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Benefits of Coordinating Plug-In Electric Vehicles in Electric Power Systems

Through Market Prices and Use-of-System Network Charges

Ilan Momber

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PROEFSCHRIFT

ter verkrijging van de graad van doctor
aan de Technische Universiteit Delft,
op gezag van de Rector Magnificus prof. ir. K.C.A.M. Luyben,
voorzitter van het College voor Promoties,
in het openbaar te verdedigen
op donderdag 15 oktober 2015 om 16:00 uur

door

Ilan MOMBER
Diplom-Wirtschaftsingenieur,
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geboren te Berlin, Duitsland

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SETS Joint Doctorate

The Erasmus Mundus Joint Doctorate in **Sustainable Energy Technologies and Strategies**, the SETS Joint Doctorate, is an international programme run by six institutions in cooperation:

- Comillas Pontifical University, Madrid, Spain
- Delft University of Technology, Delft, the Netherlands
- Florence School of Regulation, Florence, Italy
- Johns Hopkins University, Baltimore, USA
- KTH Royal Institute of Technology, Stockholm, Sweden
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The Doctoral Degrees provided upon completion of the programme are issued by Comillas Pontifical University, Delft University of Technology, and KTH Royal Institute of Technology.

The Degree Certificates are giving reference to the joint programme. The doctoral candidates are jointly supervised, and must pass a joint examination procedure set up by the three institutions issuing the degrees.

This Thesis is a part of the examination for the doctoral degree.

The invested degrees are official in Spain, the Netherlands and Sweden respectively.

SETS Joint Doctorate was awarded the Erasmus Mundus **excellence label** by the European Commission in year 2010, and the European Commission's **Education, Audiovisual and Culture Executive Agency**, EACEA, has supported the funding of this programme.

The EACEA is not to be held responsible for contents of the Thesis.

This thesis is equally dedicated to *pathos*, the parent of all dedications, as well as, to *my dear mother*, without whom this dedication would have never been conceived.

Abstract in English Language

Author: Ilan Momber
Title: Benefits of Coordinating Plug-In Electric Vehicles in Electric Power Systems Through Market Prices and Use-of-System Network Charges
Language: Written in English
Keywords: Electric Vehicles, Power Systems, Optimization

Both electric power systems and the transportation sector are essential constituents to modern life, enhancing social welfare, enabling economic prosperity and ultimately providing well-being to the people. However, to mitigate adverse climatological effects of emitting greenhouse gases, a rigorous de-carbonization of both industries has been set on the political agenda in many parts of the world. To this end, electrifying personal vehicles is believed to contribute to an affordable and reliable energy model that provides tolerable environmental impact. Representing an inherently flexible electricity demand, plug-in electric vehicles (PEVs) promise to facilitate the integration of variable renewable energy sources. *Yet, how should the PEVs' system usage be ideally coordinated for providing benefits to electric power systems in the presence of resource scarcity?*

The thesis develops a model of an aggregation agent as the interface to the wholesale electricity generators, which is envisaged to be in charge of procuring energy in electricity markets, exposed to uncertainty in prices, fleet availability and demand requirements. This aggregator could coordinate the PEV charging either with direct load control (DLC), i.e., sending power set points to the individual vehicles, or with indirect load control (ILC), i.e., by sending retail price signals.

Contributing to the technical literature this thesis has on the one hand proposed a two-stage stochastic linear program for the PEV aggregator's day-ahead and balancing decisions with DLC over a large fleet of PEVs, while accounting for conditional value at risk in the objective function. On the other hand, it has put forward a formulation of ILC coordination as a bi-level optimization problem given by mathematical programming with equilibrium constraints, in which 1) the upper level decisions on retail tariffs and optimal bidding in electricity markets are subject to 2) the lower level client-side optimization of PEV charging schedules. These decisions may respect a potential discomfort that could arise when PEV users have to deviate from their preferred charging schedule. Set in an existing, real medium voltage distribution network with urban characteristics and spatial PEV mobility, network UoS tariffs for capacity have been applied to both DLC and ILC scheduling by a PEV aggregator.

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Abstract in Spanish Language (Resumen)

Autor: Ilan Momber
Titulo: Beneficios de Coordenar Vehiculos Electricos en Sistemas de Potencia por Precios del Mercado y Tarifas de Red de Distribución
Lengua: Escrito en Inglés
Palabras clave: Vehiculos Electricos, Sistemas de Potencia, Optimización

¿Cómo sería nuestra sociedad moderna, si no existiese el acceso generalizado a la electricidad y cómo viviríamos sin transporte motorizado? Parece muy difícil imaginar nuestras sociedades contemporáneas en países desarrollados sin los sistemas eléctricos como la columna vertebral para incrementar el beneficio social, el desarrollo económico y ultimadamente el bienestar humano. No hay duda que el sector transporte es un constituyente esencial para la vida moderna. Sin embargo, para mitigar los efectos adversos de los gases de efecto invernadero, una rigorosa descarbonización del sector eléctrico y transporte ha sido establecida en la agenda política de muchas partes del mundo. En este sentido, se espera que los vehículos contribuyan a lograr un modelo energético accesible y fiable con un impacto ambiental tolerable. Pero todavía existe una duda: *¿Exactamente cuánto deberían coordinarse los vehículos eléctricos, de tal manera que puedan proveer beneficios al sistema eléctrico en la presencia de escasez de recursos?*

El principal objetivo de esta investigación es proponer herramientas de soporte que puedan mejorar la eficiencia de todo el sistema a través de la carga de vehículos eléctricos. Un agente agregador podría ser el interfaz con el mercado mayorista de electricidad en la cual el agregador está encargado de comprar energía en los mercados eléctricos exponiéndolo a la incertidumbre de precios, la disponibilidad de la flota de vehículos y los requerimientos de demanda. Este agregador podría coordinar la carga de vehículos eléctricos con control directo de carga (CDC), esto es enviando consignas a los vehículos individuales, o con control indirecto de cargas (CIC), enviando señales de precios minoristas.

Esta tesis contribuye con la literatura técnica en dos maneras, por un lado propone una programación lineal en dos etapas con CDC para el agregador de vehículos eléctricos que toma decisiones de oferta en el mercado diario y desvíos de energía para una flota grande de vehículos eléctricos, mientras se tiene en cuenta el valor en riesgo condicional. Por otro lado, se propone una formulación de coordinación con CIC como un problema de optimización binivel dado por una programación matemática con restricciones de equilibrio, donde 1) las decisiones del nivel superior son el diseño de las tarifas minoristas y las ofertas óptimas en los mercados, que dependen de 2) las decisiones de optimización de tiempo de carga de los vehículos eléctricos por parte de los clientes, que se da en un nivel inferior. Las tarifas de red han sido aplicadas a ambos CDC y CIC, estas tarifas están basadas en una red de distribución de media tensión con características urbanas y con movilidad de vehículos eléctricos.

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Abstract in Swedish Language (Sammanfattning)

Författare: Ilan Momber
Titel: Fördelar med att koordinera laddning av elbilar med marknadspriser och kapacitetsnätverkstariffer
Språk: Skriven på engelska
Uppslagsord: Elbilarna, Elkraftsystem, Optimering

Både elkraftsystem och transportsektorn är nödvändiga komponenter av vårt moderna liv – de förstärker den sociala välfärden, möjliggör ekonomisk framgång och bidrar slutligen med välmående för folket. För att undvika skadliga klimateffekter av utsläppta växthusgaser har en rigorös utfasning av fossila bränslen inom båda dessa sektorer prioriterats på politiska agendor runtom i världen. På så vis förväntas elektrifieringen av personbilar bidra till en prisvärd och pålitlig energimodell som ger en acceptabel miljöpåverkan. Med en betydande flexibilitet i efterfrågan på el har elbilarna möjlighet att underlätta integrationen av förnybara energikällor. Frågan är då, *hur ska elbilarnas elanvändning koordineras för att bäst bistå elkraftsystemet med hänsyn till resursbrist*?

Det huvudsakliga syftet med den här forskningen är att föreslå beslutsstödsverktyg som kan förbättra systemeffektiviteten genom elbilsladdning. Forskningen utvecklar en modell för en aggregatoragent som länk till grossistelproducenterna, som antas vara ansvariga för att köpa energi på elmarknaden, under osäkerhet inom priser, tillgång på bilar och efterfrågan. Aggregatorn kan koordinera elbilsladdningen antingen genom direkt efterfrågekontroll, med kraftbegräsningar för enskilda elbilar, eller genom indirekt efterfrågekontroll, men prissignaler.

Den här avhandlingen har å ena sidan föreslagit ett tvåstegs stokastiskt linjärt program för elbilsaggregatorns spotmarknads- och balansbeslut med direkt efterfrågekontroll för en stor elbilsflotta, genom att ta hänsyn till conditional value at risk i målfunktionen. Å andra sidan har den tagit fram en formulering för koordinering av indirekt efterfrågekontroll som ett bileveloptimeringsproblem med jämviktsrestriktioner, där 1) de övre besluten om slutkundspriser och optimal budgivning i elmarknaderna med förbehåll för 2) den lägre optimeringen av kundoptimeringen av laddningsscheman. Dessa beslut kan åsamka möjligt obehag för elbilsanvändarna då de behöver avvika från sina föredragna laddningsscheman. Kapacitetsnätverkstariffer har tillämpats både för direkt och indirekt laddningskontroll för en elbilsaggregator, i ett existerande distributionsnätverk med urbana egenskaper och spatiala laddningsscheman för elbilar.

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Abstract in Dutch Language (Samenvatting)

Author: Ilan Momber
Titel: Voordelen van het Gecoördineerd Opladen van Plug-in Elektrische Voertuigen in Elektrische Energiesystemen via Marktprijzen en Use-of-System Tarieven.
Taal: Geschreven in het Engels
Trefwoorden: Elektrische Voertuigen, Energiesystemen, Optimalisatie

Zowel het elektrische energiesysteem als het transportsysteem leveren een essentiële bijdrage aan de hedendaagse samenleving: het verhogen de maatschappelijke welvaart, het toelaten van economische vooruitgang, en het verbeteren van het menselijke welzijn. Echter, om de nadelige effecten van broeikasgassen te beperken, is een verregaande decarbonisatie van beide sectoren een belangrijk politiek agendapunt geworden in verschillende delen van de wereld. De elektrificatie van personenwagens wordt geacht bij te dragen aan een betaalbaar en betrouwbaar energiemodel dat een aanvaardbare milieu impact heeft. De inherente flexibiliteit in de energievraag van plug-in elektrische voertuigen (PEV's) is beloftevol voor de facilitering van de integratie van hernieuwbare energiebronnen. De vraag is: *hoe kan het opladen van PEV's het best gecoördineerd worden om voordelig te zijn voor het elektrische energiesysteem op momenten van productieschaarste?*

Het belangrijkste doel van dit onderzoek is om beleidsondersteunende hulpmiddelen aan te bieden, om het totale systeemrendement te verbeteren door middel van het gecoördineerd opladen van PEV's. Het proefschrift ontwikkelt een model van een aggregatie-agent die als interface fungeert naar de groothandelsmarkt van elektriciteitsproducenten. De aggregator is verantwoordelijk voor de aankoop van de energie op deze elektriciteitsmarkten, en is bijgevolg blootgesteld aan prijsvolatiliteiten, de beschikbaarheid van de voertuigvloot, en de vereiste energievraag. Deze aggregator kan het opladen van de PEV's coördineren via directe lastregeling (Direct Load Control, DLC), het verzenden van de vermogenssetpoints naar de individuele voertuigen, of via indirecte lastregeling (Indirect Load Control, ILC), het sturen van prijssignalen.

De bijdrage van dit proefschrift aan de technische vakliteratuur is tweeledig. Enerzijds wordt er een tweetraps stochastische lineaire programmatiemethode voorgesteld voor de beslissingen van de PEV aggregator op de day-ahead markt en de balanceringsmarkt, waarbij rekening gehouden wordt met het voorwaardelijke risicogehalte van de doelfunctie. Anderzijds wordt er een formulering van de ILC-coördinatie voorgesteld, als een bi-level optimalisatie probleem dat gebaseerd is op de wiskundige programmeringsmethode met evenwichtsbeperkingen. Hierbij zijn er 1) de high-level beslissingen omtrent de retailtarieven en de optimale biedstrategie in de elektriciteitsmarkten, en 2) de low-level optimalisatie van de individuele PEV oplaadschema's. Deze beslissingen kunnen een mogelijk ongemak creëren door de afwijking van het optimale laadschema voor de PEV-gebruiker. Voor een realistisch en bestaand stedelijk middenspanning distributienetwerk en ruimtelijk PEV mobiliteitsgedrag, zijn UoS capaciteitstarieven toegepast door een PEV-aggregator, zowel voor DLC- als ILC-gebaseerde laadcoördinatie.

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Propositions belonging to the dissertation

**Benefits of Coordinating
Plug-in Electric Vehicles in Electric Power Systems
through Market Prices and Use-of-System Network Charges**

Ilan Momber

15 Ocotber 2015

1. Quantitative and qualitative research may reinforce each other when the scientist is able to turn thoughts into equations and vice versa.
2. Even though their technical integration in power systems has been a challenge, plug-in electric vehicles are themselves powerful integrators for efficiency-promoting policies in the energy and transport sectors.
3. Plug-in electric vehicle charging presents an inherently flexible load that, if aligned to the correct signals, is very beneficial to power system operation.
4. Size matters: larger aggregations of plug-in electric vehicle fleets are more profitable when participating in electricity markets due to the decrease in relative forecasting error on bids ahead of real time.
5. Timing is not all: the alignment of plug-in electric vehicle charging in the spatial dimension must not be underrated in order to make use of spare capacity in power distribution networks.
6. Existing technical power system literature underestimates the illustrative power of superscripted mathematical notation using the LaTeX code for$\barwedge$ and $\veebar$ as symbols to indicate the directionality of plug-in electric vehicle charging.
7. Too often, scientific progress is not based on reuse but inspired by regurgitation, as practiced by some species in the real world of biology, for which the expulsion of undigested food is a valid method to feed the young.
8. Soliciting negative feedback, is more constructive than the convention of acknowledging uncritical affirmation for reassurance.
9. Even the deterministic equivalents of stochastic optimization problems cannot defy the odds of decision making under contingent information uncertainty.
10. Good and bad, success and failure, evil and good, tend to closely co-exist, yet distinguished research avoids the pernicious coalescence of it all into a gray-on-grey.

These propositions are regarded as opposable and defendable, and have been approved as such by the promotor prof.dr.ir. P.M. Herder.

Acknowledgment

With this research, my intention has always been to advocate a future that is weaned off the excessive resource depletion for the deceiving promise of short-term benefits. Frankly, I have been motivated by a vague dream of the more beautiful world our hearts must feel is possible. Yet, while devised with reverence for the abstract concept of sustainability, this thesis was also typed by the same fingers, whose tips have been firmly holding on to the cracks in the very foundations of our life-bearing planet and of us as evolved, cultured people on it. What I am trying to say is, if ever more PhD. students were to pursue internationalization on a similar path as I have been given the chance to, I wonder whether human society would continue to improve its existence, or not? Please, do not get me wrong, of course I have felt a strong affection for the essence of this European joint doctorate; yes, I very much enjoyed the freedom to travel to all the different and beautiful places. But I feel morally obliged to foremost acknowledge that my travel activities have been at least somewhat questionable.

Lack of time and effort at this very last minute before sending out the document to the printing presses unfortunately force the following estimation to not exhibit the utmost scientific rigor, but I still prefer to state it, to make my point clear: Within the past four years I flew on average once per month 2 000 - 3 000 km across the continent, i.e., in-between Germany, Spain, Sweden, Belgium and the UK, and at least once per year intercontinentally, i.e. to Africa, South America, Asia and the US, covering approx. 10 000 km for each leg. Assuming an average carbon dioxide consumption of 115 g per passenger-km flown on the short-hauls and 105 g on the long-hauls leads me to believe that I might have contributed to causing the exhaustion of up to 38 metric tons of carbon dioxide just through air travel. This is roughly equivalent to the emissions caused by the production of 73 MWh of electricity in a modern gas-fired power plant. I leave it up to the interested readers to make their own calculations of how big the marginal contribution of my thesis to an increasingly electrified future of personal transportation must be, to come out positive in a cost-benefit analysis regarding its impact.

So, as a preface to this thesis, I acknowledge: My travel activity and flesh have tended to be wonky with respect to sustainable personal transport albeit my willing thesis mind. Alas.

Nevertheless, I feel that this section should not be about me and probably because of that, it is the most dear one to me personally. To be clear, it would have never been possible for me to complete this work without the caring support of so many people, which has surprised and humbled me in many ways. It is because of you all that I have had the courage to continue in those moments of doubt.

In that spirit, I would like to start this long list by expressing my sincere gratitude towards my dear mother, **Heide** Momber, who has brought me into this world, who has given me the gift of life, raised me devotedly by herself alone, and has always - not only when it came to my education - wanted only the very best for me. I would like to continue by thanking my dear **Ännie**, who, in spite of five years of long-distances separating us, stuck by my side with her matchless naturalness, filling my life with love and indulgence. I will also never forget all that, what my young-but-wise cousin **Falk**-Jonas Momber has done for me, whose undivided friendship and support I can eternally count on. Very influential has also been my uncle, Ernst-**Axel** Momber, who, especially in the most challenging moments always has had an open ear for me, as well as some clever advice wrapped in a proverb. *"Wer weiß für was es gut is"*. My uncle **Eckhardt** Momber, whose approach to life and pleasure I admire, whose serenity I would like to adopt and who has enriched my thoughts especially in the very emotional moments. My **Großvati**, Ernst-Achim Momber, whose character and strength will always remain in good memory, will always remind me to keep posture, rectilinearity and concentration. Although I could not visit her much, the mere thought of my great aunt **Tante Li**se**lo**tte Thiemig gave me a sense of her vitalizing pragmatism in Alt-Lankwitz style. My dear American family, **Michael**, **Katie**, **Matt**, **Jud**y and **Chris**, whose openness, kind-heartedness and hospitality impressed and changed me for the better over and over again. **Silvia**, with whom the exchange has always been nurturing, soothing and helpful.

Among my academic colleagues, I foremost feel thorough gratitude for my, as we say in German, 'Doktorvater', **Tomás** Gómez, who with his abundance of patience has not only provided me with true supervision in the most literal sense of the word, but has repeatedly guided me back on the right path, not the least with a poem on this very topic by Antonio Machado. I will equally not forget the benevolence of **Lennart** Söder, whose Swedish sense for justice and equality have impressed me during my stay in Stockholm. **Afzal** Siddiqui shall also be explicitly mentioned - Quack! - the most witful Senior Lecturer at UCL, who granted me the privilege of an extraordinary research visit in the vicinity of Planet Organic, including discounts. **Lion** for inspiration, encouraging provocation and the founding of strommarktgruppe the best open discussion platform on German and international energy topics out there, as well as techtalk forum and openmod group. What will you initiate next? Don **Germán**, sunshine **Angela** and filemou **Ilias** for so many things among which sharing office space together. **Rafa**, **Luis**, **Andrea**, **Camilla**, **Mercedes**, **Cherelle**. Special thanks to **Mahdi**, who always listened to my research ideas during joint coffee breaks and taught me to remain humble not only but especially considering my chess skills. The humming lunch colleagues, including **Paolo** and **Peyman** for entertainment during 'park' break almuerzos, **Nenad**, **Prad**, **Jörn** for never-ending discussions in the ICADE cafeteria or at Tierra de B. **André** for a bet against electric aeroplanes for mass passenger transportation (I still confidently stick to my word) and the hiking adventure to 'summit' Siete Picos.

But also my private relationships and friends have kept me going. I remain forever thankful to all the Alburquerquers for taking me into the Madrilenian communal life and especially **Alvaro** & **Palomita**, **Javitchu**, **Dani**, **Cobas**, **Mariele** & **Virginia** for daring to create a meaningful cross-cultural friendship. The DIPS crew, **Sebbl**, **Philipp** and **Daniel**, the closest circle of friends from student days have strengthened me with their positive thoughts and with whom I was so fortunate to share wonderful travels, on which I was even once encouraged to bother everyone with lengthy accounts of stochastic optimization. The peacock nest of **Bastone** Earnest and Schlongie **Feelix**, a role model for good fun, laughter and caring friendship on different Bologna trips. **Sebfu** for like-minded thinking sincere openness and all the helpful thoughts. **Fred**boy Dallwitz inimitably entertained me with special visits to Madrid, Stockholm and Geneva, where once I even thought he came to actually see me. I also want to thank **Hannes** for all the fun times and laughter on surf trips, his audacity to engage in bare-chested catwalking on the roofs of London, before mounting old tanks. The refined and civilized mode of **Umberto**'s behavior, who has the gift to make the deepest intellectual e-mail conversations seem easy. Very similar things are true about **Pedro**, whose pensiveness and profoundness have affected me from Brazil to here and back. I am so glad that every now and then I got an undisguised breeze of **Sascha**'s clear pragmatism, ambition and strength of purpose. **Katja**, **Kaveri**, **Marcin**, **Siza**, for k(a)iting, hiking and golden getaways over the warm Spanish autumn weekends. **Kristina**, **Nicholas**, **Viktor** and **Mahir** for the Bydalen adventure. **Amin**, **Afshin**, **Yaser**, **Behnaz** and **Erfan** for introducing me to the Persian culture. **Harold** for being a loyal student of 'grid' theory. **Zarrar** and **Antonella** for initiating me into climbing steep walls. All attendees at Burrata and Mafia nights, including **Quentin** and his swagy ex-president rap.

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And all the others that I have not named in person.

To complete this section of sincere acknowledgments, I would like to leave you with a quote:

"I am not sure that I exist, actually. I am all the writers that I have read, all the people that I have met, all the women that I have loved; all the cities that I have visited, all my ancestors."

—Jorge Luis Borges

Contents

List of Figures

List of Tables

List of Abbreviations

AGC	Automatic Generation Control
ANF	Annuity Factor
(a)PDF	(Adjusted) Probability Distribution Function
BAU	Business-as-Usual
BRP	Balance Responsible Party
C-rate	Charging Rate
CAISO	Californa Independent System Operator
CC	CreativeCommons
CCO	Controlled Charging
CDF	Cumulative Probability Distribution Function
CEN	European Committee for Standardization
CENELEC	European Committee for Electrotechnical Standardization
CHP	Combined Heat and Power
CO2	Carbon Dioxide
CPM	Charging Point Manager
CVaR	Conditional Value at Risk
DE	Country Code for Germany (DEutschland)
DER	Distributed Energy Resources
DG	Distributed Generation
DSO	Distribution System Operator
DLC	Direct Load Control
DOD	(Battery-) Depth of Discharge
DS	Distributed Storage
EoL	End of Life
EPEC	Equilibrium Problem with Equilibrium Constraints
EPS	Electric Power Systems
ES	Country Code for Spain (ESpaña)
ESS	Energy Storage System
MPECs	Mathematical Programs with Equilibrium Constraints
ETSI	European Telecommunication Standardization Institute
EU	European Union
EEA	European Environment Agency
EVPEVA	Expected Value of PEV Aggregation
EVPEVF	Expected Value of PEV Flexibility
EVPI	Expected Value of Perfect Information

PEVSE	PEV Service Equipment
(G)ARCH	(Generalized) Auto-Regressive Conditional Heteroskedasticity
GCEC	Global Commission on the Economy and Climate
GEN	Generation
GHG	Green House Gas
GPRS	General Packet Radio Service
HV	High Voltage
HO	Private/Domestic Areas with Private Access
ICE	Internal Combustion Engine
IEA	International Energy Agency
IEC	International Electrotechnical Commission
ILC	Indirect Load Control
ISO	Independent System Operator
IPCC	Intergovernmental Panel on Climate Change
KKT	Karush-Kuhn-Tucker Optimality Conditions
LL	Lower Level of Bi-Level Problem Structure
LV	Low Voltage
LRMC	Long-Run Marginal Cost
MACC	Marginal Abatement Cost Curve
MO	Market Operation
MC	Monte-Carlo
MV	Medium Voltage
MID	Mobilität in Deutschland (German for Mobility in Germany)
MILP	Mixed Integer Linear Program
MIT	Massachusetts Institute of Technology
NEDC	New European Driving Cycle
NHTS	National Household Travel Survey
NL	Country Code for The Netherlands (NEderland)
NLP	Non-Linear Programming
NRM	Network Reference Model
NRV	System Energy Deviations in Germany
NSE	Non-supplied PEV energy
OBJ	Thesis Research Objective
OICP	Open Intercharge Protocol
OCPP	Open Charge Point Protocol
P/E-ratio	Power-to-Energy Ratio
PEVs	Plug-in Electric Vehicles
– GEV	Grid-Enabled Electric Vehicles
– EV	Electric Vehicles (Parent Class, i.e. any)
– BEV	Battery Electric Vehicles
– BEVx	Range Extended Battery Electric Vehicle
– EREVs	Extended Range Electric Vehicles
– HEV	Hybrid Electric Vehicles
– PHEV	Plug-In Hybrid Electric Vehicles
PLC	Power-Line Communication
PR	Private Areas with Public Access

PU	Public Areas
PV	Photo-Voltaic
QoS	Quality of Service
reBAP	Single Price for Balancing Energy Across all Four German TSOs
(S)ARIMA	(Seasonal) Auto-Regressive Integrated Moving Average
SA	Supplier(-Aggregator) for Retail of Electricity
– PEVSA	Supplier(-Aggregator) for Retail of Electricity dedicated to PEVs
SE	Country Code for Sweden (SvErige)
SETS	Sustainable Energy Technologies and Strategies
SoC	(Battery) State-of-Charge
SO	System Operation/Operator
ToU	Time-of-Use
TSO	Transmission System Operator
UCO	Uncontrolled Charging
UC	Unit Committment
UL	Upper Level of Bi-Level Problem Structure
UoS	Use-of-System
US	United States
V2B	Vehicle-to-Building
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home
vRES	variable Renewable Energy Sources
VSS	Value of the Stochastic Solution
xDSL	Digital Subscriber Line technologies

Chapter 1

Introduction

This chapter introduces the topic of this thesis from general to specific, defines the scope and its main objective, before indicating its structure.

1.1 Background

What would our modern societies be like, in the absence of widespread access to electricity and how would we live without motorized mobility?

It appears rather difficult to imagine contemporary societies of developed countries without electric power systems as the backbone enhancing social welfare, economic prosperity and ultimately well-being to its human constituents. This may be one of the reasons why in developed countries, the provision of electricity to the members of a society is regarded a fundamental service that in many cases has to be accessible virtually anywhere [1]. Besides being an essential, integral and even constituting element of societies, to plan, operate and maintain contemporary electric power systems is a challenging task, as they may well belong to the group of most complex engineering projects ever successfully executed by mankind. Similarly, the transportation sector in general and motorized mobility in particular bridge the distances between different places for living, producing and consuming goods. Exchange has been fostered and travel has been eased.

Limits of Growth and Climate However, these achievements have come at the cost of expending the planet earth's resources. The famous 1972 MIT report on the "Limits of Growth" commissioned by the think tank Club of Rome, warned that the planet's resource constraints could lead to an economic collapse in terms of the world's industrial and agricultural output, eventually resulting in a fall of health and education services, among many other effects. With 40 years of hindsight and substantial data collections at hand, [2] have recently confirmed that, despite the growth in population, important per-capita indicators of material and immaterial wealth have indeed closely followed the original predictions of 1972: Food, services and industrial output have risen on a global scale. It is no secret however, that this rise has come at the expense of an ever increasing demand for raw materials, as well as increasing levels of pollution. Whether the actual "collapse" is portended by these data, or merely one of many possibilities, is secondary. It seems reasonable to mitigate the exploitation of natural resources, where possible, to hedge against the risk of a potentially adverse scenarios of over-depletion.

Already in the early reports, one of the mentioned contributors to collapse is the climatological effect of emitting greenhouse gases during the process of converting fossil primary energy carriers into other forms of energy, e.g. electricity, through combustion. Research has come a long way since. Nowadays, it is state-of-the-art knowledge that measurable change in climate is partly anthropogenic, i.e. caused by human activities. Long-term measurements that substantiate this assertion include, but are not limited to direct and remote sensing, e.g. through satellites, of the earth's surface temperature, annual precipitation over land, spring snow coverage, polar region summer sea ice extent, upper ocean heat content, global average sea levels, carbon dioxide contained in the atmosphere as well as dissolved in ocean surfaces. In fact, the fifth assessment report from the Intergovernmental Panel on Climate Change (IPCC) finds that "*It is extremely likely that human influence has been the dominant cause of the observed warming since the mid-20th century,"* [3].

If the effects of climate change are undesirable, then efforts should concentrate on avoiding the anthropogenic components of it. Once determined to adjust behavior, does climate change mitigation mean a reduction in economic growth, like the early reports suggest? The recent climate economy synthesis report by The Global Commission on the Economy and Climate (GCEC) finds that a protection of the world's climate can go along with economic growth. In fact, [4] states that the opportunity of growth is not limited to the countries of high income, and that it would be feasible in combination with a reduction of climate change risks. In the context of this, the energy sector is at the tipping point towards a cleaner future.

The world energy outlook of the International Energy Agency (IEA) supports the argument that with the right policy instruments, the correlation of economic growth, energy demand and greenhouse gas emissions can be extenuated [5]. It furthermore asserts that the role of the energy sector is crucial in abating carbon emissions, being a major source of it with roughly two-thirds on its accounts.

Based on 2011 data from the European Environment Agency (EEA)[1], [6] provides an overview of the contribution of the transport sector, and in particular the road-based transport to the total greenhouse gas emissions, which are measured in tons of carbon dioxide equivalent. Other pollutants may or may not be counted as greenhouse gases, such as carbon-monoxide, nitrogen-oxides and sulfur-oxides, but remain dangerous to air quality. According to these data, the EU-27 countries average 1225 out of a total 4615 million tons equivalent

[1] Excluding Land-Use, Land-Use Change and Forestry.

Table 1.1: Greenhouse Gas Emissions from Transport in Europe [6]

Country	EU27	DE	ES	SE	NL
Total Emissions CO_2 [Mio. Tons Eqvt.]	4615	920	368	60	199
Thereof Transport [Mio. Tons Eqvt.]	1225	187	135	30	91
Thereof Transport [%]	**26.5**	**20.3**	**36.7**	**50.0**	**45.7**

contributed by the transport sector, or 26.5 percent. Depending largely on the industrial production base of a country, this share may vary substantially from member state to member state and may reach up to half of all emissions. Tab. 1.1 gives an overview of the numbers for the host countries of degree delivering institutions within the SETS program plus the most populous EU member state, i.e., Spain (ES), Sweden (SE), and The Netherlands (NL) plus Germany (DE). Hence, it may be asserted that the transportation sector is a large contributor to greenhouse gas emissions and that it is extremely likely that vehicles used for road transport account for a substantial share of human influence in the climatological effect of warming our atmosphere. Thus indeed, if energy efficiency for transport could be increased, a valuable due would be paid to the de-carbonization of modern societies.

This view is supported by many other studies. With the goal to quantify multiple benefits along with the emission reduction potential from low-carbon actions, the recent GCEC report [4] adjusted the widely-known Marginal Abatement Cost Curves (MACC) by *McKinsey & Company* [7]. Inverting the original and adding co-benefits of various options, puts the potential of plug-in electric vehicle (PEV) subclasses into perspective. Even though, the total abatement potential compared to other options is rather small, electric vehicles appear as the third most beneficial abatement option within the range of US$ 100 per tonne of carbon-dioxide emitted. Hybrid vehicles are estimated to lie in the range of US$ 80 per tonne of carbon-dioxide emitted.

PEVs as an Option for Increased Efficiency Both of these figures are partially grounded on the technological facts that electrified mobility has certain efficiency gains over the conventional internal combustion engine propulsion. [8] illustratively compares the efficiencies of currently available models based on the fundamental laws of physics underlying motorized mobility. Generally speaking, it can be shown that, mainly due to heat losses in the exhaustion fumes, the water cooling units and friction in the transmission systems, the remaining usable traction energy for propulsion provided by internal combustion engines is somewhere close to one fifth of the energy contained in the primary fuel, i.e., gasoline, diesel or natural gas. Vehicles that use an electric motor for propulsion, exhibit a substantially higher efficiency in the range of 80 - 85 %, already including the losses due to thermal management of the battery and other side aggregates, such as kinetic energy recuperation systems.

However, the emission impact of massive PEV deployment, also depend on the carbon-intensity of power systems, which is mainly based on its generation

Table 1.2: Sales Statistics and Market Share Q3 '13-Q2 '14, Source: [12]

Country	USA	Japan	China	France	Germany	Italy	Sth. Korea
Sales [#PEV in k]	111	31.3	25.4	14.3	10.3	1.6	1.1
Market Share [%]	0.7	0.73	0.13	0.79	0.35	0.12	0.09

mix. Here the benefits appear to be mutual: In case the power system is largely penetrated by renewable energy sources and therefore less carbon-intensive, the emissions accounted to PEVs are reduced; With more PEVs penetrating the system, the integration of renewable energy sources could be facilitated due to the inherent flexibility of their electricity demand [9].

It turns out that the future of power systems may look a lot different from today and its century-long past. According to projections of the IEA, until the year 2035 almost 50% of the global increase in power generation will stem from renewable sources, [5], however, this would mean that still only slightly more than 20% of electricity would be generated from renewables worldwide. Other, more optimistic road maps are sketched by a sustainable energy outlook, which, focusing on the case of the US, state that much more ambitious targets, e.g. 71% by 2030, are feasible [10].

Status Quo and Development of PEV Penetration Recent studies certify that an energy transition to a power system with high shares of renewable energy sources is indeed possible without much stationary storage technology, and the reason for that being cheap flexibility options, e.g., provided by PEVs. For the case of Germany, even though with ambitious renewable energy targets, this means that for the next 15 to 20 years time, or an energy production of up to 60 % supplied by renewables, the power system could do without stationary storage options, if PEVs are deployed as planned. Together with power-to-heat, power-to-gas, demand side management of large industrial customers, PEVs provide very cheap options to flexibilize power systems. These estimations are based on assumptions that in the year 2033, up to 80 GW of installed PEV charging capacity could be leveraged [11].

But where exactly does the PEV market stand today and what are realistic projections for the uptake? It can be noted that the overall PEV penetration and its rate of change still remain very low. What the future holds is uncertain and may include some surprises. The latest sales statistics as summarized in Tab. 1.2, indicate that the US is by far the largest market with total annual sales registered at 111 000 vehicles, while the country with the highest share of total vehicle sales stemming from PEVs is present in France with 0.79 % [12].

These data might seem like negligibly small contributions to an electrification of the entire fleet of vehicles, but it has to be noted where this rather new industry comes from. Taking the example of the largest market, the US, PEV sales grew from 2012 to 2013 by a sheer 81% while the entire automotive market only grew 7.5%. Also in terms of vehicle models offered on the market the developments are fast paced. While by the end of 2013 there were only 16 models commercially available, this number is projected to be 22 by the end of 2014 [13].

Last year's up-to-date overview of PEV penetration and sales projection studies compared to real-life observations can be found in [14]. It shows how difficult this art and science of projection is, even though a variety of analytical and computational tools to model PEV penetration is already in use.

PEVs as a Strategic Development Option and its Geo-Political Dimension The primary energy carrier of crude oil is the indispensable input for propelling today's vehicle fleets. [13] indicates that in the US, petroleum use for road transportation, counting motorcycles, cars, trucks and buses makes up 85%.

As laid out in the introduction of [15], the electrification of personal vehicle mobility permits a greater number of private end-users, i.e., vehicle mobilists, to access strategic advantages thus far exclusively inherent to the electric power sector. Electricity generation is diverse in its primary energy sources and can partially be generated from domestic, renewable sources. The obvious advantage of energy diversity lies in sourcing flexibility and potential for quick adaption to exogenous shocks. These may result from an interruption of supply or soaring prices due to unforeseen events of any sort. Crucially, domestic production allows political independence and freedom from energy imports, or rather, liberates from a necessity to maintain diplomatic relations of dependency on energy exporting countries. In the past, electricity prices have proven to be significantly less volatile than oil prices.

But the electrification of today's vehicle fleets may also have relevance pertaining to industry policy and labor markets. Supporting innovation in the automotive sector would increase internal European employment and enhance economic prospects in general. Significant reductions or diversion to other sectors from spending on imported materials would free up forces to create jobs back in other parts of the European economy. These EU-wide benefits are estimated to be around 850,000 to 1.1 million additional jobs in 2030 [16].

1.2 Motivation, Aim and Solution

Given the above background, PEVs are perhaps not a perfect panacea but certainly exhibit a plurality of benefits and co-benefits to modern society. It therefore appears stringent to tackle the challenges of integrating PEVs in current power systems as efficiently as possible. PEVs may contribute to an affordable and reliable energy model that provides tolerable environmental impact. This is the main motivation of the given thesis research.

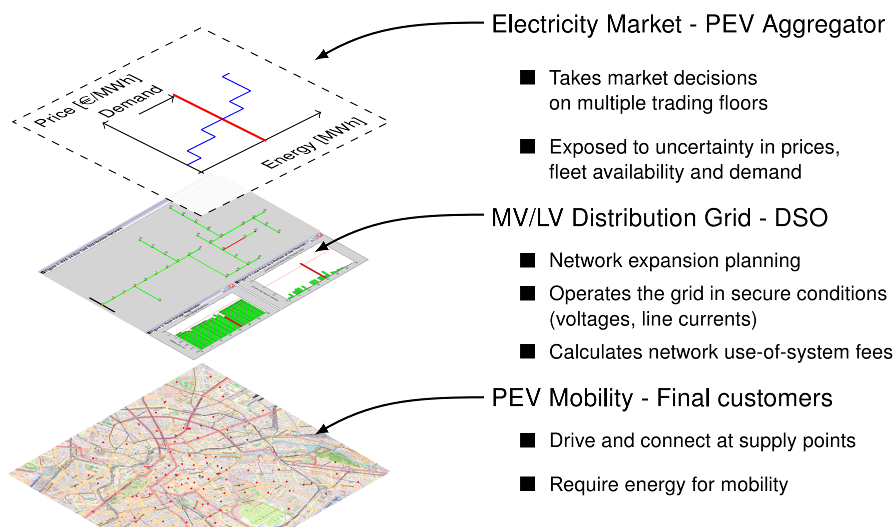


Figure 1.1: Three Layers of PEV Integration in Modern EPS

1.2.1 Motivation

Future power systems with high penetration levels of PEVs are likely to be structured in the following three layer scheme. First and foremost, PEVs are going to be used to service the mobility needs of final customers, who drive and connect at different supply points of the power system, requiring a certain amount of energy. One layer above, medium and low voltage distributions system operators are affected by the use of their system. Relevant tasks are the long-term network expansion planning and the short-term operation of the grid in secure conditions, such as voltage stability and keeping currents within thermally dictated limits. For the sake of this thesis, it will be assumed that all tasks of the distribution system operation can be boiled down to a simplified calculation of network use-of-system fees, which are incurred by the users of the grid. Finally, an aggregation agent as the interface to the wholesale electricity generators is envisaged to be in charge of procuring energy in electricity markets. This would be done similar to the way suppliers nowadays take different positions in the respective trading floors of electric power exchanges. This agent would be exposed to uncertainty in prices, fleet availability and demand requirements from the lowest level. It should be noted that from a regulatory perspective within the framework of the European Union, the regulated activities carried out by a network operator in its natural monopoly are strictly unbundled from those of the competitive aggregator agent. Fig. 1.1 gives and overview of this three-layer scheme for PEVs in power systems

1.2.2 General Thesis Objectives

This thesis claims to be a normative research work in the sense that it intends to describe, *how should PEVs be advisably coordinated, providing benefits to electric power systems in the presence of resource scarcity?* Resource scarcity refers to the general economic terminology for welfare-optimal allocation of resources. Generally speaking, these include, but are not limited to network infrastructures, generation assets, fuel, and the labor required to deliver the planning and operation of the entire system. To this end, the thesis works towards increasing total system efficiency and what in economic theory are called net social welfare. The goal is to deliver a techno-economic thesis, employing qualitative as well as quantitative methods and techniques known in regulatory theory, applied mathematics, economics and operations research.

Main Objective The main objective of this research is to propose models for decision making of existing and future power system agents that can influence the total system efficiency while charging plug-in electric vehicles.

1.2.3 Strategy and Approach

In order to pursue the research goal, individual objective functions of aggregators need to be accurately formulated and the role of network operators analyzed. Hence the thesis is set out to develop simulation algorithms to generate realistic price and availability scenarios, as well as stochastic – to account for uncertainty in the involved parameters – optimization models employing state of the art solver technology, e.g., MatLab© for handling scenario data, GAMS© and CPLEX™ for optimization. These algorithms and models will precisely represent the decision making.

The analysis shall then turn to potential measures to - and prerequisites for - achieving system optimal outcomes. For that, a representation of the network state needs to be chosen. The work will introduce location-based efficient network use-of-system (UoS) fees, in the form of capacity prices in € per kW max. demand over a given time period, for different nodes in the low and medium voltage grids. The proposed models will then accurately approximate the economic impact of these pricing schemes for the involved agents.

Significance and Impact of Proposed Research The models and tools developed in this work can be directly used by electricity sector agents to aid them in complex decision making under operational uncertainty. Using these tools will emphasize the opportunities as well as limits of the PEV technology and thereby pave the way for system optimal PEV integration. In summary, the proposed research will foster the energy efficiency of transport systems and hence contribute to the overall sustainability of future societies.

Other side objectives, intended effects and achievements include the fostering of an informed and open debate, and to contribute to the wider public policy agenda affecting the electric power sector and car manufacturing industry.

1.3 Outline and Document Organization

With the following structure, this thesis addresses the above-mentioned research objectives. The main body document is organized in two parts, both presenting different types of scientific contributions, framed by introduction Chapter 1 and conclusion Chapter 7. Part I contains conceptual ideas, general electric power system framework assumptions and qualitative discussions on existing work of PEV integration. These chapters form the foundation of this thesis, to which the subsequent sections frequently refer back. Part II presents the quantitative modeling chapters, which substantiate the methodology, point to specific assumptions for the proposed decision making tools and finally put forward a thorough analysis of an aggregator's economics with a discussion of numerical results.

