within power system operation. Therefore, a potential breakthrough of BEVs should support scheduled charging in order to decrease the impact on power system costs. The opposite is true for WAs scheduling. Opposed to BEV scheduling, WA scheduling does not influence investment decisions. This follows from the limited amount of energy resulting from the use of WAs. Nevertheless, a modest actualized cost decrease of 26 M€ is obtained by scheduling WAs following from operational benefits.

Given the investment decisions in the unscheduled and scheduled scenarios in the WA and BEV cases, power system operation is influenced in three different ways: operational costs, energy not served and renewable surplus. For both operational costs and energy not served the impact of WA scheduling is minor. Only renewable surplus is influenced to a larger extent. Nevertheless, scheduling of BEVs largely influences all three parameters. Although demand response decreases operational costs within a specific year, it is shown that they can increase over the planning horizon when demand response is implemented. The increase is caused by a deferral of investments. However, the cost benefit of the investment deferral surpasses the increase in operational costs. This chapter also illustrates that the energy not served in the power system as a consequence of the nuclear phase out can be limited by using demand response with BEVs. Finally, this chapter shows that demand response with BEVs provides an efficient means to integrate more RES by decreasing renewable surplus. Therefore, the scheduling of BEVs helps reaching Belgian policy targets.

While this chapter contributes to the state-of-the-art research concerning the impact of demand response on power system operation and investments, several improvements can still be made. A first improvement is the inclusion of interconnection capacity and the transmission grid in the operational model. Next, other technologies with various capacities can be integrated in the decision tree. Although this contributes to a more realistic outcome, the state space will increase magnifying the calculation time. Finally, a deeper assessment of the uncertainty tree can lead to a more realistic outcome.

PART IV

Conclusions and recommendations

8. Summary, conclusions and recommendations

8.1 Summary & Conclusions

Against the background of a push towards renewables, electrification of energy services and an ageing infrastructure, the need for flexibility within power system operation is growing. While flexibility can be obtained from several resources, this thesis explores the use and usefulness of flexibility at the residential demand side triggered by dynamic electricity prices, referred to as residential demand response (DR) based on dynamic electricity prices (DP).

Although residential DR based on dynamic electricity tariffs is a known topic in the literature, its use and understanding is still limited. Current electricity tariff designs fall short on incentivizing DR. Moreover, no clear indication or quantification is available on how residential users react to more dynamic pricing schemes. Finally, benefits resulting from DR remain largely unknown.

To address this limited understanding, this thesis enhances knowledge of residential DR and DP. It contributes by answering these research questions:

- What are demand response and dynamic electricity pricing?
- How should dynamic electricity prices be designed?
- To which extent do residential users modify their power pattern as a reaction to DP?
- How can this modification be quantified and predicted?
- What benefits do these load modifications bring for residential users and for power system operation and investments?

In what follows, first the answers to these research questions are provided by discussing conclusions and contributions of each chapter. Afterwards, general findings on the use and usefulness of DR are provided.

8.1.1 Research findings

Chapter 1 provides insights in the concept of DR. Different categories are discussed distinguishing between the purpose it is used for and the benefits it brings, the user classes it serves, and the load types targeted. It shows that momentum towards implementation of residential DR is gaining as all stakeholders are recognizing its value and even promoting it. This is reflected at the level of policy, regulation, standardization and the energy industry. Moreover, the rise of smart metering systems, advanced ICT and automation further pushes DR from research towards implementation. Although limited, current implementation of DR mainly covers the commercial and industrial sector. Nevertheless, the potential of residential DR is substantial and its implementation is on the verge of a breakthrough.