In detail, the subsequent content of this thesis is structured as follows: In Chapter 2, the regulatory framework of power systems with high levels of PEV integration is presented in a tutorial manner. It includes a first illustrative case study to further motivate the importance of understanding regulatory frameworks and to highlight the most important power systems agents impacted by PEV charging. Following, in Chapter 3, the existing body of literature is reviewed, structured and organized to further synthesize more detailed research questions and more concrete objectives. Chapter 4 then proceeds to apply advanced mathematical programming techniques to the decision making of PEV aggregators. The developed approach is explained while at the same time providing detailed nomenclature and algebraic formulations of the proposed optimization techniques within the stochastic and bi-level programming frameworks. In the following two case study chapters, Chapter 5 and Chapter 6, inputs and outputs of numerical cases are documented, the various aspects of PEV aggregator decision making are highlighted and quantitative results are discussed. Finally, Chapter 7 states the main findings of this thesis in the form of conclusions as well as future work. An overview of the document organization is provided in the summarizing schematic of Fig. 1.2.

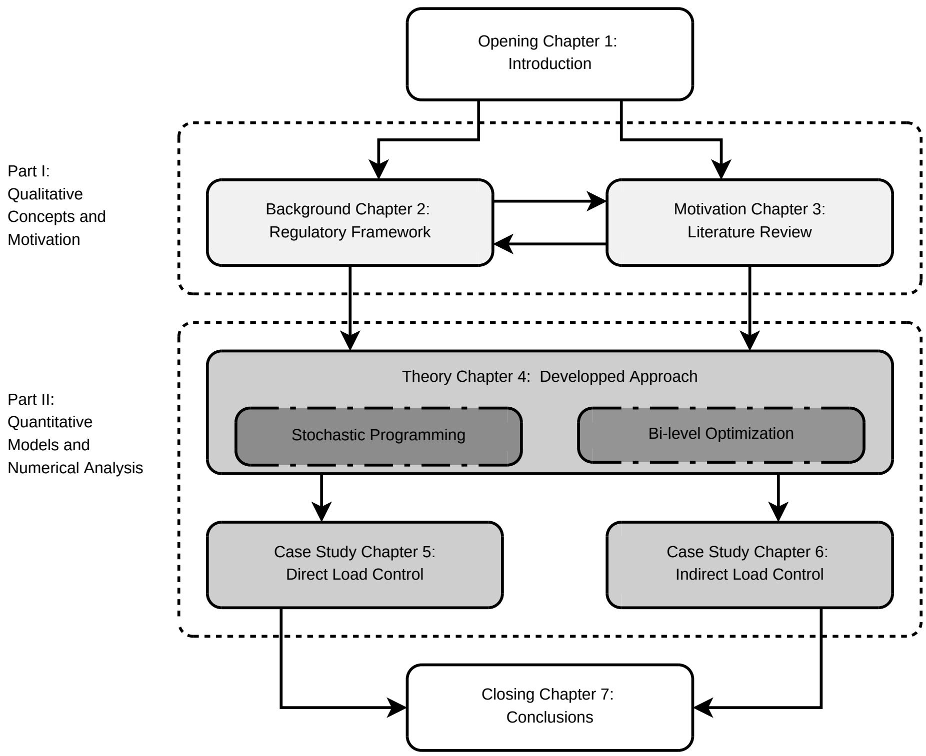


Figure 1.2: Illustration of the Thesis Outline and Document Structure

Part I

Integrating PEVs in Electric Power Systems

The Regulatory, Economic and Technical Background

Chapter 2

Regulatory Framework

This chapter forms the basis of understanding the core analysis to follow. It is a natural extension of the introduction chapter. Beginning a nearly comprehensive thesis on PEV coordination, it can only be beneficial to create a common ground of comprehension for a broad audience. However, the chapter is not merely informative to a less specialized readership. The logic amplification and deepening of basic concepts used in power systems can also serve to the well-informed power system expert, as basic concepts are reviewed, hence brushed up and solidified. All this is given in view of a projected adaption of power systems to a new era with a significant presence of PEVs.

Large parts of this chapter have been published as a book chapter in [17] and complementary discussions grounded on the similar principles have been published in [18].

Given the long and comparatively slow evolution of power systems over more than a century, the above-mentioned adaption, progressing in one or two decades, may be regarded as nothing less than drastic change and disruptive to business-as-usual (BAU). Therefore, it is deemed important to reflect and discuss along the lines of constituting elements of these complex systems. On the one hand, this chapter focuses on *current, incumbent and existing*, elements, while on the other hand, it opposes them with those that pertain to the *mid- to long-term future* and may with today's perspective understandably seem *futuristic, yet promising.*

This chapter borrows large shares of its wording, as well as its mind-set from the discipline of regulation, an across-the-board art combining technical knowledge from engineering, understanding of economics as well as surmounting legislative processes and normative policy analysis. An important piece of work on the matter shall be cited here first and foremost [1]. To the author of this thesis, "Regulation of the Power Sector" presents an integrated and concordant text on the topic, which in the form of its graduate course originated plenty of inspiration for the given chapter.

2.1 Introduction to Regulatory Aspects

A quick scan of the policy landscape governing PEV in power systems reveals that at the supra- and national level of the European Union (EU) among others, a huge variety of relevant initiatives and policy measures have been launched in recent years. Generally speaking, these include strong commitments to the allocation of funds to mitigate energy-related environmental impacts as well as to foster the energy efficiency of societies. In some parts of the world these were correlated with large government stimulus programs to decrease the exposure to a world-spanning financial, and in its consequences economic, crisis. In addition, an increasing awareness of sustainability issues in relation to energy consumption has paved part of the way for an electrification of transportation systems.

All of the above has lead to the expansion of research in energy efficiency and clean technology, specific to introducing electric vehicles for road transportation. This research intends to address a number of prerequisites to a massive deployment of PEVs. In the course of such endeavors, it has become evident that both the electric power industries and the automotive industries will have to rise to a number of challenges. The implications of these, focusing on the electricity sector, are elaborated in the subsequent paragraphs and sections. To do so, some background and basic concepts are provided.

2.1.1 Background and Basic Assertions

PEVs bring along environmental advantages compared to conventionally propelled transportation systems, which tend to be inherently fossil-fuel-dependent and based on internal combustion engines (ICEs). It is often narrated that these comparative benefits are a function of the composition and origin of energy carriers used as primary inputs to produce the alternative fuel: electricity. This is true to a large extent, although a refined argument can be added.

Internal Combustion compared to PEVs Electricity generation at the source, tends to exert less controlability, the more it is based on fluctuating, intermittent renewable energy technologies. And because it has to be consumed instantaneously, while, generally speaking, storage technologies are not yet economically viable, it has become rather clear that the benefits of PEVs depend on the advances of control strategies for the charging processes. The idea is to meet less controlability on the generation side with increased flexibility from the demand. However, it is interesting to note certain studies, which conclude that even in rather unlikely but most carbon dioxide (CO_2) intensive scenarios, i.e. with conventional power generation technologies and largely BAU, PEVs would still possess benefits: Both annual and cumulative greenhouse gas (GHG) emissions of entire systems, i.e. combining both electricity and transportation sectors, could be reduced significantly, if a certain electrification level of the car fleet under analysis [19] was to be achieved.

Comparing Alternative Fuel Options With the above in mind, it remains to be questioned, whether PEVs are the best alternative fuel option? PEVs have received a significant amount of attention both in mainstream media and research oriented publications. In this later context, the scientific interest has a twofold justification. As alluded above, in many instances, PEVs are perceived to offer a means for achieving goals related to energy efficiency, presenting environmental benefits to the arena of personal transportation. Even though detailed performance characteristics of electricity storage in mobile applications remain uncertain for the future, transportation technology options have been effectively compared to one another and evaluated, as the following citations indicate. Lithium-ion based storage technologies seem most promising in the mid-term: this technology's well-to-wheel energy consumption and emissions highly depend on the electricity generation mix for mobility. Taking a static value, consumption and emission of battery electric vehicles could range around 314–374 Wh per km and 76–90 gCO_2eq per km [20]. However, the academic opinions are diverse and divided. For the sake of neutrality, it shall not be left un-mentioned that other literature suggests PEVs do not present the best option to cut oil consumption and emissions in the transportation sector. A recent study finds that fuel cell electric vehicles powered by hydrogen made from natural gas would be more efficient in the USA [21].

PEV Promises and Concerns On the other hand, in the mid- to long term future, i.e. within the next decades to come, PEVs are expected to be able to provide ancillary services to electric power systems (EPS) and could thereby further support the integration of variable renewable electricity sources (vRES) [22], [23]. Yet, it has to be analyzed how to coordinate and to incentivize all involved participants to foster PEV adoption and create a functional basis for mass deployment of this emerging technology. To fulfill ambitious penetration targets on time, it is very demanding but necessary for all stakeholders, including regulators and policy makers, to exploit their prospective capabilities to an optimal extent for the entire system.

Storage technology is still costly and degradation, i.e., the loss of value over time due to intensive usage, is a major concern. Although capacity degradation may effectively turn out to be less severe, today's prospects are not only promising. With the currently projectable lifetime performance and the use of relevant commercial lithium-ion based batteries for grid application as peak power generators may remain economically unattractive [24]. Alternative revenue sources for battery storage valuation in power markets for ancillary services, such as secondary frequency regulation may have to be sought for [25].

At the consumer level, the proposition of PEVs compared to conventional vehicles is similarly uncertain. The currently perceived purchase premiums compared to ICEs are widely being discussed and the multitude of different policy schemes to foster PEV adoption are evaluated. A comparative study shows that, from a user perspective, one time support at the initial investment is highly appreciated. However, recurring instruments like an annual tax benefit are more effective though usually smaller in volume *[26]*.

Coordination issues for utilities, mostly distribution system operators, and car manufacturers, but also fleet operators and potentially other charging station operators, are constituted by finding functional standards for charging interfaces including physical equipment, metering, and communication protocols for billing at home or en route. The relevant standardization organizations at the level of the European Union are the European Committee for Standardization (CEN) with its sub-branch the European Committee for Electrotechnical Standardization (CENELEC) and the European Telecommunication Standardization Institute (ETSI). All of the above mentioned organizations are in collaboration with the biggest international standardization bodies: International Electrotechnical Commission (IEC) and the International Standardization Organization. Standards need to be addressed to a variety of topics to achieve interoperability, allow for competition in manufacturing, and agree on communication protocols as well as the information to be exchanged. Furthermore they can improve safety of certain products [27].

Regulation as a Means to Penetration With all the PEV promises and concerns at hand, it becomes clear that a regulatory framework can play an important role in furthering the deployment of PEV, yet even be a prerequisite to it. The further integration of PEVs may require new models of ownership and lease for personal transport vehicles and a change in thinking about the BAU practices. Mobility as a product or a service may have to be consumed under new types of arrangements and contracts. Moreover, a great challenge is the installation of a publicly available charging infrastructure for PEVs. This would demand active collaboration of national and regional policy makers, vehicle fleet managers, electricity distribution companies, payment service providers, and many other areas that may not directly be associated to the sectors of transport or energy [28]. For the latter however, finding a suitable and well established operation state description from the power system point of view for all affected entities to manage different activities such as load shifting, ancillary services provision and their interdependency, may be crucial [29].

A central responsibility for supporting the commercial introduction of PEVs lies with electric utility companies. A number of potential roles includes outreach and education to create customer acceptance, safe and secure infrastructure development, as well as understanding and potentially mitigating adverse system impacts [30].

2.1.2 Chapter Contributions

Provided the above, high-level overview of challenges and elaborating the importance of a regulatory framework, the contribution of this chapter can be summarized as:

1. Providing a tutorial introduction to the main characteristics, role allocation and distribution of crucial functions among the agents of modern,

vertically disintegrated, i.e. unbundled electric power industries, with different penetration levels of PEVs connected to the grid.

2. Introducing a classification of charging modes, i.e. different scenarios, in which PEVs can be charged, such as home charging, public charging on streets and dedicated charging stations.

3. Proposing a conceptual regulatory framework for these charging modes, governing the interaction of the involved agents and giving justification for the development of two new entities as intermediary facilitators of the final service.

2.2 PEV and Power-System-Related Taxonomy

In power system literature, there exists a number of different abbreviations that are used to describe different vehicle classes. This may stem from the fact that the research on PEV integration may be considered relatively young, and at its initial stages, a standardization of terminology had not taken place. For the sake of clarity and interoperability with other publications, the following paragraph briefly defines relevant acronyms.

Vehicle Types The following distinction between different technologies and according abbreviations will be used: The parent class contains all vehicles with motorization differing from mere conventional internal combustion engines. Electric vehicles (EVs) are driving at least partially with an electric drive train.

1. HEVs, Hybrid Electric Vehicles possess both electric and conventional drive but no capability of grid connection.

2. PHEVs, Plug-in Hybrid Electric Vehicles, are a sub-class of the forementioned, distinguished by the capability of connecting to and receiving energy from the grid. Into this category also fall EREVs, Extended Range Electric Vehicles.

3. BEVs, Battery Electric Vehicles are propelled with an electric drive train only. These are naturally equipped with grid connection capability. If a vehicle is designed to be a BEV but also equipped with a range extending ICE unit, it is sometimes called a BEVx and then actually is a PHEV, or more specifically an EREV.

4. PEVs, Plug-in Electric Vehicles, sometimes also referred to as grid-enabled vehicle (GEVs), are the conjunction class between PHEVs and BEVs, i.e. all vehicles endued with the possibility to connect to, as well as charge from the grid.

Where applicable, this document uses the term PEV instead of its synonyms, as by now, it appears to be the most commonly used abbreviation in IEEE literature.

Generic Terms Commonly Used in EPS Connected to the electricity grid, PEVs could be charged according to their users' needs for mobility, but at the same time they could provide benefits to different agents in the value chain of the electric power system. Such positive externalities would notably exist in system operation (SO), generation (GEN), retail (SA) and market operation (MO). SO can be further distinguished with respect to which part of the network is concerned: in high voltage (HV) transmission (TSO), medium and low voltage (MV and LV) distribution (DSO), or if the agent in charge of SO does not own any assets, but is constituted by a separate agent as found, e.g. in United States' (US) regulation, independent system operator (ISO). All the aforementioned elements in the electric power system value chain are depicted on the left hand side of Fig. 2.1.

A Short Excursus on Optimal Charging Schedules In an unbundled electric power system with liberalized energy markets, generators' electricity supply meets the final customer's demand represented by retailers, while system operators ensure grid stability [31], [32]. Different electricity sector agents could be involved in enhancing and valuing intelligent charging alternatives of the storage. With adequate regulation in place, the PEV charging schedules that are most important to the system as a whole could be *favored*.

In this instance, the term *system* may refer to the collection of producers and consumers represented by retailers that meet in the electricity market as well as all network operators. *Optimality* of the resource allocation can be explained with a market efficiency argument and in terms of global net social benefits. That is, the more *favorable* the PEV charging schedule is, the more it is consistent with the goal of a market-based regulatory policy. Hypothetical and implicit assumptions form the basis of this argument: primarily all network aspects are ignored, generation markets should be sufficiently competitive, where agents' decisions are based on non-regulated market prices, being the only economic signal for the generators even in the presence of planning and operational constraints [33]. It is generally believed that establishing an energy marketplace for electric power and having competitive agents interact via a spot price for buying and selling electric energy, which is determined by the economic conditions of supply and demand at that instant, supposedly, has major advantages over other ways of determining energy prices [34].

However, transmission and distribution of energy comes at a cost and network capacities are not unlimited. This enriches the aforementioned viewpoint by the fact that *optimality* may take into account planning and operational aspects of the power system networks. It may thus be *favorable* to the power system as a whole, that charging schedules are simultaneously aligned by market prices and congestion signals from the network.

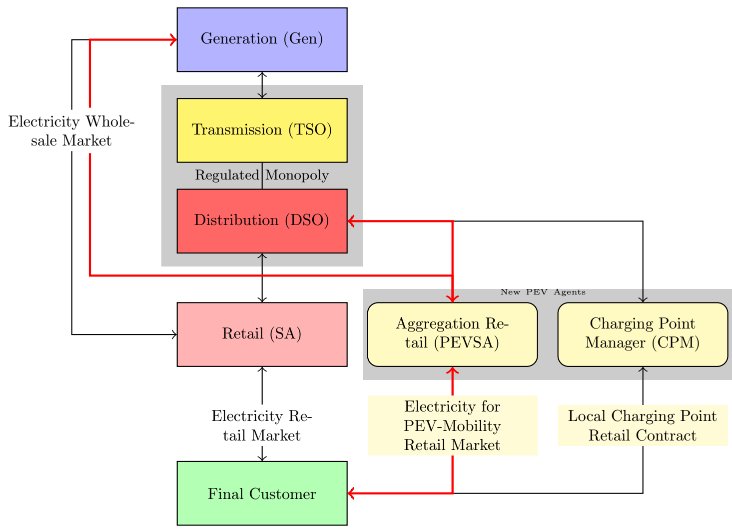


Figure 2.1: PEV Agents in Future Electric Power Systems

2.3 Existing and Future Agents in Electric Power Systems

The electric power industry has a long history, ever since its birth, strongly contributing to the technical industrialization of manufacturing goods as well as to the economic development of modern society. Until its present maturity, tremendous endeavors have gone into the improvement of current processes of planning, operating, monitoring and controlling. These have to endure in a world that is on the one hand technologically quickly advancing but, on the other hand, growing technically and economically ever more complex.

Traditional regulation of this strategically important sector was designed with electricity utility companies vertically integrating all processes of the value generation chain for the final product of electricity: procurement of primary energy sources, generation, transmission, distribution, and retail. The sector was liberalized for a variety of different reasons, usually pursuing economic efficiency in the allocation of resources. The enhancement of computing and communication technology has further propelled the intention to drive for efficiency with appropriate economic signals sent to the final customer. The innovations in production technology and the advancement of renewable energy generation equipment that can be deployed in a less centralized manner than conventionally large electricity generation plants have further weakened the stance of monopolistic ownership of vertically integrated companies such that today, the electric power industry has changed drastically.

Modern power systems since the 80s and 90s have undergone the processes of unbundling and liberalization. They have developed electricity markets with decision making hierarchies for long, medium, short term and real time horizons. The physical characteristics of electricity as such and the not yet economically attractive storage technologies demand for generation and consumption to always equal each other, which make the design of these markets for such systems a highly complex. To fulfill it, technically both the frequency of the alternating current and the voltage magnitudes at the different physical nodes of the network have to be kept within a certain range around the nominal value. The terminology and the technical specification of the services may vary, however such services have to be provided. Usually, in liberalized systems, the SO procures them from other agents ***[31]***. The services are usually called ancillary, as in addition to being needed they help optimize the utilization of the system, such that for instance reactive power reduces the technical losses in the network. Setting up and designing these markets properly is not a trivial task [31].

The following subsections give rise to the functions that are taken on by the various agents in the electric power system. On the one hand, first, those known and well defined existing agents are introduced that current regulation has already defined. On the other hand, the expected, yet sketched and upcoming agents in a changing picture of PEVs penetrating the power system, are explained thereafter. Finally, a small example on how these agents may interact in a coordinated way is provided.

2.3.1 Existing Agents: The Known and Well-Defined

Electric power system agents can be distinguished by the nature of their basic activity: some agents may be referred to as non-regulated agents with competitive activity. These include generation companies, acting on wholesale energy markets, and suppliers, acting on both wholesale and retail markets. The other group of agents can be referred to as regulated agents and mostly includes the network infrastructure operators. Due to the economies of scale in network infrastructures, these agents, including the operators of transmission and distribution networks, TSOs and DSOs, act in natural monopolies, commonly under what is called incentive-based regulation.

As opposed to what is commonly referred to as traditional cost of service regulation, under an incentive based approach, the remuneration of the network operation service is determined by revenue caps. This is done with the intention of emulating the competition of markets to artificially induce efficiency gains in the operation and planning of the networks.

For the charging modes and their classification further on, mostly DSOs, TSOs and suppliers are of particular interest and hence are further introduced and abbreviated at this point:

- TSOs: are responsible for keeping a secure system operation at the regional or national HV to extra-HV transmission level. For meeting this obligation these agents procure system services, such as operational reserves and frequency regulation, from market participants. In other systems outside the European framework, especially in the US, independent system operators are also frequently found. Such a model distinguishes the ownership of the transmission system assets from their operation.

- DSOs: are the owners and operators of the mostly LV/MV distribution grids. In the context of this thesis, it is assumed that distribution is legally unbundled from generation, transmission and particularly from supply and retail. Therefore, DSOs cannot trade energy. They only provide network services and are fully regulated agents operating in a monopoly. This complies with the existing regulation in Europe and presents a fundamentally different approach than, e.g., in some US American states, where traditionally retail and distribution are provided by the same entity, the electric utility. In the EU, DSOs are strictly regulated monopolies, subject to incentive- or performance-based regulation and unbundled as imposed by the European Commission Directive 2009/72/EC [35]. Under these incentive-based schemes network operators are generally provided with incentives in order to improve their performance regarding system efficiency and attain better quality-of-service (QoS) levels. The objective is to strike an optimal equilibrium of investment and operation cost on the one hand, with and optimal QoS on the other.

- SAs: Supplier(-Aggregator)s or Retailers are the agents who sell energy to final customers, the electricity end consumers. Under the assumption that distribution and supply have been fully unbundled, final customers remunerate their suppliers for their service, who in return procure the energy from the electricity markets and pay the DSOs respective regulated charges for grid services and other system costs.

- Final Customer: is the agent that requires electricity for end-uses and purchases this from an SA. In general, by legislation, a final customer is not allowed to resell electricity to another final customer or to another agent. Final customers are residential, commercial or industrial customers. In some countries, as an intermediate step towards a complete liberalization, small residential customers have purchased electricity at regulated rates, while large customers have negotiated a supply contract with any supplier.

2.3.2 Future Agents: Sketching Expectations

In addition to the known, well defined electric power system agents named in the previous section, the penetration of PEVs in the system would require new agents. Besides the PEV driver, two new agents would become relevant. Their respective relevance depends on the later to be introduced PEV charging modes. These expected agents are sketched as follows:

- Plug-in Electric Vehicle Owner: is the agent that owns a PEV and requires electricity to charge its PEV battery. This could be a private person, or an organization that owns a fleet of vehicles. In the future, this agent could be able to provide other services to the networks as well. When charging, PEVs would be physically connected to a charging point and in some scenarios a specific PEV supplier aggregator will procure system services from the PEVs under his control (see definition below). In the following, we consider two main alternatives regarding the development of charging infrastructure:

i) privately owned charging areas with private or public access for PEV owners, and

ii) public charging areas with public access for PEV owners.

- PEV Supplier-Aggregator (PEVSA): the PEV supplier is the agent selling electricity to the PEV owner. PEV suppliers are retailers and therefore similar to other wholesale market agents. Their business should be declared as a competitive activity, fully unbundled from other vertical functions in the electric power system. PEV suppliers in general are expected to aggregate multiple PEVs to conduct an integrated management and may hence also be referred to as PEV aggregator. All terms, PEVSA, PEV aggregator are used interchangeable in this document. The nuanced differences to the traditional SA are elaborated in the following sections.

- Charging Point Manager (CPM): assuming that the installation of charging infrastructure on private property will in some instances be made by the property owner, acting as a final customer, CPMs would buy the required electricity. This energy would be used to either charge the own PEVs or to resell it to other PEV owners connected to the charging station under a commercial agreement. Different situations could be possible, such as:

  - An office building owner who installs several PEV charging points in the office parking area for private use of its employees.
  - A commercial building owner who installs several PEV charging points in its parking area for use of its clients.
  - A PEV charging station owner who installs several charging points with different charging options, specifically fast charging modes, for delivering this service to the public.

By legislation until recently, CPMs who resell electricity to a third party, i.e., a PEV owner, in a competitive activity would be defined as suppliers or retailers. In this case, the access to the charging services would be made available on the terms and conditions set by the CPM. For obtaining a license to exercise this type of activity, they should demonstrate technical capability and financial liability according to legislation. In Spain, the role of CPMs has been adopted and defined as outlined above.

In public parking areas, streets and areas with public access, the installation of PEV charging points is likely to be more expensive, given the state-of-the art technology and its most likely future. To have a large roll out might therefore

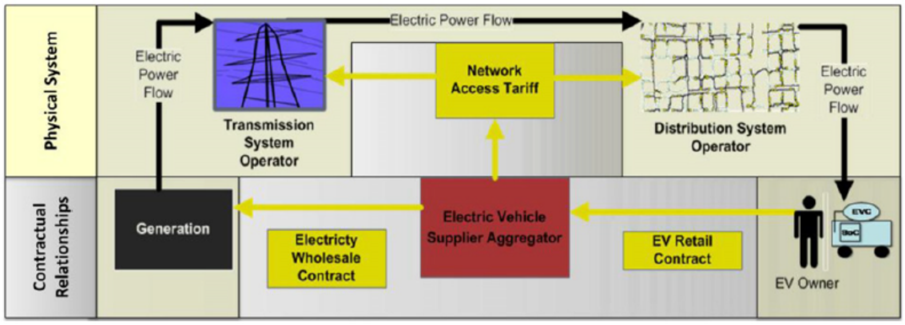


Figure 2.2: Old and New Agents in Interaction

involve substantial expenditure and risk. When involving the use of a public good such as the public location, there is a strong argument, that the business should be regulated and charging stations developed by either the corresponding DSO or the municipality in the area. In this case, the infrastructure would be considered as other grid expenditures and the access to the charging points should be made universal to PEV owners contracted with different PEV suppliers. In this way, private companies monopolizing the scarce resource would be avoided. In the case of CPMs acting on privately owned property, however, infrastructure could be installed and investment risk assumed by private agents. The activity would be open to competition depending on the development rights of the location.

2.3.3 Interactions of new and old agents

To sum up this sub-section, Fig. 2.2 brings the above together and shows the potential interactions of new and old agents of the electric power system with the PEVSA as the facilitating agent of the most generic charging process. The physical flow of electric power is tracked via the HV transmission system over MV to LV distribution to the final customer. The network operators recover their costs via the network access tariffs, which are collected by the PEVSA, together with the energy generation costs and passed on to the respective agents.

2.4 PEV Charging Modes

As mentioned in the previous sub-sections, for the purpose of this thesis, a charging mode is defined as a situation in which a PEV can be charged [18]. This definition is so important, because these situations may vary a lot and therefore there is significant value in determining the characteristics that distinguish and categorize these situations. To this end, certain characteristics of charging modes have been made out: the determining factors are the charging point location, interacting agents and their relations for delivering the final product or providing the final service, as well as the level of control over the charge and degree of sophistication for the charge.

Clarifying the boundaries to similar notions: Different terms describing similar concepts are widely used. According to the above outline of a charging mode, it could be freely translated as a use-case as well. However, it is different from the notion of a business model. As opposed to charging modes, business models describe how a product or service is provided, including the perceived value creation of a certain product for a final customer. It is internal to one single agent and usually easy to assess by spending strategic thoughts on opportunities and threats. On the other hand, charging modes provide the access to the changing interrelations as they put each single agent into perspective in relation with others. In that sense, charging modes are the more general first and necessary step to formulate the business models of the agents.

2.4.1 Location and Access

The location and access of the charge is defined by the property ownership on which the charging process itself is taking place. The different cases are: charging points located on public areas, private areas with public access and private areas with private access.

2.4.1.1 Public Areas

For public (PU) areas being municipal, regional or national property, merely public access is possible, therefore a charging station or a charging point should enable free access to all citizens, which does not mean that the electricity should be sold for free. However, dealing with a public good, the assumption that the distribution system company, or the local municipality would be developing the infrastructure, is not very far-fetched.

At this point it seems important to note that it has been implicitly assumed that DSOs are likely or favorable to develop public charging infrastructure. However the outcome of this market development, and therefore also its regulation is uncertain. It remains to be seen what will happen in the future as different approaches for developing public charging infrastructure from different stakeholders with diverging interests are currently co-existing.

Regulatory Options for Charging Infrastructure The Union of the Electricity Industry at pan-European level initiated the discussion about the "structure of the e-mobility market" in September 2010 [36], this excerpt picks up the dialogue and aims at introducing the given regulatory options for fostering the deployment of public charging infrastructure. The paragraphs below illustrate the proposed regulatory options for rolling out the public infrastructure for charging PEVs. These are potential alternative for the ownership and operation of the infrastructure placed in public areas with public access.

Option 1: *The Integrated Infrastructure*: This option is characterized through full integration of the charging infrastructure in the asset base of the DSO. This would mean that retail and distribution of the electricity for electric mobility are unbundled from each other. This would entail that the incremental capital and operational expenses would be acknowledged by the regulatory authorities and the allowed revenues of DSOs would be adjusted accordingly. The advantage of this first option is that siting of the charge points could be aligned with network needs, i.e. if possible favoring the most efficient connection points, which cause the least cost for the overall system.

Option 2: *The Separated Infrastructure*: The charging infrastructure would be a completely new and separate step in the value chain of PEV electricity delivery, at least legally unbundled from the rest of the distribution network as well as from retailing. Although this solution may not exhibit the optimal siting in terms of network expansion according to already existing DSO assets, potential adverse effects for the operation of distribution networks, could be offset by higher revenues from optimal retailing strategies of new dedicated agents.

Option 3: *Independent E-Mobility*: Here the ownership of assets and the retailing of the electricity for PEV are combined under one roof. Like in the second option, the charging infrastructure would be outside the asset base of the distribution system company, yet the retailing would be part of the functions for the new entity. There would be a proprietary network with the licensed and conceded territory. This territory could be maximally as big as the territory of the country or as little as a few spots.

Option 4: *Spot Operators*: Finally the fourth option proposed is a derivative of number three with the main difference that the license is single spot based and not for a regional territory. The prime example is a parking lot or a gas station that also offers charging services. Similar to the previous option, location-specific delivery generating location rents could be the driving force behind development.

In principle it can be argued that Option 1 is the most desirable. The DSO developing the charging infrastructure in public spaces as the network operator have the best knowledge about the grid behavior and can take direct measures in the planning and operation processes to keep the costs as small as possible. However, it would require that charging infrastructure would be regarded as a public good and essential service similar to the cases of electricity itself, water, telecommunications and gas. Only then would a considerable need for capital be justified.

The importance of this discussion lies in finding appropriate solutions as to how these investments are going to be acknowledged as costs to DSOs and how electricity customers or PEV owners, or both are going to pay for them. All this should ideally be compliant with incentive-based monopoly regulation for networks in place [1, Ch. 4, pp. 140].

Interoperability: a Case for Monopoly Regulation? In EU member states, different initiatives exist with the intent of creating a freely accessible charging infrastructure to all clients, who may be contractually related only to one single charging infrastructure operator with a local service territory. The idea is to provide a billing and settlement platform, such that different infrastructure operators, especially valid in ***Option 4*** with Spot Operators, could have a means of providing a roaming service, similar to the ones known in mobile phone communications, or bank cards: in case the customer finds himself in the situation to arrive to a new charging spot operated by a different agent than the one he has contracted already, it would be valuable to the client to be granted access, without having to enter in a new contractual relation, especially not one that is, e.g. long-term binding. There is a value in roaming capability for the client: access to the infrastructure in new locations; as well as for the operator: additional revenue from external clients that are roaming in their network.

The developments of information-technology-based platforms that enable the billing and settlement of payments for charging of roaming processes may therefore be regarded as likely. In case, for any reason, the roaming service provider becomes the sole supplier of the product, a case for monopoly and its regulation may be given [1, Ch. 4, pp. 140]. To give an example, in Germany the industry consortium *Hubject,* providing such an IT platform, is already monitored by the *Federal Cartel Office* to ensure that the establishment of interoperability benefits the well-being of the final customers as proclaimed.

2.4.1.2 Private Areas with Public Access

For private areas (PR) with public access, the case is different. These areas include company owned parking lots or dedicated charging stations. Here, the property owner can decide to commercialize the service of charging PEVs himself, subcontract other companies or sell a license to do so. The arrangement would be made between the operator of the charging point and possibly multiple PEV users. Other contractual relationships, such as office or commercial building owners giving the service away for free are possible.

Especially offices with a high share of the staff commuting with personal vehicles might be an interesting field of application for PEVs. There, the managed fleet size could be significant, cars are usually parked during multiple hour periods of time. In these locations, sophisticated energy management systems are in some instances already in place, sometimes integrating on-site generation with small-scale photovoltaic arrays and combined heat and power systems.

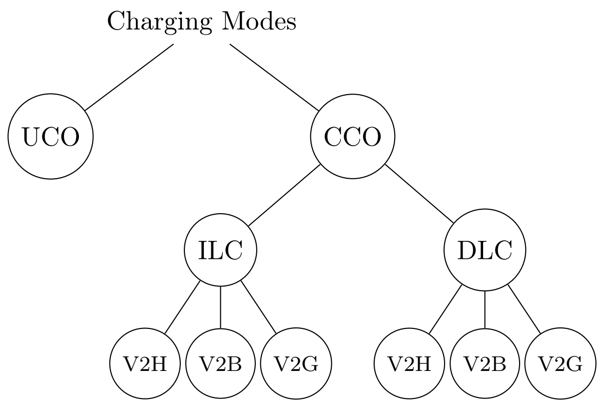


Figure 2.3: Hierarchy of Charging Modes

2.4.1.3 Private Areas with Private Access

Private areas with private access (HO) are the third and last group of charging modes, concerned with all the charging processes with restricted access to a limited group of PEV owners. Examples are home charging in domestic garages or mutli-dwelling units. In this case the electric vehicle service equipment (PEVSE) for the charge is most probably going to be owned by the PEV user himself and the cost can be added to the purchase price for the vehicle itself.

2.4.2 Control Modes

Concerning the technical grid aspects of PEV integration, different control modes are imaginable. The following gives a short introduction to the differentiation of control in the charging modes presented underneath. There are five different denominations for control modes: Uncontrolled Charging (UCO), Controlled Charging (CCO), which splits up into Direct (DLC) and Indirect Load Control (ILC), Vehicle-to-Home (V2H), Vehicle-to-Building (V2B) and finally Vehicle-to-Grid (V2G). Even though in the final nomenclature they are presented equally, a certain degree of hierarchy exists. This is shown in Figure 2.3 and individually explained in the subsequent subsections.

2.4.2.1 Uncontrolled Charging

Uncontrolled charging stands for the simplest, least sophisticated way of operating the charging of a PEV. UCO is the intuitive, traditional way of supplying any given electrical device with power: plugging it in and instantaneously taking the required power. Since there is no intelligence to improve the scheduling of the charge to any criterion whatsoever, it is often times referred to as *dumb charging*. It is thus assumed that under UCO, there is no tariff, or electricity price structure in place that incentivizes final customers to adapt their consumption or UoS in any way. In reality, this would be rather similar to the current situation of flat energy-based, volumetric prices that are discriminating neither time, nor consumption level.

With sufficient PEV penetration in the system, the co-incidence of PEV UCO may drive up peak load and hence lead to adverse impacts on the network. High costs for investment (in capacity of generation and network assets) as well as operation would be the consequence. However, it is expected to be the most prominent way of charging PEVs in the near term until high penetration scenarios require more sophisticated control modes.

2.4.2.2 Controlled Charging

Controlled charging complements uncontrolled charging. CCO is more sophisticated, hence sometimes merely called *smart charging*, than UCO as it disposes of a certain degree of control over the charge. This control can be either exercised via a price signal, which is here called ILC, or via setting a specific load level, which is here denominated DLC.

In its most trivial form, CCO under DLC may be a simple switch that cuts off the load if it negatively impacts on the system – for instance in the case of overloads or voltage problems in the network – or if it becomes too expensive for the system to reinforce itself against these impacts. More advanced solutions may permit the controller of the charging to send exact power set points to the vehicle and thereby actively modulating the charging according to a set of defined criteria. The most futuristic control modes include bidirectional energy flow between the battery storage system of the vehicles and the local network at the grid connection.

With CCO under ILC however, appropriate electricity prices are used as economic signals, such that beneficial behavior of the final customer is induced and thereby reducing the negative impact of PEV charging. A good example are peak and off-peak prices to promote charging at off-peak hours, or with higher time resolution a contract with hourly prices. Hence, CCO under ILC in the form of time- or load-variable end-user tariffs, supported through smart metering,[1] appear to be the natural next step in the evolution towards a *smarter* grid.

Whether directly or indirectly exercising CCO, the control may be exercised by different energy management systems operated by different entities such as PEV aggregators, DSOs, or local CPMs. When PEV sales have sufficient uptake such that high penetration levels and concentration of PEV charging in certain feeders becomes significant, CCO may have to be strongly incentivized by legislation.

The following three charging modes pertain to the main beneficiary and criterion used in order to control the charging. All three could be enacted under ILC or DLC.

[1] Smart metering in this context refers to the ability of the measurement device to distinguish between different time periods (resolution may vary from two periods per day, up to 15-minute intervals) and potentially even communicate this data close to real-time to the DSO.

2.4.2.3 Vehicle-to-Home

Vehicle-to-home is the first element in the subset of CCO control modes for charging electric vehicles. It specifies the criterion for the optimization of the charge control to be according to local domestic devices. Assuming that a household has a local energy management system[2] installed, V2H charging could be controlled to level out the net load of the home avoiding peak demand charges or shift electricity consumption to off-peak hours.

2.4.2.4 Vehicle-to-Building

Vehicle-to-building charging control is very similar to the preceding control mode and not clearly distinguishable from the above. However, it is recently more frequently used and therefore listed here. In this classification it refers to situations in which the PEVs are connected to an integrated management of a greater size building. In addition to the energy management system in V2H this may compose of an integrated control with local loads and even other distributed energy resources (DER), low voltage distributed generation (DG), from e.g., small-scale combined heat and power (CHP) units, solar photovoltaic panels (solar-PV or simply PV), or distributed storage (DS) devices.

2.4.2.5 Vehicle-to-Grid

The control mode V2G has received a lot of attention in scientific literature. This section is not ample enough to give an exhaustive explanation but intends to deliver an introductory overview of what is often referred to. In any case, V2G presents the most sophisticated and hence futuristic application of connecting electric vehicles to power networks.

Security of the physical operation of the electric power system requires, as noted above, the frequency of the alternating currents, as well as the node voltage magnitudes of the network to stay within a certain range around their nominal values. During the process of unbundling vertically integrated utility companies and liberalizing energy markets, most systems adopted fundamentally similar designs for procuring ancillary services in market arrangements. Although in research there has been an abundant intuitive use of the term *vehicle-to-grid,* two completely different understandings of the term can be distinguished:

On the one hand, to some it means that there is a bidirectional power flow, for which the vehicles sometimes act as a generator, injecting electricity into the grid.

On the other hand it is understood in a more general way, as providing an ancillary service to the grid, which could be delivered by unidirectional power flow as well. From a technical view point, lowering the aggregated power draw of a given fleet of cars has the same effect on the system as an injection of the same amount of power. What counts is the rate of change in power draw

[2] Sometimes referred to as *energy box*.

indifferent of the current level of own demand. Hence, just the stopping of a charge when regulation energy to lower demand is required[3] would be provided by an interruptible power connection of a PEV. [37] argues that, even though further limited in capacity, unidirectional V2G should be logically addressed first, as it requires less sophisticated PEVSE.[4] Along a similar train of thought, the aggregator of electric vehicles for V2G is believed to be the potential link between automatic generation control (AGC) entities and the fleet of vehicles for providing secondary frequency regulation [39].

In best-case scenario simulations of German and Swedish power markets, [25] found that secondary frequency regulation markets could be significantly profitable but may saturate quickly if high capacity connections are available to a broader mass of vehicles.

2.4.3 Communication Protocols

With regard to the communication protocols, during the early stages of the discussions within the standardization process, [40] analyzed different V2G protocols, that are in general also relevant for CCO charging. The protocols are distinguished by the link on which they operate. There are generally two possibilities:

1. V2G front-end: The link between the PEV and the EVSE and
2. V2G back-end: The link between the EVSE and the legacy electricity grid.

Here, legacy electricity grid refers to any type of electric power system entity and physical equipment, which may include the DSO, TSO, MO, as well as of course the PEVSA. Depending on the technical set-up, i.e. voltage levels, current ratings, phases involved etc., and charging functionality, different protocols may be involved. From 32 amperes upward for example the requirements for safety are rather strict: on the lower layer, dedicated safety signals, circuits and control pilots may be required.

Furthermore, according to [40], on the V2G front-end, a) IEC 15118, b) IEC 61851 and c) IEC 62196 can be found. According to [41], c) mainly addresses the physical interoperability, i.e., the electrical equipment, extending b) which defines technical set-up from slow charging using typical household sockets to fast charging with dedicated EVSE, however does not accommodate standardization of communication necessary for load control. Hence, a), the newest and most relevant standard for this thesis, was necessary. Among many features, it contains provisions for “active charge control”, i.e., CCO, renegotiation as well as processes necessary to settle payments.

On the V2G back-end however, besides the existing legacy protocols for communication and control, IEC 61850 may be found. Offering data modeling

[3] Also referred to as regulation up.

[4] This claim is backed up by the PEV interface studies of [38] and it avoids negative effects of depleting PEV batteries in cases where the charge is highly valued by the customer.

and mapping of logical nodes, this standard is applicable not only to PEV charging but to communicating with any smart grid device that is equipped with a certain degree of intelligence.

Having discussed the different control modes and communication protocols above, the following paragraph links them to the future agents in their respective roles, for the final classification of charging modes provided underneath.

2.5 Discussing the Role of Future Agents

The following sections come back to rather market related, economic aspects of PEV integration. They explain the regulatory setting and once again give justification, why two new figures, CPMs and PEVSAs, may in a future with high penetration levels of PEV in the power system complement the incumbent SAs.

2.5.1 Incumbent Retailers, Supplier Aggregators (SAs)

This sub-section focuses on the interactions of SAs as market agents and the regulation they have to follow in order to perform their tasks when supplying PEV users. Day-ahead and intra-day markets refer to the wholesale energy market, where generators meet SAs which procure electricity to resell it to final customers on the retail market.

The activities of SAs comprise technical and economic tasks. They include the billing of the energy consumed by the final customer according to energy and capacity prices set in the agreed contract. A retailer also has to store and use the information on the consumption of each final customer for load forecasting to optimize its involvement in the markets. Furthermore, the tasks embrace the procurement of energy, e.g. in a power exchange, and managing the commercial relationships with the existing and potential new customers.

The SAs are market players that bridge the trading gap between generation and demand, fulfilling various functions from the wholesale to the retail market. In capital market theory these functions mainly include transforming lot sizes, i.e. trading volumes and quantities of goods, risk transformation, i.e. hedging against undesirable events, and term transformation, i.e. monthly payments for domestic customers while procuring energy in 15-minute intervals on the wholesale market.

An SA's profits result from the difference in prices, quantities, terms and risks at wholesale compared to final customer level. In order to assure a viable business model, the aggregated demand for the final customers has to be as accurately forecasted as possible, and then accordingly procured. If positions do not close as expected, that is, if the forecasting errors are causing a need for balancing of previously purchased supply and the aggregated SA's demand, more costly ancillary service products have to be procured on the balancing markets. In countries where electricity distribution and supply have been unbundled to favor competition among agents, all final customers should have access to competing generators through their choice of SAs. Fully regulated tariffs, if they exist, are intended to only present a back-up option. In these cases, final customers remunerate the electricity supplier for the service, who in return procures the energy and pays the distributors regulated charges for grid services and other system costs.

Due to uncertainty, stand-alone retailing is regarded a high-risk and low-return business. In theory it is of high interest to the SA to obtain a very flexible demand which is able to respond to varying market prices in order to reflect the actual opportunity cost of the customers more appropriately and pass on part of the risk exposure to the final customers. In this sense, including a percentage of flexible demand procured by smart charging of PEVs in their portfolio can be of interest for SAs in the future.

2.5.2 Charging Point Managers (CPMs)

CPMs are yet new to the power system. Slowly, regulation has started to sketch these figures as vague understanding has hit the regulatory authorities that an agent for reselling electricity in local contexts is demanded by a world of massive propagation of PEVs.

CPMs are expected to be acting as final customers on private property with public access. They are understood to be buying the required electricity to resell it to PEV owners connected to the local charging station under a commercial agreement with specific terms and conditions. It is very important to understand that, to the distribution system, however, a CPM is regarded as a single final customer. The final customer, depending on the size of the parking lot managed, could have an electricity demand as big as a small industrial customer in terms of energy consumption, or constitute just a few cars and therefore be similar to a household. The CPM in general would have a supply contract with a supplier. The supplier would have to pay the regulated access tariff according to the contracted capacity and consumption measured on the interface to the network.

CPMs should be free to define an objective function that is most beneficial to them. This could include an installation of PEVSE that meters the connection points of each and every car and design according rates for the usage of this infrastructure. On the other hand, it could be favorable for the CPM to simply charge for parking time and space without measuring user specific consumption and internalizing energy procurement and infrastructure investment costs on an aggregated level in the parking time rates. Hence, the CPM could be offering the charging of the electric vehicle as an additional service to customers with whom there already is some other type of commercial agreement, like in a shopping mall or for the commuting staff of an office building. The second arrangement alludes to the main challenge of a regulatory framework forming the basis of legislation that fixes the rules for such operation of the charging service. Any set of requirements concerning metering layouts, financial liability and technical capability should be designed according to the principle of non-over-complication, applying restrictions only where absolutely necessary.

2.5.3 PEV Supplier Aggregators (PEVSAs)

PEVSAs are expected to be the agent that sells energy to final customers, the electricity end consumers using PEV. The supplier therefore aggregates contracts with final customers and procures the energy in the wholesale markets, and possibly agrees on demand side reduction measures of the final customers to be offering other services to the market. Hence, these agents already exist and are denominated supplier aggregators (SAs), with the only distinction of being specialized in serving a theoretically highly flexible load of a fleet of electric vehicles.

These functions have been extensively discussed and numerically shown in literature: On the one hand, the study of aggregators' performance in terms of revenue and cost implications during charging processes with different programming algorithms can be considered as very important [42]. On the other hand, however, the problem of the aggregator should not be regarded in a completely isolated way from other agents in the system. To relax network constraints and assume the absence of a grid topology that needs to be operated securely and cost efficiently may present a major shortcoming to analysis when considering the opportunities of further DG penetration [43].

In the near-term uncontrolled and home charging modes are very likely to dominate the scene, in which most of the functions and objectives of the SA stay the same. In the HO scenarios where PEVs are charged at home, the PEVs will merely present an additional net load to the SAs of domestic electricity customers. In short, this load is more volatile because it is a flexibly schedulable charge and hence presents the opportunity for more business, but also the threat of adding uncertainty to the forecasting. As there is no control over the charging process from the SA, the main means of influencing the charge of the electric vehicles will be the offer of PEV user-customized electricity prices with at least ToU differentiation. In general, the main objective is to get the demand side involved in the market game by passing on the volatility of prices and thereby reducing its own risk.

The proposition by electric vehicles could be theoretically a valuable one, as they present schedulable loads, which if reacting to the price signals, or being controlled, may contribute to reduce uncertainty and risk exposure of the SAs, while increasing turnover significantly. However, if the PEV penetration gets very large, PEV demand becomes very relevant, new specialized PEV aggregators might arise and additionally, in close interactions with DSOs, the operation of distribution networks would also have to be considered. In such a case, the DSO would offer special contracts, pricing the use of the network to the SAs or would perhaps even be called to validate power flows caused by PEV demand from a technical point of view or at least be informed about the amounts to be bought by the aggregators.

In general, the use of PEVSAs may be viewed under the aspect of enhancing many small entities that by themselves would not present a very meaningful class of agents to the system. This has implication in terms of energy demand and capacity for market participation as well as buying power with low transaction

Table 2.1: A Nomenclature for Classifying Different PEV Charging Modes

LOCATION		*AGENT*		*CONTROL*	
Home	***HO***	Supplier-Aggregator	***SA***	Uncontrolled Charging	***UCO***
				Controlled Charging	***CCO***
Private Property	***PR***	Charging Point Manager	***CPM***	Vehicle-to-Home	***V2H***
				Vehicle-to-Building	***V2B***
Public Property	***PU***	PEV Supplier-Aggregator	***PEVSA***	Vehicle-to-Grid	***V2G***

cost [44].

However, in literature, the most common aspect that is mentioned is the concept of V2G [22], in which the vehicles provide ancillary services to the system. This is why in the following classification PEVSAs are mentioned as the intermediary for facilitating these services.

2.5.4 Classification of the Charging Modes

Having introduced the different factors that define a charging mode, the following classification and denomination becomes more evident. It is consistent with what has been published in [17], [45]. Tab. 2.1 provides a tabular overview.

Each charging mode is named according to its classification, including the characteristics: charging point location <*LOCATION*>, intermediate agent for organizing energy procurement or system services <*AGENT*>, and the degree of optimization and control over the charging process <*CONTROL*>. Each three characteristics can assume the above introduced occurrence ***HO***, ***PR*** and ***PU*** for the location, ***SA***, ***PEVSA*** and ***CPM*** for the intermediate agent as well as ***UCO***, ***CCO***, ***V2H***, ***V2B*** and ***V2G*** for the control.

A typical future charging mode for street parking with charging infrastructure would then be for instance **PU-PEVSA-CCO**, in which the PEV user has a contract with a PEV aggregator providing a controlled charge according to electricity market prices.

In Part II of this thesis, the PEV charging modes covered do not particularize, whether the *LOCATION* is in a home, private or public property. The assumption is that charging infrastructure is extensively deployed and that the ***PEVSA***, as the main agent exercising control and given the presence of standardized communication protocols, would be able to influence the charging irrespective of the location.

The control modes that are being represented in the models developed in this thesis, are mainly addressing PEV scheduling under controlled charging with ***CCO*** and ***V2G***. A few calculations also make use of ***UCO*** to provide reference cases and benchmark the quality of the ***CCO*** modes.

Note that in EU regulation of unbundling, the DSO is never the agent controlling the charging. As a regulated entity, it only sets prices to reconcile revenues in the most efficient way, which nevertheless may play an influential role. The following illustrative case study highlights the above-mentioned aspects further.

2.6 Illustrative Case Study

The following case study is published in [46].

2.6.1 Introduction to the Case

The succeeding sub-section highlights the meaning of the above-outlined regulatory topics and tightens the focus of the preceding chapters on interactions of the PEVSA while representing DSO implications as well.

Thus, the illustrative case study further analyzes the interactions of an existing agent, the unbundled DSO and a future power systems agent, the PEV aggregator. Each agent's objectives and functions are presented for charging electric vehicles in two different deterministic schedules: dumb charging occurring coincident to peak system load and valley charging as a smart approach. First, the analysis turns to the different aspects of selling energy to final customers by looking at three alternative pricing schemes: hourly pricing, time-of-use tariffs and a flat energy rates. Then, the DSO as a regulated entity is analyzed in its function to postpone network investments. Thereby, the simple case study quantifies the benefits from PEV charging during low price night hours in terms of energy trading for the aggregator and deferring network investments for DSO.

To that end, the following builds upon the conceptual regulatory framework outlined above. The given classification suggests implications on many regulatory topics. Here, however, only a certain number of the charging modes are treated, in which the intermediate agent in facilitating the charging process is the PEVSA. But it focuses on deriving the main objectives of DSO and load aggregators, taking into account the agents' internal business models. In particular, the case study quantifies the value created by both agents and proposes a method for benefit calculation and sharing among the two agents in interaction.

As the forthcoming analysis shows, the communication link between DSOs and the PEVSA can be regarded as a key aspect of the aggregator's functions in order to value the opportunity presented by the dispersed storage to the system. For the DSO, load management generally permits optimized usage of its infrastructures, which can be valuable to defer investments in grid infrastructure reinforcements, minimize losses and CO2 emissions, as well as achieve quality of service objectives set by the regulatory institutions. In summary, there is a high interest in proper charging schedules of electric vehicles if there are high penetrations of them in the grid [47]. It has been shown, that the peak shaving from coordinated charging of an aggregated PEV fleet can lower power losses and voltage deviations [48]. In the following case study, the main cost savings are derived from deferring or avoiding network investments due to optimized charging.

Table 2.2: Characteristics of the Considered PEV Fleet

High Penetration Scenario – Year 2030				
PEV class	PEV Type	# Vehicles	Standard Charging rate [kW]	Average Charging Hours per day
L7e	BEV	309	3	1.02
	BEV	13,001	3	2.05
M1	PHEV	9,722	3	1.99
	EREV	4,474	3	3.23
	BEV	1,477	3	2.99
N1	PHEV	1,105	3	2.73
	EREV	508	3	2.99
N2	BEV	604	10	8.03
TOTAL		31,201		—

2.6.2 Case Study Description

This section presents a simple but insightful case study to illustrate the benefits of two alternative charging scenarios of a fleet of vehicles managed by a PEVSA and connected to a distribution network that is owned and operated by an incentive-based-regulated DSO. The site under analysis is a real distribution network of a tourist destination in the south of Spain, currently consisting of 34,351 supply points and 170,444 final customers in low, medium and high voltage, with a minimal demand of around 120 MW and a peak load of approximately 315 MW on a given day.

2.6.2.1 PEV Fleet Composition

According to a high penetration scenario in the year 2030, the connection of a PEV fleet of in total 31,201 BEVs, PHEVs and EREVs of four different classes is considered: 309 L7e (passenger vehicle with maximum unladen mass of 0.55 tons and a maximum power train output of 15 kW), 27,197 M1 (passenger vehicle with up to 8 seats in addition to the driver's seat), 3090 N1 (goods-carrying vehicle with a maximum laden mass of 3.5 tons) and 604 N2 (goods-carrying vehicle, four wheels, with a maximum laden mass of 12 tons). In Tab. 2.2, all these can be assessed in further detail. PEV locations were selected randomly between customers, hence, in terms of probability the number of PEV in each node was related to the number of customers in each node, and therefore indirectly linked to their total contracted power [49].

2.6.2.2 Demand Scenarios

The demand of the aggregated fleet of cars is calculated with average charging rates limited by grid connection from 3 kW (10 kW for industrial goods carrying vehicles) and average charging hours per day ranging from approximately 1-8h (derived from battery sizes and daily mobility as well as energy consumption depending on the class and type of PEV). Hence, on an average day the vehicles would consume a total 257.7 MWh of electricity, presenting a considerable 4.5% of the 5.374 GWh total demand. Simply extrapolating the PEV demand over the course of a full year yields an annual consumption of 94.04 GWh of electricity.

To emphasize the effect on networks, two deterministic charging strategies are compared to each other: peak charging and valley charging. Assuming a high simultaneity of charge either upon arrival at home after work or at a specific time during the night, the load profiles (except for N2 BEV) have been adjusted to start at the same time, to consider the worst case of dumb charging [49]. These two deterministic schedules are shown in Fig. 2.4a. Furthermore, it can be observed that the scheduling in the peak scenario causes the aggregated load of the system to rise by considerable 22.11%, shifting from hour 14 to hour 21. The Fig. 2.4b further illustrates the scheduling of the load in the respective cases, where the red bars present the aggregate load of residential and industrial customers without electric vehicles, while the green bars show the valley scenario and the blue bars the peak scenario of the additional electric vehicles charging. From this illustration it already becomes evident why, in the following sections of this case study, the two charging schedules are referred to as valley and peak charging.

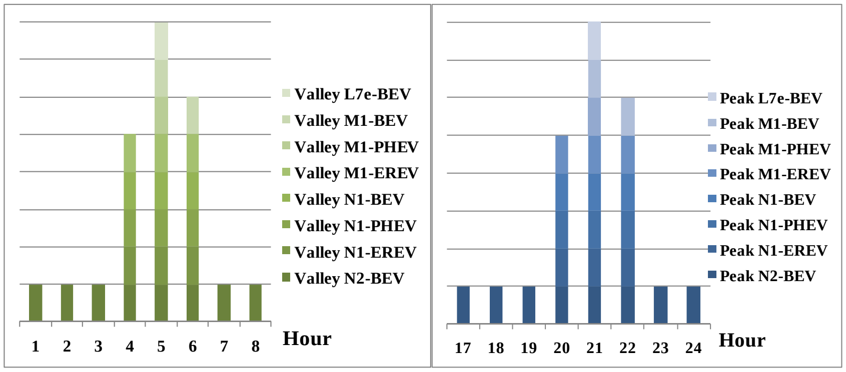
2.6.2.3 Market Prices

To calculate the profits of the aggregating agent, the hourly marginal wholesale day-ahead market prices from the Spanish system have been used as happened on Wednesday, March 2nd 2011 [50]. The hourly time series of the chosen date is illustrated in Fig. 2.5. This date is chosen, because it is deemed representative in its characteristics of total energy traded 584.99 GWh, high maximum price of € 53.50 per MWh occurring during the midday, low minimum price of € 32.15 per MWh occurring during night hours, intermediate arithmetic mean price of € 45.52 MWh and average trading volume weighted price of € 46.41 MWh. Please note that the profit calculation does not include price components from intra-day or balancing markets, capacity payments or other cost constraints. In particular, it is acknowledged that the wholesale electricity price only makes up about 49.2% of the total electricity price to final customers. In September 2010, the components of electricity prices to final customers with hourly varying prices in Spain made up: Fixed Access Tariff €-cent 1.9 per kWh (16.8%), Variable Access Tariff €-cent 3.43 per kWh (30.3%), Commercialization Margin €-cent 0.41 kWh (3.6%) and Wholesale Energy Cost €-cent 5.57 kWh (49.2%) [51].

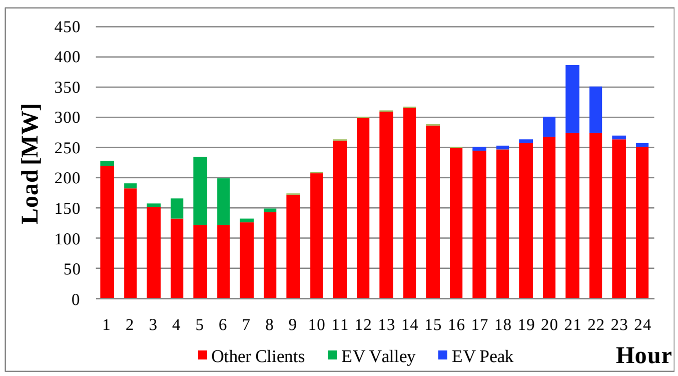
2.6.3 Peak Charging Related Network Costs

2.6.3.1 Economic Impact on the DSO

To determine the DSO's value of charging the vehicles in valley hours rather than in peak hours a network reference model (NRM) is used considering the same technical constraints and planning principles as in the actual network of

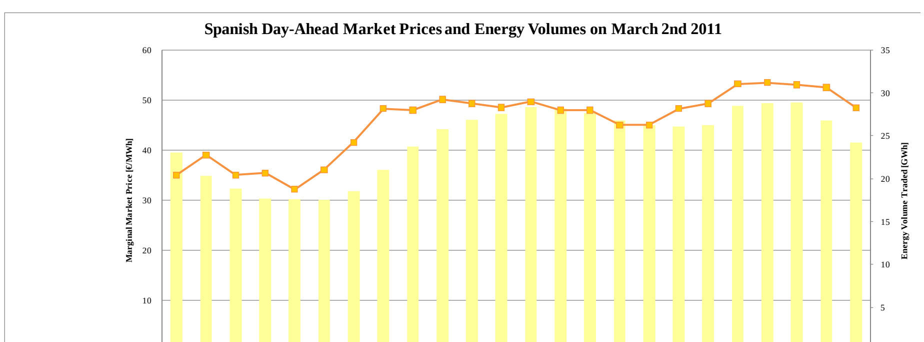


(a) PEV Off-Peak and On-Peak Load



(b) PEV Load-On Top of Other Clients

Figure 2.4: Load and Charging Scenarios



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Energy Volume Traded [GWh]	23.02	20.32	18.88	17.67	17.58	17.49	18.55	21.01	23.73	25.79	26.85	27.55	28.30	28.16	27.64	26.81	26.21	26.05	26.21	28.51	28.80	28.88	26.76	24.22
Marginal Market Price [€/MWh]	35.00	39.00	35.00	35.42	32.15	36.07	41.53	48.30	48.00	50.12	49.33	48.50	49.66	48.00	48.00	45.00	45.00	48.30	49.33	53.23	53.50	53.03	52.50	48.46

Figure 2.5: *MIBEL* Market Prices and Energy Volumes on March 2^{nd} 2011

Table 2.3: Incremental Network Investment by Voltage Level [€/PEV]

	Low Voltage	MV-LV Transformers	Medium Voltage	Total
Valley	45.25	17.41	5.29	67.95
Peak	230.17	298.06	197.56	725.78

the described area [51]. For this, detailed geographical features of settlements, street maps, aerial and underground topology, as well as voltage, capacity and reliability restrictions are taken into account. The expansion plan designs the network for a vertical[5] demand increase of 2% for 3 years, disposing of a standardized equipment library for conductors, transformers, switching gear, etc. for all voltage levels.

Incremental Network Investment Tab. 2.3 indicates a summary of the results of the incurred expansion planning costs for the two indicated PEV load scenarios of valley and peak charging in terms of incremental network investment. Here, the term *incremental expansion costs* refers to those costs that are additionally incurred compared to an expansion plan without any PEV load considerations. The numbers are provided disaggregated for different voltage levels. The total incremental investment amounts to € 725.78 per PEV in the peak scenario, whereas the reinforcements only cost € 67.95 per PEV in the valley charging scenario. The main driver for this pronounced difference is the additional network capacity that is needed to service the increased peak load.

Annualized Peak Charging Cost One could assume that PEVs are going to penetrate electric power systems no matter what. In this case, as opposed to merely reporting the integration costs compared to a no-PEV world, the more interesting focus lies on how existing resources can be managed as efficiently as possible, given PEV penetration. Ideally, this could be done without excessive investment in additional network capacity to accommodate peak charging. To emphasize this point, the difference between valley and peak charging is calculated by aggregating voltage levels, subtracting the incremental investment cost of the valley scenario from the peak scenario. The result is denoted *comparative charging cost*.

Furthermore, besides the up front investment cost, it appears interesting to analyze how these costs amount on an annual basis. To this end, the annuity factor (ANF) is calculated:

$$\mathrm{ANF}_{T,i} = \frac{(1+i)^T \cdot i}{(1+i)^T - 1} \tag{2.1}$$

[5]In electricity distribution network planning, load growth is further distinguished being either *vertical*, or *horizontal*. *Vertical* refers to the type of growth that is incurred by the same given set of supply points, e.g. because customers buy new electrical devices. *Horizontal* refers to additional demand arising because of new, before not-existing supply points, e.g., a new urbanization being added to a given city development.

Table 2.4: DSO's Comparative Equivalent Annual Cost of Peak Charging

Total Equivalent Annual Cost		
€	€ per PEV	€ per MWh
1,721,248	55.17	18.30

with an interest rate of $i = 8\%$ as well as a maturity T of 40 years, providing an $ANF_{T,i} = 8.39\,\%$. Applying this to the comparative charging cost, conceptually gives the equivalent annual cost of the investment. The peak charging would lead to an additional cost of € 55.17 per PEV or € 1,721,248 in total compared to the valley charging scenario. Tab. 2.4 indicates the values in Euros per vehicle, treating all vehicles equally for the allocation of the cost, as well as in total. If this price was spread out evenly among the extrapolated yearly energy consumed by the PEV[6], the electricity price effect would be in the rough range of € 18.30 per MWh or €-cents 1.83 per kWh.

2.6.3.2 Economic Impact on the PEVSA

Having assessed the economic impact of different charging schedules on the DSO, the illustrative case study turns its focus on the PEVSA. In the following, an approximation of the profit implications stemming from the two charging schedules is carried out.

The value of different charging schedules to the aggregator is calculated ex-post, summing up the arbitrage potential under three different hypothetical retail tariff settings, i.e., hourly varying, time-of-use (day-night tariff) and flat rate energy tariff. For the sake of simplicity, the hourly varying tariff assumes a constant 10% profit margin above the hourly wholesale price. Again with the intent to keep it simple, the ToU tariff assumes a 10% profit margin above the average wholesale price between hours 10 and 21 for on-peak during the day as well as the same profit margin above the average wholesale price between the remaining hours 22 to 9 for off-peak. The flat rate retail tariff is assuming simply a constant volumetric energy tariff that is derived from the arithmetic average, i.e. not trading-volume-weighted, wholesale price over the full day. A further explanation of different retail tariff options can be found in the case study of section 6.1.1 on distributed decision making reacting to PEVSA price signals.

The sum of profits in all hours of the representative day extrapolated to annual values yields the following outcome. All scenarios except the peak charging under flat rate would be profitable to the aggregator. The results can be observed in Tab. 2.5.[7]

[6] This is merely an indicative approximation of the cost per energy, not suggesting it as an adequate method to calculate a network tariff for PEV, as it is violating many principles of complex network tariff designs.

[7] In the tables of this illustrative case study, negative figures (<0) are enclosed by parenthesis.

Table 2.5: Annual Profits of the Aggregator in Different Tariff Settings [€]

	ILC		DLC
	Hourly Variable	Day-Night ToU	Flat Rate
Valley	327,103	1,053,442	1,010,409
Peak	495,514	98,108	(673,701)

Then, again the peak and the valley charging schedule can be compared to each other. Inversely to the DSO's case since dealing with profits instead of costs, subtracting the profits in the peak scenario from the ones in the valley scenario yields the following value of valley charging for the aggregator, indicated in Euros per vehicle and total. See Tab. 2.6.

From this data, it might counter-intuitively appear as if peak charging can be more profitable to aggregators depending on the wholesale purchase price variation over the course of the day and the margin calculation. If the cost during the hours in which the vehicles charged in the valley case were lower than the ones in the peak case, and the margin assumed proportional to the sales volume as in our example, the aggregator would theoretically profit more from peak charging. In such a case, the only determinant of profit is the revenue, i.e. any schedule with higher revenue means higher profit. The commercialization margin being the same however, there would still be profit in the valley case. At this point it is important to note that some combinations, pairing a tariff setting with a charging schedule are unlikely to occur due to the underlying assumptions on charging control. In the two tariff settings including time discrimination, i.e., hourly variable and day-night ToU, ILC is prevalent such that the final customers would have the control, reacting to the price signals of the tariff setting. Final customers with flexibility on the timing of their charging schedule would probably not opt for the more expensive charging schedule during peak charging, but rather charge in the valley. In that sense, the results in Tab. 2.5 and Tab. 2.6 should never be used to recommend any tariff scheme over another, by comparatively looking at the difference in value of rows or columns.

Nevertheless they contain a lot of insightful information. The most important take away is: If the aggregator has control over the charging, i.e., DLC is prevalent and therefore a flat rate is offered to the final customers, there are high comparative profits for the aggregator to align the PEV charging schedule with the prices in the wholesale electricity market. This comparative profits are in the same order of magnitude and in the same range as the comparative equivalent annual costs to the DSO.

2.6.3.3 Economic Impact on the Final Customer

To the final customer the energy costs are always minimized when charging in the valley scenario, except for the flat rate tariff, in which the customer is obviously indifferent to the timing of the charge. Similar as for the DSO and the PEVSA, the extrapolated annual energy cost, only considering wholesale

Table 2.6: The Aggregator's Annual Comparative Profits of Valley Charging

Tariff	CCO	€	€ per PEV
Hourly Variable	ILC	(168,411)	(5.40)
Day-Night ToU		955,334	30.62
Flat Rate	DLC	1,684,110	53.98

Table 2.7: Annual Energy Cost to the Final Customer [€]

Tariff	CCO	Valley	Peak
Hourly Variable	ILC	(3,598,132)	(5,450,653)
Day-Night ToU		(4,324,471)	(5,053,248)
Flat Rate	DLC	(4,281,438)	(4,281,438)

prices plus commercialization margin of the aggregators are shown in Tab. 2.7. The comparative value of valley charging to the final customer, as shown in Tab. 2.8, then amounts to as much as € 59.73 per vehicle on an annual basis. Again, if this value was spread out evenly among the extrapolated yearly energy consumed by the PEV, the electricity price effect would be in the rough range of € 19.70 per MWh or €-cents 1.97 per kWh.

The main take away of these data is that from a final customer perspective, the highest incentive to participate in a load shifting charging schedule is under ILC with hourly variable prices, i.e. being exposed to the variability of wholesale electricity markets, because benefits are passed on.

2.6.4 Comparing Impacts for Both DSO and PEVSA

This section with its illustrative case study has shown the interactions of the unbundled DSO and the future power system agent, the PEV aggregator. Each agent's objectives and functions have been presented for charging PEV in two different times of the day, charging PEV at peak or valley hours. The coincidence with other non PEV load is a major driver for costs, as the used capacity of both generation and networks is scarcer. In this simple case study, the benefits of charging the vehicles during low price night hours have been quantified in terms of energy trading and deferring network investments.

Depending on the retail tariff, to the aggregator, the annual value of charging in valley hours amounts to as much as € 53.98 per vehicle, while it ranges around

Table 2.8: Comparative Value of Valley Charging to the Final Customer

Tariff	CCO	€	€ per PEV	€ per MWh
Hourly Variable	ILC	1,852,521	59.37	19.70
Day-Night ToU		728,777	23.36	7.75
Flat Rate	DLC	–	–	–

€ 55.17 to the network operator. The comparative value of deferred charging in low-load valley hours is approximately of the same order of magnitude to the DSO, as it is to the aggregator. It can also be seen that the different pricing options of the aggregator affect the benefit sharing between itself and the vehicle users, who in the best case gain € 59.37 per vehicle.

On an extending end-note to this case, one should bare in mind, that in the presented case, the load in the local distribution system is positively correlated with the system load reflected in market prices. Hence, there are generally no conflicts of interest between the main agents involved in facilitated CCO to the fleet of vehicles because the optimal charging schedules of both agents also coincide. Nevertheless, it is noted that scenarios of diverging incentives would paint a different picture. It is therefore important that the optimal charging schedules not only take into account price signals coming from wholesale markets, but also from network tariffs.

Final Remarks on Case Study Implications All results representing economic consequences for the involved agents of this illustrative case study are calculated using a spread-sheet. The two charging schedules for the valley and for the peak are manually constructed. This implies that no optimization of the charging schedule is carried out. However, the case study provides a number of valuable insights for the type of problem that the agents in interaction are facing.

The developed models in the subsequent parts of thesis are overcoming the methodological shortcomings of these first approximations with the adequate, more sophisticated techniques required. As the following chapters sequentially reveal, this thesis makes an important modeling assumption. It takes the perspective of the competitive agent, the PEVSA and optimizes from a single firm perspective the profits of this central agent. It is assumed that for the purpose of this document, all activities of the DSO regarding long term planning, i.e. incremental network investment cost as shown in the illustrative case study, but also more short term operational constraints, can be reduced to a set of network prices that are fed into the PEVSA's problem. This is fully aligned with the regulatory framework of the EU, respecting unbundling principles of network operation and market involvement. Therefore it appears to be the most practicable solution to the PEV coordination problem.

2.7 Concluding Summary

Generally speaking, it may be sustained that power systems are well regulated for the challenges that had to be faced until now. This chapter has set out to further envisage a future power system with a massive presence of vehicles connecting to and needing the system to fulfill mobility and ultimately electricity requirements. With the intention to structure possible implications and sketch particular challenges of participating agents, it has further resorted to descriptive techniques of classifying nomenclature.

Future Agents for Coordinated Charging This chapter has given a tutorial introduction to the electric power system agents involved in coordinated PEV charging. In particular these are PEV owners, PEV aggregators, and DSOs, among others.

It is fundamental to understand the different objectives and value propositions of the intermediary agents, the facilitators of coordination, to the electric power system. There are manifold value-adding services that an aggregator could theoretically bring to the system, e.g. proposing prices for PEV charging incurred by the consumer or directly controlling the power set points during the charging schedule. If these services are economically attractive enough to the consumers, they would potentially agree on charging contracts that enable either ways of load control, direct and indirect. In countries, where electricity distribution and supply have been unbundled from each other to favor competition among agents, all final customers have access to competing generators through their choice of suppliers. In these cases, final customers remunerate the electricity supplier for the service who in return procures the energy and pays the distributors regulated charges for grid services and other system costs [17], [18], [52]. The same applies for the choice of the aggregator, which acts like a supplier dedicated to PEVs with specialised services.

Classifying Charging Modes The remaining contents of this thesis build upon a conceptual regulatory framework aligned with European Directives that define a set of possible scenarios in which PEVs could be charged. As thoroughly laid out in [17], [18], [52], one way of classifying charging modes, is by the following characteristics:

- location and access to the charging point: private or public parking areas with private or public access,
- the intermediary agents involved in facilitating the final products as depicted on the right hand side of Fig. 2.1:
  - competitive agents procuring energy in wholesale electricity markets [52, section 7.1.2],
  - local rather regulated entities as final customers reselling energy on private grounds [52, section 7.1.3-4],
  - and DSOs [52, section 7.2], as well as
- the level of sophistication in communication, control and optimization strategies over the battery charging process.

This classification of charging modes leads to more concrete descriptions of business models for future electric vehicle applications and more importantly suggests implications for regulatory topics. By means of an illustrative case study that relies on very simple arithmetic, the implications of different system outcomes on DSOs and on aggregators have been highlighted, to give a taste of the types of problems that are modeled in this thesis. The subsequent chapters take advantage of this common ground, when going deeper into the topic's matter.

The following points summarize, what types of services are evisaged to be delivered by PEVs in future power systems.

Power System Operation By Service

- Ancillary services
  - Frequency regulation
    - Primary, Secondary, Tertiary control
  - Voltage control
- Flexibility provision through load shifting
  - Peak shaving, valley filling
  - Network investment deferral
  - Integration of vRES

To point out more directly what is included in the scope of this thesis: it covers the topics of peak shaving and valley filling reacting to market and grid prices in order cost optimally charge and to avoid the excessive use of capacity in distribution networks. This includes the benefit of avoiding or at least deferring network investment in grids. It does not specifically cover ancillary service provision for explicit frequency regulation or voltage control, because it reduces the power system operation to the market interface of day-ahead and balancing markets. vRES integration is only indirectly achieved. The charging schemes proposed in this thesis include price signals from electricity markets. So if it is assumed that the availability of renewables negatively correlates with the wholesale market prices, because these production sources are direct and influential participants in the markets and because of their low marginal cost, or even because of priority dispatch then the flexibility provision within the scope of this thesis also allows for more vRES integration.

Chapter 3

State of the Art Literature Review and Contributions

This chapter presents a review of carefully selected literature constituting PEV integration in modern, unbundled and deregulated power systems. Contributions from [53], are for the most part included herein.

3.1 Structuring Existing Work

The integration of PEVs in future societies has been vastly explored across many disciplines from operations research electrical and industrial engineering to manufacturing and transportation science. To identify knowledge gaps and research needs, the existing plethora of work on PEVs needs structure. Therefore, this chapter specifically reviews technical literature with respect to operational, planning and policy implications for modern electric power systems. Within this scope, it assesses the current state of technical, economic and regulatory research on electric power systems with increasing penetration levels of PEVs. It looks at effects on electricity markets, the planning of network investments and reinforcements under uncertainty, optimal charge scheduling under active network management and operation, design of real-time prices and tariffs, as well as other smart-grid developments.

The literature review of PEV in power systems in this chapter is selective yet comprehensive. Relevant and recent scientific publications are critically discussed according to the following characteristics:

- inherent approach,
- problem ownership, i.e. the agent(s) whose problem is solved
- representation of crucial elements such as
    - fleet mobility

  - technical characteristics of networks
  - employed methodology
  - used software tools
  - geographical scope of case study

- as well as the main conclusions drawn.

It is acknowledged that any classification has its limitations and to a small extent ignores significant heterogeneity within each sub-group. There are certainly more dimensions to include, but in this way it is deemed meaningful to, finally, from this analysis, highlight shortcomings of the existing literature and identify promising areas of research.

3.2 Problem Ownership and Agent Responsible for Coordination

Depending on the regulatory framework, as introduced in the preceding chapter, different agents have different objectives in EPS. Even though the presented allocation may not be exact, the following classification of reviewed literature takes into account different problem owners: the final customer or PEV driver, CPMs, PEV aggregators, TSOs and DSOs. Concentrated focus is centered around PEVSAs and DSOs.

3.2.1 PEV Aggregators

This section reviews those scientific contributions that, in the understanding and definition of PEV aggregation agents as provided in section 2.3, on the regulatory framework and the power systems agents therein, fulfill the criteria of competitive market agents or electricity retailers for PEV mobility. Once again, from a regulatory point of view, the entire system should be designed so that PEV aggregators are serving the unbundled electric power industry in various ways [52]. The competition among them is supposed to reduce the costs of customer services, while they are adapting the final price options and tariff schemes to the specific preferences of the final customer by promoting new products and services. Under this competitive activity fall further sub-tasks such as procuring energy, passing on economic signals where desired, contracting demand side measures and rescheduling of load forecasts while absorbing higher financial risk in interaction with generating units on market places. Hence, at first glance the use of PEV aggregators may be viewed under a strictly quantitative aspect of consolidating many small entities to represent a more powerful agent to the system in terms of energy demand and market participation capabilities [44], [54].

Along those lines, [44] laid out a basic conceptual framework of PEV aggregators, including their interactions with other agents in electric power systems. A very detailed literature review of algorithms used in modeling PEV aggregation is provided by a comprehensive bibliographic survey [54]. The relevance of aggregators in the context of PEV uptake and the fostering of massive deployment is discussed with various explanations and justifications of future necessity.

However, in the literature, the most commonly mentioned aspect is the concept of V2G, in which the PEV provide ancillary services to the system. The logic behind V2G is, if there is a massive deployment of electricity storage in the car fleet, this storage could be used for supplemental purposes that are beneficial to the electric power system, and therefore remunerated. If vehicles are purchased, that is if the initial capital cost of the battery is attributed to providing mobility, then the only additional cost for indulging in V2G may merely be more sophisticated chargers and controllers. With these ideas, in a seminal contribution, [55] identified PEV as the most attractive vehicle type for quick-response, high value services. The study established the basic concept of making use of the power generation capacity installed by existing fleets of vehicles for transportation purposes as a resource for operating electric power systems. All this, so the authors argue, could be done by providing so-called ancillary services [31], e.g. frequency regulation services. For the provision of ancillary services by PEVs, different market design implementations can be studied with an assortment of country specific instances presented in [31], [32].

Further on, [56, section 2.3.4.2] identifies three markets that are considered amenable to V2G power provision: peak power, spinning reserves and voltage regulation. In short, it is argued that these markets require generators to increasingly and rapidly respond to control signals, such that small scale generators, which are scurried about the electrical landscape, i.e also in low voltage distribution feeders, in the form of vehicles, could serve these functions. Along the same succession of thought the aggregator is believed to be capable of providing automatic generation control [39]. The added value of such service compared to the cost of installing communication and charging infrastructure for fast-response is not convincingly argued.

Besides qualitatively analyzing the opportunities in different markets and showing the potential in downward secondary frequency regulation, [25] approximates revenues for PEVs participating in the German and Swedish frequency regulation markets. Evidence is found, that regulation market participation is limited as it may become saturated at approximately 3% PEV penetration, which obviously limits enthusiasm. In fact, the reason for other works, such as [24], is to exclude ancillary service provision from PEV value assessment. Nevertheless [24] computes the profits from energy arbitrage and peak power provisions in selected years and finds that these would not have offset hypothetical costs of providing PEV grid storage. Disregarding avoided network reinforcement costs, an estimated $ 300-400 annual net social welfare benefit per vehicle transferable for owners engaging in PEV night charging is found.

Despite the harboring misgivings of some authors, that V2G markets might be limited, other work shows how an aggregating control system to conduct such market participation could be implemented [57]. [58] even tackles the problem of reusing PEV batteries and tries to value stationary storage (as a secondary use option of the mobile storage) versus on-board batteries considering wholesale energy as well as secondary frequency regulation markets of the California independent system operator (CAISO). Furthermore, grouping processes to fulfill symmetric and asymmetric control bids have been developed [59], showing that ancillary service designs with symmetric bid requirements would be disadvantageous for PEV aggregators, as the fleet's available capacity determined by its mobility is not accordingly symmetric.

Similarly, [23] employs dynamic simulation to estimate the economic impacts of vehicle participation in ancillary service markets in Germany. Discussing the pre-qualification criteria for secondary frequency regulation in the German context, policy recommendations to adapt market rules, e.g., bid size and hourly/daily procuring, are presented. It is highlighted that a fleet size of 10,000 PEVs is reasonable to self balance the stochasticity in the underlying mobility processes. Explicitly, the daily or at least weekly procurement of these services is recommended as better compared to the monthly tenders.

Ancillary services can also be provided, however slightly limited, only by increasing or decreasing optimized unidirectional charging as explicitly shown by [37] for different smart charging algorithms with according profit distributions. [60] develops a mathematical formulation of market participation with unidirectional power flows, which includes optimization algorithms with quasi-spatial mobility simulation relating driving pattens to network nodes. Indicative results show that downward regulation could be attractive for charging PEV and decreasing charging costs.

Finally, there is still an ongoing discussion on the environmental impacts of PEV integration: [22] claims to highlight that PEVs with V2G capability in conjunction with other technologies such as CHP in national aggregate systems allow higher integration of vRES and reduce spillage as well as CO_2 emissions. [61], [62] show that this depends on many factors. For instance, [63] argues that in power systems with a mix such as in Germany, market power will even increase the effect that controlled charging contributes to the use of emission intensive least cost generation technology, which overall would have a negative environmental impact. Finally, [23] employing price-based load shifting with feedback loops in an agent based electricity market equilibrium model, shows that under certain assumption on 2030 power mix in the same country, PEVs using very high power/energy ratios can contribute to balancing intermittent vRES to the extent that negative residual load is reduced by 15–22%.

All of the above named literature focusing on PEV aggregators as problem owners is summarized in Tab. 3.1.

Market Interaction: Uncertainty Modeling As alluded in Section 2.3 on regulatory framework the key component in optimal charging should be market driven. The PEV aggregation agent should hence have an objective function that is consistent with other agents known in electric power systems. This subsection hence reviews literature that has dealt with electricity market participation, which usually involves the explicit modeling of uncertainty and risk

Table 3.1: Overview of Selected Literature: PEV Aggregators

Ref.	Charging Mode	Problem Ownership	Mobility Representation	Network Representation Charging Infrastructure	Time Horizon Time Resolution	Optimization Calculation	Methodology	Software Solution | Solver	Key Findings Main Conclusions
[55]	Ubiquitous charging	PEV owner	Generic US driver: half of average daily miles are traveled at connection	Copperplate	N/A	Deterministic	"Equations"	N/A	• Coins V2G with engineering rationale and economics • Identifies PEV as most attractive vehicle type for quick-response, high-value electric services.
[64]	PEV aggregator with direct load control	PEV aggregator	Stochastic simulation using Germany MID 2002 as a data basis [65], [66]	Copperplate Charging infrastructure costs included	Hourly periods 1 year	Deterministic	Static vs. dynamic (Monte Carlo-) simulation and optimization	MatLab SimuLink	• 10 000 PEV reasonable fleet size self balancing stochasticity • Daily or hourly bid period is recommended for German regulation market
[23]	PEV aggregator with indirect load control and ubiquitous charging infrastructure	PEV owner	Stochastic simulation using Germany MID 2008 as a data basis [65], [66] 2030 penetration scenario	Copperplate vehicle groups, quadratic transformer capacity dependent grid fee	15 minute intervals 1 year	Deterministic	Agent-based electricity market equilibrium model	Java	• PEVs can contribute to balancing intermittent vRES: negative residual load was reduced by 15–22% • Price-based load shifting requires a feedback loop • PEVs provide a very high power/energy ratio
[25]	Single entity PEV aggregator for home and work charging	PEV aggregator & PEV owner	Generic driving pattern: 2x35min per day. No weekly or seasonal variation	Copperplate Charging infrastructure costs excluded	1 minute 4 x 1 month (January, April, July and October 2008)	Deterministic	Simulation	MatLab	• Regulation market saturation at 3% penetration • Qualitative and quantitative comparison: German market significantly more profitable than Swedish and night time periods more attractive than day-time • PEVs especially suitable for downward regulation offers
[59][57]	PEV aggregator ubiquitous city charging	PEV aggregator	Average speed and normal distribution of distances	Copperplate	N/A 24 hours	Stochastic	Monte Carlo Simulation	MatLab	• Strategies for control bids on the German control markets • Symmetric control power is disadvantageous
[24]	Home Charging only all times except 9-17h	PEV (battery) owner	N/A Driving profiles calculated using Data from 2001 US NHTS	Copperplate	1 hour 6 x 1 year (2003-2008)	Deterministic	Simulation	N/A MatLab ?	• Energy profits from arbitrage in selected years did not offset hypothetical costs of providing PEV grid storage • Disregarding avoided network costs estimated $ 300-400 annual net social welfare benefits transferable for owners engaging in PEV night charging
[42]	PEV aggregator ubiquitous charging	PEV aggregator	Generic	Copperplate	1 hour N/A	Deterministic	Dynamic Programming	N/A	Applying determinist dynamic programming aggregator's problem of optimal vehicle control
[37]	CPM work place charging between 9-17h	PEV aggregator	Each vehicle is randomly assigned a commute distance from Puget Sound commute distance data	Copperplate	5 min | 1 year (each weekday 2007)	Deterministic	Simulation of mobility Linear Programming for charge optimization	MatLab CVX solver	• Uni-directional V2G can be a viable source of income for PEV aggregators among other benefits and impacts on the electric power system • Profit distributions under different smart charging algorithms are presented
[60]	PEV aggregator with direct load control and ubiquitous charging	PEV aggregator	Northern Portuguese driving behavior simulated assigning distributed nodes proportionally to installed capacities	Stylized Network	1 hour, 2x1 year (8760 hour – in 2009 and 2010)	Stochastic Simulation and Deterministic Optimization	Discrete state and time Markov Chain for Mobility, Divisive Analysis Clustering and Linear Programming	N/A R N/A	• Formulation of market bidding and charging optimization algorithms with quasi-spatial mobility simulation relating driving pattens to network nodes • Indicative results show that: downward regulation attractive for charging PEV decreasing charging costs
[22]	Ubiquitous controlled charging	System Operator	US a-12 (transportation demand profile) with assumed shares on driving and connection	N/A	1hour 1 Week (168 hours)	Deterministic	Simulation: EnergyPLAN energy systems input-output computer model	N/A	PEVs with V2G capability in conjunction of other technologies such as CHP in national aggregate systems allow integration vRES and reduce spillage CO_2 emissions

aversion:

Consider therefore the problem of an electricity retailer that intends to aggregate a PEV as a resource in electricity markets. The operational challenge of such a PEV aggregator presents a combination of the classic problems of a retailer (sometimes also referred to as supplier or marketer) [67], a large consumer (with potential on-site generation) [68], and a conventional power producer with resource unavailability [69], as well as of an energy storage system (ESS) operator.