Chapter 2 elaborates on price-based DR programs. More specifically, focus is on locational dynamic pricing (LDP) in which prices depend on time and location. While traditional tariff schemes fail to reflect costs that specific households cause and fail to trigger DR, LDP aims at valuing residential consumption and generation against their contribution to the whole electricity system. Moreover, it aims at triggering DR. In this context, this chapter provides a theoretical framework to design and assess LDP. It starts from specific costs incurred at the generation, transmission, distribution and retail level. Locational and time dependency of each cost is assessed according to its cost drivers: energy usage, system's peak, and cost independent of usage or peak. As usage and peak typically depend on the time of the day, most costs driven by these drivers can be made time dependent. This leaves substantial potential for adding dynamics to tariff schemes. Moreover, locational dependency of costs also relates to locational dependency of its cost drivers. If costs are driven by usage or system's peak at local level, costs should be assigned to this local level. If costs are induced by usage or peak at global level, costs should be shared among its beneficiaries at the global level. When translating these costs into tariff schemes, general principles of tariff design need to be accounted for. Hereby, distinction is made between principles related to practical consideration and social acceptability on the one hand and cost related principles on the other. While traditional tariff schemes typically align with the former, cost related principles such as cost causality are harmed. In contrast, LDP largely meets cost related principles. Although practicalities to attain perfect cost causality still exist, technological and economic breakthroughs in ICT, metering and automation lead the way to the implementation of LDP. Apart from meeting cost causality, this also triggers DR. Hereby, the level of DR depends on tariff design. The latter is determined by concepts such as advance notice, length of price blocks and length of price pattern. These concepts in their turn affect the general tariff principles related to social acceptability and cost, often in a contradictory way. Therefore, a balance should be found between tariff principles related to costs and social acceptability on the one hand and its resulting DR incentive on the other.

Chapter 3 develops different dynamic pricing schemes. They differ in advance notice, length of price blocks and length of price patterns. Hereby, averaging over multiple price periods reduces the peak and increases the off-peak tariff. Therefore, variability decreases and the DR incentive gets smaller as price differences lower. Five tariff designs are discussed: flat, time-of-use (ToU), critical peak (CPP), real-time (RTP) and renewable pricing (REN). These tariff schemes are categorized in three types based on their objectives: meet cost causality, decrease demand during critical events, and align demand with power generation from RES. The first type covers flat, ToU, and RTP tariff schemes. While flat schemes allow meeting cost causality over the year, they do not meet cost causality over a shorter time horizon. ToU tariff schemes go one step further by allowing cost causality over peak and off-peak periods within the year. Moreover, it stimulates short-term DR due to the difference between peak and off-peak prices. RTP tariff schemes meet cost causality reflecting hourly underlying costs, therefore incentivizing DR on an hourly basis. The second type of tariff schemes covers CPP. This is typically used within a capacity constrained power system that is not able to meet demand during a limited number of hours a year. Hereby, focus is on reducing demand during infrequent critical events. Nevertheless, intermittency in a power generation portfolio based on RES cannot be addressed. The final type of tariff schemes covers REN pricing. This tariff aims at more efficient integration of intermittent RES by aligning demand with available power generation from RES.

Following theory and development of dynamic pricing, Chapter 4 describes the DR effects. To provide comprehensive insights in DR under its various forms, both DR based on theory and practice is covered. While theoretical simulations serve as a benchmark, practical evidence provides a reality check. Simulations with wet appliances (WAs) based on RTP show shifts of consumption away from noon and late evening periods towards the afternoon and night. This leads to new peaks on appliance consumption level. Nevertheless, these peaks fill valleys when considering household consumption levels. The impact on household consumption peaks is limited as initial WA consumption during those peaks is relatively small. On the contrary, consumption of battery electric vehicles (BEVs) is substantial and just adding these vehicles to the household consumption profile creates new peaks even if DR is not used. This new peak arises just before midnight as most vehicles have returned home. Applying DR based on RTP, this new peak is shifted towards the night. On average, it is almost double of the reference household consumption peak. Considering other dynamic pricing schemes than RTP, simulations show that consumption patterns are largely affected by the choice of the schemes. Compared to flat pricing, adding dynamics to the tariff scheme leads to more variation in household consumption profiles. This is shown with RTP and REN pricing bringing the biggest changes in consumption patterns. Hereby, new peaks under REN pricing start earlier than under RTP as REN prices are averaged over longer periods. The drawback is that consumption is not always shifted towards the most advantageous periods leading to new peaks during initial shoulder periods. Apart from the impact of dynamics of tariff schemes on consumption patterns, also the amount of household savings is affected. In general, more dynamics in tariff schemes leads to higher savings. For instance, savings under RTP are 6 to 7 times higher than under ToU. Savings largely depend on the load type. Hereby, savings under load shifting with BEVs are a multitude compared to those with WAs. Nevertheless, for both load types a relative high spread of savings is found over the different households. Apart from theoretical results, evidence from the LINEAR project also shows that REN pricing impacts demand. Under the manual interaction model, consumers manually reduce consumption in the morning and late evening periods. Nevertheless, no clear impact during the night period is observed. In this perspective, automating WAs helps shifting consumption deeper in the night. Moreover, it adds to controllability and predictability of DR. This is shown by the clear demand increase during low price periods and vice versa.