The primary goal of the retailer, as an intermediary between producers and consumers [68], is the medium term procurement of energy in electricity markets for a subsequent resale to final customers at an agreed price. The main source of profit for a retailer is the difference in procurement cost and resale revenue. Typically, retailers cover a large amount of energy demand in the futures market and procure the rest from short-term pool markets. In short, the retailer buys electricity at an uncertain price and resells it to an uncertain demand [67].

The main objective of a producer is to sell its available energy and capacity in the futures, pool and ancillary service markets. The futures market provides fixed prices through futures contracts over a pre-defined time horizon, while pool prices allow the producer to sell energy at higher prices in the short term. Reserve being an important product to guarantee sufficient generation capacity available in the electric power system to assure short term functioning, presents a valuable opportunity to fast response equipment. Balancing energy is an important tool for readjusting previous market commitments closer to real time. If the production of this agent is subject to some technical constraints and bound to suffer from unavailability, the producer may have to procure energy in the pool to meet the futures contracting obligations [69]. The problem of resource unavailability becomes even more prevalent if the production stems from vRES such as uncontrollable win power production. A detailed model of a wind power producer participating in short term electricity markets under uncertainty and risk aversion is found in [70]

However, there is not only similarity with known problems considering electricity market involvement, the following basic aspects differentiate the conventional agents and the new PEV aggregation agent, namely: demand is set via consumption of vehicles, consumption as well as the unavailability of an aggregated battery is defined by the mobility of the vehicles. Therefore modeling of mobility is crucial and identified as a key element for classifying existing literature.

[71] model a similar problem, of an storage owner scheduling capacity in balancing markets to compensate uncertainty in wind availability, however it can be assumed that the owner of the wind farm is also the owner of the ESS.

The methodological heart of all studies mentioned in this subsection is dealing with uncertainty via stochastic programming. An overview is provided in Tab. 3.2.

Table 3.2: Literature Overview: Risk-Averse Market Participation

Ref.	Problem Ownership	Market Participation	Uncertain Inputs	Time Horizon Time Resolution	Methodology	Software Solution | Solver	Key Findings Main Conclusions
[67]	Retailer	Futures Market Pool Trading	Demand Pool Prices	72 periods of 1 year	Non-linear bi-level Stochastic Programming	GAMS CPLEX 10.2	• Purchases from peak contracts can be higher than those from base contracts due to the high volatility of pool prices in peak periods • A retailer aiming to offer competitive selling prices must be willing to take on relatively high risk
[68]	Large Consumer	Bilateral Contracting Pool Trading	Demand Pool Prices	8 hour 4 weeks	Stochastic Programming	GAMS CPLEX 9.0	• The share of bilateral contracts considerably increases with the weight on risk-aversion in the objective in order to hedge against risk exposure to pool prices volatility • With increasing volume of energy self-produced by the consumer keeps at a stable share around 20%.
[69]	Producer	Day-Ahead, Regulation and Adjustment Market	Market Prices and Unit Unavailability	1 hour, 1day (24 hours)	Stochastic Programming	GAMS CPLEX 10.2	Description of a certainty gain effect: economic surplus obtained if offering strategy in day-ahead market is built with a greater level of certainty on wind energy production
[70]	vRES Producer	Day-Ahead, Adjustment and Balancing Market	Market Prices and Wind Resource Unavailability	N/A	Stochastic Programming	GAMS CPLEX 11.0.1	• Electricity derivatives constitute one of the main instruments for power producers to hedge against price risk • Electricity options provide another mechanism to hedge against the risks faced by power producers
[71]	vRES Producer	Day-Ahead and Balancing Market	Market Prices and Wind Resource Unavailability	1 hour 1 year	Stochastic Programming	GAMS CPLEX 6.0	• Optimal operation of EES and wind farm with day-ahead and balancing market participation. • Effects on market closure lead times on added value

Direct and Indirect Load Control Approaches As the the literature review has demonstrated to this point, a consensus can be manifested, that PEVs may present potential benefits to the operation of power systems, depending on their charging schedules. However, to achieve efficient resource allocation, their potentially flexible demand is envisaged to be coordinated by an aggregation agent [44]. This coordination is achieved either via DLC, in which one entity centrally determines power set points according to a single objective function [48], [72]–[75], or via ILC, for which the decision making is distributed over more than one actor, as in [23], applying agent-based simulation. Hybrid approaches of DLC and ILC have been proposed as well [76]. To evaluate DLC and ILC approches, different optimization methodologies have been introduced and utilized in the literature.

Optimization based methodologies are adequate for ILC, having a long history in theory and application [77], [78]. In power systems research, the modeling of different agents interacting in electricity markets is a well known and widely studied issue. Recent reference [79] comprehensively elaborates many different applications of complementarity models in this context, among which mathematical programs with equilibrium constraints (MPECs) are particularly suited for strategic interactions between two levels of decision making. For instance, studying the generation capacity expansion problem in liberalized systems, the work presented by [80] applies a stochastic MPEC. But also for modeling the decision making of demand-side electricity market agents, such as retailers, stochastic bi-level optimization has been applied, as in [67].

So far, there exists little literature applying MPECs to the PEV scheduling problem. References [81] and [82] focus on the PEV aggregator's profit-optimal bidding subject to the optimal power flow and market clearing constraints. Nevertheless, the retailing for PEV is also an important part of the PEV aggregator business and merits some attention. [83] and [84] analyze different signals for procuring demand-side flexibility by employing two separate optimization problems, one for the final customers and one for the aggregator of flexible demand, though without integrating them in an MPEC.

Multi-level optimization approaches, in which different actors interact to find an equilibrium point on the retail price interface are rare. [85] develops a decentralized power-frequency droop based control algorithm. However, the load shifting only approximates a global optimal solution through estimated charging gradient functions of the PEV. [86] proposes an ILC scheme, but the study assumes a central agent for the entire system. This may be less practical for applications in vertically unbundled power systems with liberalized electricity markets, such as in the majority of EU countries, e.g. Spain, UK, Germany, as well as Nordic countries from Scandinavia etc., and in other parts of world such as Chile etc.

In this setting, electricity tariff design is of marked importance to ensure cost recovery for all power system activities in generation, transmission, distribution and retailing [87], [88]. Among the overlapping price signals, to which final customers are exposed, the aggregator would only be responsible for setting the wholesale component of the bill. Nevertheless, distribution level impact on planning, operation and maintenance and therefore the related charges for incremental investment recovery may be important at high PEV penetration rates [47]. Although for integrating distributed generation, long run marginal cost pricing for computing network UoS tariffs has been proposed [89], [90], the application of it to the context of PEV charging is relatively unexplored [91].

3.2.2 LV and MV Distribution System Operation

Besides many studies' focus on transmission system operators, PEV aggregators and final customers, an increasing share of literature tends to focus on distribution system level effects, whose problem ownership can be clearly identified as DSOs. A review and outlook on literature dealing with PEV charging impact on distribution system levels is provided by [92], in which the need for standardized reliability metrics is expressed.

The literature reviewed with respect to the DSO's decision problem always necessarily involves a network representation. For the IEEE 34-node test feeder, which represents a radial network with voltage levels from 230 V to 24.9 kV, [48] used a quadratic and dynamic programming framework to measure the potential impact of PEV charging on the distribution system. For the load flow analysis of multiple samples of diurnal system load profiles, the study shows that coordinated charging leads to increased power quality in terms of energy losses and voltage deviations on the one hand, as well as to a higher utilization of the network on the other. Finally, [48] also conducts a first global estimation of network reinforcement measures for the given, small scale network topology.

This directly links to [51], which present a type of model referred to as NRM. NRMs are tools for regulators and policy makers to reduce information asymmetries compared to DSOs when it comes to setting regulated revenues and performance incentives. This single period tool features green field and brown field large scale high voltage, including substations, medium voltage including transformers, and low voltage planning, by making use of standardized cost libraries for network components of all types. Such single period models are capable of computing detailed costs for network reinforcements in a big scale, as done in the corresponding contribution by [47], in which PEV charging impact is estimated in terms of network reinforcements and energy losses. It shows that in two large scale case studies for an urban area with underground cables and high load density as well as a rural area with dispersed loads, that both incremental investment costs as well as network losses may increase substantially if charging is not coordinated.

Also for a typical semi-urban network at MV level of 15 kV, [93] run a detailed 24h PSSE simulation, analyzing how home charging, with on average 1.5 PEVs distributed proportionally to installed capacities among households affects the distribution system operation. The study uses an advanced centralized PEV charging control mechanism that alludes to avoided network reinforcements, however, without actually quantifying them. [93] furthermore promotes a high level of local control for islanded operation modes and safe increase in vRES shares.

Similarly, [94] simulated home charging under DSO control for 40 household nodes with one 160 kVA transformer, from 20 kV MV level to 400 V LV level using *DIgSILENT*, PowerFactory and MatLab with 10 seconds resolution for a horizon of 150 hours. [94] include the storage degradation for a battery with linear single cell voltage behavior from 3.4-4.2 V. It is claimed that via battery state of charge (SoC) distribution analysis, the computed life time savings avoiding mainly high SoCs from uncontrolled charging are circa twice as high as revenues from energy trading.

Also in high detail, [95] model a real metropolitan distribution network with voltage levels including 11 kV, 22 kV, 150 kV, 220 kV, 380 kV and 400 kV transformers to combine a sophisticated agent based simulation and PEV charge optimization. Based on assumptions clarified in [29], and a active recharging management scheme with different levels of hierarchical control detailed in [96], the authors actually study a potential service of PEV fleet servicing V2G for local vRES in-feed.

Finally, Tab. 3.3 summarizes the most important features and gives an overview of the reviewed literature on PEV integration on power systems, solving DSO related decision making, while 3.4 groups other auxiliary sources.

3.2.3 TSOs and Unit Commitment

Mostly in the US, where network unconstrained market clearing and economic dispatch are less popular, electric power systems research with unit commitment (UC) models, i.e. short term (one day to one week) generation unit start up and shot down decisions, has been of great interest because it is economically significant for proper operation and mathematically challenging (large scale, non-convex, and integer variables). It is only logical that these models have recently been extended to identify impacts of PEV in the operation of power systems. Accordingly, with a mixed integer linear programming (MILP) formulation, [61], [62] shows that in Texas, up to 15% of PEV penetration decreases generator NO_x emissions, and approximately $200 per vehicle could be annually saved from the system perspective.

[98] also takes the perspective of a system operator and solves a unit commitment problem of scheduling generators as well as a fleet of vehicles of determined size. Total cost as well as emissions are minimized with a particle swarm optimization, to tackle the combinatorial nature of comparatively large amounts of integer as well as continuous variables involved. [99] combines a MILP formulation for mid-term UC with a Monte-Carlo (MC) simulation for unit unavailability and re-dispatch. A Spanish case study demonstrates that system savings can vary with PEV penetration level and driving pattern.

In a planning and dispatch model, [102] conclude that neither the system costs, as low as 36 € per vehicle per year, nor the price of electricity in the market clearing become very high.

The author of this thesis has also contributed to the body of literature regarding PEV in UC models [103]. However, it is only mentioned here in the

Table 3.3: Overview of Selected Literature: Distribution System Operators

Ref.	**Charging Mode**	**Problem Ownership**	**Mobility Representation**	**Network Representation**	**Time Horizon Time Resolution**	**Optimization Calculation**	**Methodology**	**Software Solution | Solver**	**Key Findings Main Conclusions**
[94]	Home charging under PEV aggregator control	PEV aggregator, DSO	German Mobility Panel 2008	40 household nodes 160 kVA transformer, MV: 20 kV, LV: 400 V linear single cell voltage behavior of 3.4-4.2 V	10 seconds 150 hours	Deterministic	Mobility, Charging and Power Flow Simulation	DIgSILENT PowerFactory MatLab	With the consideration of storage degradation (via battery SOC distribution analysis) and network constraints battery life time savings (avoiding mainly high SOCs from uncontrolled charging) are circa twice as high as revenues from energy trading
[48]	Controlled and uncontrolled home charging	DSO	Qualitative: most vehicles home 21h - 6h PEVs randomly assigned to node/household	IEEE 34-node test feeder, radial 230 V - 24.9 kV	15 min Multiple samples of 24 hour periods	Deterministic and Stochastic	Quadratic and Dynamic Programming Backward-forward sweep for load flow analysis	N/A MatLab ?	• Coordinated charging leads to increased power quality in terms of losses and voltage deviations as well as grid utilization • A global estimation of network reinforcement measures is provided
[51]	Any	Regulator, Policy Maker, DSO	None	HV/MV/LV, including substations and transformers, millions of loads at geographically localized (GIS) nodes	Single-period	Deterministic	Single-period heuristic algorithms including contingency analysis: Minimum spanning tree branch exchange	Kernel: C++	• Reference Network Models are proposed as a tool for regulators and policy makers for setting regulated revenues and performance incentives. • Features such as large scale HV/MV/LV planning, allow PEV impact assessment in urban areas
[47]	Random charging point allocation (ubiquitous charging infrastructure) Varying simultaneity of charge (un-/controlled)	Regulator, Policy Maker, DSO	Static share of connected PEV in valley and peak hours with varying penetration levels	HV/MV/LV, including substations and transformers, millions of loads at geographically localized (GIS) nodes	Single-period	Deterministic	Single-period heuristic algorithms including contingency analysis: Minimum spanning tree branch exchange	Kernel: C++	• Approach to measure PEV charging impact on distribution network investment (increase up to 15%) and incremental energy losses (increase up to 40%) two large scale areas: **1)** an urban area with underground cables and high load density and **2)** a rural area with dispersed loads
[96]	PEV Aggregator with Ubiquitous Charging	PEV aggregator, DSO, see [95]	Detailed agent based micro simulation model	Real 11, 22, 150, 220 and 380 kV levels of urban network, nodes represent 400V transformer	15 min	Deterministic	Combination of sophisticated agent based simulation and charge optimization	MatSim	• Impact assessment with a detailed active recharging management scheme of a large fleet of vehicles with hierarchical control in existing distribution network • Studies V2G service for local vRES in-feed
[93]	Home charging, on average 1.5 PEVs are distributed proportionally to installed capacities among households	PEV aggregator, DSO	Assumptions on average distance traveled, charging frequency and energy. Worst case: all vehicles charge simultaneously	Typical semi-urban 15 kV medium voltage network	N/A 24h	Deterministic	Simulation	N/A PSSE ?	• Proposes a advanced centralized PEV charging control mechanism alluding to avoided network reinforcements without quantifying them • Promotes local level of control, for islanded operation mode and a safe increase of vRES
[58]	CPM controlled office building charging	CPM	Secondary use after mobile life (average daily travel distance, annual driving days, years)	No network considered	Type days 1 year	Deterministic	Mixed Integer Linear Programming	GAMS Excel	• The dismantling of batteries creates value • Embedded batteries can serve the internal CPM and provide frequency regulation as stationary storage • Single use for building has not proven economic

Table 3.4: Overview of Selected Literature: Other – Auxiliary

Ref.	Charging Mode	Problem Ownership	Mobility Representation	Network Representation	Time Horizon Time Resolution	Optimization Calculation	Methodology	Software Solution | Solver	Key Findings Main Conclusions
[20]	N/A	PEV owner	Detailed drive cycle simulation using NEDC	N/A	Seconds N/A	Deterministic	Simulation and spread sheet analysis	Excel	Cost and emissions projections of different battery technologies
[97]	CPM with controlled fast charging	CPM	Geographically independent stylized charging pattern	Single spot	1 year 10-15 years	N/A	Investment cost spread sheet analysis	(Excel)	Fast charging station ownership currently unprofitable. Returns on investment very risky.
[63]	N/A Ubiquitous ?	PEV Aggregator, PEV owner, or Integrated Utility	Average connection capacities from [55], recharge requirement as well as arbitrage capacity for 1m vehicles in 2020	Copperplate Single Bus	1 hour 2 weeks (336 hours)	Deterministic	Mixed complementary problem, game-theoretic, oligopolistic (Cournot-Nash Equilibrium) electricity market model (ElStorM)	GAMS PATH Solver (Generalized Newton's method)	• Uncontrolled uni-directional PEV charging increases generator profits but decreases consumer surplus • With bi-directionality the welfare effect is reversed • Controlled charging in Germany draws on emission intensive electricity
[61], [62]	N/A Ubiquitous ?	System Operator	Empirical driving data East West Gateway Coordinating Council household travel survey	N/A	1 hour 1 year	Stochastic	ERCOT unit commitment model (MILP)	GAMS CPLEX 9.0	• In Texas up to 15% PEV penetration decreases generator NO_x emission • V2G services and arbitrage increase generator efficiency and reduce CO_2 SO_2 and NO_x further • Annual cost savings per vehicle in the range of $ 200
[98]	Ubiquitous Charging	System Operator	Generic: yearly distance driven and time parked	Copperplate	1 hour 1 day (24 hours)	Stochastic	Particle Swarm Optimization UC	Visual C++	• Amounts of "gridable" vehicles are computed for UC, with need to control a percentage of those
[99]	Ubiquitous Charging	System Operator	Generic for commuter, leisure, business, etc.	Copperplate	1 hour 1 year	Deterministic & Stochastic	MILP for UC and Monte-Carlo for Operation	GAMS, CPLEX	PEV Driving pattern has impact on hourly generation by technology, system marginal cost, emissions, RES integration, curtailment and use of reserve
[100]	Decentralized control ubiquitous charging infrastructure	System Operator & PEV owner	10 % penetration of UK fleet – Exact method unclear	N/A	1 hour 1 day	Deterministic	Lagrangian Relaxation Quasi-Newton Heuristic (Secant Methods NLP)	N/A	• System demand profiles are almost independent of charging flexibility • Flexibility brings system cost savings of up to 3.06 %
[101]	Ubiquitous V2G: based on flexible demand bids using price elasticity	System Operator (TSO)	Agent-based demand modeling framework	10-bus, 14 line Swiss-Italian-French transmission network	1 hour	Deterministic	Optimal Power Flow for Locational Marginal Pricing in Transmission	MATSim	• Proposes charging strategy with locational marginal pricing highlighting grid strain when uncontrolled • Battery degradation limits peak shaving potential

literature review section and not provided as an integral part of this thesis, because a very specific problem ownership perspective is taken.

3.2.4 Welfare Effects and Other Problem Owners

Also from a system perspective and formulated as a MILP, [63] models PEV participation in the oligopolistic electricity market of Germany in Cournot-Nash equilibrium to highlight selected instances of market failure and regulation. Evidence is found that welfare effects lead uncontrolled uni-directional PEV charging to increase generator profits but decrease consumer surplus. However with bi-directionality, these welfare effects are reversed. [101] proposes a smart charging strategy with locational marginal pricing highlighting transmission network strain in the Swiss-Italian-French interconnection, when PEV charging is uncontrolled. It is also emphasized that battery degradation limits peak shaving potential.

To provide insights into the business model of one local, controlled fast charging station, [97] looks at the profitability in terms of risk and return on investment. [100] uses a quasi-newton heuristic and secant methods non-linear programming (NLP) to find that the flexibility of a decentralized control of charging PEV would bring approximately up to 3% cost savings to the system. [20] solves the problem of the PEV owner and makes projections of costs and emissions for various battery technologies.

It is important to note that many studies implicitly or explicitly assume the availability of ubiquitous charging infrastructure for future charging modes. Although, it is hard to foresee technological proof in the future, intellectual property publications of small yet innovative start up firms indicate business models building upon the technical capability of future power systems providing inexpensive and pervasive plug-in capability. *Ubitricity* for instance has secured a patent on metering and measuring point systems for electrical energy drawn from PEVs featuring a mobile/non-stationary measuring, metering and billing/clearing of the electrical current [104], which seems promising.

3.3 Assumptions on Mobility Behavior

Most of the here presented studies on PEVs try to measure a technical, economic or environmental impact on the way electric power systems are regulated, planned or operated. For that it is almost indispensable to make an assumption on the way electric vehicles are *plugged-in*, i.e. at what times connection and disconnection is performed. Although the mobility assumptions are deemed crucial, many studies, in spite of naming a data source for empirical knowledge, tend to lack detailed technical description of the algorithms used to compute driving and connection profiles.

3.3.1 Qualitative, Generic Mobility

On the assumption that the non-electric mobility past is a reasonably good indicator for forecasting future electrified mobility – with high levels of PEV penetration –, most studies resort to empirical studies of fleet movements observed on conventional vehicles. That is, PEV driving and hence connection behavior is assumed to not be significantly different from what can be derived from driving patterns of conventional vehicles with charging when being parked. One could on the other hand of course argue that this is highly dependent on how future PEV owners and drivers understand and perceive the technology they are using. Perhaps city dwellers of the future will admit that a significant share of their mobility can be covered by range limited full battery electric vehicles and longer trips will be assured by rental cars. This is just to name one of the many instances of potential behavior alterations that could ensue. Despite the fact that electrification of transportation is a game changer, the simplest, and most straightforward assumptions observed in the bulk of reviewed literature, are linked to regular commuting. For instance, it is common to assume for instance always connecting and disconnecting at the same hours, which in this classification is referred to as *qualitative* or *generic* and found in studies [22], [25], [37], [42], [47], [48], [55], [58], [63], [93], [97], [105], [106].

3.3.2 Travel Surveys and Driving Cycles

To gain further insight one can make use of data obtained from household travel surveys, in which representative samples of people indicate personal mobility, or more precisely personal perception of own mobility. Even though it may be questionable whether this methodology gives rise to true future mobility of PEV it is a standard procedure as used in [22], [23], [37], [61], [62], [64], [66], [94], [97], [100], [105], [107]–[109] and may give an acceptable indication. Depending on the geographical scope, different sources have been identified in the reviewed literature. In the USA, the use of the *National Household Travel Survey* (NHTS) is prominent as even the generic mobility is sometimes claimed to represent this data set [24]; one of the newest analysis with regard to PEV can be found in [107] on 2009 data. Claiming that most of the studies using NHTS have led to inaccurate results, [108] proposes a detailed methodology for deriving uncontrolled connection (charging) patterns from the 2009 data set. Other US regions are covered for instance in [61], [62] resorting to data from the East West Gateway Coordinating Council, or in Puget Sound in the North West [37]. [22] stands out from the the studies claiming to model US mobility, as it takes the *US a-12 transportation demand profile* and then applies *qualitative* assumptions for average daily travel distance and annual driving days.

[100], claims to base connection patterns on the 2008 National Travel Survey Database in the United Kingdom. Finally, the PEV integration literature with German focus either makes use of the *Mobilitätspanel* [94] or *Mobilität in Deutschland (MID) 2002* [64], [65] and *2008* [23], respectively. The former provides a smaller sample size but across the duration of a whole week, while

the latter covers a greater sample with only one day's driving. However both [23], [109] manage to derive the weekly profile from MID data.

For cost and emissions projection, [20] went further into detail by modeling the new European driving cycle (NEDC), which, in contrast to the other more higher level studies, contributes to the state of the art by including a combination of varying driving speeds and consumptions in urban and rural settings.

3.3.3 Advanced Simulation Models

Very progressive representation of PEV mobility including spatial components is given in [60], in which a cyclostationary discrete state and time Markov Chain assigns vehicles to network nodes. A detailed description of the according mobility simulation is provided in [110]. However, it is not clearly justified, why this is done proportional to installed network capacity. The most advanced mobility modeling was found in [96], [101], with an agent based micro simulation model for the city of Zurich, and in [23], which even provides input data to reproduce as stochastic mobility simulation. The latter mainly used three types of information in the form of discrete cumulative probability distribution functions: travel on a certain day, starting a trip on a specific day and hour as well as a trip to be of a certain length on a specific day. As mentioned the data basis is MID 2008 [65]. However, the analysis is not performed for the average driver. The yields of this data were limited to select German respondents, who are most likely to adopt electric vehicles in terms of availability of private home charging facilities, sufficient yearly travel distances, and among other criteria positive net present values comparing total costs of ownership to conventional vehicles motorized with internal combustion engines [66]. Reference [109] uses the same set of raw data from MID, however, without filtering the user groups with respect to likelihood of adopting PEVs, weekly mobility patterns by trip usage are mapped, which could be valuable in constructing connection scenarios for local CPMs, as done in [97]. Finally, future research should include spatial mobility mapping to find out realistic impacts on network topologies. [111] provides highly useful insights about individual human mobility patterns obtained from data of mobile phone connections. [112] reviews the former among other findings regarding the nature of human movements and classifies them along spatial, temporal and social dimensions of mobility. This could also be a promising starting point for redefining the methodology and approach used for modeling PEV impacts on power systems.

3.4 Battery Degradation

Battery degradation, i.e. the loss in functionality and thus value of a storage system, has been widely addressed in the context of PEV coordination, as it may have a valid impact on the economics of it. In the context of this thesis, battery degradation is not the main focus, and thus where possible it has been assumed that the effects of it can be quantified and tied to the amount of energy processed like in [105]. The exact method to arrive to a cost estimate of degradation lies out of scope of this document. Nevertheless, for the sake of completeness, the following paragraphs provide some background information, quoted, based on and extended from the candidate's own co-authored diploma thesis [15]:

3.4.1 End-of-Life Requirements

Battery cells degrade over their lifetime due to battery wear-out as well as energy and power fade. Two different processes are mainly responsible for degradation: "Cycling life" describes the shortened lifetime caused by energy throughput. Battery cells deteriorate because of changes in structure and composition caused by cycling. "Calendar lifespan" accounts for deterioration resulting from damaging chemical reactions between cell materials. This process is independent of battery cycling and specific for each battery type.

The shortened lifetime due to cycling depends on the used depth of discharge (DOD). DOD describes the percentage of total battery capacity that is used during cycling. The higher DOD, the lower is the total energy throughput achievable by a battery over its lifetime: The energy content delivered by one type of Li-ion battery at an average 40 % DOD is twice as high as the energy delivered at 80 % DOD [113, p. 30].

Calendar life of batteries highly depends on the temperature of batteries, at which they are operated as well as on their SOC. The higher the temperature and the higher the SOC, the faster batteries deteriorate. Tested Li-ion battery cells which were left at 100 % SOC at 40°C for four years degraded less than 5 %. Hence, under the assumption of a steady degradation, a presumed lifespan of 12 years until 20 % degradation would be reached. However, if battery temperature is kept below 45°C and the average SOC below 50 %, an increased lifetime of 15 years can be expected [113, p. 34]. For their high power/medium energy cell MI 26650, developers of "A123 Systems" even claim a cycle life expectancy of 7,000 cycles at 100 % DOD and a calendar life expectancy of more than 15 years.

Battery manufacturers must account for degradation and allow for a margin when designing batteries so that they still comply with requirements at their end of life (EOL). This margin is usually assumed to be about 20 % of the initial battery capacity. A PHEV-10 battery with required EOL capacity of 3.4 kWh would therefore need 4.25 kWh of initial energy storage.

In addition to a margin for battery wear-out, one has to consider the SOC range that batteries can operate in. As exhaustive charging and discharging considerably shortens lifetime expectancies for most battery types, batteries must not be cycled over their total energy capacity. The SOC range therefore represents a trade-off between battery weight and lifetime. The more "extra space" is allowed for in a battery, the longer the expected lifetime will be. Each battery manufacturer sets this margin for its batteries. It typically lies around 20 % of the total battery capacity.

USABC targets for battery lifetime are 15 years for both high power-to-energy (P/E) and low P/E ratios [114]. However, they represent merely research targets which are deduced from an average lifetime of 14 years for passenger cars. The lifetime shall be reached at 35°C operating temperature as PHEV batteries will have to cope with higher temperatures than HEV batteries (which operate at around 30°C) caused by regular complete charging cycles. The number of required deep discharge cycles for a PHEV-10 battery is about 5,000[1] cycles at 3.4 kWh, which leads to 17 MWh total energy throughput over the battery lifetime. For charge sustaining, mode 300,000 shallow cycles at 50 Wh are required.

3.4.2 A Detailed Model Account

The following summary provides a detailed account on the type of linear degradation model that can be deducted from the laboratory testing provided in [105]. This lays down the physical model for which high-power LiFePO4 cells were cycled, simulating realistic driving conditions and V2G use.

In this context a common term is the charging rate (C-rate). The power-based C-Rate describes the charge and discharge rate of a battery normalized to its total energy content. A C-rate of one signifies that the battery can provide the equivalent of its energy content during one hour in power, i.e. a 5 kWh battery with a C-rate of one can provide 5 kW in power. A C-rate of C/2 states that it can provide half of its energy content in power, i.e. 2.5 kW for a 5 kWh battery. Together with the residual energy content of the batteries the C-rate determines the power that can be delivered by a battery.

The tested battery cycles were based on driving patterns from the 2001 NHTS for selected households, representing commuters in four metropolitan areas. The data was overlaid with US driving profiles. The resulting cycling conditions represented four trips of traveling per day with a total daily amount traveled of 29 km, an energy use of 0.28 kWh /mile (or 0.175 kWh /km) and an experienced discharge at a maximum C-rate value of 2.85 [105].

Li-ion batteries can have very high C-rates depending on their design. In the case of cells from a certain chemistry, denominated LiFePO4, C-rates with a nominal value up to 20 are possible. For V2G energy use, discharge with a constant C-rate of C/2 was tested over changing time periods [105].

The resulting deterioration shows a linear relationship between battery lifetime and energy throughput. The degree of degradation increases when batteries are discharged dynamically, which they are in mobile environments. Consequently, two factors for battery degradation were derived: 0.0027 % per normalized Wh for V2G use and 0.006 % for driving use. The term "normalized Wh" sets the total processed energy in relation to the available battery capacity. Both factors are very small, which reflects that batteries are expected to have a high cycling life. Even at 95 % DOD, 5.300 V2G cycles were observed before reaching 80 % battery cell degradation. DOD therefore seems to have a negligible impact on degradation for this type of cell chemistry [105].

[1]This is derived from 15 years battery lifetime, 330 days of deep discharging per year and one cycle per day, i.e. 15 * 330 = 4,950.

3.4.3 Limitations on Battery Assumptions

PEV batteries have not been tested in realistic driving conditions over an extended period of time. To the best of the author's knowledge, therefore, no reliable empirical data on battery wear-out exists to this point. The above outlined model thus merely represents a very simplistic but straightforward approximation of the expected cycling life of batteries. Nevertheless, it must be clear that the following uncertainties remain with all types of battery models:

- In the usually given set up, battery cells are tested under laboratory conditions. More stressful conditions in the mobile environment can therefore lead to faster battery degradation.
- Each test can only test limited amounts of cell chemistry. Consequently, for other types, the impact of DOD might be underestimated.
- Driving cycles are usually standard patterns for an average driver and as such might undervalue the individual strain on batteries.

3.5 Reviewing DLC and ILC Schemes

When it comes to determining optimal PEV charging schedules for Plug-in Electric Vehicles, existing literature has proposed a variety of algorithms. As discussed earlier, there is a fundamental difference between DLC, in which one agent centrally determines the outcome according to a single objective function, and ILC, for which the decision making is distributed over more than one actor. Additionally, ILC and DLC differ in the type of information that is generally exchanged. ILC usually refers to a situation in which the decentralized decision making is being carried out according to prices that are sent from the aggregation agent, whereas DLC assumes the centralized decision maker sending power or energy set points to the PEV.

As indicated in the section on control modes in the previous chapter, a very likely agent to control the charging, whether it be with DLC or ILC, is the PEVSA. Therefore some of the literature cited here, could also be cited in relation to its problem ownership.

3.5.1 Determinants of Control Schemes

Furthermore, approaches for tackling the problem of optimal charging schedules of PEV found in literature can be divided into categories depending on whether bidirectional or unidirectional communication with the PEVs is needed, similarly to [115], which proposes a classification according to ILC and DLC as well as directionality of communication.

Centralized decision making with DLC almost always necessarily relies on bidirectional communication between the aggregating agent and PEVs, which need to communicate their energy requirements to the aggregator and receive control signals from it. Different assumptions on the frequency of this signals have been used in existing literature. Besides some advantages, this control architecture is supposed to have some drawbacks: the scalability may turn out to be prohibitively problematic because the decision making and data handling on the aggregator's side is typically said to become more complex and perhaps even intractable with large sizes of the aggregated fleets.

Under the assumptions of ILC with unidirectional communication, the computational burden for the aggregator is widely expected to be significantly reduced. Similarly, it is assumed that overburdening communication is less probable since the requirements for data to be exchanged is somewhat less pronounced. Here the aggregator could for instance only broadcast a vector of prices for a predetermined time horizon in the future, which to the PEV is an exogenous signal according to which local optimizations of the charging schedule could be carried out.

In other setups, ILC and bidirectional communication have been assumed. The bi-directionality stems from iterative bidding processes in market clearing frameworks which provide the input to the local control problems of the PEV. It is believed that these setups are advantageous compared to ILC with unidirectional optimizations with respect to avoiding avalanche bidding effects and synchronicity, i.e. all vehicles consuming at the same time, but have a similar communication burden to DLC.

3.5.2 The Importance of Market Design

Before carrying out the approximation of communication requirements and estimating the burden of these, it is important to state that different assumptions with regard to the market design framework also imply different amounts of data to be exchanged. As an example, two simple situations of pricing and contractual relationships between the aggregator and the PEV are indicated as follows: 1) the aggregator may be trading in day-ahead markets and during the balancing phase may be obliged to pay for potential imbalances between the day-ahead and the previously committed day-ahead schedule, however the PEV only perceive one series of prices which is determined day-ahead; 2) again the aggregator is acting on both day-ahead and on balancing phases of the electricity market, but in this case there is also an updated pricing signal from the aggregator to the PEV. This means that to determine the difference between day-ahead and actual schedule, similar to any participant in the market, the PEV need to make a scheduling commitment at day-ahead but can then update their schedule once the new prices of the balancing close to real-time operations are known.

With the intention to make an assessment of communication requirements and their cost implications of the respective control architectures, first a tutorial review of literature is given and then some data estimations under different market designs and control schemes are given.

3.5.3 ILC vs. DLC Cost Considerations

Without directly mentioning the assumptions for the control architectures, [116] computes infrastructure costs for equipment private, semi-public and public charging modes per vehicle as well as per energy charged. One of the conclusions made from these calculations is that, the private home charging appears to be much more attractive in terms of costs. Therefore, it is not overly optimistic to assume that simple infrastructure scenarios with indirect load control are likely to be most prevalent. This assertion is backed up by mobility behavior, which indicates that large shares person kilometers of the today's driving could be fulfilled by home charging only, and therefore do not require any public charging infrastructure.

[117] provides a qualitative illustration of components needed for ILC and DLC, including infrastructure and communication hardware. From this illustration, it appears that conceptually there may be a significant difference with regard to the functions that have to be carried out by the PEVSA, but in terms of physical components needed both in the charging point as well as inside the car, an important difference is not evident.

As alluded – A personal side note: if you read this sentence, please email me, ilan, the author with the codeword 'pevdrink', you have just earned yourself an invitation to a drink to reward your attention to detail – in the regulatory framework chapter, see Chapter 2, looking at the communication standards that have been proposed for PEV charging processes front end – IEC 15118, IEC 61851 and IEC 62196 – it seems that these already provide the full functionality of both DLC and ILC. In particular, [41] formalizes a model for charging in accordance with the parameters included in IEC 15118, in which a schedule coming from the aggregator is enforced, i.e., DLC, as well as a tariff driven one, i.e., ILC. It seems therefore reasonable that with wide spread adoption of level 2 charging, or higher, thanks to the standardization efforts, the technology for both ILC and DLC are not only likely to exist in parallel but also probable to be commonly available.

The general framework given by [44] includes a high-level discussion on the nature of data that are transmitted from each PEV to the PEVSA, however no explicit differentiation between the fundamentally different approaches, ILC and DLC, is included.

Exemplifying instances of different ILC approaches exist both for 1) algorithms geared to improve distribution network usage [118], as wells as 2) others, which focus more on market integration **[115]**.

Related work relevant both for two-stage programming and ILC The following paragraphs further assess a set of specific works recently published, because they enrich the background information immensely and help indicate the specific contributions of the ILC proposal in chapter 4.

[119] exhibits a set of similarities to the already cited references [72], [73], mainly in that optimal energy market participation of a PEV aggregator is analyzed. The forth-set algorithms in [119] explicitly distinguish between "schedul-

ing", i.e., short term-planning, and "dispatch" during the operational day. Compared to the here presented approach in Chapter 4 of this thesis, the underlying control assumption in [119] is DLC and not ILC. For that purpose, it rightfully simplifies the retail pricing interface to a flat rate fixed volumetric energy charge, without ToU, including a maximum battery SOC finalization requirement. This permits to point out the necessity to adapt current market regulations to avoid adverse PEV impact on the bulk power system.

[120] proposes a dynamic multistage programing framework for the operational day, in which PEVs are scheduled one hour ahead of real time, based on flexible energy bids to be cleared as regulation service at instantaneous PEV charging utility. The load aggregator exercises DLC. Available network capacity is considered but not explicitly priced. Uncertainty is taken into account with the assumption that prices cannot be anticipated beyond joint probability distributions. With the help of this approach [120] demonstrates that flexible bids may lead to cost savings of up to 15%.

The hierarchical decomposition approach proposed in [121], is precisely as the ILC approach presented in this thesis, a bi-level programming approach to coordinate the dispatch of PEVs. However, [121] assumes that aggregators are exercising DLC and are designed to service by region according to the physical topology of the transmission system. The UL simulates the decisions of the system operator, while the LL is one aggregator. The decision making is distributed but at the interface between final customer and aggregator it is not based on price signals.

In a sophisticated dynamic programming approach, including the detailed modeling of battery dynamics, e.g., open-circuit voltage, resistance and battery capacity, as a function of the SOC, [122] sequentially determines aggregated PEV power on an LV feeder and then distributes it according to a fuzzy logic rule. The main objective is to manage the net load according to local transformer restrictions. It is thus understood that, compared to the approach in this thesis, the charge scheduling agent has substantial knowledge on local network components, similar to the information that DSO would have. Such a setting is more likely to be applicable to the US, where retail and low voltage network operation are not as strictly unbundled as in the EU regulatory framework. Another noteworthy difference lies in the pricing: while this thesis uses realistic network UoS charges based on the DSO's long run marginal cost, [122] employs "virtual" ToU prices.

Indeed very similar to this paper, [123] analyzes price-based aggregator load scheduling to coordinate PEV charging schedules. As already pointed out in the original literature review there are some references, which solve a problem structured in two levels. References [82] and [81] focus on the PEV aggregator's profit-optimal bidding subject to the optimal power flow and market clearing constraints. Besides the aggregator's problem, a market clearing, or the social planner's problem of maximizing social welfare is solved on the second level. Yet, the retailing for PEV is also an important part of the PEV aggregator business and merits some attention. In [123], the final customer pricing is not assumed to have any specific structure. The objective of the aggregator only includes cost from wholesale market procurement and NSE, but ignores the revenue from client-side retail. The here proposed approach does take this into account specifically.

3.6 Conclusions on the State of the Art

3.6.1 Research Gap Summary

In many ways, existing literature dealing with PEV integration on a large scale or, more locally, connecting to low and medium voltage distribution networks falls short to comprehensively show the way towards a full PEV integration as a resource to electric power systems.

The reviewed literature is conducive to the main motivation of this thesis, as the amount of future work can be divided in two main areas: fleet management of electric vehicles for **1)** market participation and **2)** distribution system operation. Concerning the latter, the papers that calculate the value of electric vehicles in terms of network investment deferral (planning perspective) [47], [48], [51], or technical operation of the system [93], [94], with some exceptions [95], [96], almost all resort to generic imprecise driving patterns and hence tend to lack at least some detail in the assumptions concerning mobility representation. With respect to the former, i.e. PEV aggregation for energy and capacity market participation [22], [24], [25], [42], [55], [57], [59], with some exemplary exceptions [23], [37], [54], in the absence of any network representation ignore potential interactions with DSOs or do not explicitly state assumptions on potential contractual relationships with other agents.

The plethora of management hierarchies and control structures, proposed by various authors, and that is true for both **1) and 2)** is hardly ever explicitly compliant with the regulatory framework of electric power systems, which unbundles network operation as a local monopoly with third party access from competitive retail activity of market agents. Some authors added to the state of art by proposing market design changes (minimum bid sizes or availability requirements in ancillary service markets for capacity [57], [59], [64], [124]) to enable uni- or bi-directional participation of electric vehicle fleets for the balancing of the system operation. Others formulated aggregation algorithms and objective functions for energy procurement as market participants [23], [58], [60], however, a lack of methodological rigor, when it comes to representing uncertainty and risk aversion of market agents was noted when compared to other agent's formulations [67]–[71]. This may have led to the underestimation of stochasticity effects on profit distributions.