Building on the descriptive analysis of theoretical and practical DR, Chapter 5 provides a deeper quantification of the responsiveness of demand to electricity price changes by means of price elasticities. While the literature on DR is not conclusive on the level of residential price elasticities in general, also evidence on elasticities following from dynamic pricing schemes such as RTP and REN is missing. Moreover, the impact of new type of loads or of automation is another topic not well addressed. Therefore, this thesis derives optimal price elasticities for simulated DR with WAs and BEVs and elasticities for manual and automated DR within LINEAR, all under REN pricing. Simulated DR serves as a benchmark for DR under automation and also shows the impact of new load types such as BEVs. Note however that the use of price elasticities for simulated and automated cases do not align with economic theory and therefore results have to interpreted with care. Results show that most optimal elasticities within the elasticity matrix are significant. Especially with BEV simulation, optimal elasticities are significant due to the high level of electricity demand resulting from BEV charging. High sensitivity of BEV demand towards pricing can also be seen in the level of elasticity coefficients. They are a multitude of elasticities following from WA scheduling. Compared to the simulated cases, practical evidence from LINEAR is less straightforward. While significant elasticities are found, impact compared to the simulated cases is lower. This follows from the fact that not all households actively participated in LINEAR. Moreover, commercial implementation is expected to lead to higher response levels. Nevertheless, it is clearly shown that automation leads to more significant levels of DR.

While previous chapters focus on the household level, Chapter 6 describes the impact of residential DR on power system operation. Therefore, this chapter provides an operational model quantifying power system operation benefits of residential DR with WAs and BEVs tested within a Belgian case study. Contrary to the available literature, this model provides a detailed representation of demand, DR and generation covering a full year. Results show that based on optimal power system operation, demand valleys are filled with consumption from WAs and BEVs. Hereby, BEVs cycles are mainly shifted towards the night while WAs are shifted towards the afternoon and night. This aligns with results from previous chapters. Moreover, this chapter shows that in general DR decreases loading of mid-peak and peak plants over the year and during peak moments. This is also reflected in the reduced number of start-ups of those plants. This renewed plant operation also impacts reliability, environment and costs of power system operation. While reliability is affected to a limited extent, DR provides an efficient means to integrate RES and avoid surplus. By shifting only 2% of total consumption towards moments with an excess of generation from RES, up to 41% of renewable surplus is avoided. Finally, DR decreases thermal costs as less peaking plants need to be operated. Hereby, it has to be noted that the impact of DR depends on the load type and the underlying power generation portfolio. Consistent with the previous chapter, benefits under BEV scheduling surpass WA benefits. Moreover, highest benefits of DR are accrued in a portfolio with a high amount of uncontrollable and renewable capacity.

Following the operational impact of DR, Chapter 7 discusses the impact of DR on power generation investment decisions. To this end, a detailed generation expansion planning model is developed. Contrary to models from the available literature, this model combines detailed a short-term operational model with real options theory accounting for long-term uncertainty in DR and demand growth. This approach is tested within a Belgian case and allows policy makers to assess the feasibility of DR to help realizing policy targets such as the integration of renewables or a phase-out of conventional generation capacity. Results show that DR can limit investments in quantity and time. Nevertheless, 1.2 GW of additional capacity on top of planned investments is required towards 2026 to maintain cost-effective operation. If BEVs are integrated, the required capacity even reaches between 1.8 and 2.4 GW. In the latter case, scheduling BEVs leads to a reduction of invested capacity of 0.6 GW in 19% of cases depending on the speed of BEV integration. Moreover, during the planning horizon investments can be postponed in time also decreasing actualized costs. Overall, an actualized cost reduction of 223 M€ or 1.3% of total costs is reached by BEV scheduling. Given that no BEVs are integrated yet and that future power consumption of BEVs is limited compared to total demand, this cost decrease is substantial and calls for the inclusion of DR within power system operation. Therefore, a potential breakthrough of BEVs should support scheduled charging in order to decrease the impact on power system costs. The contrary is true for the scheduling of WAs. Opposed to BEV scheduling, WA scheduling does not influence investment decisions. This follows from the limited amount of energy resulting from the use of WAs. Nevertheless, a modest actualized cost decrease of 26 M€ is obtained by scheduling WAs following from operational benefits.