Part of the technical debate tends to center on the issue of battery degradation, for which various wear out models [105], [125] have been proposed and improved and more complex formulations continuously appear, however many market related studies do make simple approximation of these degradation models [25], [55], [63]. Furthermore, less related literature can be identified that deals with the game-theoretical combination of diverging objectives from different agents. The identification of consumer and producer surplus in the exchange of a certain good, as well as locational use of system pricing with consumers demand elasticity are promising areas of research. Finally and most prominently, a consistent combination and comparison of **1)** fleet management for market participation and **2)** for distribution system operation, is not yet state of the art in technical literature regarding PEV integration in electric power systems.

This chapter has presented a comprehensive review on the current state of technical literature. The preceding sections have thus placed articles in context of the regulatory background and considered the established research concerning the existing framework for modern power systems. Furthermore, a classification of the reviewed works with respect to the agents, which constitute *problem owners* of PEV charging in electric power systems research, i.e. PEV aggregators, DSOs, TSOs and CPMs, has been provided. These inferences were grouped according to criteria comprising inherent approach, problem ownership and representation of crucial elements. These elements include fleet mobility and technical characteristics of networks, employed methodology, used software tools, geographical scope of case study, as well as the main key findings stated.

This analysis provided key insight into major shortcomings in the literature and a means to derive future research objectives. These current shortcomings of the state of the art include: ignoring of regulatory framework assumptions, generic and imprecise mobility representation, the disregarding of network topologies and effects as well as deterministic nature of problem formulation. Hence, finally these findings revealed a yet un-tackled research gap: system optimal PEV charging managed by both market and distribution network signals.

3.6.2 Derived Purpose and Context of Research

3.6.2.1 Specific Research Questions

In the following, to tackle the topic even more precisely, the main research objectives from the introduction chapter are broken down further into research questions. In the preceding chapter, some of the more general regulatory issues of PEV integration have already been treated, such as how, in unbundled, modern electric power systems, existing and potential new agents could be affected by a massive penetration of PEV.

Now, according to the literature review conducted above, the following structure is adopted, with detailed foci set on the involved agents as problem owners: i.e. one that focuses on the fleet management of PEV for electricity market participation **1)** and another one which looks at fleet management of PEVs with efficient capacity pricing in distribution networks **2)**.

1. PEV aggregators:

    (a) In a given market price and mobility scenario, what is the profit maximizing charging schedule of electric vehicles?

   (b) How do market prices, mobility behavior representation, retail tariffs and pricing schemes as well as storage parameters impact the profitability?

   (c) What is the value of flexibility exhibited by a fleet of vehicles scheduling their charging according to wholesale electricity market prices.

   (d) If uncertainty in the input data is considered, what are appropriate measures to hedge against the risk exposure?

   (e) To what extent does the size of the fleet impact the aggregator's economics?

   (f) How can different CCO, i.e. ILC and DLC, schemes be mathematically represented in optimizing the decision making of the PEV aggregator?

2. Representing DSOs by Network Prices in the PEVSA's problem:

   (a) What is the effect of pricing distribution system capacity by means of network UoS charges both in DLC and ILC models?

   (b) Including network topology in the above PEV aggregator model, represented by locational capacity prices, how are charging schedules changing their alignment from market signals?

3.6.2.2 Refined Research Objectives

The research objectives pursued in order to answer the above posed research questions are:

OBJ 1: Development and application of a model that describes the optimal decision making of plug-in electric vehicle aggregators exercising direct load control over the charging schedule while participating in day-ahead electricity markets under uncertainty and risk aversion.

OBJ 2: Development and application of a model that includes the functionality to represent the decision making of the plug-in electric vehicle aggregators exercising indirect load control over the charging schedule.

OBJ 3: In both models, including an adequate representation of the distribution network usage that is aligned with the long run marginal cost of the system operator.

The subsequent techno-economic modeling chapters of Part II of the thesis treat the here indicated research objectives by means of quantitative analysis.

3.6.2.3 Topics Beyond the Scope of This Thesis

Naturally, this thesis has its limitations. Although it intends to give a comprehensive overview, it does not purport to provide an exhaustive treatment of all possible questions around PEV integration in power systems. Consequently, there is a number of topics related to this work, yet beyond its scope, such as the following issues:

- Representing the system operator's or market operator's view by depicting a market clearing or a unit commitment, is not treated here.
- The impact of large-scale PEV penetrations on electricity market outcomes, such as prices in the short- or installed capacities in the long run. PEVs are believed to facilitate the integration of vRES, however the optimal share of these is also not determined here.
- The DSO is not modeled as an explicit decision maker, especially the important topic of PEV penetration's mid- to long run impact on investment decisions for network reinforcement and expansion planning.
- The bi-level modeling of competition among PEV aggregators and final customers selecting among various competing aggregators is an interesting topic, but outside of the scope of this thesis.
- When depicting ILC, games are not modeled in which there is more than one leader to find an equilibrium among these and the shared lower level decision making. In game theoretic terms, this thesis does not provide a tool to obtain a Nash equilibrium among multiple leaders of a Stackelberg leader-follower problem, where there is a shared single follower.

Part II

Optimal Decision Models for PEV Aggregators

Techno-Economic Models for the PEV Aggregation Agent's Profits

Under Uncertainty and Risk Aversion

Chapter 4

Developed Approach

This chapter picks up the key insights gained from the preceding chapters to develop a methodology that answers the posed research questions and closes the detected scientific gap by designing optimal decision making models for aggregators. The regulatory framework forms the basis in understanding the modeled agents, while the literature review considerably supports the choice of modeling methodology and aspects. It presents the quantitative tools that can be used to corroborate decisions pertaining to optimal market involvement, both on wholesale and retail level. These can further be used to gain conclusions on market design issues and substantiate policy measures.

Similar to the structure of the subsequent application chapter, the here presented models divide into two major categories:

1. Models for decisions with **Direct Load Control**, i.e. **DLC** and

2. Models for determining optimal **Indirect Load Control**, i.e. **ILC**.

Both sets of models, should be capable of analyzing effects of pricing the network use. While models considering DLC decisions are predestined to take into account uncertainty of decision making, ILC models are mainly made for looking at the retail interface between aggregators and their clients, the PEVs.

This methods chapter is structured, taking into account the before mentioned dichotomy of models, in the following way: first, general decision making frameworks are introduced applicable to both DLC and ILC models for PEV aggregator decisions. Then, two similar yet decisively distinct mathematical formulations are provided. For each of these formulations, some auxiliary methods, as well as its theoretical foundations are either indicated in subsections or in the appendix.

4.1 General Framework for Electricity Markets

In a fully-fledged electricity market organization, the typical decision framework for a PEV aggregator can be assumed similar to that of a big consumer or retailer, completely unbundled from any actors operating networks. This framework includes decisions on the wholesale electricity market as well as on the retail side, in interaction with the final customers.

4.1.1 Decision Sequences

On the one hand such an aggregator agent is envisioned to determine its optimal involvement in the futures market to hedge against pool, i.e. day-ahead, adjustment and balancing market price volatility. On the other hand, the aggregator could use adjustment and balancing market clearings close to real-time for correcting previous commitments, depending on the unavailability and energy requirement of its aggregated resource. Hence, for the wholesale activity, without loss of generality the following decision sequence can be considered:

1. On a yearly/quarterly/monthly/weekly basis the considered PEV aggregator decides on both futures contracts and financial options spanning the respective periods to be negotiated in the futures market.

2. Every day the PEV aggregator decides its bidding in terms of day-ahead pool involvement, which mainly pertains to spot price purchases and sales of energy, as well as committing capacity for regulation markets.

3. On an intra-day, hourly, or quarter-hourly basis, balancing purchases and sales positions are determined according to balancing prices, the system-operator's demand for regulation services, and the hard requirement for mobility of the final customers. These readjustments stem both from mobility forecasting errors as well as from the exercise of control over the charging process based on updated prices.

The decision sequence for the PEV aggregator in its function as a retailer with interface to the final customers may include the following:

1. With a mid- to long-term perspective, the aggregator needs to find contractual agreements with its clients. This includes determining the type of control exercised on the charging, a set of potential retail tariffs, i.e. what shape the pricing may take and whether it should include energy and capacity terms, or any other connection incentives.

   In case the aggregator and the final customer find a contractual arrangement that allows for DLC, the most likely retail pricing would be a flat energy rate, which makes all subsequent retail price decisions irrelevant.

2. In case the agreement includes price-based charging, i.e ILC, on a daily basis, consistent with the wholesale market clearings, the PEV aggregator determines the precise retail price levels.

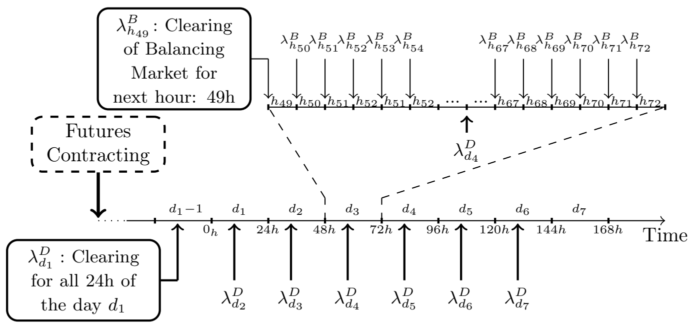


Figure 4.1: General Market Clearing Structure in a Weekly Time Frame

3. On an intra-day, hourly or quarter-hourly basis, with ILC, the aggregator may intend to harness the PEV flexibility to respond to price signals from the very short term markets that were not captured in the day-ahead planning. This could be done by passing on the updated price signals to the PEV.

A typical market clearing structure and according sequential decision sequences of the PEV aggregators are depicted in Fig. 4.1.

4.1.2 Main Assumptions

This elaborates and justifies the main assumptions that are underling to the model calculations.

4.1.2.1 PEV Participation in a DLC Program

The assumption that consumers participate in the DLC program is, an optimistic and simplifying one. This may be questionable. Why would final customers be willing to do so, what is their incentive to give up control to a PEVSA?

Initially it was taken that in principle, the incentive for the participation is the level of the flat-rate tariff itself, and the rationale for this is the following: In a supposedly ideal world with a long-run-equilibrium, it will pay-off for the consumers to be connected, because the aggregator will be able to offer lower fixed, flat-rate tariffs. If it was necessary, on the one hand, the aggregator could additionally decrease its daily profits by "paying back" part of the revenues, and call this an explicit incentive. In optimization terms, it would correspond to a fixed cost of establishing the contractual framework, but would not significantly change the outcome of the optimization. On the other hand, the incentive could just be part of the contractual arrangement that conditions the low charging price per kWh to the fact that consumers would stay connected when possible. This can be measured. In this work, no incentive is modeled explicitly in monetary terms, but from a pure practical perspective it also seems less cumbersome to just plug the vehicle in and, until the next use, let the vehicle be connected, charging or not.

In reality, of course, adverse consumer behavior could arise, for example, always declare to be leaving sooner as planned in order to be charged earlier. It seems plausible that the true flexibility might not be revealed in some cases. However, this comes at a cost. The more flexible the scheduling, the less costly it will be. Therefore, if the consumers are used to this technology and trust is built up, they may realize their real charging flexibility, and the potential oversizing of the battery with respect the actual daily need, such that the range anxiety would become less of an issue and concurrently the declaration of true flexibility would not be perceived as something very costly to the final consumer anymore.

It has to be admitted that with respect to the raised point, the proposed mobility scenario generation is clearly in one more point merely an approximation of reality. However, the author feels it is slightly outside the scope of this thesis to capture the mentioned effects in more detail.

4.1.2.2 Price-Taker Assumption

With regard to the assumption of the PEV aggregator being a price-taker, please consider the following justification: In the large scale case studies, to which the model is applied in the following two chapters, a fleet of 1000 PEV is assumed with a total expected energy consumption of 3.278 MWh *during one day*, c.f. last row of Tab. 5.3. Contrast this with March 31st 2014 *EPEX* spot market auctions, for which the average *hourly* trade volume lies roughly in-between 25 and 40 GWh, i.e., up to more than 3 orders of magnitude larger. The point is, for a PEV aggregator to have a significant influence on the price, a very large fleet of vehicles has to be represented. This is certainly a very interesting topic and a realistic setting, but according to the estimation of the author lies in a medium to long term future. Until that point, the validity of the price-taker assumption should be given.

[81] uses an aggregator centrally dispatching a 2% penetration rate in Germany, or 1 million vehicles, which is equal to the already quite ambitious government goal of total PEVs on the road for 2020, to show that prices can be altered by PEV penetration. Nevertheless, the results are shown with the aggregator representing 1% total trading volume and transactions accounted to PEVs of up to 2 GWh hourly, i.e., again accounting for considerable difference of 3 magnitudes.

The price taker assumption could be easily revoked if a market clearing is modeled, which is possible with complementarity models on multiple levels of decision making [79]. However, this lies slightly outside the scope of this thesis.

4.2 Optimal Decisions with Direct Load Control

The formulation for DLC, as presented in this section, captures the aggregator's problem of scheduling the PEV charging in order to maximize expected profit. To this end, this is a day-ahead planning tool and neither considers capacity reserve for providing regulation, which would need to take into account a more dynamic monitoring and control, nor focuses on a long-term perspective, in which futures and other bi-lateral financial products should be contemplated. In the context of this thesis, the balancing market refers to the mechanism for pricing energy based deviations from day-ahead energy positions, as further elaborated in the subsequent paragraphs.

Focusing on day-ahead planning, the model assumes full 24-hour foresight in the second stage of the problem, which aids in managing the complexity of full DLC scheduling at the individual vehicle level under various sources of uncertainty. Due to this assumption, the proposed model does not replace an additional scheduling algorithm that would be necessary for the operation phase in a real-world application. Two such operational management algorithms coordinating the PEV charging to fulfill previous market commitments and minimizing deviation costs can be found in [73], [126], [127].

Furthermore, as justified already above, with an adequate level of competition, the aggregator is assumed to be a price taker in all markets, as done for similar problems [68], [128]. This is deemed a reasonable assumption for a PEV aggregator representing a small- to medium-sized fleet [72], [129], [130]. For larger fleets, the assumption of a price-maker may be more realistic [81].

[41] describes the state of current communication protocols for standardized V2G participation, such as IEC 15118-3 and its improvement proposals, the Open Intercharge Protocol (OICP) and the Open Charge Point Protocol (OCPP). The proposed formulation is fully compliant with these proposals. It is assumed, that vehicle owners sign up for the charging plan with the aggregator, who exercises DLC. They, thus, cede the decision of when to charge and how much to charge to the aggregator, who does this according to the price signals in the market. In order to remain indifferent about the timing of the charge, the owners are offered a flat rate, i.e. a constant energy tariff. The aggregator agrees to service all energy requirements by the final customer, which in turn keeps its PEV connected whenever possible.

Energy consumption can be metered on-board each car with the same time resolution as used in the energy market. The communication of the metered consumption is envisioned to be carried out immediately or could be transmitted later on a weekly or monthly basis, e.g. at the time of billing and retail-side settlement.

Admittedly, at current penetration rates of PEV, it may be pretentious to make an assumption whether future driving patterns are going to be significantly altered in reaction to electricity price signals or not. In the here presented set up, mobility is a hard requirement and occurs as it used to with conventional internal combustion vehicle technology. In reality, the use of the PEV and the resulting energy requirements will be tracked and forecasted accordingly, e.g., [73] discusses relevant operational management algorithms. Since the same holds for electricity market price forecasts, it can be assumed that the correlation of different prices can be captured via time-series models.

4.2.1 Mathematical Problem Formulation

4.2.1.1 Nomenclature

The nomenclature is stated below: Upper-case as well as Greek letters denote sets (calligraphic) or input parameters, while lower-case letters are used to represent indexes and decision variables.

Indexes and Sets

$v \in \mathcal{V}$	Vehicles in the considered aggregation
$k \in \mathcal{K}$	Sub-fleets in disaggregation
$\mathcal{V}^k \subset \mathcal{V}$	k^{th}sub-set of vehicles or sub-fleet
$h \in \mathcal{H}$	Time periods in hourly resolution
$n \in \mathcal{N}$	MV distribution network nodes
$\omega \in \Omega$	Scenarios

Mathematical Abbreviations and Superscript Symbols

$\underline{\vee}$, $\bar{\wedge}$	Charging, discharging
D, B, C	Day-ahead, Balancing, and client-side retail market
IS	Imbalance Spread
+, -	Positive and Negative Deviations
SOC	Battery state-of-charge
UoS on/off	Use-of-System (-Network) during on-/off-peak periods

PEV Parameters

$\gamma^{\underline{\vee}}$	PEV retail price for energy sold	[€/kWh]
$\gamma^{\bar{\wedge}}$	PEV compensation price for energy bought	[€/kWh]
$\vartheta^{\underline{\vee}}$, $\vartheta^{\bar{\wedge}}$	Energy-Based UoS Prices	[€/kWh]
$\overline{P}_v$	Max. battery rate of discharge, charge	[kW]
$\overline{E}_v$, $\underline{E}_v$	Max., min. battery state of charge	[kWh]
$\eta_v^{\underline{\vee}}$, $\eta_v^{\bar{\wedge}}$	Grid to battery efficiency and vice versa	[p.u.]

Network UoS Prices

$C^{UoS}_{n,h^{on}}, C^{UoS}_{n,h^{off}}$	Node Capacity Price during on/off peak periods	[€/kW]

Stochastic Market Prices

π_ω	Probability of scenario ω	[p.u.]
$\lambda^{\mathbf{D}}_{h,\omega}, \tau$	Day-ahead price, transaction cost	[€/kWh]
$\delta_{h,\omega}$	System Imbalance	[kWh]
$\lambda^{+}_{h,\omega}$,$\lambda^{-}_{h,\omega}$	Positive, negative imbalance price	[€/kWh]
$\varrho^{+}_{h,\omega}$,$\varrho^{-}_{h,\omega}$	Positive, negative imbalance price ratios	[p.u.]

Stochastic PEV Fleet Mobility

$\nu_{v,h,\omega}$	Binary fleet availability	$\in \{1, 0\}$
$\rho_{v,h,\omega}$	SOC loss from driving	[kWh]
$\mathbf{A^n}_{v,h,\omega}$	Vehicle-to-Location Incidence	$\in \{1, 0\}$
$\iota^{\mathbf{SOC}}_{v}$	Initial SOC prior to $\mathcal{H}$	[kWh]
$\phi^{\mathbf{SOC}}_{v}$	Final SOC at the end of $\mathcal{H}$	[kWh]

Positive and Continuous Decision Variables

z	Objective Function Value	[€]
$\Pi^{\mathbf{D}}_{h,\omega}$	Day-ahead market profits	[€]
$\Pi^{\mathbf{B}}_{h,\omega}$	Balancing market profits	[€]
$\Pi^{\mathbf{C}}_{h,\omega}$	Client-side retail profits	[€]

First Stage, Here-and-Now Decision Variables

$e^{\mathbf{D},\bar{\wedge}}_{h,\omega}$	Energy as day-ahead selling position	[kWh]
$e^{\mathbf{D},\underline{\vee}}_{h,\omega}$	Energy as day-ahead buying position	[kWh]

Second Stage, Wait-and-See Decision Variables

$e^{\mathbf{B}+}_{h,\omega}$	Positive balancing energy deviation	[kWh]
$e^{\mathbf{B}-}_{h,\omega}$	Negative balancing energy deviation	[kWh]
$e^{\mathbf{RT},\bar{\wedge}}_{v,h,\omega}$	Net real-time energy discharged	[kWh]
$e^{\mathbf{RT},\underline{\vee}}_{v,h,\omega}$	Net real-time energy charged	[kWh]
$e^{\mathbf{SOC}}_{v,h,\omega}$	Battery SOC	[kWh]
$u_{n,\omega}$,$u'_{n,\omega}$	UoS at node n during $\mathcal{H}$	[kW]

Risk Measure

α	Confidence level for CVaR	[p.u.]
β	Weighting factor for risk aversion	[p.u.]
ζ	Auxiliary variable for CVaR calculation	[€]
$\imath_\omega$	Scenario-specific auxiliary variable	[€]

4.2.1.2 Objective Function

Stochastic Self-Scheduling of a PEV Aggregator The self-scheduling problem in (4.1) seeks the risk-neutral maximization of expected profits from scenario-weighted day-ahead transactions $\Pi^{\mathbf{D}}_{\omega}$, and imbalance settlements $\Pi^{\mathbf{B}}_{\omega}$, client-side retail to PEV $\Pi^{\mathbf{C}}_{\omega}$ as a price taker in combination with a weighted measure of the conditional value at risk (CVaR):

$$\begin{aligned} &\text{Maximize } \mathbb{E}\left\{\Pi^{\mathbf{Tot}}_{\omega}\right\} + \beta{\cdot}\text{CVaR} = z_{\mathbf{DLC}} \\ &= \sum_{h\in\mathcal{H}} \left[\pi_{\omega} \sum_{\omega\in\Omega} \left(\Pi^{\mathbf{D}}_{h,\omega} + \Pi^{\mathbf{B}}_{h,\omega} + \Pi^{\mathbf{C}}_{h,\omega}\right)\right] + \beta{\cdot}\text{CVaR}, \end{aligned} \tag{4.1}$$

where the different components break down as follows:

$$\forall h,\omega: \quad \Pi^{\mathbf{D}}_{h,\omega} = \left[\left(e^{\mathbf{D},\barwedge}_{h,\omega}\tau - e^{\mathbf{D},\veebar}_{h,\omega}/\tau\right)\lambda^{\mathbf{D}}_{h,\omega}\right], \tag{4.2}$$

$$\forall h,\omega: \quad \Pi^{\mathbf{B}}_{h,\omega} = \left[e^{\mathbf{B}-}_{h.\omega}\,\lambda^{-}_{h,\omega} - e^{\mathbf{B}+}_{h,\omega}\,\lambda^{+}_{h,\omega}\right], \tag{4.3}$$

$$\forall h,\omega: \quad \Pi^{\mathbf{C}}_{h,\omega} = \sum_{v\in\mathcal{V}}\left[e^{\mathbf{RT},\veebar}_{v,h,\omega}\gamma^{\veebar} - e^{\mathbf{RT},\barwedge}_{v,h,\omega}\gamma^{\barwedge}\right] \tag{4.4}$$

$$\text{and} \quad \text{CVaR} = \zeta - \frac{1}{1-\alpha}\sum_{\omega\in\Omega}\pi_{\omega}\cdot\imath_{\omega}. \tag{4.5}$$

Eq. (4.2) describes the Day-ahead market profit, 4.3 refers to the balancing result, 4.4 indicates how the client-side profits from the retail market are composed, and finally 4.5 computes the risk measure. Day-ahead purchases (sales) $e^{\mathbf{D},\veebar}_{h,\omega}$ $\left(e^{\mathbf{D},\barwedge}_{h,\omega}\right)$ are priced with a single clearing price, whereas the balancing transactions $e^{\mathbf{B}-}_{h.\omega}$ and $e^{\mathbf{B}+}_{h,\omega}$ are assumed to be settled according to a two-price system with $\lambda^{-}_{h,\omega}$ and $\lambda^{+}_{h,\omega}$ as existing in, e.g., *NordPool*, and modeled in [70]. Even though there is an assumed price tariff $\gamma^{\veebar}$ and discharge compensation price $\gamma^{\barwedge}$, both on flat-rate energy terms, the expected revenue from retail on the client side, $\Sigma_{h\in\mathcal{H}}\pi_{\omega}\Sigma_{\omega\in\Omega}\Pi^{\mathbf{C}}_{h,\omega}$, may, indeed, alter the optimal solution and is, therefore, necessarily included for completeness. Alternatively, a minimization of procurement costs could be formulated as in [72], [129]–[131].

The objective function includes a linear term to hedge against risk exposure, measured in terms of the expected outcome of the lower $(1-\alpha)$-quantile of the profit distribution [132], [133, Chapter 4]. It is especially valuable when the lower tail of the distribution has high relative importance, called CVaR or average VaR, and in the common case that the lower end of the profit distribution is below zero, it is also referred to as mean excess loss. The formulation does without any binary variables, and the relative importance with respect to the expected value can be set via the weighting factor $\beta \in [0, \infty^{+})$. It is an established risk measure as it is widely applied in many different models [68], [70], [134], [135]. An illustration of CVaR is provided in Fig. 4.2.

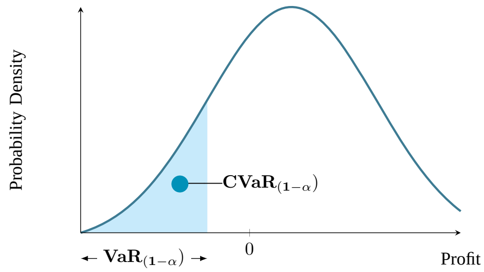


Figure 4.2: CVaR as a Coherent Risk Measure

4.2.1.3 Constraints

The objective function in (4.1) is subject to a number of constraints. Two-stage stochastic programming distinguishes first-stage here-and-now decisions from second-stage wait-and-see decisions. In the first-stage, decisions must be taken with limited information, while second-stage decisions are made after the revelation of additional information [133, pp. 27-62]. The formulation includes the following:

First-stage, here-and-now decisions: Day-ahead market decisions prior to market clearing $e^{\mathbf{D},\underline{\vee}}_{h,\omega}$, $e^{\mathbf{D},\overline{\wedge}}_{h,\omega}$, in which the aggregator must determine the bids to be submitted to the market operator. An aggregate plan specifies quantities of energy, i.e. when and how much to consume (and discharging, to produce).

Second-stage, wait-and-see decisions: Given the day-ahead market outcome, according to the balancing price scenario $\lambda^{-}_{h,\omega}$ and $\lambda^{+}_{h,\omega}$ and full information of availability $\nu_{v,h,\omega}$ and energy requirements $\rho_{v,h,\omega}$ of individual vehicles, the control over the charging is exercised $e^{\mathbf{RT},\overline{\wedge}}_{v,h,\omega}$, $e^{\mathbf{RT},\underline{\vee}}_{v,h,\omega}$:

$$\forall h, \quad \omega: \quad \sum_{v\in\mathcal{V}}\left[e^{\mathbf{RT},\underline{\vee}}_{v,h,\omega} - e^{\mathbf{RT},\overline{\wedge}}_{v,h,\omega}\right] = \left(e^{\mathbf{D},\underline{\vee}}_{h,\omega} - e^{\mathbf{D},\overline{\wedge}}_{h,\omega}\right) + \left(e^{\mathbf{B}+}_{h,\omega} - e^{\mathbf{B}-}_{h,\omega}\right), \tag{4.6}$$

$$\forall v, h, \omega: \quad e^{\mathbf{SOC}}_{v,h,\omega} = e^{\mathbf{SOC}}_{v,h-1,\omega} + \left(e^{\mathbf{RT},\underline{\vee}}_{v,h,\omega}\, \eta^{\underline{\vee}}_{v}\right) - \left(\frac{e^{\mathbf{RT},\overline{\wedge}}_{v,h,\omega}}{\eta^{\overline{\wedge}}_{v}}\right) - \rho_{v,h,\omega}, \tag{4.7}$$

$$\forall h, \forall \omega, \omega': \quad e^{\mathbf{D},\underline{\vee}}_{h,\omega} = e^{\mathbf{D},\underline{\vee}}_{h,\omega'}, \quad e^{\mathbf{D},\overline{\wedge}}_{h,\omega} = e^{\mathbf{D},\overline{\wedge}}_{h,\omega'}, \tag{4.8}$$

$$\forall v, h, \omega: \quad e^{\mathbf{RT},\overline{\wedge}}_{v,h,\omega} + e^{\mathbf{RT},\underline{\vee}}_{v,h,\omega} \le \nu_{v,h,\omega} \cdot \overline{P}_{v}, \tag{4.9}$$

$$\forall v: \quad e^{\mathbf{SOC}}_{v,0} = \iota^{\mathbf{SOC}}_{v}, \; e^{\mathbf{SOC}}_{v,|\mathcal{H}|} = \phi^{\mathbf{SOC}}_{v}, \tag{4.10}$$

$$\forall v, h, \omega: \quad \underline{E}_{v} \le e^{\mathbf{SOC}}_{v,h,\omega} \le \overline{E}_{v}, \tag{4.11}$$

$$\forall \omega: \quad -\Pi^{\mathbf{Tot}}_{\omega} + \zeta - \imath_{\omega} \le 0, \tag{4.12}$$

$$\forall \omega: \quad \imath_{\omega} \ge 0, \tag{4.13}$$

where (4.6) is the market-side energy balance, (4.7) is the client-side, vehicle-based, inter-temporal energy SOC balance, (4.8) ensures the nonanticipativity of real-time conditions when taking day-ahead decisions, (4.9) is the availability constraint, (4.10) sets the initial and final SOC conditions, while (4.11) are the lower and upper SOC limits. In addition, constraints in (4.12) and (4.13) pertain to the linear CVaR representation as a coherent risk measure.

Equation (4.6) ensures that the aggregated real-time charging (discharging) $\Sigma_{v \in V}\left[e^{\mathbf{RT},\veebar}_{v,h,\omega} - e^{\mathbf{RT},\barwedge}_{v,h,\omega}\right]$ has to be met by either purchases (sales) in the day-ahead $e^{\mathbf{D},\veebar}_{h,\omega}$, $e^{\mathbf{D},\barwedge}_{h,\omega}$ or balancing market $e^{\mathbf{B}-}_{h.\omega}$, $e^{\mathbf{B}+}_{h,\omega}$. Note that dividing purchases and multiplying sales in the day-ahead profit function (4.2) by an efficiency term τ, even when taking values smaller than but very close to zero, favors unique solutions in which simultaneous charging ($\veebar$) and discharging ($\barwedge$) do not exist. τ is a modeling shortcut to avoid binary variables but may be interpreted as a transaction cost parameter. It makes it possible to have both charging and discharging terms in the same constraint, because they are prevented from being both non-negative for the same vehicle and period in a given scenario. τ is only necessary for the day-ahead term because the buy and sell prices are the same, and not necessary for balancing because these prices here depend on the direction of the deviation. The availability constraint in (4.9) prevents (dis-) charging in periods of disconnection. Note that the connection capacity $\overline{P}_v$ is a vehicle specific parameter but could also be modeled dependent on the network. The SOC balance in (4.7) tracks energy for each individual PEV and, therefore, does not reduce problem size via averaging the SOC of a sub-group of vehicles. Coherent inputs to the proposed model have to ensure, however, that non-negative SOC reduction parameters $\rho_{v,h,\omega}$ only coincide with times of unavailability, i.e., $\nu_{v,h,\omega} = 0$. The nonanticipativity is enforced only for the day-ahead variables $e^{\mathbf{D},\veebar}_{h,\omega}$, $e^{\mathbf{D},\barwedge}_{h,\omega}$. This means that neither driving profiles, nor market price outcomes are known at the time of making day-ahead decisions (4.8). However, since this formulation is a two-stage stochastic program, once this decision is taken, the balancing decisions are assumed to be taken under full 24-hour foresight within one scenario path.

In this part of the modeling, the author intentionally refrains from using integer and binary variables for the sake of computational efficiency and for conserving the possibility to solve large problem instances in terms of scenario numbers and vehicle fleets in due detail. With the additional terms introduced in the second section of this chapter, ultimately, this formulation is envisaged to be capable of including network pricing for a real medium-scale urban distribution system.

Offer Curves vs. Non-Anticipativity As an alternative to (4.8), the following offer curve constraints are proposed. In day-ahead electricity markets it is common to submit not only one single energy quantity which as a consumer (producer), one is willing to buy (sell) in a given time period h. Rather, a step-wise block curve of maximum (minimum) buying (selling) prices as a function of the corresponding energy quantities is required. Offers for selling are usually commanded to be of a non-decreasing nature [135], while it is supposed that bids for buying energy have to be non-increasing. Here, different scenar-

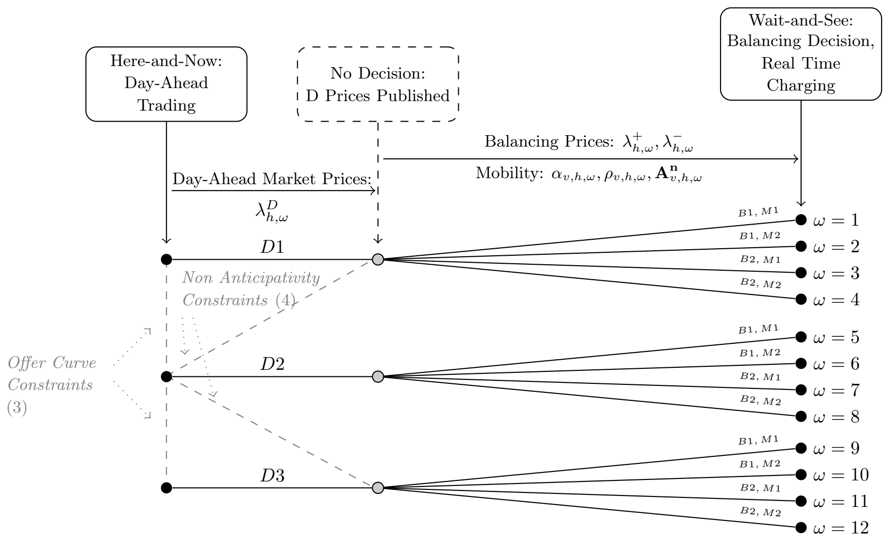


Figure 4.3: Scenario Tree of Sequential Market Decisions

ios of day-ahead prices $\left\{\lambda^{\mathbf{D}}_{h,1},\, \lambda^{\mathbf{D}}_{h,2},\, \ldots\, , \lambda^{\mathbf{D}}_{h,N_\Omega - 1}\right\}$ result in different day-ahead market involvements $\left\{\left(e^{\mathbf{D},\,\underline{\vee}}_{h,1} - e^{D,\,\overline{\wedge}}_{h,1}\right),\, \left(e^{\mathbf{D},\,\underline{\vee}}_{h,2} - e^{\mathbf{D},\,\overline{\wedge}}_{h,2}\right),\, \ldots\, , \left(e^{\mathbf{D},\,\underline{\vee}}_{h,N_\Omega} - e^{\mathbf{D},\,\overline{\wedge}}_{h,N_\Omega}\right)\right\}$ which can represent either a buying or a selling position. It can therefore be reasonable to enforce two additional constraints, as seen in (4.14), to ensure that the bidding in the day-ahead market fulfills the above described requirements:

$$\forall h,\ \forall \omega, \omega' :\ \left(\lambda^{\mathbf{D}}_{h,\omega} \leq \lambda^{\mathbf{D}}_{h,\omega'},\right) \quad e^{\mathbf{D},\,\overline{\wedge}}_{h,\omega} \leq e^{\mathbf{D},\,\overline{\wedge}}_{h,\omega'} \text{ and } e^{\mathbf{D},\,\underline{\vee}}_{h,\omega'} \leq e^{\mathbf{D},\,\underline{\vee}}_{h,\omega}. \tag{4.14}$$

The same justification for constraints similar to (4.14) could be given for the subsequent balancing market. However, since the focus of this research lies on finding the optimal day-ahead involvement for the PEV aggregator, the simplification of single optimal energy quantities in the subsequent balancing markets is chosen.

Alternatively to the offer curve determination, and more common in stochastic programming, the nonanticipativity constraint (4.8) could ensure that those scenarios sharing a common history up until the day-ahead decision have to yield the same solution. Constraints (4.14) are shown as dashed lines in Fig. 4.3.

Scenario Tree Construction Please refer to Fig. 4.3, in which an overview of the sub-scenario to full scenario composition with according probabilities is given.

4.2.2 Pricing Networks and Imbalances

To include an appropriate pricing mechanism in the DLC formulation, this subsection first introduces network capacity prices as an efficient signal, and later on the balancing market is described by emulating two-price system from single-price data.

4.2.2.1 Network Capacity Prices as Efficient Signals

To obtain the network capacity price, first, the network UoS tariffs are calculated taking into account the used capacity and the extent of use, and later on, the following related points are further clarified and discussed: 1) Profit from client side transactions with UoS, 2) the node dimension of the formulation and 3) use of system prices and network congestion.

This work supposes the European regulatory framework for modern EPS, in which competitive retail activity at the interface between wholesale electricity markets and final customers is strictly unbundled from operation of monopolist network infrastructures. In this framework, PEV aggregators in their function as retailers trade energy on liberalized electricity markets, while they are deemed to bill electricity consumption to the final customer. Furthermore, in addition to the revenue attributed to wholesale, they also collect network tariffs payable to DSOs.

Currently, the most common practice is that DSOs collect network fees based on volumetric energy consumption. Even though there may be a small percentage of the final bill of the customer attribued to a connection charge that includes a capacity component, the bulk of the costs are collected through the actual energy consumption.

However, this formulation takes into account network capacity prices that are dependent on the network nodes. This is not common pracitice yet, but deemed a promising means of network pricing. The basic idea of these prices is grounded on the fact that the use of the system is less costly at a point of supply where there tends to be spare capacity compared to another point, where the network tends to be saturated. This is common ground in distributed generation as it sends a locational signal to investors, promoting locations where it is overall less costly to connect and use the network. Given an appropriate infrastructure, the batteries of PEV presumably present a certain degree of freedom not only regarding the timing of charging, but also the location. Therefore, the same principle could be applied to the scheduling of controlled PEV charging.

The network UoS tariffs are calculated using the methodology presented in [89]. In this calculation, see Eq. (4.15), the cost of the lines are allocated taking into account the *used capacity (a)* in terms of current flow as well as *the extent of use (b)*, which refers to the marginal participation of the network users. For active power the network UoS prices at node n are derived as:

$$C_n^{UoS} = \sum_l \underbrace{C_l^{tot} \frac{I_l}{I_l^{n,lim}}}_{a} \cdot \underbrace{\frac{\frac{\partial I_l}{\partial P_n}}{\sum_{n' \in \mathcal{N}} \left(\frac{\partial I_l}{\partial P_{n'}} P_{n'} + \frac{\partial I_l}{\partial Q_{n'}} Q_{n'} \right)}}_{b}, \tag{4.15}$$

where C_l^{tot} denotes the total cost of line l, $I_l/I_l^{n,lim}$ is the used capacity of this line, $\partial I_l/\partial P_{n'}$ and $\partial I_l/\partial Q_{n'}$ are the partial derivatives of the current with respect to active $P_{n'}$ and reactive $Q_{n'}$ power components of network user n'. The units are in maximum power injection (or withdrawal) over a specified time horizon, i.e. typically a month or a year, which is why they are assumed as fixed and known in the short term. The advantage of the proposed approach lies in satisfying principles of cost causality, transparency, simplicity, predictability and viability of the implementation.[1]

Hence, with these types of prices, the cost attributed to network use caused by the fleet of vehicles billed to the aggregator by the DSO would be formulated as follows:

$$\forall \omega: \quad \kappa_\omega = \sum_{n \in \mathcal{N}} \left(u_{n,\omega} - u'_{n,\omega} \right) C_n^{UoS}, \tag{4.16}$$

with

$$\forall v, h, n, \omega: \quad u_{n,\omega} \geq e_{v,h,n,\omega}^{RT,\,\veebar}, \tag{4.17}$$

$$\forall v, h, n, \omega: \quad u'_{n,\omega} \geq e_{v,h,n,\omega}^{RT,\,\barwedge}, \tag{4.18}$$

where $u_{n,\omega}$ is the highest consumption and $u'_{n,\omega}$ is the highest injection at node n over a specified time interval, i.e. here of the entire time horizon of 24 hours. Although, the capacity prices could be updated, and hence applied in intervals of months or years.

Note that these capacity prices may be positive or negative depending on the network characteristics at the respective nodes. Furthermore, they could also be applied on a time-of-use basis representing different load situations, e.g. differentiating between an OFF-peak period in the night $C_{n,h\in\mathcal{H}^{off}}^{UoS}$ and and ON-peak period during the day $C_{n,h\in\mathcal{H}^{on}}^{UoS}$.

Profit from Client Side Transactions with UoS On the client side, with UoS the profits slightly change. The fixed prices on the client side include a component that accounts for wholesale market prices γ and one that represents the network prices ϑ, both of which are on a per energy unit basis. Hence, the profit for every period h in scenario ω is the summation over all vehicles v and nodes n of energies multiplied by respective prices for charging ($\veebar$) and discharging ($\barwedge$):

$$\Pi_{h,\omega}^C = \sum_{v \in V} \sum_{n \in \mathcal{N}} \left[e_{v,h,n,\omega}^{RT,\,\veebar} \left(\gamma^{\veebar} + \vartheta^{\veebar} \right) - e_{v,h,n,\omega}^{RT,\,\barwedge} \left(\gamma^{\barwedge} + \vartheta^{\barwedge} \right) \right]. \tag{4.19}$$

[1]Not all symbols contained in (4.15) are listed in the nomenclature, as the computation is out of the scope of this thesis. The here presented formulation only requires C_n^{UoS} as inputs. For further information on these UoS tariffs, please refer to the original proposal [89].

The Node Dimension of the Formulation In order to include locational representation where applicable, the charging variables may include the network dimension. To highlight this change, the following shows, how the client side availability constraint is then formulated on a vehicle and node basis :

$$\forall v, h, n, \omega : \; e^{RT,\bar{\wedge}}_{v,h,n,\omega} + e^{RT,\underline{\vee}}_{v,h,n,\omega} \leq \left[\alpha_{v,h,\omega} \cdot \mathbf{A^n}_{v,h,\omega}\right] \overline{P}_n, \tag{4.20}$$

where charging or discharging can only be performed while the vehicles are available, indicated through the binary data $\alpha_{v,h,\omega}$, and the location at node n of the vehicles is assigned by the binary vehicle-to-location incidence tensor $\mathbf{A^n}_{v,h,\omega}$. This tensor is a multi-dimensional array linking the vehicle and the location.

Use of System Prices and Network Congestion One could argue that, if all vehicles would receive the same price signal and there were sufficient PEV penetration in the local network, congestion could arise during the low price periods. The topic of congestion and its management is slightly outside the scope of this thesis, nevertheless a short discussion is provided. In fact, a remedy to congestion could indeed be the pricing of the network as proposed in this thesis, not only differentiating between network nodes, but also including time discrimination in the access tariff would treat vehicles at different locations individually. PEV penetration is a slow process and as such it can be well included in the planning processes of network operators including both the tariff design in the short- to medium term, as well as investment decisions for reinforcement in congested areas.

In principle, the pricing of UoS based on capacity is already an effective tool to make use of the system. However, additionally, it sends a signal to the users that is well aligned with the long run marginal cost of operating the network. If the lack of spare capacity is more prominent in certain parts of the grids, the higher capacity prices give a strong signal, always relative to the other components of the final customer bill, such as the wholesale parts, to the PEV to smoothen the charging curve. If the danger of congestion prevails, the additional revenue from higher UoS revenues should permit the grid operator to reinforce the network by upgrading lines and transformer capacity.

4.2.2.2 Market Design Regarding Balancing

Different electricity market designs with regard to the imbalance pricing mechanisms exist today [136]. The major differences between the designs lie in the way, capacity for balancing is reserved by the TSO, the way imbalance settlement fees are calculated as well as how costs are allocated among the balancing responsible parties[137]. Different designs have different advantages, however it can be assumed that economic theory does not mandate any asymmetry between the supply and demand side, nor between suppliers and consumers. In principle, a flexible load should be able to provide the same services as a flexible generator and therefore should be granted access to the same markets. Regarding the settlement, there exist single-price systems, in which the direction of imbalances determines different prices incurred by the market participants. In two-price or dual-price systems, the direction of energy deviations matters for the imbalance settlement fee. Then, additionally one can further distinguish, how the costs for procurement are allocated to the balancing responsible parties. These could be based on average cost or on marginal costs.

A discussion of advantages and disadvantages, in particular the adverse effects of average reserve costs in case of balancing-area-internal congestion, is provided in [138].

Emulating Two-Price System from Single-Price Data For the given analysis, the following is assumed. There is an energy only balancing market. Any market agent expecting a deviation from the day-ahead energy schedule is commanded to participate in the balancing market or incur the financial penalties for unbalanced schedules ex-post. System imbalances, $\delta_{h,\omega} \neq 0$, can be positive or negative. For the purpose of this paper, the convention is as follows: a ***negative*** energy deviation, $\delta_{h,\omega} < 0$, is a lower system consumption (or higher system production) than scheduled. A ***positive*** deviation, $\delta_{h,\omega} > 0$, vice versa.

To emulate a two-price balancing market, as supposed in this thesis, the single balancing price $\lambda^{\mathbf{B}}$, such as, e.g., the reBAP in Germany, is split up into two prices for each period: λ^{+} and λ^{-}. The price λ^{+} is *paid* by the balancing responsible party (BRP) in case it deviates positively by an energy amount denoted by $e^{\mathbf{B},+}$. Vice versa, the BRP *receives* the price λ^{-} for the negative energy deviation denoted by $e^{\mathbf{B},-}$.

In these two-price systems, the difference in day-ahead (or last liquid intraday) market spot price $\lambda^{\mathbf{D}}$ and balancing price $\lambda^{\mathbf{B}}$ is taken to calculate what is referred to as the imbalance spread is $\lambda^{\mathbf{IS}} = \lambda^{\mathbf{B}} - \lambda^{\mathbf{D}}$, from which the two prices can be deducted as follows:

$$\lambda^{+} = \begin{cases} \lambda^{\mathbf{RT}} & \text{if } \lambda^{\mathbf{IS}} > 0 \\ \lambda^{\mathbf{D}} & \text{otherwise,} \end{cases} \qquad \lambda^{-} = \begin{cases} \lambda^{\mathbf{RT}} & \text{if } \lambda^{\mathbf{IS}} \leq 0 \\ \lambda^{\mathbf{D}} & \text{otherwise.} \end{cases} \tag{4.21}$$

In addition, to avoid absolute values, linear combinations of positive or negative imbalance price ratios may be used [70]**:**

$$\varrho^{+} = \frac{\lambda^{+}}{\lambda^{\mathbf{D}}}, \qquad \varrho^{-} = \frac{\lambda^{-}}{\lambda^{\mathbf{D}}}, \tag{4.22}$$

where λ^{+} and λ^{-}, refer to the balancing market prices in a two-price system. By this definition, negative deviations $e^{\mathbf{B},-}$ are priced with λ^{-}, which differ from the day-ahead market price $\lambda^{\mathbf{D}}$ in case $\delta_{h,\omega} < 0$. Accordingly, positive deviations $e^{\mathbf{B},+}$ are weighted with the price for positive imbalances λ^{+}, which is only different from the day-ahead market price $\lambda^{\mathbf{D}}$ in case of $\delta_{h,\omega} > 0$. If deemed necessary, then the balancing price can be reconstructed by $\lambda^{\mathbf{B}} = (\varrho^{+} + \varrho^{-} - 1) \cdot \lambda^{\mathbf{D}}$.

4.3 Modeling Indirect Load Control

In the previous Section, the formulation of a DLC program was developed and presented, this Section develops a model for the ILC program.

4.3.1 Mathematical Problem Formulation

The following section illustrates the proposed mathematical problem formulation for modeling indirect load control by a PEVSA. To reduce the formulation complexity, the following model only includes the formulation for uni-directional charging, even though the bi-directional case follows the same logic as under DLC. There is no other explicit justification for using a uni-directional case but for the ease of understanding the principles. The proof of concept can be achieved by uni-directional formulations.

Note that the DLC problem formulation was a single level problem, whereas the ILC problem formulation is a two level problem. Therefore after presenting the additional ILC nomenclature, first programing on the upper and lower levels is presented. The upper level objective pertains to aggregators, while the lower level to final customers. To achieve a consistent formulation, in the end, the UL and LL are combined with an affine demand.

4.3.1.1 Additional ILC Nomenclature

The nomenclature is stated below: Upper-case as well as Greek letters denote sets (calligraphic) or input parameters, while lower-case letters are used to represent indexes and decision variables.

Mathematical Abbreviations, Superscripts and General Symbols

UL, LL	Upper and lower level problem
NSE	Non-supplied PEV energy
BS	Benefit Sharing
$\mathbf{f}$, $\mathbf{g}$, $\mathbf{h}$	Objective function, inequality and equality constraints
$\mu^{\mathbf{h}}$, $\theta^{\mathbf{g}}$	Dual variables for inequality and equality constraints
$\nabla\mathcal{L}$	Gradient of the Lagrangian function

UL Parameters

ϵ	Price Difference between ToU periods	[€/kWh]

UL Decision Variables

$z_{\mathbf{UL}}$	Upper level objective function value	[€]
$\gamma_h^{\vee}$	Retail energy selling price	[€/kWh]

LL PEV Parameters

$\phi_v^{\mathbf{SOC}}$	*Minimum* final SOC at the end of $\mathcal{H}$	[kWh]
$\check{\mathbf{E}}_{v,h}^{\mathbf{RT},\vee}$	Reference Demand with no Discomfort	[kWh]

LL PEV Objective Function Cost Factors

Ξ_v	NSE cost	[€/kWh]
Λ_v	Charging Deviation Discomfort	[€/kWh]

LL Decision Variables

z_{LL}	Lower level objective function value	[€]
$e_{v,h}^{\mathbf{NSE}}$	Non-supplied Energy	[kWh]
$e_v^{\mathbf{tot}}$	Total demand (RT and NSE) per vehicle	[kWh]
$e_{v,h}^{\mathbf{DR}}$	SOC reduction due to alternative transport	[kWh]
$e_v^{\mathbf{UoS},\veebar}$	Network UoS over defined time horizon	[kW]
$t_{v,h}^{+}$, $t_{v,h}^{-}$, $t_{v,h}$	Positive, Negative and Total shift from $\check{\mathbf{E}}_{v,h}^{\mathbf{RT},\veebar}$	[kWh]

Affine Demand Parameters

$\underline{D}_v$, $\overline{D}_v$	Minimum and maximum vehicle demand	[kWh]
α_v	Vehicle specific slope of demand reduction	[kWh^2/€]
$\tilde{\lambda}^{\mathbf{D}}$	Lowest feasible retail price reference	[€/kWh]
$\tilde{\gamma}^{\veebar}$	Mean retail price level over $\mathcal{H}$	[€/kWh]

4.3.1.2 Programming On Two Levels

In order to formulate the ILC program, interactions between aggregators and final costumers must be modeled that results into a bi-level formulation. Thus in the following, some important considerations of aggregators and final customers are highlighted and discussed, and accordingly the bi-level formulation is detailed.

Aggregators As outlined in the previous sections on DLC, in a fully-fledged electricity market organization, the typical decision framework for a PEV aggregator shares characteristics with that of big consumers and retailers, unbundled from network infrastructure entities [44], [74], [75]. For the ILC formulation the main role of the aggregator remains unaltered.

In general, this formulation comes a bit closer to the reality of current retailers already today. The aggregator acts between wholesale and retail markets. On the one hand, such an agent is envisaged to determine its optimal involvement in the various trading stages of electricity markets, i.e. in the sequential clearings of futures and bilateral contracts for mid- to long term procurement, as well as day-ahead, adjustment and balancing markets for the short run. On the wholesale side, the PEV aggregator is competing against other demand-side market participants for the cost optimal purchases of electricity as well as profit-optimal provision of ancillary services. On the client-side retail market, the aggregator is competing for final customers against other agents, who are offering similar products and services. These offers boil down to energy retail prices determined on a daily, monthly, quarterly or yearly basis.

In this context, the main role of the aggregator consists in facilitating the participation of flexible PEV loads in electricity markets by assuming relevant price and quantity risk, while providing a simple retail interface for final customers. It is acknowledged that some literature, contrary to the here employed concepts, has proposed the direct market participation of PEVs without the necessity of any intermediary agent, such as the PEV aggregator. In principle, with enough local intelligence, PEV could theoretically become active market participants and place bids autonomously, without any intermediary agent. However, there are some obvious objections against that, e.g. PEV would then also be liable and have to pay financial compensation for unfulfilled market positions.

Regarding contractual relationships, the underlying assumption of this work is that most of the PEV charging would occur at low voltage supply points that are counted as residential final customers. For PEV charging, regardless whether at an industrial, commercial or residential supply point, one could plausibly assume that consumption could be metered on-board the vehicle, or with a dedicated metering device. This would enable tailor-made contracts distinguishing PEV consumption from other existing loads. In [18], a detailed account of many possible charging modes, or PEV use-cases, is given, including the different power systems agents involved in facilitating and controlling the charging.

Nevertheless, it is deemed helpful to distinguish two cases in which the PEV aggregator exercises ILC. The first involves the day-to-day operational practices of a real life aggregator. If the fleet of vehicles is reacting to day-ahead communicated hourly varying retail prices, no particular information has to be transmitted to the aggregator besides the consumption, like any other final costumer today. This should be measured with time-discrimination but would not have to be submitted until some time ex-post for billing and settlement. In that case there would also not really be any need for solving any particular scheduling problem day-ahead. The vehicle just uses electricity when available according to the agreed prices.

The second case is to be understood as more in a general planning, offline, perhaps rather long term perspective, to determine optimal retail price margins assuming the perfect reaction and rational behavior of the LL PEV. For this case, this proposed method together with its nomenclature gives a good overview of the aggregator's required information regarding the final customers, the PEV. Under the two headlines LL PEV parameters and LL PEV Mobility parameters all necessary inputs are listed.

Part of this information is certainly directly available to the final customers, i.e., such as the maximum battery rate of discharge and charge, the maximum, minimum battery SOC or the grid-to-battery and vice-versa efficiencies. These would come as specifications to the vehicle that is purchased or if the grid connection point is the limiting factor, the rating of a plug could be easily consulted. Of course these types of data are not changing over time as opposed to next day's mobility, i.e., fleet availability, consumption in km or kWh, initial and final conditions of the SOC. Nevertheless, it can be asserted that means for making a good forecast may exist either automatically integrated in the charging intelligence of the vehicle, or, by good rule of thumb from personal experience.

Final customers Arguably, PEVs prefer to keep charging under their own control [23], [76], i.e. localized in the internal on-board electronics or in the external charging equipment, reacting to a given price interface. The inclination towards cost-optimal fulfillment of the energy requirement derived from PEV use for mobility should lead final customers to select the most competitive aggregator for their energy purchases. This selection would be similar to choosing a retailer for electricity[67]. Preferences for this choice are manifold, however, once an aggregator is chosen they may within the existing retail contract vary from user to user, and could include willingness to pay, temporal price elasticity and minimum SOC requirements.

Bi-level formulation Hence, the following mathematical program is proposed in order to account for both types of the above mentioned agents and their respective objective functions.

To obtain optimal PEV charging schedules a bi-level optimization program is proposed. This structure is particularly well suited for the described interactions, as it entails one problem embedded within another: on the upper level (UL), the problem of the PEV aggregator is formulated, while on the lower level (LL), the problem of the PEVs is described. Besides the aggregator's decisions in wholesale day-ahead markets, the UL includes a maximization of revenues from retail. On the LL however, the final customers minimize the costs of PEV charging subject to physical operation constraints and the respective mobility profiles. In that sense, the here proposed formulation does not explicitly model the aspects of aggregator competition and PEV selecting aggregator's in a functional retail market. Nevertheless, it can serve as a basis for analyzing the strategic interactions in a two-agent leader-follower games, where a single leader correctly anticipates the equilibrium reaction of the followers. The insights gained with this model are directly transferable for the design of and indeed motivate the necessity of retail equilibrium models.

Fig. 4.4 depicts the typical scheme of bi-level decision making for the case of the PEV aggregator in interaction with the final customers. It visualizes the respective information exchanged between the two types of agents. In principle, the aggregator sends different retail prices $\gamma_h^{\vee}$ down to the LL. Given these prices as parameters, the final customers determine the cost-minimal PEV charging schedule $e_{v,h}^{RT}$, which in turn is sent up to the UL.

Not impeding that other mathematical decomposition techniques could be used to tackle the given problem, in mathematical terms, the above described decision framework with bi-level structure leads to an MPEC because typical characteristics are given: a) inherently conflicting objectives between UL and LL, b) clear sequence of and considerable time delay between decisions on UL and LL as well as c) strategic interactions between the two agents. In effect these interactions present a Stackelberg leader-follower game [77, Ch. 3], in which the aggregator on the UL would be the leader and the PEVs on the LL

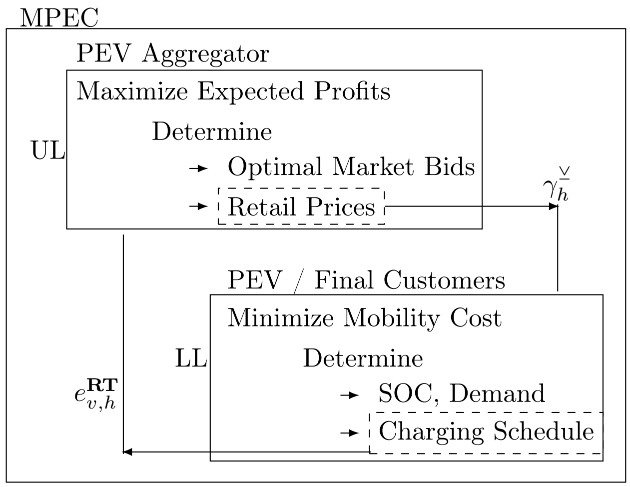


Figure 4.4: Bi-level Decision Making of Aggregator and PEV

would be the followers.

The here presented formulation concentrates on one energy based day-ahead market clearing and does not consider balancing issues, which have been widely discussed in [72], [74], [75]. Furthermore, the aggregator is put in a hypothetical case of a simplified monopoly. Nevertheless, the formulation could serve as a valid foundation for continuative research, specifically modeling competition on the retail market, e.g., via an Equilibrium Program with Equilibrium Constraints (EPEC). However the formulation of EPECs remains out of scope of this thesis.

4.3.1.3 Upper Level Objective: PEV Aggregator

The stochastic DLC equivalent of the PEV aggregator's problem has been presented by the same authors in the previous section of this chapter. Now with ILC, the self-scheduling problem in (4.23) seeks the risk-neutral maximization of expected net profits from price taking day-ahead transactions $\kappa^{\mathbf{D}}_{h}$, and revenue interactions from the client-side retail to PEV $\Pi^{\mathbf{C}}_{h}$:

$$\text{Max. } z_{\mathbf{UL}} = \mathbf{f_{UL}}\left(e^{\mathbf{D},\vee}_{h,}, \gamma^{\vee}_{h}\right) = \sum_{h\in\mathcal{H}} \left(\kappa^{\mathbf{D}}_{h} + \Pi^{\mathbf{C}}_{h}\right), \tag{4.23}$$

$$\text{with } \kappa^{\mathbf{D}}_{h} = -\left[e^{\mathbf{D},\vee}_{h} \cdot \lambda^{\mathbf{D}}_{h}\right], \tag{4.24}$$

$$\Pi^{\mathbf{C}}_{h} = \sum_{v} \left[e^{\mathbf{RT},\vee}_{v,h} \cdot \gamma^{\vee}_{h}\right], \tag{4.25}$$

where the components of the objective function $z_{\mathbf{UL}}$ depending on energy bought day-ahead and retail prices $\mathbf{f_{UL}}\left(e^{\mathbf{D},\vee}_{h,}, \gamma^{\vee}_{h}\right)$ are the negative profit, i.e. costs of purchasing energy day-ahead (4.24) and the revenue from electricity retail (4.25). Market prices $\lambda_h^{\mathbf{D}}$ are exogenous parameters. This is a simplifying assumption that is only valid as long as the modeled fleet of vehicles does not surpass a critical size, such that a significant level of the traded energy in wholesale electricity markets comes from vehicles.

On the UL, this objective is subject to the market energy balance (4.26), which ensures that all individual charging $e_{v,h}^{\mathbf{RT},\veebar}$ has to be bought day-ahead:

$$\forall h : \sum_{v \in V} \left[e_{v,h}^{\mathbf{RT},\veebar} \right] = \left(e_h^{\mathbf{D},\veebar} \right). \tag{4.26}$$

The most intuitive appears that the PEV aggregator directly passes on price signals with the same time resolution as assumed in the day-ahead electricity market, i.e. hourly prices, which are composed of the market price plus a constant margin m [€/kWh]:

$$\forall h : \quad \gamma_h^{\veebar} = \lambda_h^{\mathbf{D}} + m. \tag{4.27}$$

Retail Tariff Options With regard to the tariff choice, the PEV aggregator could set mutually exclusive constraints on the shape of the hourly retail price curve $\gamma_h^{\veebar}$:

A. flat rate tariff with a constant energy price :

$$\forall h, h' : \quad \gamma_h^{\veebar} = \gamma_{h'}^{\veebar} \tag{4.28}$$

B. time-of-use (TOU), e.g. day-night, two-step energy price, for ex-ante defined time periods:

$$\forall h, h' \in \mathcal{H}^{\mathbf{on}} : \quad \gamma_h^{\veebar} = \gamma_{h'}^{\veebar}, \tag{4.29}$$

$$\forall h, h' \in \mathcal{H}^{\mathbf{off}} : \quad \gamma_h^{\veebar} = \gamma_{h'}^{\veebar}, \tag{4.30}$$

$$\forall h \in \mathcal{H}^{\mathbf{on}}, h' \in \mathcal{H}^{\mathbf{off}} : \quad \gamma_h^{\veebar} = \gamma_{h'}^{\veebar} + \epsilon. \tag{4.31}$$

C. hourly prices, which are composed of the market price plus a margin m [€/kWh]:

$$\forall h : \quad \gamma_h^{\veebar} = \lambda_h^{\mathbf{D}} + m. \tag{4.32}$$

Excursion on Endogenous Tariff Selection The tariff constraints are never simultaneously binding in one run. In principle, it is possible to include integer variables to ensure simultaneous tariff selection, but it adds to the computational burden while conceptually not providing any supplemental insights. Therefore, the tariff options are recommended to be tested in multiple optimization runs.

However, if simultaneous tariff selection is desired, the following could be considered:

Assume there is a set of tariffs or retail prices shapes named $p \in \mathcal{P} = \{1, 2, 3\}$. Binary variables would indicated the selection of the tariff $s_p \in [0, 1]$.

In the objective function $\gamma_h^{\vee}$ would then be replaced by $(\gamma_{h,1}^{\vee}+\gamma_{h,2}^{\vee}+\gamma_{h,3}^{\vee})$, with the non-coincidence constraints:

$$\forall h,p:\ \gamma_{h,p}^{\vee} \leq s_p, \qquad \Sigma_p\, s_p = 1. \tag{4.33}$$

The different prices in the tariff options could then be constrained:

$$p = 1, \quad \forall h,h': \quad \gamma_{h,p}^{\vee} = \gamma_{h',p}^{\vee} \tag{4.34}$$

$$p = 2, \quad \forall h,h' \in \mathcal{H}^{\text{on}}:\ \gamma_{h,p}^{\vee} = \gamma_{h',p}^{\vee} \text{ and } \forall h,h' \in \mathcal{H}^{\text{off}}:\ \gamma_{h,p}^{\vee} = \gamma_{h',p}^{\vee} \tag{4.35}$$

$$p = 3 \quad \forall h: \quad \gamma_{h,p}^{\vee} = \lambda_h^D + m. \tag{4.36}$$

Realistic Short Term Practices vs. General Studies The timing of information being unveiled in reality matters. The proposed work is used to determine hourly aggregator involvement in the day-ahead electricity markets market. One critical assumption of the here presented bi-level optimization is that the market prices λ_h^D are exogenous parameters. In practice, however, market participants need to submit their bids first, and then the day-ahead market is cleared, where cleared prices and amount of purchases are determined simultaneously. So it is plausible to pose the question, how it would be possible for PEV aggregators to take decisions based on exogenous energy prices before bids have been submitted to the market, and the clearing outcome determined?

In practice, it is true that PEV aggregators would not receive energy prices before the submission of the bids and the subsequent market clearing. And therefore this is not a pre-requisite for the proposed approach. In reality, many price-taking electricity market participants simply predict prices to determine their optimal energy schedules. And accordingly, lots of theoretical research work bases its proposed bidding algorithms on the existence of a sufficiently good forecast of the market price outcome to determine merely energy quantities, at zero cost, e.g., a generator that intends to be dispatched, or alternatively market price caps, e.g. a demand agent that needs energy no matter the cost. This means scheduling is carried out in terms of energy quantities and not in terms of prices, which goes hand-in-hand with this work's core assumption of the aggregator being a price-taker.

While the proposed DLC formulation of the preceding sections uses a two-stage stochastic programming framework to highlight the importance of uncertainty and risk that may be involved in scheduling PEVs, the ILC proposal does not focus on these issues, as it concentrates mainly on the day-ahead short term planning stage. Thus the whole modeling world collapses into one instant. This is of course a simplifying assumption, but deemed suitable for the purposes of this section, which would like to emphasize the bi-level structure of the aggregator's retail problem in interactions with the final customers. Nevertheless, without loss of validity of the here shown concepts, another scenario dimension along with nonanticipativity constraints could be introduced to approximate the uncertainty range involved in actual realizations of the day-ahead market prices. For simplicity and the sake of understanding, this has been avoided. The exogenous market day-ahead wholesale price parameters used for this part of the model can thus be conceptualized as expected values from the best forecast that the aggregator has at hand.

4.3.1.4 Lower Level Formulation: Final Customers, PEV

There are a number of ways how to represent the final customer's decisions on the LL. This thesis features two of them: 1) including a reference schedule of highest comfort and via optimality conditions with complementarity and 2) representing the demand response via an affine demand constraint and optimality by the strong duality-theorem.

1) Reference Schedule On the lower level, the final customers optimize their charging schedule according to an objective of minimum cost incurred:

$$\begin{aligned} \text{Minimize } z_{\mathbf{LL}} &= \mathbf{f_{LL}}(e^{\mathbf{RT},\veebar}_{v,h},\, e^{\mathbf{SOC}}_{v,h},\, t^{+}_{v,h},\, t^{-}_{v,h},\, e^{\mathbf{DR}}_{v,h}) \\ &= \Sigma_{v,h}\left[e^{\mathbf{RT},\veebar}_{v,h} \cdot \gamma^{\veebar}_{h}\right] + \Sigma_v\left[\Lambda_v \cdot \Sigma_h\left(t^{+}_{v,h} + t^{-}_{v,h}\right)\right] \\ &+ \Sigma_v\left[\Xi_v \cdot \Sigma_h e^{\mathbf{DR}}_{v,h}\right]. \end{aligned} \tag{4.37}$$

The incurred cost includes terms pertaining to the monetary cost of electricity $\Sigma_{v,h}\left[e^{\mathbf{RT},\veebar}_{v,h} \cdot \gamma^{\veebar}_{h}\right]$, a level of discomfort created by deviating from the most convenient schedule $\Sigma_v\left[\Lambda_v \cdot \Sigma_h\left(t^{+}_{v,h} + t^{-}_{v,h}\right)\right]$ and a demand response energy term $\Sigma_v\left[\Xi_v \cdot \Sigma_h e^{\mathbf{DR}}_{v,h}\right]$. Hence, (4.37) includes PEV specific costs of discomfort Λ_v, and alternative transportation Ξ_v. The discomfort is created for energy deviations $t_{v,h}$ from the preferred schedule. Demand response $e^{\mathrm{DR}}_{v,h}$ only happens, in case the costs of alternative transportation Ξ_v, e.g. the next cheapest substitute for providing the same mobility, are not prohibitively high. For PEVs with hybrid propulsion systems, Ξ_v could be the cost of gasoline or diesel per gross kWh, i.e. accounting for efficiencies.

This objective function is subject to the following constraints:

$$\forall v,h\colon\ \mathbf{g^1} = -\,e^{\mathbf{RT},\veebar}_{v,h} + \nu_{v,h}\overline{P}_v \quad \geq 0 \;:\; \theta^{\mathbf{g^1}}_{v,h}, \tag{4.38}$$

$$\forall v,h\colon\ \mathbf{g^2} = -\,e^{\mathbf{SOC}}_{v,h} + \overline{E}_v \quad \geq 0 \;:\; \theta^{\mathbf{g^2}}_{v,h}, \tag{4.39}$$

$$\begin{aligned} \forall v,h\colon\ \mathbf{h^1} = &-\,e^{\mathbf{RT},\veebar}_{v,h} \cdot \eta^{\veebar}_{v} + e^{\mathbf{SOC}}_{v,h} - e^{\mathbf{DR}}_{v,h} + \rho_{v,h} \\ &-\underbrace{e^{\mathbf{SOC}}_{v,h-1}}_{h \in \{2..|\mathcal{H}|\}} - \underbrace{\iota^{\mathbf{SOC}}_{v}}_{h=1} \quad = 0 \;:\; \mu^{\mathbf{h^1}}_{v,h}, \end{aligned} \tag{4.40}$$

$$\forall v,h\colon\ \mathbf{h^2} = -\,e^{\mathbf{RT},\veebar}_{v,h} - t^{+}_{v,h} + t^{-}_{v,h} + \check{\mathbf{E}}^{\mathbf{RT},\veebar}_{v,h} \quad = 0 \;:\; \mu^{\mathbf{h^2}}_{v,h}, \tag{4.41}$$

$$\forall v_{,|\mathcal{H}|}\colon\ \mathbf{h^3} = e^{\mathbf{SOC}}_{v,h} - \phi^{\mathbf{SOC}}_{v} \quad = 0 \;:\; \mu^{\mathbf{h^3}}_{v,|\mathcal{H}|}, \tag{4.42}$$

where (4.38) ensures PEV charging only when vehicles are available, (4.39) ensures the upper bound on the battery SOC, (4.40) stands for the inter-temporal battery SOC balance, (4.41) quantifies the energy deviation from the reference schedule $\check{\mathbf{E}}^{\mathbf{RT},\veebar}_{v,h,\omega}$ and finally (4.42) sets the requirements for the final SOC. The dual variables related to inequality $\mathbf{g}$ and equality $\mathbf{h}$ are denoted $\theta^{\mathbf{g}}$ and $\mu^{\mathbf{h}}$, respectively. Another set of inequalities and respective dual variables $\mathbf{g^3} \ldots \mathbf{g^7} : \theta^{\mathbf{g^3}} \ldots \theta^{\mathbf{g^7}}$ that is not explicitly given above but of equal formal importance, describes the constraints of non-negativity of the involved variables $\forall v, h : (e^{\mathbf{RT},\veebar}_{v,h}, e^{\mathbf{SOC}}_{v,h}, t^{+}_{v,h}, t^{-}_{v,h}, e^{\mathbf{DR}}_{v,h}) \geq 0$.

The reference schedule $\check{\mathbf{E}}^{\mathbf{RT},\veebar}_{v,h}$ is considered to be most convenient in the sense that it is calculated as the immediate charging upon arrival from a trip. Any deference of the charging to other hours leads to a perceived loss in utility for the customer. Obviously this parameter depends on personal utility, varies from user to user and is assumed to be measurable in reality.

The reference profile $\check{\mathbf{E}}^{\mathbf{RT},\veebar}_{v,h}$ can be obtained from the solution to a simple optimization problem in which the objective is ASAP charging, achieved by:

$$\text{Minimize}_{\{e^{\mathbf{RT},\veebar}_{v,h}\}} \quad e^{\mathbf{RT},\veebar}_{v,h} \cdot h, \tag{4.43}$$

and subject to the immediate post trip charging constraint:

$$\Sigma^{h}_{1} e^{\mathbf{RT},\veebar}_{v,h} \leq \Sigma^{h}_{1} \frac{\rho_{v,h}}{\eta_v}. \tag{4.44}$$

Besides (4.43) and (4.44), only the physical constraints given by availability (4.38), SOC balance (4.40), upper SOC bounds (4.39) as well as final SOC conditions (4.42) are enforced.

The LL problem can thus be completely replaced by its first order optimality conditions. Since the LL is linear and thus convex, the recast LL is directly included as constraints in the UL. The bi-level problem is thus presented by (4.23)-(4.26) in addition to the LL's system of Karush-Kuhn-Tucker (KKT) equations (A.1)-(A.22) given in the appendix **??**.

2) Affine Daily Demand On the LL, the final customers optimize their charging schedule according to an objective of minimum cost incurred:

$$\begin{aligned} &\text{Min.} z_{\mathbf{LL}} = \mathbf{f_{LL}}(e^{\mathbf{RT}}_{v,h}, e^{\mathbf{SOC}}_{v,h}, e^{\mathbf{NSE}}_{v,h}, e^{\mathbf{UoS,off}}_{v}, e^{\mathbf{UoS,off}}_{v}) \\ = &\sum_{v} \Bigg(\sum_{h} \Bigg[\underbrace{e^{\mathbf{RT},\veebar}_{v,h} \cdot \gamma^{\veebar}_{h}}_{\mathbf{I}} + \underbrace{e^{\mathbf{NSE}}_{v,h} \cdot \Xi_v}_{\mathbf{II}} \Bigg] \\ + &\underbrace{e^{\mathbf{UoS,on},\veebar}_{v} \cdot \mathbf{C}^{\mathbf{UoS,on}} + e^{\mathbf{UoS,off},\veebar}_{v} \cdot \mathbf{C}^{\mathbf{UoS,off}}}_{\mathbf{III}} \Bigg), \end{aligned} \tag{4.45}$$

including terms for costs of supplied (4.45.I), non-supplied (4.45.II) energy, and network UoS charges (4.45.III).

As provided in the nomenclature, the required information for day-ahead scheduling, by individual PEVs are listed under the two headlines LL PEV parameters and LL PEV Mobility parameters. Part of this information is directly available to the final customers, such as the maximum battery rate of discharge and charge $\overline{P}_v$, the maximum, minimum battery SOC $\overline{E}_v$, $\underline{E}_v$ or the grid-to-battery and vice-versa efficiencies, $\eta_v^{\vee}$, $\eta_v^{\wedge}$. These would come as specifications to the purchased vehicle or if the grid connection point is the limiting factor, the rating of a plug could be easily consulted. These data are not changing over time as opposed to next day's mobility, i.e., fleet availability $\nu_{v,h}$, consumption $\rho_{v,h}$, initial $\iota_v^{\mathbf{SOC}}$ and final ϕ_v^{SOC} conditions of the SOC. Nevertheless, it can be asserted that means for making a good forecast may exist either automatically integrated in the charging intelligence of the vehicle, or, by good rule of thumb from personal experience.

The LL objective function in (4.45) is subject to the following constraints, which further explain all its elements. The charging decision $e_{v,h}^{\mathbf{RT},\vee}$ is constrained to the periods of availability $\nu_{v,h}$ and when connected, it is limited to the connection capacity $\overline{P}_v$:

$$\forall v, h: \quad \mathbf{g^1} = e_{v,h}^{\mathbf{RT},\vee} - \nu_{v,h}\overline{P}_v \leq 0 \quad : \mu_{v,h}^{\mathbf{g^1}}. \tag{4.46}$$

The SOC variable $e_{v,h}^{\mathbf{SOC}}$ has the physical capacity limit of the battery $\overline{E}_v$ as its upper bound:

$$\forall v, h: \quad \mathbf{g^2} = e_{v,h}^{\mathbf{SOC}} - \overline{E}_v \leq 0 \quad : \mu_{v,h}^{\mathbf{g^2}}. \tag{4.47}$$

Equality $\mathbf{h^1}$ tracks the typical energy balance of each individual vehicle, in which the current SOC $e_{v,h}^{\mathbf{SOC}}$ is equal to the previous hour's SOC $e_{v,h-1}^{\mathbf{SOC}}$ plus the energy intake $e_{v,h}^{\vee} \cdot \eta_v^{\vee}$, less the energy consumption during driving $\rho_{v,h}$. In $h = 1$, the balance is initialized with $\iota_v^{\mathbf{SOC}}$ and does without the previous hour's SOC:

$$\forall v, h \ : \mathbf{h^1} = e_{v,h}^{\vee} \cdot \eta_v^{\vee} - e_{v,h}^{\mathbf{SOC}} - \rho_{v,h} + \underbrace{e_{v,h\text{-}1}^{\mathbf{SOC}}}_{h \in \{2..|\mathcal{H}|\}} + \underbrace{\iota_v^{\mathbf{SOC}}}_{h=1} = 0 : \ \theta_{v,h}^{\mathbf{h^1}}, \tag{4.48}$$

where $e_{v,h}^{\vee}$ is met by charging $e_{v,h}^{\mathbf{RT}}$ and non-supplied energy $e_{v,h}^{\mathbf{NSE}}$. Note that in the LL objective (4.45.II), the latter is penalized with the user-specific willingness to pay Ξ_v. This cost of non-supplied energy (NSE) is interpreted as the reservation price, which is set at the price of the next best alternative to fulfill vehicle demand for mobility, e.g. at the price of secondary fuel for hybrid PEVs.

To make the charging schedule responsive to the retail prices, $\gamma_h^{\vee}$ determines the total demand per vehicle, which is given by:

$$\sum_h e_{v,h}^{\vee} \quad = \quad e_v^{\mathbf{tot}} \tag{4.49}$$

$$\underline{D}_v \leq e_v^{\mathbf{tot}} \leq \overline{D}_v, \tag{4.50}$$

with $\overline{D}_v = \overline{E}_v - \iota_v^{\mathbf{SOC}} + \sum_h \frac{\rho_{v,h}}{\eta_v}$ and $\underline{D}_v = \phi_v^{SOC} - \iota_v^{\mathbf{SOC}} + \sum_h \frac{\rho_{v,h}}{\eta_v}$, where ϕ_v^{SOC} is the minimum final SOC at the end of the optimization horizon. In-between its bounds, $e_v^{\mathbf{tot}}$ follows an affine relationship with retail prices, in which the slope α is:

$$\alpha_v = \frac{\overline{D}_v - \underline{D}_v}{\Xi_v - \tilde{\lambda}^{\mathbf{D}}} = \frac{\overline{E}_v - \phi_v^{SOC}}{\Xi_v - \tilde{\lambda}^{\mathbf{D}}}, \tag{4.51}$$

where $\tilde{\lambda}^{\mathbf{D}} \geq 0$ is some reference price, defining the left hand starting point on the x-axis. Below this price, the problem is designed to be infeasible, as it is unlikely that a strategic aggregator would not require a significant margin above its procurement cost.

While (4.49) and (4.50) are implicitly included, the explicit constraint admitted in the LL optimization is:

$$\forall v: \; \mathbf{h^2} = \overline{D}_v - \alpha_v \cdot \left(\tilde{\gamma}^{\underline{\vee}} - \tilde{\lambda}^{\mathbf{D}}\right) - \sum_h \left[e_{v,h}^{\mathbf{RT},\underline{\vee}} + e_{v,h}^{\mathbf{NSE}}\right] + s_v = 0 \; : \; \theta_v^{\mathbf{h^2}}, \tag{4.52}$$

where $\tilde{\gamma}^{\underline{\vee}}$ is defined as the mean retail price level $\frac{1}{|\mathcal{H}|}\sum_h \gamma_h^{\underline{\vee}}$ and the last term s_v is included as slack for robustness and feasibility of the model. Compared to earlier formulations, the NSE cost Ξ_v here is the mean hourly retail price threshold above which $e_v^{\mathbf{tot}}$ is below its minimum, i.e. $\underline{D}_v$. With further increasing price levels, the respective vehicle is assumed to gradually replace electricity consumption from the aggregator $e_{v,h}^{\mathbf{RT}}$ by $e_{v,h}^{\mathbf{NSE}}$. To this end, the following two constraints ensure, that $\underline{D}_v$ is always met (4.53), and that $e_{v,h}^{\mathbf{NSE}}$ does not surpass its conceptual boundary (4.54):

$$\forall v: \; \mathbf{g^3} = \underline{D}_v - \sum_h \left(e_{v,h}^{\mathbf{RT},\underline{\vee}} + e_{v,h}^{\mathbf{NSE}}\right) \leq 0 \; : \; \mu_v^{\mathbf{g^3}}, \tag{4.53}$$

$$\forall v: \; \mathbf{g^4} = \sum_h e_{v,h}^{\mathbf{NSE}} - \underline{D}_v \leq 0 \; : \; \mu_v^{\mathbf{g^4}}. \tag{4.54}$$

These demand side reactions are further illustrated by the diagram in Fig. 4.5. Note that the equality (4.52) has to be met for $\forall v$, but not on an hourly basis. This means that the LL is still free to react to the price signal and can allocate the charging in the cost optimal periods. To this end, it captures the functionality of cross-elasticity and is preferred tieing demand reactions to hourly price levels.

In order to apply capacity UoS network charges $\mathbf{C^{UoS,on}}$ and $\mathbf{C^{UoS,off}}$, the variables $e_v^{\mathbf{UoS,on},\underline{\vee}}$ and $e_v^{\mathbf{UoS,off},\underline{\vee}}$ take the values of the respective highest consumption within the subsets of on-peak $\left|\mathcal{H}^{\mathbf{on}}\right|$ and off-peak $\left|\mathcal{H}^{\mathbf{off}}\right|$ periods of the time horizon through:

$$\forall v, h \in \mathcal{H}^{\mathbf{on}}: \mathbf{g^5} = e_{v,h}^{\mathbf{RT},\underline{\vee}} - e_v^{\mathbf{UoS,on},\underline{\vee}} \leq 0 \; : \; \mu_{v,h \in |\mathcal{H}^{\mathbf{on}}|}^{\mathbf{g^5}}, \tag{4.55}$$

$$\forall v, h \in \mathcal{H}^{\mathbf{off}}: \mathbf{g^6} = e_{v,h}^{\mathbf{RT},\underline{\vee}} - e_v^{\mathbf{UoS,off},\underline{\vee}} \leq 0 \; : \; \mu_{v,h \in |\mathcal{H}^{\mathbf{off}}|}^{\mathbf{g^6}}. \tag{4.56}$$

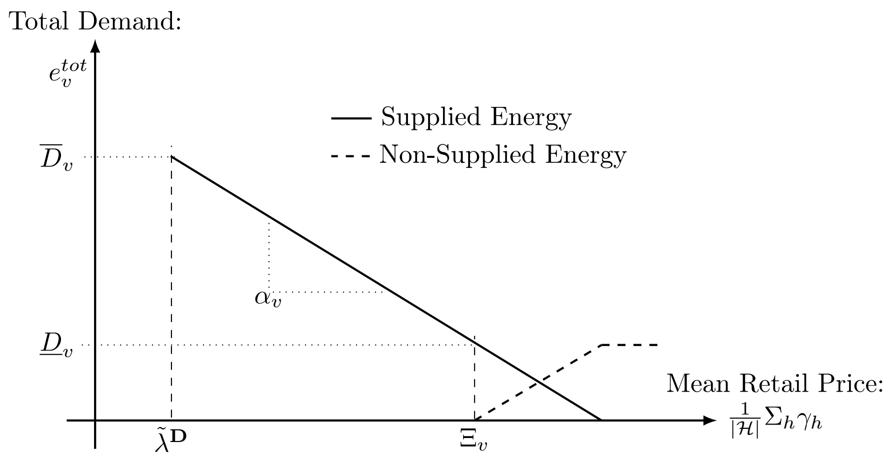


Figure 4.5: Affine Price-Demand Relationship

The dual variables related to inequalities $\mathbf{g}$ and equalities $\mathbf{h}$ are denoted $\mu^{\mathbf{g}}$ and $\theta^{\mathbf{h}}$, respectively. Another set of inequalities and respective dual variables $\{\mathbf{g^7} \ldots \mathbf{g^{11}}\} : \{\mu^{\mathbf{g^7}} \ldots \mu^{\mathbf{g^{11}}}\}$ that are not explicitly given above but of equal formal importance, refers to the non-negativity constraints of all involved variables $\forall v, h : \; (e_{v,h}^{\mathbf{RT},\underline{\vee}}, e_{v,h}^{\mathbf{SOC}}, e_{v,h}^{\mathbf{NSE}}, e_v^{\mathbf{UoS,off},\underline{\vee}}, e_v^{\mathbf{UoS,off},\underline{\vee}}) \geq 0$.