8.1.2 General findings on the use and usefulness of demand response

The aim of this thesis is to enhance the knowledge of residential DR and DP. Additionally, it also wants to enable more informed decision making by policy makers, industry and residential users. As different topics related to DR are addressed using different models, interpretation of results can be a challenging task. Therefore, this section aims at providing a general summary on the implications of results describing the use and usefulness of DR. As most results in this thesis follow from Belgian case studies, conclusions in this section also focus on Belgium.

Throughout this thesis, it was pointed out that momentum is building towards implementation of residential DR. The driver of this momentum is the increased need for flexibility due to the rise of renewables, phase-out of conventional generation capacity, ageing assets, and electrification of energy services. This need is only expected to become more stringent as more renewables are integrated and conventional generation capacity is phased-out.

The enabler of this momentum is the rise of technology as advanced metering, ICT and automation have taken a leap. These technologies are prerequisites for the successful implementation of DR and DP. Metering enables to measure and verify demand reactions to certain events. First experiences with DR have learned that this is essential for utilities in order to rely on the triggered flexibility and remunerate it accordingly. The same principle holds when DP is implemented. In this perspective, correct billing according to electricity consumption in every price block is essential. Progress in ICT adds to social acceptability and practicality of DR and DP. Hereby, technologies such as online monitoring, graphical user-interfaces and in-house displays can provide useful information to households. This results in higher customer involvement and enables them to make informed decisions concerning their electricity consumption. Finally, also automation adds to social acceptability and practicality as it entails to trigger DR without compromising comfort. Moreover, it allows households to keep their level of response over time as the effort needed to provide DR is limited. From the point of view of utilities, this also benefits reliability and controllability of DR facilitating easier integration in power system operation.

Following from the rise of technology and the increased need for flexibility, energy industry and policy makers recognize the usefulness of DR. This is the case for generators, retailers, transmission system operators, and distribution system operators. Their interest sprouts either from regulatory, economic, or reliability incentives.

Benefits for households and power system operation resulting from DR can be substantial. This is shown to be the case for WA and BEV shifting based on DP. Under RTP, nearly all BEV owners annually save between 100 and €200 by scheduling consumption. If these savings do not come at costs of comfort, participation of vehicle owners seems viable. For WAs, the picture looks different as the average household saves €18 by scheduling consumption. Nevertheless, some households save more than double. The latter might be interested in shifting consumption to reap these savings. Apart from financial incentives, environmental incentives are not considered. Following from DR at household level, also significant cost savings can be reaped at the power system level. Hereby, integration of BEVs has considerable impact on power system operation and investment. Under the assumptions that no BEVs are integrated yet and that the expected share of BEVs amounts 30% of all light-duty vehicles in 2025, 223 M€ or 1.3% of total Belgian operating and investment costs can be saved. Moreover, DR with BEVs provides an efficient means to prevent curtailment of generation from RES. Therefore, scheduled charging of those vehicles seems appropriate upon massive integration as this helps reaching policy targets such as the integration of renewables while saving money. For WA scheduling, again this picture looks different as savings are more limited. Hereby, the amount of demand is not large enough to influence investment decisions, nor to influence operational costs to a considerable extent. Nevertheless, DR again proves to be an efficient means to prevent curtailment of generation from renewables.

Demand response can be triggered using different dynamic pricing schemes. As stipulated, a balance needs to be found between tariff principles related to costs and social acceptability and practicality on the one hand and its resulting demand response incentive on the other. In order to reach substantial savings following from DR, sufficient dynamics in tariff schemes are key. Therefore, smaller price blocks implying larger price differences seem appropriate in order to incentivize DR. An example of such a tariff scheme is real-time pricing (RTP). To allow residential users to react to variability in prices while keeping their comfort level, inclusion of automation seems essential. It allows meeting principles of social acceptability and practicality, while prevailing cost related tariff principles and triggering DR.

8.2 Recommendations for further research

Recommendations for further research following from this thesis are twofold. First of all, expansions and improvements of the models discussed in this thesis are suggested. Second, other interesting research paths linked to this thesis are discussed.

8.2.1 Model expansions and improvements

This thesis covers several models: a model for development of dynamic pricing schemes, a WA and WG scheduler, a statistical model for calculating price elasticities, an operational model which includes DR in power system operation, and an investment model which includes short-term system operation and long-term demand uncertainty. Possible improvements for each of these models are possible.

Currently, the model for development of dynamic prices is based on wholesale prices and residential load profiles. Adding to cost causality, a more detailed inclusion of several cost categories seems appropriate. Nevertheless, detailed cost information from DSOs, TSOs, generators and retailers is not readily available. Moreover, the relationship between costs and residential generation or consumption is not straightforward. Note also that translating costs into prices based on a mixture of rate designs such as energy based pricing, capacity based pricing, and fixed pricing remains subject to further research.

The WA scheduler assumes residential users to set a shifting potential of 8 hours during which the appliance cycle needs to be finished. Although this aligns with averages derived from the LINEAR-project, including a distribution of shifting potential over different households would further add to a realistic outcome of simulations.

The scheduler assumes that BEVs can charge during stand-still at home, covering the period from arriving until departing. Specific charging settings of vehicle owners are neglected. Moreover, fast charging and vehicle-to-grid charging are neglected.

The almost ideal demand system (AIDS) within this thesis estimates price elasticities based on REN-pricing. Expanding this model in order to estimate hourly elasticities would be interesting as this leads to more detailed results of demand changes over the course of the day. Another interesting research path would be to compare results from AIDS with other functional forms such as generalized Leontief and generalized McFadden. Moreover, including elasticity results in classical models for predicting demand would allow to further test the usefulness of estimated price elasticities. Finally, as shown in this thesis, a quantification of DR based on price elasticities does not fully align with economic theory in the simulated and automated cases. Therefore, developing new models that allow for a more accurate and finer representation of DR shows significant potential.

In modeling power system operation, interconnection capacity, transmission capacity, market behavior, demand uncertainty, and uncertainty in power generation from solar plants are neglected. Moreover, no stochasticity is included in the day-ahead optimization stage. In modeling DR, the willingness of households to provide flexibility and the cost it brings are not included. Furthermore, individual WA characteristics per household are not considered. Integrating this would further benefit a realistic outcome. Other paths for future research are the inclusion of a sensitivity analysis on reserve requirements, residential controllable generation technologies and vehicle-to-grid charging. Finally, including DR in the second stage of the operational model would allow it to contribute to corrective actions needed due to forced outages or forecast errors of power generation from RES. This real-time DR could significantly impact results.

A first improvement of the investment model is to integrate other technologies with various capacities in the decision tree. Although this contributes to a more realistic outcome, the enlarged state space increases calculation time enormously. Second, a deeper assessment of the uncertainty tree can lead to a more realistic outcome.

8.2.2 Other research paths

Several research paths related to DR and DP remain open to be explored.

The impact of remuneration schemes for residential generation facilities on residential bills but also on the DR incentive is largely untested. Different remuneration schemes exist, yet the impact on DR is often not considered during implementation. Nevertheless, it is considerable as partly shown in Chapter 2. Therefore, more elaborated research to describe this impact seems necessary.

Within this thesis, simulations of residential DR focus on WAs and BEVs. Including other residential appliances such as heat pumps and cold appliances could expand current conclusions.

Practical results in this thesis are based on the LINEAR project. This project enabled a first step towards implementation of DR and DP. Nevertheless, additional testing is needed to reach commercial implementation. Therefore, additional field tests involving more households, different user interfaces, and different dynamic pricing schemes may contribute to better knowledge of consumer behavior.

Distribution and transmission constraints are not considered in this thesis. Including these technical constraints in economic optimizations provides insights in feasibility of results as described.

While this thesis provides insights in savings for households and the power system as a whole, the distribution of these savings and the value flows amongst the different stakeholders are not discussed. Moreover, cost aspects of including DR within the system are not covered. Both distribution of savings and inclusion of costs remain subject to further research.

Appendices

Appendix A

Optimal price elasticities based on simulation with wet appliances under different tariff schemes

Within this thesis dissertation, *optimal elasticities under renewable pricing* are derived for the cases in which wet appliances and battery electric vehicles are simulated. This naming is chosen as these elasticities follow from optimized flexible demand profiles. Hereby, flexible demand is always shifted to the lowest price period independent of relative price differences between periods. Therefore, these elasticities align with a best case scenario as households are extremely price sensitive within the boundaries of their comfort zone.