4.3.1.5 Combining LL with UL with Affine Demand

Having formulated the UL and the LL independently, the following lines elaborate how to represent the final MPEC joining the two. The LL problem can be completely replaced by its first order optimality conditions. Since the LL is linear and thus convex, its recast can be directly included as constraints of the UL. The bi-level problem is thus presented by (4.23)–(4.27) in addition to the LL's (4.46)–(4.56) with its system of KKT-stationarity equations, because any local optimum is a global one. To this end, the partial derivative of the Lagrangian form of (4.45) is taken with respect to primal decision variables, which at the optimum have to fulfill the first-order stationarity condition:

$$\nabla \mathcal{L} \begin{pmatrix} \vdots \end{pmatrix} = \nabla \mathbf{f} \begin{pmatrix} \vdots \end{pmatrix} + \mu^{\intercal} \cdot \nabla \mathbf{g} \begin{pmatrix} \vdots \end{pmatrix} + \theta^{\intercal} \cdot \nabla \mathbf{h} \begin{pmatrix} \vdots \end{pmatrix} = 0. \tag{4.57}$$

These are given in (**??**)–(**??**) of the appendix. However, instead of including the KKT-feasibility and -complementarity of inequalities $\{\mathbf{g^7} \ldots \mathbf{g^{11}}\} \perp \{\mu^{\mathbf{g^7}} \ldots \mu^{\mathbf{g^{11}}}\}$, this formulation makes use of the strong duality theorem [79, pp. 37]:

$$c^T x = \lambda^T b, \tag{4.58}$$

which leads to the optimality condition given in (4.59). Hence, an equivalent single-level optimization problem is obtained, which is a non-convex and nonlinear MPEC.

$$z_{\mathbf{LL}}=c^T x=\lambda^T b=\sum_v \Bigg(\Bigg[\sum_h \mu^{\mathbf{g^1}}_{v,h} \cdot (\text{-}\nu_{v,h} \overline{P}_v) + \mu^{\mathbf{g^2}}_{v,h} \cdot (\text{-}\overline{E}_v) + \theta^{\mathbf{h^1}}_{v,h} \cdot \Bigg(\text{-}\rho_{v,h} + \underbrace{\iota^{\mathbf{SOC}}_v}_{h=1} \Bigg) \Bigg] \tag{4.59}$$
$$+ \quad \mu^{\mathbf{g^3}}_v \cdot (\underline{D}_v) + \mu^{\mathbf{g^4}}_v \cdot (-\underline{D}_v) + \theta^{\mathbf{h^2}}_v \cdot \left[\overline{D}_v - \alpha_v \cdot \left(\tilde{\gamma}^{\underline{\vee}} - \tilde{\lambda}^{\mathbf{D}} \right) \right] \Bigg)$$

Discretizing Retail Prices The only three instances of non-linearity in the problem remain 1) the multiplication of price $\gamma_h^{\underline{\vee}}$ and demand $e^{\mathbf{RT},\underline{\vee}}_{v,h}$ in the UL objective function (4.23) as well as 2) in the LL primal objective function (4.45), in addition to 3) the dual of the affine-demand constraint $\theta^{\mathbf{h^3}}_v$ with sum of retail prices from $\tilde{\gamma}^{\underline{\vee}}$ in the LL dual objective function (4.59). However, fortunately all of these terms are bi-linear and involve the retail price . Hence, discretizing $\gamma_h^{\underline{\vee}}$ with reasonable granularity (e.g., step size $\Delta\gamma$ = €{}.001/kWh) seems a sufficiently accurate approximation. This can be done as follows:

$$m = \Delta\gamma \cdot \Sigma_k 2^{k-1} \cdot b_k \,, \tag{4.60}$$

where b_k are $|k|$ **binary** variables. Thus, the charging cost between PEV and aggregator, i.e. the product of the total hourly demand $\Sigma_{v,h} \left[e^{\mathbf{RT},\underline{\vee}}_{v,h} \right] = e^{\mathbf{tot}}$ with the margin m can be linearized as follows:

$$\begin{aligned} e^{\mathbf{tot}} \cdot m &= e^{\mathbf{tot}} \cdot \Delta\gamma \cdot \Sigma_k 2^{k-1} \cdot b_k \\ &= \Delta\gamma \cdot \Sigma_k 2^{k-1} \cdot z_k \,, \end{aligned} \tag{4.61}$$

where z_k are $|k|$ **positive continuous** variables, representing the margin-demand product, when summed up over k and subject to the two following constraints:

$$\forall k\colon 0 \leq \quad z_k \quad \leq \mathbf{M} \cdot b_k \,, \tag{4.62}$$
$$\forall k\colon 0 \leq \; e^{\mathbf{tot}} - z_k \; \leq \mathbf{M} \cdot (1 - b_k) \,, \tag{4.63}$$

which ensure that if the binary b_k takes the value 0, z_k is forced to be 0, while in case of $b_k = 1 \Rightarrow e^{\mathbf{tot}}\text{-}z_k = 0$, which means z_k takes the value of $e^{\mathbf{tot}}$.

Since the affine-demand constraint dual $\theta^{\mathbf{h^2}}_v$ must be capable of taking positive and negative values, the product $\theta^{\mathbf{h^2}}_v \cdot m$ can be linearized similarly as follows:

$$\begin{aligned} \forall v\colon \qquad \theta^{\mathbf{h^2}}_v \cdot m &= \left[\theta^{+\mathbf{h^2}}_v - \theta^{-\mathbf{h^2}}_v \right] \cdot m \\ &= \Sigma_k \left(\widetilde{z}^{+}_{k,v} - \widetilde{z}^{-}_{k,v} \right) \cdot \qquad \Delta\gamma \cdot 2^{k-1} \cdot \,, \end{aligned} \tag{4.64}$$

where, $\widetilde{z}^{+}_{k,v} - \widetilde{z}^{-}_{k,v}$ are, respectively, the positive and negative continuous components of $\theta^{\mathbf{h^2}}_v \cdot m$, when subject to:

$$\forall k,v\colon \qquad 0 \leq \qquad \widetilde{z}^{+}_{k,v} \qquad \leq \mathbf{M} \cdot \; b_k \,, \tag{4.65}$$
$$\forall k,v\colon \qquad 0 \leq \; \theta^{+\mathbf{h^2}}_v - \widetilde{z}^{+}_{k,v} \; \leq \mathbf{M} \cdot (1 - b_k) \,, \tag{4.66}$$
$$\forall k,v\colon \qquad 0 \leq \qquad \widetilde{z}^{-}_{k,v} \qquad \leq \mathbf{M} \cdot \; b_k \,, \tag{4.67}$$
$$\forall k,v\colon \qquad 0 \leq \; \theta^{-\mathbf{h^2}}_v - \widetilde{z}^{-}_{k,v} \; \leq \mathbf{M} \cdot (1 - b_k) \,, \tag{4.68}$$

Replacing non-linearity by (4.60)–(4.68), leads to and MPEC formulation as a single-stage MIP.

Comparing different approaches to represent the UL Both presented approaches, 1) the Reference Schedule and 2) Affine Daily Demand, have their advantages and disadvantages. This paragraph briefly outlines their pros and cons, before alluding to other possible implementations, that however, have not been studied in the following cases.

The advantage of approach 1) lies in the explicit modeling of the discomfort and possibility to find a unique charging schedule according to the reference when there is no time-dependent electricity price signal. However, a clear disadvantage of this approach is that at the price of NSE, there is a discrete all or nothing demand response from the lower level, when the UL increases prices up to the individual reservation, or willingness to pay. On the upside of 2), a linear reaction of the total daily demand is given, which provides a smooth feedback to the UL based on the slope of the affine gradient. Nevertheless, on its downside, the concept also has its limits. Arguably, in reality the demand does not follow this constant rate of change with the mean electricity price, but rather reacts to hourly signals like in 1).

There are at least two other possible ways to model the LL reaction to the UL without a reference schedule, which our just briefly-sketched and commented on in the following:

1. Budget constraint:
$$\Sigma_{v,h} \left[e^{\mathrm{RT},\underline{\vee}}_{v,h} \cdot \gamma^{\underline{\vee}}_{h} \right] \leq \overline{\mathbf{B}}, \tag{4.69}$$
where $\overline{\mathbf{B}}$ is a fixed budget that cannot be exceeded for the electricity expenditures. The constraint could be visualized as in Fig. D.1a of the appendix.

2. ***Hourly*** affine demand constraint:
$$e^{\mathbf{RT}}_{v,h} = \overline{D}_{v,h} - \alpha \cdot \gamma^{\underline{\vee}}_{h}, \tag{4.70}$$
which would resemble the sketch in Fig. D.1b of the appendix. Even though, this type of constraint would alleviate some of the complexity, the drawback of this kind of constraint is, that the hourly demand is basically already set by the price and there is no continuous scaling, hence to optimality conditions needed and the whole bi-level structure becomes obsolete.

Day-Ahead Planning vs. Operational Day Please note that the above proposed model for ILC does not include the subsequent stage of the operational day, it only provides an optimal decision at the time of making day-ahead transactions under various assumptions. Some of the most prominent ones are the single-stage decision framework together with the 24-hour foresight. In reality however, it is very common to settle potential differences between two subsequent trading floors. For simplification, day-ahead vs. balancing is commonly assumed in literature that looks at this type of problem. The aggregator would then be at least balancing responsible, i.e., be financially responsible for energy deviations from previous commitments. Different electricity market designs with regard to the imbalance pricing mechanisms exist today. The major differences between the designs lie in the way, capacity for balancing is reserved by the TSO, the way imbalance settlement fees are calculated as well as how costs are allocated among the balancing responsible parties. If second-stage variables would be included here, at least the UL would account for the balancing stage. At the retail side on the LL, however, one could assume two things, either that only day-ahead planning is carried out, or that similarly as the aggregator commits positions day-ahead to the market, the PEV would commit the aggregator based on an ex-ante agreed imbalance settling. This would require further communication, as as well as intelligence in the battery and charging management systems.

The absence of uncertainty and forecasting errors significantly improve the economics of decision making and therefore, the final result should be taken as an optimistic approximation. References [119], as well as [73] contain two operational management algorithms coordinating the PEV charging to fulfill previous market commitments and thereby minimizing deviation costs.

4.4 Methods for Generating Stochastic Parameters

As described in the DLC stochastic model, there are two main sources of uncertainty faced by a PEV aggregator: market price uncertainty and uncertainty about mobility, which boils down to resource availability and demand.

The former is a known subject of research and includes forecasting of futures prices as well as day-ahead, regulation, intra-day, and balancing market prices [133, Chapter 3]. The latter uncertainty regarding PEV availability and demand is less explored, but may be significant. It may be approximated by modeling the stochastic processes that determine the mobility of each vehicle in the fleet, i.e., the trips traveled, during which the vehicles are unavailable because of disconnection, which make up the energy demand.

In the following, the methods used for generating stochastic parameters are briefly described. However, since these methods do not manifest important contributions of this thesis, the full set of information can be accessed in the appendix.

4.4.1 Time Series Based Price Forecasting

(S)ARIMA and GARCH Specification

L	Time-series index for backward shift or lag	$\in \mathbb{N}$
ϕ_L	Auto-regressive (AR) coefficient at lag L	[p.u.]
θ_L	Moving average (MA) coefficient at lag L	[p.u.]
Φ_L	Seasonal AR coefficient at lag L	[p.u.]
Θ_L	Seasonal MA coefficient at lag L	[p.u.]
Γ_L, Υ_L	GARCH and ARCH coefficients at lag L	[p.u.]
c, σ^2	Time-series constant and variance	[€, €^{2}]

In the following subsections, this document compiles steps that are followed for SARIMA time series model identification, estimation and scenario generation to provide a sufficiently good forecasting model for the *EEX* 2011 electricity market data. In particular, the 8760 hourly data points for the *EPEX* spot day-ahead market are analyzed and used for building a time series model. Furthermore, in this document, the methodology to construct corresponding real-time balancing market prices for imbalance settlement based on so-called single price for balancing energy across all four German control areas (reBAP) is presented. This includes a general introduction, how imbalance settlement fees can be modeled as well as a time series model identification and estimation for the 2011 reBAP data.

Time series analysis has proven in various studies to be a very convenient instrument to forecast for instance day-ahead market clearings. The challenge lies in capturing characteristics such as daily and weekly seasonalities, high frequency and high volatility. Especially irrational bidding behavior by market agents, make price series more volatile than for instance demand series [139].

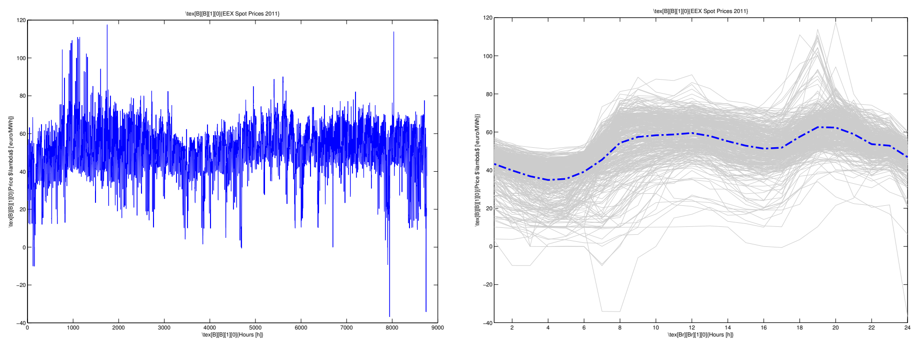
Estimating parameters of auto-regressive integrated moving average (ARIMA) models, is well described by [140], [141]. ARIMA relate current prices to past prices and current errors to past errors. They can be characterized by (p, d, q) corresponding to the number of autoregressive terms p, the differencing order d, and the number of moving-average terms q, respectively, while seasonal SARIMA models include differencing for the daily or weekly seasonality. This study uses the notation from [133], given by $SARIMA(p, d, q) \times (P, D, Q)_S$:

$$\left(1-\sum_{j=1}^{p}\phi_j B^j\right)\left(1-\sum_{j=1}^{P}\Phi_j B^j\right)(1-B)^d\left(1-B^S\right)^D y_t=\left(1-\sum_{j=1}^{q}\theta_j B^j\right)\left(1-\sum_{j=1}^{Q}\Theta_j B^j\right)\varepsilon_t \tag{4.71}$$

with a seasonal component of P autoregressive parameters $\Phi_1, \Phi_2..., \Phi_P$, Q moving average parameters $\Theta_1, \Theta_2, ..., \Theta_Q$ and a differentiation order D.

4.4.1.1 Day-Ahead Spot Prices

Single hour prices from the *EPEX* spot price auction market are presented in the following. First, the prices from the *EPEX* auction market are shown in Fig. 4.6a. In 4.6b, the same prices are drawn in 24 hour intervals for 365 days, including the mean daily price over all days. For this illustration and all further analysis the original data has been changed from a quarterly hour resolution to an hourly resolution by unweighted simple averaging. It can be observed that the hourly time series exhibits typical features of day-ahead market prices in electric



(a) EPEX Auction Market Spot Price Time Series 2011

(b) EPEX Auction Market Spot Price in 24 Hour Intervals for 365 Days

Figure 4.6: EEX 2011 Data Description

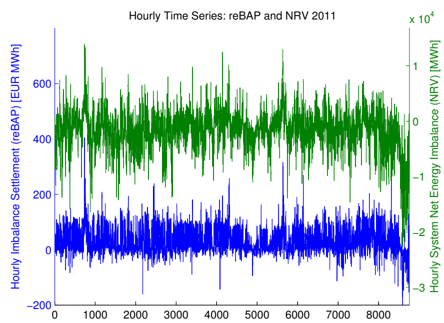
power system: high volatility, daily and weekly seasonality, comparatively large share of outliers as well as non stationary mean and variance.

4.4.1.2 Real Time Balancing Prices

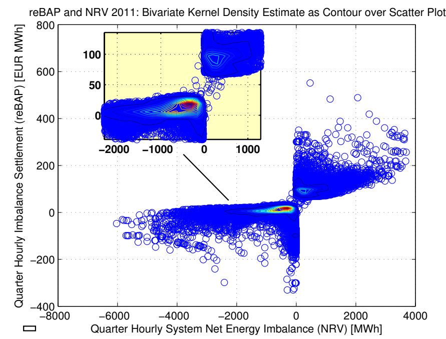
Notes on Balancing Market Forecasting Forecasting balancing prices is not as straight forward as day-ahead spot prices. In the case of balancing prices, capacity and energy price have to be joint together into an energy price for the given period. There are very many different market designs. One of the most distinguishing characteristics pertains to single- or two-price systems. In the single price system, market participants may have a financial interest in speculating about the net system deviations, whereas the two-price system is usually designed to make it unprofitable to engage in balancing. All four TSOs in Germany used to employ a single-price system and settle deviations only 20 days after real time.

Note that this document is only concerned with the imbalance settlement prices and not with the capacity auctioning prices for regulating power. In Germany there has been a reform of calculating the single so-called single price for compensation energy across all four German control areas (reBAP) in late 2012. The calculation methodology is based on average cost pricing. The reBAP basically takes into account all balancing energy costs in all control areas, which are equally distributed over the system imbalances, netted over each quarter hour [142].

Data The reBAPs for each month were first joined in one single time series. Then quarter hourly values were aggregated together as unweighted hourly averages. The resulting data are shown in 4.7, where the time series of the hourly prices (reBAP) and system deviations, denoted NRV in Germany, are plotted together with a scatter plot showing estimated bi-variate kernel density depicted



(a) Hourly Time Series reBAP and NRV 2011



(b) Bi-variate Kernel Density Estimate as Contour over Scatter Plot

Figure 4.7: Single Price for Compensation Energy: reBAP 2011

as a contour graph.

From the figures it becomes evident that the German system was more often short of balancing energy than otherwise, which would have hinted strategic bidding behavior of market participants. There appears to have been a systematic negative deviation of the system. [137] show a similar graph for 2012 data and suggest some significant changes in the way single compensation energy prices should be computed and published. Namely, a one price-system without punitive charges, computed using an approach based on marginal costs of control energy delivery and close-to-real-time publication. There is an argument that theoretically, balancing markets should be cleared as close as possible to the period of physical energy delivery so that as precisely as possible the available production means and the actual consumption needs are known. Nevertheless, in the following a two-price system based on average pricing is assumed.

4.4.1.3 Remarks on the Balancing Price Prediction

The balancing prices $\lambda^+_{h,\omega}$,$\lambda^-_{h,\omega}$ are 24-h vectors for each scenario, i.e. matrices with dimensions of $|\Omega| \times |\mathcal{H}|$. Each of these scenarios corresponds to a simulated sample path of a potential realization of the prices. The software used to carry out this simulation is the Econometrics Toolbox in MatLab.

Choosing the right forecasting horizon is not a trivial matter. Of course, it could be chosen to have the value 24, but then all sample paths would be completely independent of each other. As this is a day-ahead optimization problem, it is assumed that in reality balancing would be carried out hourly, e.g., 10 minutes ahead of real time. The intention is to approximate these decisions as realistically as possible beforehand. Therefore, at day-ahead, what is simulated, is the use of the forecasting model for balancing prices at each hour, one hour ahead of real time, using the actual original series up until the hour before as an input to have temporal correlations between the sample paths.

This means that the respective functions are called with forecasting horizon of one hour each h once, with increasing length of the realized historical series.

4.4.2 Mobility Simulation

This section provides further clarification of the scenario generation of the PEV data for mobility. The used method for the prediction is rather straight forward. It is a Monte-Carlo simulation realized by means of a manually programmed set of MatLab functions that conduct consecutive draws from the indicated cumulative probability distribution functions. In principle, all sampling is carried out independently, as the original data sources do not provide conditional probabilities. However, for coherent outcomes in terms of starting and arrival times, length and duration of the trip, some back-testing is included which triggers re-sampling in case of inconsistency until the prescribed cardinality of the scenario set is achieved.

In the following, the nomenclature specific to the mobility scenario generation is provided.

Indexes and Abbreviations

$d \in \mathcal{D}$ Index of *type days* 1..5 within weekly horizon.

$t \in \mathcal{T}$ Index of *trips*.

$l \in \mathcal{L}$ Index of *length classes* of trips t.

Inputs

$|\otimes|$ Number of equiprobable scenarios to be generated.

$\pi^{\mathbf{T}}_{d}$ The probability of travel on a certain day d, $\in [0,1]$.

$\pi^{\mathbf{H}}_{d,h}$ The probability of starting a trip on a specific day d and hour h, $\in [0,1]$.

$\pi^{\mathbf{L}}_{d,l}$ The probability of a trip to be within a certain length class l on a specific day d, $\in [0,1]$.

$\mathbb{E}\left|t\right|_{d}$ The expected number of trips conditional on traveling vehicles for a given day, $\in \mathbb{N}^{+}$.

$\mathbb{E}\left[s\right]$ The expected traveling velocity or driving speed in km/h, $\in \mathbb{R}^{+}$.

η_{v} PEV Drive Train Efficiency in kWh/km, $\in [0,1]$.

Model Parameters

$\mathbf{T}_{d,v}$ Binary matrix indicating the travel of a vehicle, $\in \{0;1\}$.

$\mathbf{S}_{d,v,t}$ Positive integer matrix indicating the trip starting hour, $\in \mathcal{H}$.

$\mathbf{R}_{d,v,t}$ Positive integer matrix indicating the trip return hour, $\in \mathcal{H}$.

$\mathbf{L}_{d,v,t}$ Positive real matrix indicating the trip length, $\in \mathbb{R}^{+}$.

Other Flow Chart Conventions

Generic processing step.

$\omega \leftarrow 0$ Initialize scenario counter.

$\omega \leftarrow \omega+1$ Increment scenario counter.

$\blacklozenge$ Decision block.

$\lambda^{\mathbf{T}}(\omega)$ Random draw from $\pi_d^{\mathbf{T}}$.

$\lceil \cdot \rceil$ Ceiling function evaluation of .

Output

$\mathbf{A}_{d,v,h,\omega}$ Binary matrix indicating availability in scenario ω, $\in \{0;1\}$.

$\mathbf{E}_{d,v,h,\omega}$ Positive real matrix indicating the energy consumption in kWh for scenario ω, $\in \mathbb{R}^{+}$.

To represent the uncertainty in driving behavior, a two-state single-node Monte-Carlo simulation for mobility scenario generation is used. For a PEV fleet of a given size and composition as well as technological parameters of vehicle classes and battery specifications, the algorithm intends to approximate the known statistical properties of driving behavior in the input data to the above described optimization programs.

In short, it is assumed that there exist information on: The expected number of trips for each of the moving vehicles on a given day ntr_d^{avg} and vehicle specific expected constant trip speeds ϑ_c to calculate trip durations given the distance.

For modeling the fleet unavailability, mainly three types of information were obtained, given by [23] in the form of discrete cumulative distribution functions (CDFs):

- The probability of travel on day d, $\pi_d^{travel} = \hat{\pi}_d^{travel}$.
- The probability of starting a trip on a certain day d and hour h, $\pi_{d,h}^{startH} = \sum_{j=1}^{4} \hat{\pi}_{d,t\cdot 4-j}^{startH}$.
- The probability of a trip to be of a certain length l on a specific day $\pi_{d,l}^{range} = \hat{\pi}_{d,l}^{range} - \hat{\pi}_{d,l-1}^{range}$,

where the week is represented by a set of typical days with similar characteristics, i.e. $d \in \{Monday, Weekdays, Friday, Saturday, Sunday\}$, the time slots resolve the day in 24 hours, $h \in \{1, 2, ..., 24\}$, and the trip lengths l are sorted into 20 different classes with increasing intervals between class centers. Hats, $\hat{}$, refer to the original unchanged data from [23], $\pi^{start}_{d,t}$ is aggregated from original t 96 15-Minute to 24 hourly data points and $\pi^{range}_{d,l}$ is transformed from original CDF to adjusted probability distribution function (aPDF). For further details please refer to the appendix. In particular, the numerical data for the distributions are given in Tab. D.2, Tab. D.1 and Tab. D.4.

Scenario Generation for PEV Mobility Data Flow charts have been used for a long time and experience in many practical engineering applications still supports the use of these types of diagrams for communicating algorithm content. In fact, evidence from teaching experiments corroborates that the use of flow charts may improve accessibility and understanding of complex computation structures. To this end, this section makes use of flow charts to convey part of the algorithm contents. The symbol convention is standard: rectangle or plain text for generic processing commands, conditionals or decisions are represented as a diamond or rhombus, and the arrows simply indicate the direction of flow.

A high level overview of the mobility simulation algorithm used for generating PEV mobility data is provided in Fig. 4.8. Between the processing steps of data input and output the algorithm is grouped into four modules which are inter-connected through looping over the different dimension, according to the random draws carried out from the different PDFs: travel on a given day, starting hours for trips, lengths of the realized trip and the resulting availability profiles. With the given inputs, in *Module I*, a first ***sampling of travel probability*** is carried out before *Module II* draws the ***trip start hours*** for the traveling vehicles. By sampling from ***trip length*** statistics, ***return hours*** are calculated in *Module III.* Finally, with some plausibility checks, *Module IV* calculates the outputs in terms of ***availability and energy demand*** for the PEV fleet in the given scenarios.

Break down in specific algorithm modules In addition to the overview chart, the processes within each of the four modules are described in technical detail by means of specific flow diagrams. To enhance accessibility to the flow charts, the following text discusses Module I in detail, see Fig. 4.9. It is given as a step-by-step example, while modules II to IV are given in the appendix of this document.

To this end, Fig. 4.9 documents, how in a first step both the scenario counter ω as well as the binary matrix indicating the PEV travels on a certain day $\mathbf{T}_{d,v}$ are initialized with zeros. In the second step the scenario counter ω is incremented and the index for day counters d is set to 1. The third block visualizes the first decision via a diamond shaped element to check whether the days are within the horizon. If this is found true, a loop over the entire fleet is

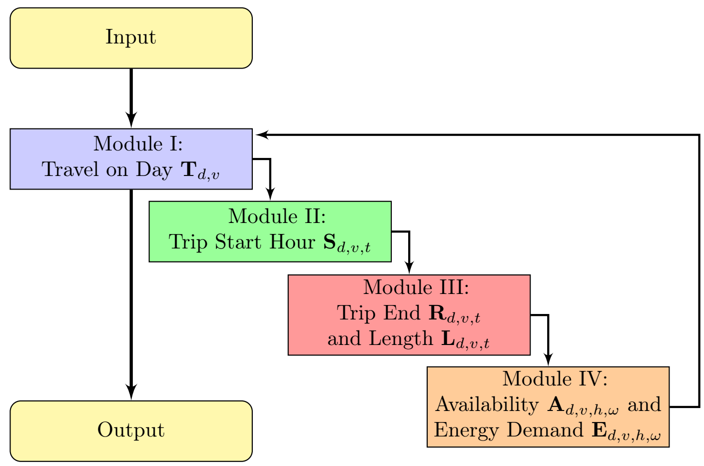


Figure 4.8: Overview Flow Chart of Mobility Simulation Algorithm

initiated, where the actual randomization is taking place. A a random variable generator finds a value between 0 and 1 to take the inverse of the cumulative travel distribution to find, whether each car is traveling or not. This process step being of most importance for the Monte-Carlo sampling, is marked with red text color.

The Algorithm's Output Structure Furthermore, one can categorize two sets of "PEV variables" that are relevant in the provided simulation algorithm. Please note that all of these are the realized values for the second stage of the previously described stochastic DLC optimization program. In the ILC scheduling, there is only one decision stage.

One set refers to the stochastic processes from the mobility. From the perspective of the optimization model, these are exogenous, i.e. represented by input parameters in the form of matrices that are defined over the dimension of scenarios ω, which can be found under the heading "Stochastic PEV Fleet Mobility" in the nomenclature:

$\nu_{v,h,\omega}$	Binary fleet availability	$\in \{1, 0\}$
$\rho_{v,h,\omega}$	SOC loss from driving	[kWh]

Simply to be clear and to avoid ambiguity, the "PEV variables" pertaining to the mobility, within the context of this thesis document, are denoted *mobility parameters* even though they may describe realizations of stochastic processes (or variables).

The other set of "PEV variables" is the one containing the endogenous decision variables, and are hence part of the optimization outcome in the optimal solution. These can be found under the heading "Second Stage, Wait-and-See Decision Variables" in the nomenclature of the DLC optimization program:

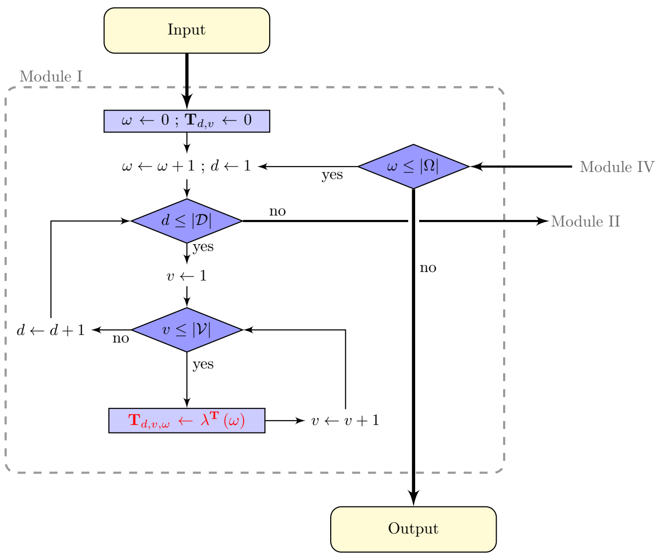


Figure 4.9: Detailed Flow Chart for Module I of the Algorithm

$e^{RT,\barwedge}_{v,h,\omega}$, $e^{RT,\veebar}_{v,h,\omega}$	Net real-time energy discharged and charged
$e^{SOC}_{v,h,\omega}$	Battery SOC

However, please note that the “PEV variables” pertaining to the charging and SOC levels, within the context of this manuscript, are denoted *PEV decision variables*. These are also defined over the scenario index ω, because these may take different optimal values for different scenarios.

Mainly, the *mobility parameters* are considered an input to the problem and the proposed model could be applied to solve case studies for which the mobility scenarios would have been generated in a different way, with a special focus on the temporal correlations. To give an example, [73] provides a very detailed model which would serve perfectly to generate appropriate input.

However, accurate models for mobility representation, i.e. for forecasting future behavior of PEV fleet is a whole new field of research in the realm of transportation simulation science, this thesis doesnot contribute or innovate in that field. The contributions of this thesis are seen more in the formulation and application of the optimization model to take decisions by the aggregator under risk consideration, for a given set of inputs.

Interplay of Availability and Consumption The decision variable $e^{\mathbf{SOC}}_{h}$ conveniently tracks the SOC while being connected to the system indicated by the availability ν=1, as well as while being disconnected from the system, indicated by the availability ν=0. Caution has to be paid while generating the mobility scenarios. The SOC losses from driving $\rho_{v,h}$ are strictly greater than zero, when the vehicle is not available.

To provide an illustrative example of how these data should conceptually look like in a given scenario realization, please see the following two tables but note that this is a stylized illustration for 3 cars and 6 periods:

$\nu_{v,h}$	h					
v	1	0	1	0	1	1
	0	0	1	0	0	1
	1	0	1	1	0	1

$\rho_{v,h}$	h					
v	0	1	0	1.5	0	0
	2	1	0	1.6	2	0
	0	2	0	0	1	0

It can be seen how SOC loss from driving occurs only when availability to the system is 0, because of disconnection and driving, and vice versa.

A sample of the aggregated two-state output is provided in the graphical illustrations of Fig. 4.10. Shown are the resulting connection and disconnection over the course of one week, i.e., 168 hourly periods, 10, 100 and 1000 vehicles, as well as 20 scenarios. The standard error bars allude to the order of magnitude in which input data for optimization problems can, with a relatively strong dependence on the fleet size, vary for the same day and hence, in how far these variations may impact the optimal scheduling outcome.

For the interested reader, a detailed a step-by-step description of the algorithm can be found in the appendix.

4.5 Concluding Summary on the Methodology

This chapter has presented the first most technical sections of the thesis. It has provided the developed approach to tackle the thesis objectives, explaining the main characteristics of the different methodologies used in this thesis and highlighting the used mathematical optimization and simulation models that are later on employed for computing numerical results.

At first, the general decision framework of PEV aggregators in modern, unbundled power systems has been presented, before detailing the specific assumptions taken for the subsequent models.

Then, to give structure to the different parts of the models here presented, they have been sorted according to the control modes employed for the decision making involved in PEV scheduling according to market and network signals. Two optimization models, one within the stochastic programming framework, and another within the complementarity modeling framework are presented. The former is able to depict the decision making of a PEV aggregator exercising direct load control, while scheduling its market involvement in day-ahead markets according to balancing prices. The latter is a tool for the PEV aggregator with indirect load control to endogenously determine optimal retail prices given tariff constraints. Centered around the single firm profit perspective of

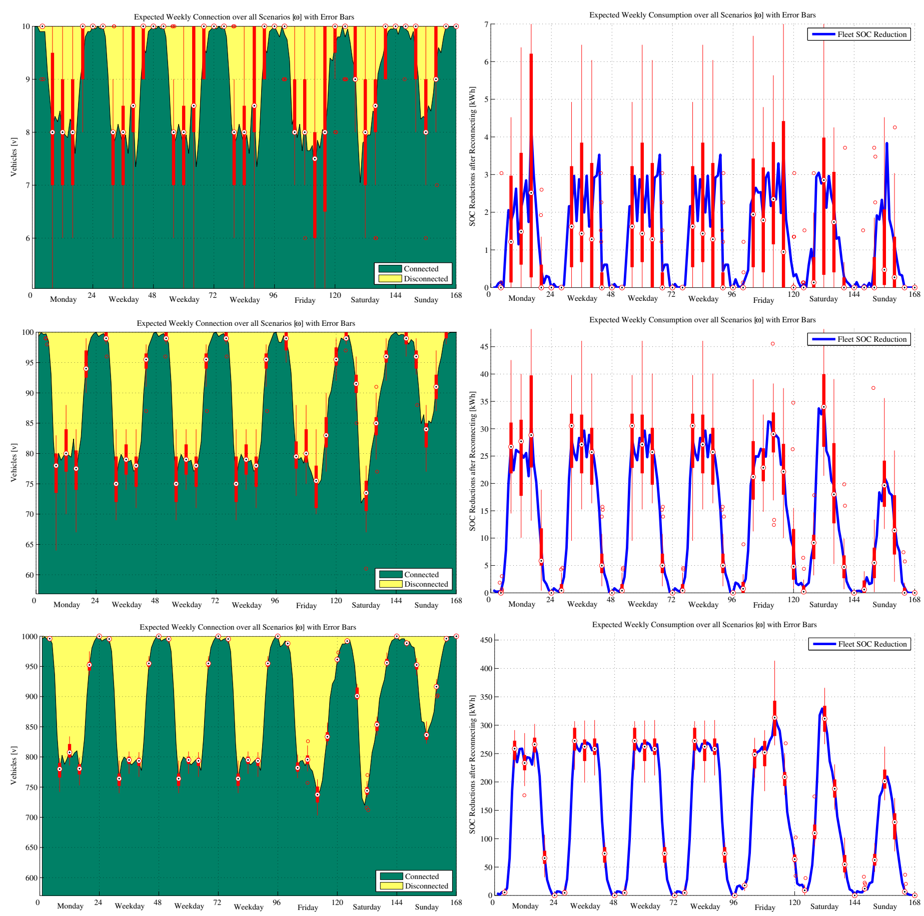


Figure 4.10: Uncertainty of Mobility: Availability and Consumption

the aggregator, both models determine optimal PEV charging schedules in the short term, day-ahead planning horizon for 24-hours, while taking into account network use-of-system prices, and being capable of finding individual energy quantities for each modeled PEV.

To this end, the models are required to be fed with input parameters regarding market prices and PEV mobility. Therefore, in the last two sections of this chapter, the simulation models to forecast PEV mobility and electricity market prices both for the day-ahead clearings, as well as the imbalance settlement fees of a supposed dual, or two-price system are reported.

Chapter 5

PEV Coordination with DLC

Via a set of case studies, this chapter applies the afore-described model for direct load control and computes numerical results for further analysis. The case studies have been selected to highlight certain aspects of PEV coordination under DLC. In that sense each one of them is self-sufficient yet complementary to the others.

According to the research objectives laid out in Part I of this thesis, the first three case studies look at PEV coordination for market participation the direct load control approach. The described model for the optimal decision making of plug-in electric vehicle aggregators participating in day-ahead electricity markets under uncertainty and risk aversion is applied.

First, in subsection 5.1.2, a large-scale case study, without network representation highlights aspects of risk management, while calculating basic values that stand in favor of this approach. Then, subsection 5.1.2 features a small-scale case study with very stylized data mainly to motivate stochastic programming methodology. Finally, subsection 5.2 combines the two previous studies, as it applies the PEV energy retail problem with interactions in day-ahead and balancing markets from the aggregator's perspective, taking into account location dependent network UoS tariffs in the form of capacity prices for active power.

5.1 Market Participation Under Uncertainty

The following case study is published in [74].

5.1.1 Large Scale PEV Fleet Participation

This very first case study applies the developed methodology to a realistic set of data. Hence, it shows how the model can be used to maximize PEV aggregator profits taking decisions in day-ahead and balancing markets while considering risk aversion. Under uncertain market prices and fleet mobility, the proposed two-stage linear stochastic program finds optimal PEV charging schedules at

Table 5.1: Maximum Likelihood Estimation Results: Model Parameters

Model	Specification	AR	MA	SAR	SMA	Constant	GARCH (1,1) Variance
Day-Ahead	$\text{SARIMA}(1,1,2) \times (1,1,2)_{168}$	$\phi_1 = 0.775$	$\theta_1 = -0.657$	$\Phi_1 = -0.189$	$\Theta_{24} = 0.152$	$c_{\mathbf{D}} = 0.585 \times 10^{-3}$	$\Gamma_1 = 0.550,\ \Upsilon_1 = 0.287$
			$\theta_2 = -0.318$		$\Theta_{168} = -0.704$		$c_{\sigma^2} = 3.323$
Balancing	$\text{ARIMA}(2,1,2)$	$\phi_1 = 0.616$	$\theta_1 = -1.103$	-	-	$c_{\mathbf{B}} = -0.034$	$\Gamma_1 = 0.581,\ \Upsilon_1 = 0.246$
			$\theta_2 = 0.1295$		-		$c_{\sigma^2} = 220.1$

the vehicle level, assuming that the aggregator can exercise DLC. Specifically, it highlights the effects of including the CVaR term in the objective function and calculates two metrics referred to as the expected value of aggregation and flexibility.

5.1.1.1 Uncertainty of Input Data and Parameter Settings

Market Data Acquisition 2011 data for the day-ahead market spot price (EPEX) and the single price for balancing energy across all four German control areas (reBAP) have been obtained from the European Energy Exchange platform [143] and 50 Hertz Transmission [142].

Market Price Scenario Generation These data, converted to hourly resolution, have been used to estimate parameters of ARIMA models [140], [141]. The ARIMA models are characterized by the number of auto-regressive terms, the differencing order, and the number of moving-average terms, respectively, while seasonal SARIMA models include differencing for the daily or weekly seasonality. To account for time-dependent variance, σ^2 terms are estimated using GARCH models. Parameters from the maximum likelihood estimation for both EPEX and reBAP can be viewed in Tab. 5.1.

Using the error terms from the time-series estimation, 200 equiprobable scenarios are generated over a 24-hour horizon. The reBAP is treated as a single price-time series and after the scenarios are generated, the two-price system is emulated from the obtained data, see appendix. Another approach would be to combine SARIMA models with Markov Processes [144].

The typical day-ahead market is cleared 12-36 hours ahead, while prices for the coming 12 hours are already determined by the previous clearing. The balancing prices are predicted over a one-hour horizon. This horizon is chosen to replicate presumed conditions, in which rolling forecasts are performed every hour with updated information on past price realizations . The conditions in the system correspond to day 301 of the year (Monday, October 28). From the 6000-hour training period, the observed series and inferred residuals are used as pre-samples.

Fig. 5.1 and 5.2 show the price scenarios and hourly volatilities for both *EPEX* and reBAP. The box plot figures and the variance plots indicate the amount of uncertainty and variability in the input data. An illustration of the time-series forecasting is given as follows. The original series plotted against the model forecasts for the validation period in hour 6000-8760 is shown in Fig. 5.3 and characterized in different levels of zoom. Also, for a given time interval,

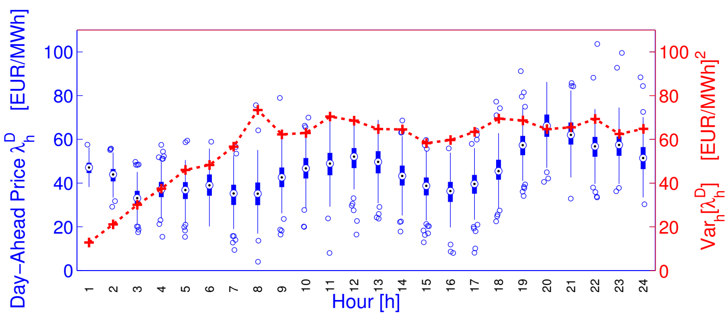


Figure 5.1: Scenarios for day-Ahead Market Prices

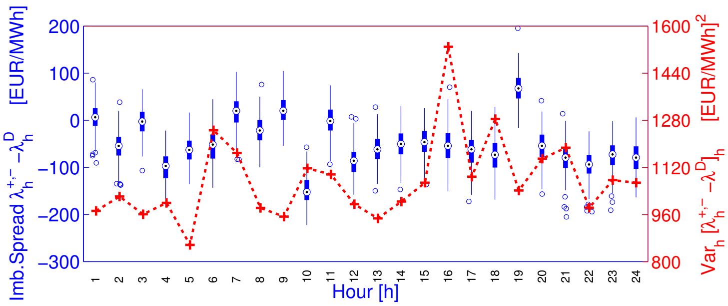


Figure 5.2: Variance and box plot of system imbalance price spread

observed data of the original series are sequenced by the sample paths for the forecasting, while the mean and the 95-percentile regions are plotted in addition, see Fig. 5.4.

Mobility Simulation To represent the uncertainty in driving behavior, the two-state single-node Monte-Carlo simulation for mobility scenario generation has been used as described in the previous chapter. 200 equiprobable mobility scenarios are generated and combined with the 200 price scenarios. Please note, this is a simplified means of attaining input data serving the main purpose of the given case study, but are arguably not comparable to more advanced methods for mobility scenario generation, as used in e.g. [73].