To illustrate the dependency of the optimal elasticities on price, the own elasticities based on wet appliance shifting for three different pricing schemes are shown in Fig. A.1. The different pricing schemes are all obtained based on the renewable pricing scheme (REN) as described in this dissertation. The base pricing scheme equals REN, while in the other pricing schemes a flat component of 5 and 15 c€/kWh is added on top of REN. This ensures that absolute price differences between price periods remain the same, while relative price differences change.

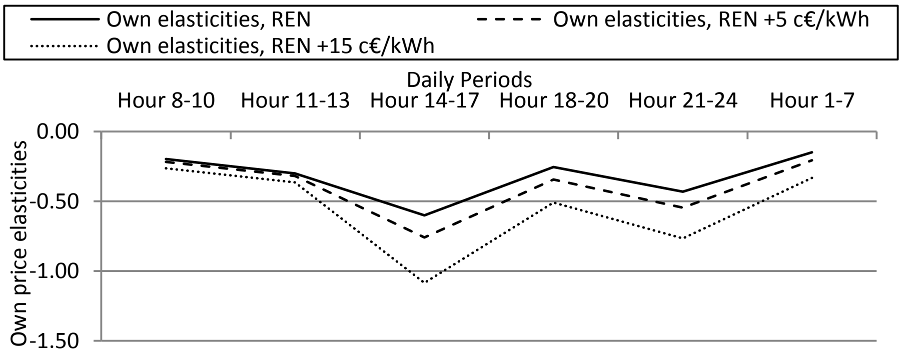

Fig. A.1. Own price elasticities based on wet appliance shifting under three different pricing schemes: renewable pricing (REN), REN plus a flat component of 5 c€/kWh, and REN plus a flat component of 15 c€/kWh.

As shown in Fig. A.1., own optimal elasticities depend on the pricing scheme itself. Own optimal price elasticities become more negative when a flat component is added to the REN pricing scheme. This follows from a decrease of the relative pricing differences between peak and off-peak periods while the demand shift remains the same. In other words, the same demand response following from smaller relative price differences leads to more negative price elasticities. This illustrates the importance of the naming of the optimal price elasticities throughout this thesis. As a consequence, the optimal elasticities based on simulation within this thesis are only valid under similar tariff schemes.

Appendix B

Inclusion of residential demand response in power system operation

This appendix provides the specific mathematical formulation of the inclusion of demand response within the deterministic unit commitment and economic dispatch model used in this dissertation. Therefore, the main indices, parameters, variables, and equations are provided. A distinction is made between demand response with wet appliances (WAs) and demand response with battery electric vehicles (BEVs). A detailed description of the former can be found in Dietrich et al. [126], while the latter is thoroughly discussed in Ramos et al. [139] and Bañez et al. [131]. Constraints related to reserve requirements or technical characteristics of power plants are omitted for simplicity, but can be found in Dietrich et al. [126].

Indices

General

p, p'	Time period.
g	Generators.
t	Thermal plants ($\{t\} \cdots \{g\}$).
h	Pumped storage hydro plants ($\{h\} \cdots \{g\}$).

Inclusion WAs

a	Types of appliances.

Inclusion BEVs

e	Types of BEVs.
s, s'	State of the BEV {sc (connected to the grid), sm (moving)}.

Parameters

General

D_p	Demand for period p [MW].
$UncG_p$	Power generation from uncontrollable capacity (wind capacity, solar, biomass, CHP, hydro run-of-river capacity) in period p [MW].
$UResC, DResC$	Upward and downward reserve deficit cost [€/MWh].
$NSEC$	Non-supplied energy cost [€/MWh].
FC^t	Fixed cost of thermal unit t [€/h].

VC^t — Variable cost of thermal unit *t* [€/MWh].
SC^t — Start-up cost of thermal unit *t* [€].

Inclusion WAs

$DUpMax_a$ — Maximum upward variation of demand for each appliance type *a* [p.u.].
$DDoMax_a$ — Maximum downward variation of demand for each appliance type *a* [p.u.].

Inclusion BEVs

$ECMax_p^e$ — Maximum power charged by BEV *e* in period *p* [MW].
$EEMax^e$ — Maximum energy charged by BEV *e* [MWh].
$EP_p^{e,s}$ — Percentage of BEV of type *e* and in the state *s* for each period *p* [p.u.].
$EPT_p^{e,s,s\prime}$ — Percentage of BEV of type *e* and in the state *s′* that move to the state *s* for each period *p* [p.u.].
$ET_p^{e,s}$ — Battery energy used in transport of each type of BEV *e* in each state *s* for each period *p* [MWh].
$EEfGtB^e$ — Grid-to-battery efficiency for each type of BEV *e* [p.u.].
$EEfBtW^e$ — Battery-to-wheel efficiency for each type of BEV *e* [p.u.].

Variables

General

$opcost$ — Total operational cost [€].
nse_p — Non-supplied power in period *p* [MW].
wc_p — Wind curtailment in period *p* [MW].
$urdef_p, drdef_p$ — Upward and downward reserve deficit in period *p* [MW].
st_p^t — Start-up thermal unit *t* in period *p* {0,1}.
uc_p^t — Commitment of thermal unit *t* in period *p* {0,1}.
gp_p^g — Output of generator *g* in period *p* [MW].
gc_p^h — Consumption of pumped storage hydro plant *h* in period *p* [MW].

Inclusion WAs

$dup_{p,a}$, $ddo_{p,a}$ — Upward and downward demand variation for each type of appliance in period p [MW].

Inclusion BEVs

$soc_p^{e,s}$ — State of charge (SOC) of the battery of BEV *e* at the end of period *p* in each state *s* [MWh].
$ec_p^{e,s}$ — Consumption of BEV *e* in state *s* in period *p* [MW].
ch_p^e — BEV *e* charging indicator in period *p* {0,1}.

Objective function

$$\text{Min.}\, opcost = \sum_{p}\left[\begin{array}{c}\sum_{t}\left(FC^{t}\cdot uc_{p}^{t} + SC^{t}\cdot st_{p}^{t} + VC^{t}\cdot gp_{p}^{t}\right) + \\ NSEC\cdot nse_{p} + UResC\cdot urdef_{p} + DResC\cdot drdef_{p}\end{array}\right] \quad \text{(A.1)}$$

Constraints related to inclusion of WAs

Modified demand-supply balance constraint

$$D_{p} + dup_{p,a} - ddo_{p,a} - UncG_{p} - nse_{p} + wc_{p} = \sum_{g} gp_{p}^{g} - \sum_{h} gc_{p}^{h} \qquad \forall\, p \quad \text{(A.2)}$$

Upward and downward daily demand variation balance per appliance type

$$\sum_{p\in\{1,24\}} dup_{p,a} = \sum_{p\in\{1,24\}} ddo_{p,a} \qquad \forall\, a \quad \text{(A.3)}$$

Maximum demand shift per appliance type

$$\begin{pmatrix} DDoMax_{a} \\ DUpMax_{a}\end{pmatrix}\cdot D_{p} \geq \begin{pmatrix} ddo_{p,a} \\ dup_{p,a}\end{pmatrix} \geq 0 \qquad \forall\, p,a \quad \text{(A.4)}$$

Constraints related to inclusion of BEVs

Modified demand-supply balance constraint

$$D_{p} + \sum_{e,s} ec_{p}^{e,s} - UncG_{p} - nse_{p} + wc_{p} = \sum_{g} gp_{p}^{g} - \sum_{h} gc_{p}^{h} \qquad \forall\, p \quad \text{(A.5)}$$

State of charge of battery

$$soc_{p}^{e,s} - soc_{p-1}^{e,s} = ec_{p}^{e,s}\cdot EEfGtB^{e} - \frac{ET_{p}^{e,s}}{EEfBtW^{e}} + \sum_{s'\neq s} soc_{p-1}^{e,s'}\cdot EPT_{p-1}^{e,s,s'} \qquad \forall\, p,e,s \quad \text{(A.6)}$$

Logical BEV constraints of BEV when moving and plugged-in

$$\begin{array}{ll} ec_{p}^{e,s} = 0 & \forall\, s\in sm \\ ET_{p}^{e,s} = 0 & \forall\, s\in sc \end{array} \qquad \forall\, p,e,s \quad \text{(A.7)}$$

Maximum charging power

$$ec_{p}^{e,s} \leq \left(1 - ch_{p}^{e}\right)\cdot ECMax_{p}^{e}\cdot EP_{p}^{e,s} \qquad \forall\, p,e,s \quad \text{(A.8)}$$

Maximum energy that can be charged in one period

$$ec_{p}^{e,s} \leq EP_{p}^{e,s}\cdot\left(EEMax^{e} - soc_{p}^{e,s}\right) \qquad \forall\, p,e,s \quad \text{(A.9)}$$

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Curriculum Vitae

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List of publications

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