For the case study, data on German driving statistics is taken as provided by the MID Mobility Survey Data given in [23], [65], [66]. The data is collected from a survey with a comparably large number of individual participants and thus responses. However, the data was only collected on a given day of the week, respectively. So the challenge lies in connecting the diurnal simulations, represented by 5 typical days of the week, to a weekly result profile. Fig. 5.5 shows the respective probability distributions defining the case study input, notably the probability of starting a trip at a given time and the probability of different trip length classes. For further reference, these and more numerical

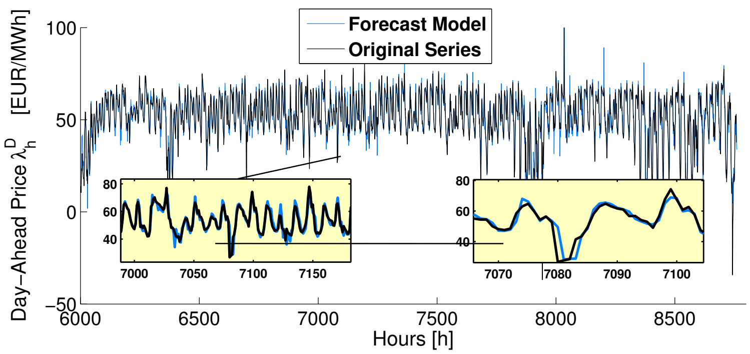


Figure 5.3: Example Simulation with SARIMA$(1,1,2) \times (1,1,2)_{168}$

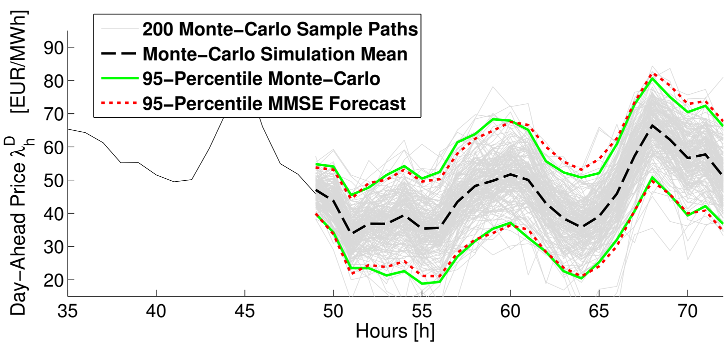


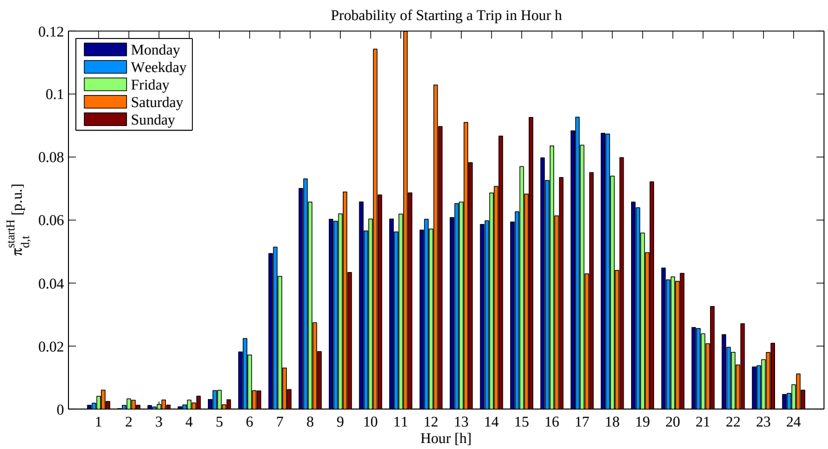
Figure 5.4: Sample Paths for given Forecasting Period

values are provided in Tab. D.1, Tab. D.2, Tab. D.3 and Tab. D.4 of the appendix with supplemental material.

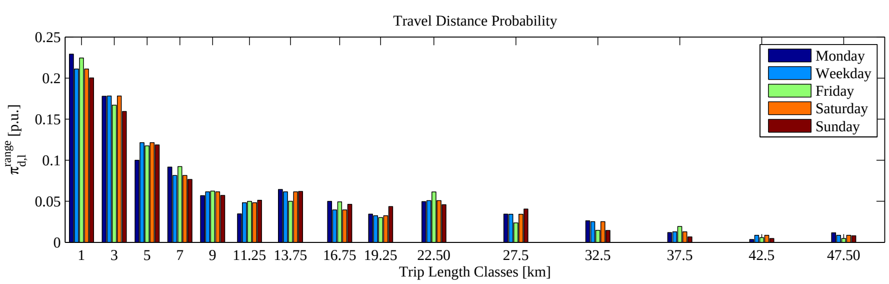
Client-Side PEV Parameters On the client side, the wholesale price component is a flat rate of $\gamma^{\underline{\vee}} = €\ 0.033$ /kWh, excluding the tariff components related to using the network. This parameter is calibrated to achieve an adequate level of profits for the aggregator, which would in reality be set by the degree of competition in the retail market. Just to provide an illustrative number for comparison, according to the digital information board of *EPEX SPOT*, the average EPEX base price cleared for the year 2011 was € 51.12 per MWh or € 0.05112 per kWh.

In the numerical results provided here in the thesis, discharging is always turned off. Only uni-directional cases are provided, and thus making $\gamma^{\overline{\wedge}}$ irrelevant for this specific application, without questioning its general validity.

The PEV fleet features characteristics mainly based on [64], [145], including available battery capacity $\overline{E}_v = 12$ [kWh] and (dis-)charging efficiency $\eta^{\overline{\wedge}} =$



(a) Probability of Starting a Trip at a given Time



(b) Probability of Trip Length Classes

Figure 5.5: MID Mobility Survey Data [23], [65], [66]

$\eta^{\vee}_{-} = 0.93$ [p.u.]. Regardless of the scenario, the target SOC is the same as the initial SOC forcing equal net energy exchange over the course of the day for all vehicles, i.e., in all mobility sub-scenarios $\iota_v^{SOC} = 8$ kWh and $\phi_v^{SOC} = 8$ kWh. In this case, the values are identical, which is similar to modeling water reservoirs with daily cycles. However, other settings with differing initial and final values would be possible as well.

Risk Parameters Unless otherwise indicated in specific runs, the parameters for controlling the risk are $1 - \alpha = 0.05$, and $\beta = 0.01$.

In order to illustrate the applicability of the above presented model with its main features, a uni-directional, charging-only example is studied. Discharging is turned off. Therefore, setting the transaction cost parameter, τ to value close to but smaller than 1, i.e. ≈ 0.99 is not necessary.

Since discharging is turned off, this case study presents only results regarding uni-directional battery charging. Nevertheless, as long as the discharging can be priced appropriately according to the energy processed - for more information on the cost of battery degradation, please refer to the specific section in the literature review, Chapter 3 - the conclusions from the there presented results are transferable. However, for the sake of simplicity and ease of understanding the main contributions of this model, it is not deemed necessary to include discharging.

5.1.1.2 Number of Scenarios and Stability of the Solution

[129] proposes a stochastic optimization of PEV participation in electricity markets, using *SCENRED* to reduce scenarios and to represent vehicles at a fleet level, while incorporating VaR in the coordination. *SCENRED* is a well established tool for the reduction of scenarios modeling random data processes [146]. For the given two-stage program the scenario reduction can be directly implemented within *GAMS* using the built-in *SCENRED2* library, specifying either prescribed cardinality of the reduced set of scenarios, or relative probability distances between the resulting distributions.

A critical issue when using scenario-based stochastic programming is the actual number of scenarios to consider. Too few scenarios might result in inaccuracies, while too many could be computationally burdensome. In a calibration step, to determine the right number of scenarios, a reduction technique is carried out as much as necessary while trading off the stability of the objective function value and the computation time. Taking an initial set of scenarios, the problem is solved, while both objective function value and execution time are recorded for an iteratively increasing number of reduced scenarios The scenario-reduction algorithm, thus, uses a prescribed cardinality, i.e., not accuracy, of the reduced set of scenarios as the stopping rule. During this calibration, the objective function value stabilizes when including approximately 40 scenarios; however, including up to 100 scenarios does not involve a significantly higher computational burden. Beyond this value, the increase in computation time does not justify the improvement in uncertainty approximation through the larger scenario-reduction set. Therefore, scenario reduction with prescribed cardinality of the reduced set equal to 100 is carried out.

5.1.1.3 Expected Value of PEV Flexibility

After scenario-reduction, the economic benefit of aligning the PEV schedule with market prices is quantified. To estimate this value of flexibility, first, the optimal objective function value, (4.1) in the original formulation with DLC is denoted $z_{\mathbf{DLC}}$ as opposed to that of a schedule over which the aggregator cannot exercise control $z_{\mathbf{noC}}$. Therefore, a reference charging schedule $\check{\mathrm{E}}_{v,h,\omega}$ is obtained from a trivial optimization in which the objective is immediate charging after each trip:

$$\text{Minimize} \quad e^{\mathbf{RT},\veebar}_{v,h,\omega} \cdot h, \tag{5.1}$$

and subject to a constraint that ensures post-trip charging:

$$\Sigma_1^h e^{\mathbf{RT},\veebar}_{v,h,\omega} \leq \Sigma_1^h \frac{\rho_{v,h,\omega}}{\eta_v}. \tag{5.2}$$

This charging schedule is found ignoring market-side prices (4.2)-(4.5) and relaxing market balance (4.6), (5.9) and CVaR (4.12)-(4.13) constraints while only enforcing the physical constraints given by availability (4.9), SOC balance (4.7), lower SOC bounds (4.11) as well as initial and final SOC conditions (4.10).

Finally, to calculate the resulting profits of such a charging schedule, $\check{\mathrm{E}}_{v,h,\omega}$ is forced as the solution to the original problem formulated in (4.1)-(4.13). This is achieved by fixing the decision variables pertaining to real-time charging to the consumption as it could occur in an uncontrolled mode

$$e^{\mathbf{RT},\veebar}_{v,h,\omega} \overset{\mathbf{fix}}{=} \check{\mathrm{E}}_{v,h,\omega} \ .$$

The EVPEVF is then calculated as

$$z_{\mathbf{flex}} = z_{\mathbf{DLC}} - z_{\mathbf{noC}} \quad \text{and} \ z_{\mathbf{flex}\%} = \tfrac{z_{\mathbf{DLC}} - z_{\mathbf{noC}}}{z_{\mathbf{noC}}}. \tag{5.3}$$

5.1.1.4 Expected Value of PEV Aggregation

To analyze how much the stochasticity of a single PEV's mobility influences the economics of the charging schedule in the day-ahead planning, the following disaggregation and calculation is proposed. For the given fleet of $|\mathcal{V}| = 1000$ vehicles, the problem is solved with varying aggregation sizes of the sub-fleet $\left|\mathcal{V}^k\right|$. The (number $|\mathcal{K}|$, size $\left|\mathcal{V}^k\right|$) pairs of the sub-fleet are set to every possible combination of two integer factors of the total fleet size, which in this case are a total of 16 pairs: (1,1000); (2,500); (4,250); (5,200); (8,125); (10,100); (20,50); (25,40); (40,25); (50,20); (100,10); (125,8); (200,5); (250,4); (500,2); (1000,1). For each of these pairs, the problem given in (4.1)-(4.13) is solved for every

Table 5.2: Expected Value of Aggregation for Selected Sub-Fleet Sizes

Sub-Fleetsize $\lvert\mathcal{V}^k\rvert$	**1000**	**250**	**40**	**25**	**10**	**4**
# **Aggregations** $\lvert\mathcal{K}\rvert$	**1**	**4**	**25**	**40**	**100**	**250**
$z_{\mathbf{sf}}=\Sigma_k[\mathbb{E}\left\{\Pi_\omega^{\mathbf{Tot}}\right\}+\beta\cdot\mathbf{CVaR}]_k$ [€]	16.89	16.71	16.48	16.01	14.47	13.61
EVPEVA $z_{\mathbf{agg}}$ [€]	-	0.18	0.41	0.89	2.43	3.28
Relative EVPEVA $\frac{z_{\mathbf{agg}}\lvert\mathcal{V}\rvert}{z_{\mathbf{DLC}}}$ [%]	-	1.08%	2.43%	5.24%	14.37%	19.42%

sub-fleet, hence in this case a total of 2340 times. Then, for each (number, size) pair, the sum of the expected profits of the k sub-fleet problems is computed as:

$$z_{\mathbf{sf}} = \Sigma_k[\mathbb{E}\left\{\Pi_\omega^{\mathbf{Tot}}\right\} + \beta\cdot\mathrm{CVaR}]_k \,. \tag{5.4}$$

This leads to the EVPEVA, which is then calculated as:

$$z_{\mathbf{agg}} = z_{\mathbf{DLC}} - z_{\mathbf{sf}} \,.$$

Controlling the CVaR The main part of the analysis focuses on the inclusion of the CVaR measure and the sensitivity of the solutions to the risk aversion of the PEV aggregator. Starting from a risk-neutral case with $\beta = 0$, the problem given in (4.1)-(4.13) is successively solved for increasing weighting factors: $\beta = [.01, .02, .13, .20, .31, .47, .72, 1.10, 1.69, 2.60, 3.98]$. The effects on the distribution of profits $\Pi_\omega^{\mathbf{Tot}}$, as well as on day-ahead vs. balancing trading positions, indicated by diurnal expected schedules and the scenario weighted total sums of $e_{h,\omega}^{\mathbf{D},\barwedge}$, $e_{h,\omega}^{\mathbf{D},\veebar}$, $e_{h,\omega}^{\mathbf{B}+}$, $e_{h,\omega}^{\mathbf{B}-}$, $e_{v,h,\omega}^{\mathbf{RT},\barwedge}$, and $e_{v,h,\omega}^{\mathbf{RT},\veebar}$, are analyzed.

5.1.1.5 Numerical Results

The EVPEVF is significant. It amounts to

$$z_{\mathbf{flex}} = z_{\mathbf{DLC}} - z_{\mathbf{noC}} = € \, 16.93 - € \, 12.72 = € \, 4.21 \tag{5.5}$$

and

$$z_{\mathbf{flex}\%} = \frac{z_{\mathbf{DLC}} - z_{\mathbf{noC}}}{z_{\mathbf{noC}}} = 33.1\% \,. \tag{5.6}$$

Essentially, there is value in aligning demand with market price signals.

For selected $(\lvert\mathcal{K}\rvert, \lvert\mathcal{V}^k\rvert)$-pairs, the results relating to the EVPEVA are summarized in Tab. 5.2. It can be observed that with further disaggregation ($\lvert\mathcal{K}\rvert \uparrow$, $\lvert\mathcal{V}^k\rvert \downarrow$) the expected mean sub-fleet profit decreases. This finding is intuitive, as it is supported by the law of large numbers: the confidence with which day-ahead forecasts of vehicle mobility, i.e., energy demand and unavailability, can be carried out increases with the fleet size. Hence, a larger fleet incurs lower imbalance settlement fees as compared to the same fleet broken up in smaller sub-fleets. In effect, the more vehicles are controlled by the same entity, the better the individual vehicles compensate for the uncertainty in mobility of the others within the same aggregation.

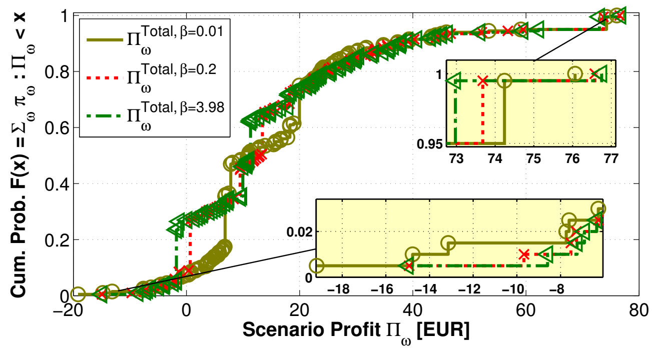


Figure 5.6: Cumulative Profit Distributions for Increasing Risk Aversion

Regarding risk aversion in the form of CVaR weights, Fig. 5.6 shows the cumulative distribution functions of the scenario profits plotted for different levels of β. The effect of risk control results in the absolute decrease of the expected loss in the lowest (1-α)-quantile scenarios of the profit distribution. It can be observed that improvements in the lower tail of the distribution, i.e., higher worst-off scenarios, are accepted at the cost of altering the shape of the upper part. However visible, it has to be noted that the overall effect seems less pronounced in this graphical resolution.

In the supplemental Fig. D.5, it can be seen how the variability of the objective function and its components over all elements in the reduced scenario set behaves. Although the relative stochasticity of the mobility reflected in retail revenue Π^C_ω is rather small with the large fleet size$|\mathcal{V}| = 1000$, the total profit is mainly driven by moderately high prices when selling excess balancing energy.

To analyze these effects quantitatively, in Fig. 5.7 the numerical results of the expected profits $\mathbb{E}\{\Pi^{\mathbf{Tot}}_\omega\}$ are plotted against their corresponding CVaR values $\zeta - 1/\left(1-\alpha\right)\Sigma_\omega \pi_\omega \cdot \imath_\omega$. The results illustrate how increasingly risk averse PEV aggregators trade off expected profit for higher CVaR. The efficient frontier indicates a critical level of β, beyond which additional risk aversion would induce negligible impact on the CVaR and would not effectively control the losses in expected profits. For the given numerical case, this level is $\beta > .31$.

Having presented that hedging against adverse lower-tail profits is achieved, the analysis forthwith turns to strategies of reaching outcome distributions with lower risk. Therefore, for selected risk aversion levels, Tab. 5.3 provides the different trading positions taken in the respective markets: cumulative energy quantities of day-ahead purchases $\Sigma_{h,\omega}\pi_\omega e^{\mathbf{D},\veebar}_{h,\omega}$ as well as expected positive $\Sigma_{h,\omega}\pi_\omega e^{\mathbf{B},+}_{h,\omega}$ and negative $\Sigma_{h,\omega}\pi_\omega e^{\mathbf{B},-}_{h,\omega}$ balancing. Interestingly, the results are rather counter-intuitive: for the same mobility requirement, which is constituted by the expected aggregated real-time charging $\Sigma_{v,h,\omega}\pi_\omega e^{\mathbf{RT},\veebar}_{v,h,\omega}$, higher risk aversion and controlling for the CVaR leads to altered day-ahead purchases such that less negative and more positive balancing is required. This is consistent with the findings in [70]. However, it has to be noted that the strong shift from

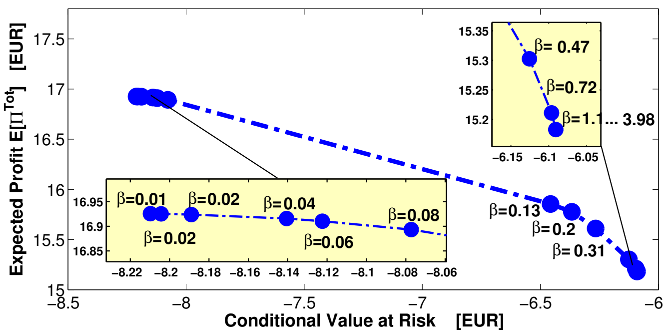


Figure 5.7: Risk Aversion: higher CVaR and lower Expected Profits

Table 5.3: Expected Trading Positions in the Different Markets

β	**0.01**	**0.08**	**0.13**	**0.31**	**0.47**	**3.89**
$\Sigma_{h,\omega}\pi_\omega e^{\mathbf{D},\veebar}_{h,\omega}$**[kWh]**	2655	2575	1773	1604	1310	1181
$\Sigma_{h,\omega}\pi_\omega e^{\mathbf{B},+}_{h,\omega}$**[kWh]**	1276	1339	2031	2166	2361	2457
$\Sigma_{h,\omega}\pi_\omega e^{\mathbf{B},-}_{h,\omega}$**[kWh]**	653	636	525	492	393	360
$\Sigma_{v,h,\omega}\pi_\omega e^{\mathbf{RT},\veebar}_{v,h,\omega}$**[kWh]**	3278	3278	3278	3278	3278	3278

day-ahead towards the involvement in balancing positions may be the result of the simplifying but necessary assumption of full foresight within the 24-hour scenarios in the second stage of the optimization. At the cost of lower expected profit, the opportunity of balancing the inherently flexible schedule provides the aggregator with diminished uncertainty, which improves the CVaR.

In the absence of futures markets and bi-lateral contracts, on its own the PEV aggregator's only means of controlling risk lies in the amount and timing of day-ahead purchases and balancing. Note that day-ahead purchases are made under uncertainty, while balancing is made with full knowledge of prices as well as diurnal energy requirement and unavailability. For selected risk-aversion levels, the diurnal schedules of the day-ahead market positions are given in Fig. 5.8 and the expected deviations in the balancing market are given in Fig. 5.9.

The observations pertaining to the nearly risk-neutral, i.e., $\beta = 0.01$, schedule of day-ahead positions are straightforward: among other small positions, the PEV aggregator purchases more than 2 MWh in hour 3 as well as ca. 0.2 MWh in hour 16, which directly correspond to the smallest values of the expected market prices $\mathbb{E}\{\lambda^{\mathbf{D}}_h\}$. This leads to expected *positive balancing* positions in hours 8 (0.1 MWh) and 15-17 (0.23-0.27) for which the expected prices $\mathbb{E}\{\lambda^{\mathbf{B}}_h\}$ show a favorably strong negative expected imbalance price spread. Vice versa, expected *negative balancing* is the outcome for hour 3 with a rather large position of 0.5 kWh. In expected terms, this seems reasonable because day-ahead price spreads are minimal and imbalance price spreads close to zero. Another small position in hour 9 shows moderately low day-ahead price and among the

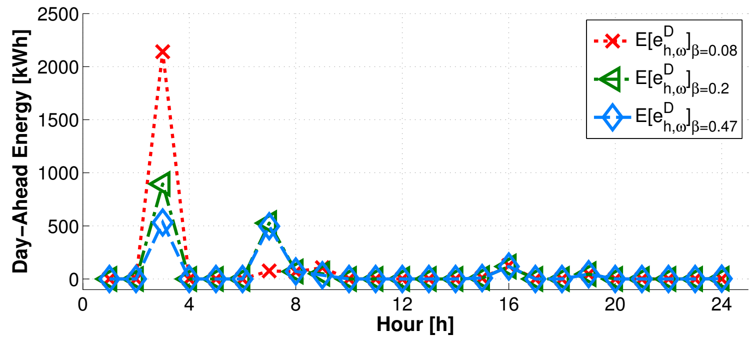


Figure 5.8: Risk Aversion Shift in Diurnal Day-Ahead Schedules

second highest imbalance price spread.

At the other end of the spectrum, a highly risk-averse schedule $\beta = 3.89$ of a PEV aggregator exhibits a reduced day-ahead position in hour 3 but a new position in hour 7. The balancing shift is in accordance: there is pronouncedly more *positive balancing* for hours 3, 4, 5, and 7, whereas the *negative balancing* is reduced in hours 3 and 7.

A key observation is that the risk aversion does not necessarily lead to decreased profit variability. It can be seen that day-ahead as well as balancing schedules do not decrease positions in those hours for which the price variance is higher, for back reference, compare Fig. 5.1 and (5.2). The distribution of prices in the respective hourly periods, indicated both by the box plot as well as the absolute variance, shows, which positions are more likely to be volatile and, thus, prone to more uncertainty. However, the aggregator's hedging strategy against risk includes more than the preparation against adversely variable profit. Rather, the positioning of the PEV aggregator is driven towards those hours with higher worst-off outcomes, even at the cost of giving up part of the expected profitability and lower variance of the profits.

5.1.1.6 Operational Day vs. Day-Ahead Planning

It is true that in the formulation presented, the optimization phase for the operational day is only approximated. In reality, the proposed model only provides an optimal decision at the time of making day-ahead transactions under various assumptions. One of the most prominent ones is information about future scenarios. The 24-hour foresight within one scenario path significantly improves the economics of making decisions and therefore, the final result should be taken as an optimistic approximation. However, for the sake of tractability, this assumption appears important, given the modeling of the rest of the problem. If this perfect foresight was taken away, additional decision stages would have to be enforced by nonanticipativity constraints, which in this case are complicat-

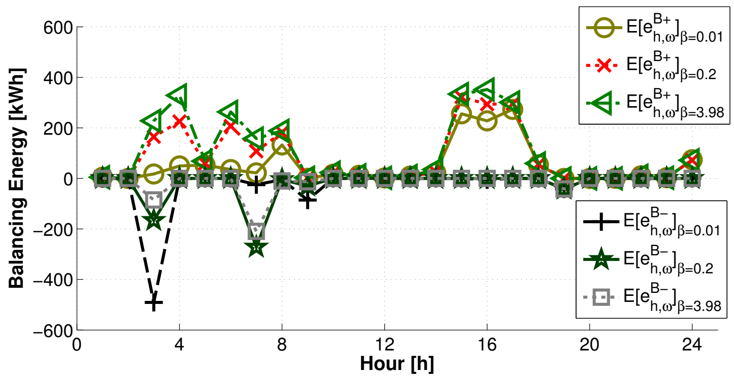


Figure 5.9: Changes in Positive and Negative Balancing Schedules

ing, because they are linking even more variables. Furthermore, if this was not modeled as a two-stage problem, the scenario reduction techniques provided by the SCENRED package could not be applied in the straight forward manner as it is now. Therefore, it seems fair to admit this important simplification as necessary and therefore acceptable.

5.1.1.7 Tractability and Scaling Limits of the Approach

Most bidding approaches proposed so far, including [130], schedule vehicles as an aggregate. Others, such as reference [72] however, do actually not schedule an aggregate but rather determine schedules for individual vehicles. The rationale for not representing vehicles individually is computational tractability [76]. It is therefore interesting to analyze the limits of the proposed approach and to see whether it could be applied larger fleets. The following paragraphs hence elaborate on the limits of computational tractability of the proposed approach.

Clearly, the advantages of detailed representation of individual vehicles comes at the cost of losing the ability to model very large fleets on the same machine at the same time. However, as mentioned in the future work paragraph of the conclusions, future work on decomposition techniques seems promising. And in general it is believed that both aggregate as well as individual vehicle formulations have their advantages.

Computational tractability is indeed an issue, which for the practical purpose of this thesis is understood as follows: the problem instance becomes intractable if it takes longer to solve it than its time horizon or any other system component, e.g. available memory, reaches its resource limit. Naturally, this time is determined by the machine or system of machines that the problem instance is solved on. Here, the tractability is is merely reported for the available 64-bit MS Windows© 2003 Server machine with 32 GB RAM and an Intel© Xeon™ E-5520 CPU clocked at 2.26 GHz. However, the evolution of computing power is difficult to predict. Especially, with the development of parallel, cloud computing services and their costs, it might be acceptable to acknowledge the possibility

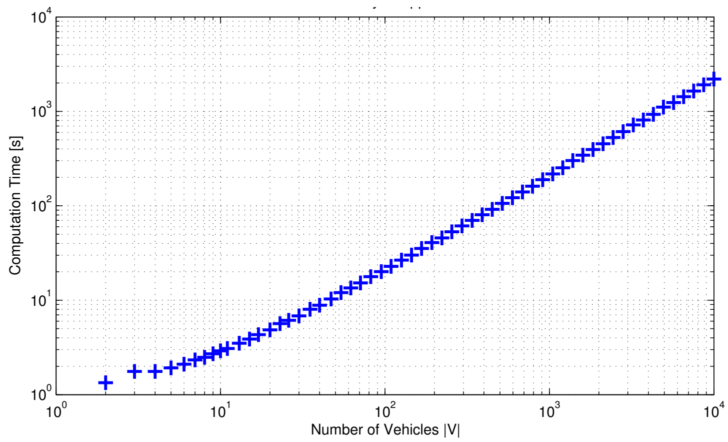


Figure 5.10: Tractability of the Stochastic DLC Model

of a dedicated PEV aggregator being able to solve very large instances of this problem to schedule PEVs individually approximately within the coming decade.

To estimate the limits of the proposed approach on the given machine, the mobility scenario generation algorithm was used to create two new tensors $\nu_{v,h,\omega}$ and $\rho_{v,h,\omega}$ in the dimensions of $|\mathcal{V}| \times |\mathcal{H}| \times |\Omega| = 10\,000 \times 24 \times 200$. All other inputs remaining the same, iterative GAMS calls from MatLab with the sub-problem only including the first j vehicles of $|\mathcal{V}|$, with $j = \{2, 3, 4...|\mathcal{V}|\}$ are solved and computation times recorded with `tic` and `toc` function commands. Fig. 5.10 illustrates the results of this analysis.

5.1.1.8 Remarks on Risk Management Under DLC

Via a stochastic linear programming approach, this case study has assessed sequential decision making by a PEV aggregator under uncertainty and risk aversion. With 1000 vehicles, 200 initial, and 100 reduced scenarios for market prices and mobility, the expected value of PEV flexibility under direct load control by the aggregator has been found to be substantial. It lies in the range of 33%. Furthermore, with the proposed methodology, the relationship of profits and the fleet aggregation size is derived, suggesting that with further disaggregation, the expected mean sub-fleet profits decrease considerably. These are likely due to decreasing forecasting errors and consequentially diminishing relative imbalance settlement penalties. This expected value of PEV aggregation has been found to lie in the range of 19% comparing the scheduling of 250 four-vehicle big sub-fleets with the scheduling of one fleet of 1000 vehicles.

The study finally points out that there might be a potential of and strategies for controlling risk via CVaR modeling. In the given case, the conditional value at risk can be approximately reduced from € 8.2 to € 6.1 decreasing the expected value of aggregator profit from € 16.9 to € 15.2 during a scheduling horizon of 24 hours. To avoid losses on the lower end of the profit distribution, the PEV aggregator reduces day-ahead positions and strongly increases positive balancing. Consistently, the negative balancing positions are slightly decreased. It must be noted that this observed shift of demand from the day-ahead to the balancing market is partly due to the assumption of perfect foresight in the second stage of the model. Nevertheless, this observation seems coherent with better forecasts of driving patterns in the operational stage.

Taking a broader policy perspective, the implications of these findings mainly concern electricity market design. The level of uncertainty involved in the self-scheduling of a PEV aggregator requires sequential trading floors for an efficient allocation of resources. These are existent today. Thus, the supposed decision-making framework seems adequate for such new electric power system agents to integrate successfully in this environment.

With the proposed methodology, conclusions concerning the viability of the assumed business model cannot be drawn, as they mainly depend on the exogenously set retail prices, ergo the customer's willingness to pay. While this case study suggests that the aggregator can achieve an expectation value of raw trading profit in the range of €-cent 1.5 to 1.7 per vehicle during the analyzed 24-hour horizon, it could just as well be much more or less than that. But assuming that this result is based result on good assumptions regarding the retail price, one can estimate the net present value of supplying an individual vehicle via DLC for the aggregator. Extrapolating the expected raw trading profit to annual terms yields € 6.16 per vehicle. Assuming perpetuity of the cash flows and a weighted average cost of capital for the aggregator of 10 % p.a. yields a net present value of € 61.69 per vehicle, or € 61 685 for the entire fleet with 1000 vehicles. Larger fleets, i.e. further aggregation should provide higher yields per vehicle.

Nevertheless, this first large-scale DLC case study has made it clear that a different type of modeling is necessary to make an improved assessment of the aggregator's business model, in which retail prices are set endogenously according to the final customer's price elasticity. The following case studies of Chapter 6 intend to tackle this by means of modeling indirect load control.

The case study presented in the following subsections is published in [147].

5.1.2 Illustrating the Importance of Uncertainty

Thus far, the large scale DLC case study has calculated results based on full nonanticipativity between the first-stage, here-and-now decision variables and the second-stage, wait-and-see variables. This second case study now intends to relax this assumption. It uses standard methodology to calculate well established stochastic programming quality metrics:

- the value of the stochastic solution (VSS) and
- the expected value of private information (EVPI) for the established PEV energy retail aggregator model.

Applied to a real medium voltage system with urban characteristics and realistic spatial PEV mobility, information with different precision levels of the mobility forecasts are included at the first-stage here and now decisions.

All this is carried out to justify the effort of analyzing the aggregator's decision making under uncertainty and further motivating the use of the stochastic programming approach. Therefore, this section analyzes whether or not it is even necessary to account for the uncertainty involved via the proposed scenario-based approach. It may be sufficient to merely schedule the charging of PEV according to expected values of the supposedly uncertain parameters, whether this provides unacceptable opportunity costs.

Please note, to distinguish between existing literature it is deemed important to mention that [70] analyzed the effect of certainty gained when trading in shorter term adjustment markets on wind power producers. Aligned with the findings for the first DLC case study, [70] shows that in principle, the closer to real time the producer can participate in markets, the better the forecast, i.e., yielding a smaller forecasting error, and therefore the more profitable because imbalance settlements are reduced. In this section containing the second DLC case study, however, a different approach is used to assess certainty gain. By including limited, indicative mobility forecasts as information at the first-stage here and now decisions, impacts on typical stochastic programming quality metrics can be observed. The standard methodology of calculating the VSS and EVPI is followed, before results are presented.

5.1.2.1 Quality Metrics in Stochastic Programming

To motivate the use of the stochastic programming framework [133, pp. 48-57,] including various sources of uncertainty [91], the following quality metrics are studied. Let z_{sto} be the value of the objective function with binding nonanticipativity constraints, then the following holds:

Expected Value of Perfect Information - EVPI The EVPI is a measure of how much would one be willing to spend for acquiring a perfect forecast:

$$z_{\text{EVPI}} = z_{\text{pf}} - z_{\text{sto}}, \tag{5.7}$$

where z_{pf} with perfect forecast stands for the objective function value with fully relaxed nonanticipativity constraints. It is a theoretical measure that helps quantify the importance of using a stochastic programming approach.

Value of the Stochastic Solution - VSS: The VSS is a measure of how much it would be worth to know the distribution of the stochastic inputs beyond their mere expectation value:

$$z_{\text{VSS}} = z_{\text{sto}} - z_{\text{det}}, \tag{5.8}$$

where z_{det} is the objective function value when first-stage decision variables are fixed at the optimal solution of the problem, in which stochastic inputs are replaced by expected values. A practical interpretation of this quality metric is that it represents the potential benefit from solving the stochastic program over solving a deterministic, i.e. a lot smaller and computationally less demanding, program in which expected values have replaced random parameters.

Since the aggregator's scheduling problem treats the maximization of profits, by definition $z_{\text{pf}} \geq z_{\text{sto}} \geq z_{\text{det}}$ and thus $z_{\text{EVPI}} \geq 0$, and $z_{\text{VSS}} \geq 0$.

5.1.2.2 Information Constraints

The mathematical formulation, as provided in Chapter 4 on the Developed Approach, includes a brief discussion of the common constraint alternatives for nonanticipativity (5.9) and offer-curves (5.10):

$$\forall h,\, \forall \omega, \omega' : \qquad e^{D,\underline{\vee}}_{h,\omega} = e^{D,\underline{\vee}}_{h,\omega'}, \qquad e^{D,\overline{\wedge}}_{h,\omega} = e^{D,\overline{\wedge}}_{h,\omega'}, \tag{5.9}$$

$$\forall h,\, \forall \omega, \omega', \left(\lambda^{D}_{h,\omega} \leq \lambda^{D}_{h,\omega'}\right) : \qquad e^{D,\overline{\wedge}}_{h,\omega} \leq e^{D,\overline{\wedge}}_{h,\omega'}, \qquad e^{D,\underline{\vee}}_{h,\omega'} \leq e^{D,\underline{\vee}}_{h,\omega}. \tag{5.10}$$

Note that offer-curves (5.10) are a relaxation of nonanticipativity constraints (5.9). Hence, when including both, (5.10) is overruled. When only including (5.10), the program has more knowledge available at the first-stage decision making, permitting it to distinguish between different day-ahead price scenarios.

Besides these common constraints and to gain further insights, one can construct further degrees of information available to the DLC scheduling aggregator, pertaining to information about other stochastic processes revealed only close to real time. This case study specifically analyzes the effects of including either one of the following constraints, pertaining to different aspects of the PEV mobility behavior.

$$\forall h,\, \forall \omega, \omega', \left(\sum_{v \in V} \nu_{v,h,\omega} = \sum_{v \in V} \nu_{v,h,\omega'} \right): \qquad e_{h,\omega}^{D,\underline{\vee}} = e_{h,\omega'}^{D,\underline{\vee}}, \qquad e_{h,\omega}^{D,\overline{\wedge}} = e_{h,\omega'}^{D,\overline{\wedge}}. \tag{5.11}$$

$$\forall h,\, \forall \omega, \omega', \left(\sum_{v \in V} \rho_{v,h,\omega} = \sum_{v \in V} \rho_{v,h,\omega'} \right): \qquad e_{h,\omega}^{D,\underline{\vee}} = e_{h,\omega'}^{D,\underline{\vee}}, \qquad e_{h,\omega}^{D,\overline{\wedge}} = e_{h,\omega'}^{D,\overline{\wedge}}. \tag{5.12}$$

By including one single constraint out of (5.11)-(5.12) per run, different levels of restrictions are applied to the decision making at the first stage of day-ahead market involvement. Since, (5.11) and (5.12) are each a relaxation of (5.9), it would be misleading to introduce the contraints progressively. On the contrary, it is important to test them each one at a time.

Equation (5.11) makes knowledge of an indicative mobility forecast available, in the form of $\nu_{v,h,\omega}$. Thus it would allow to distinguish between scenarios of high and low *unavailability*, measured by the connection and disconnection of each vehicle in the respective hours. And finally, (5.12) permits a perfect aggregated mobility forecast in the form of $\rho_{v,h,\omega}$. With the help of this forecast the program could distinguish between scenarios of high and low *unavailability* and *consumption*, measured by the SOC reductions during travel. The disconnection of each vehicle in the same hour would be implied automatically. This would leave the program only with second stage uncertainty regarding the balancing market prices.

5.1.2.3 Case Study Definition and Specific Input Data

Day-Ahead Market Price Scenarios The stylized day-ahead market price scenarios, constituted by three vectors of 24 hourly price elements are depicted in Fig. 5.11. Note that these are not generated by time series but manually constructed for illustration purposes. These are all following the same diurnal price profile with a high maximum price of approx. $\mathbb{E}\left\{\lambda^D\right\} + 20\%$ €/kWh occurring at night (21h), low minimum price of approx. $\mathbb{E}\left\{\lambda^D\right\} - 30\%$ €/kWh occurring during the early morning hours (3h), which can be regarded as representative for a typical market outcome in Spain.

Balancing Market Price Scenarios Presented in Fig. 5.12, the imbalance price settlements, ϱ_h^+ and ϱ_h^-, express the ratio of real-time price to each hourly day-ahead market price. There exist different probabilities to have increasing ($\pi_{B1} = 0.6$) or decreasing($\pi_{B2} = 0.4$) positive imbalance, and the amount of imbalance represented in the prices are time dependent.

Client Side Prices On the client side, the sales price component attributable to wholesale, excluding network tariff components, is $\gamma^{\underline{\vee}} = 0.065$ €/kWh. Again, discharging is turned off in the uni-directional case, hence $\gamma^{\overline{\wedge}}$ becomes irrelevant.

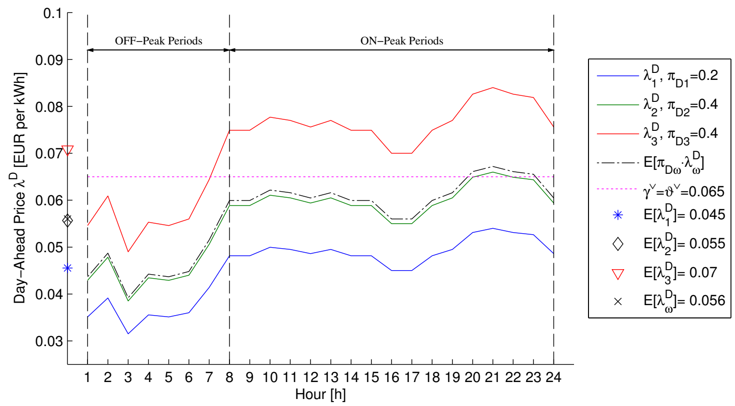


Figure 5.11: Scenarios of Day-Ahead Market Price Profiles

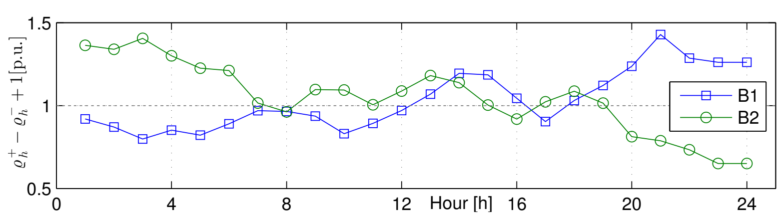


Figure 5.12: Scenarios of Balancing Market Price Profiles

Table 5.4: Mobility Sub-Scenario 1 - $\nu_{v,h,M1}$, $\rho_{v,h,M1}$, $\varphi_{v,\omega}$

Vehicles	7	8	9	10	11	12	13	14	15	16	17	18
1				**1.52**		**1.86**			**3.95**	**2.46**	**2.45**	
2		**3.95**	**1.44**					**3.95**	**3.95**	**0.1**	**1.68**	**2.26**
3		**0.95**	**2.45**						**2.14**			**2.86**
4	**2.26**				**2.45**						**2.68**	**2.22**
5		**2.14**		**2.95**		**2.14**						**2.22**

Hours $h \in \mathcal{H}$ [h]

Table 5.5: Mobility Sub-Scenario 2 - $\nu_{v,h,M2}$, $\rho_{v,h,M2}$, $\varphi_{v,\omega}$

Vehicles	7	8	9	10	11	12	13	14	15	16	17	18
1												
2	**2.95**	**2.68**					**2.14**			**2.14**		
3												
4												
5												

Hours $h \in \mathcal{H}$ [h]

Table 5.6: Mobility Sub-Scenario 3 - $\nu_{v,h,M3}$, $\rho_{v,h,M3}$, $\varphi_{v,\omega}$

Vehicles	7	8	9	10	11	12	13	14	15	16	17	18
1				**0.52**		**0.86**			**3.95**	**0.46**	**0.45**	
2		**3.95**	**0.44**					**3.95**	**3.95**	**0.1**	**0.68**	**0.26**
3		**0.95**	**0.45**						**0.14**			**0.86**
4	**0.26**				**0.45**						**0.68**	**0.22**
5		**0.14**		**0.95**		**0.14**						**0.22**

Hours $h \in \mathcal{H}$ [h]

Table 5.7: Mobility Sub-Scenario 4 - $\nu_{v,h,M4}$, $\rho_{v,h,M4}$, $\varphi_{v,\omega}$

Vehicles	7	8	9	10	11	12	13	14	15	16	17	18
1												
2	**0.95**	**0.68**					**0.14**			**0.14**		
3												
4												
5												

Hours $h \in \mathcal{H}$ [h]

Table 5.8: PEV Fleet Characteristics [23], [145]

Parameter	PEV	Units
Available Battery Capacity $\overline{E}_v$	12	[kWh]
Dis-, Charging efficiency $\eta^{\wedge} = \eta^{\vee}$	0.93	[p.u.]
Initial SOC ι_v^{SOC}	8	[kWh]
Final SOC ϕ_v^{SOC}	8	[kWh]

PEV Data - Unavailability Scenarios Suppose a small fleet of 5 vehicles, which are made up of PHEVs only, whose characteristics are mainly based on [64], [145], are shown in Tab. 5.8.

The PEV mobility sub-scenarios M1, M2, M3 and M4 are equiprobable ($\pi_{M1..4} = 0.25$). The numerical data specifying this mobility is depicted in Tab. 5.4, 5.5, 5.6 and 5.7, which show $\varphi_{v,\omega}$, as well as $\nu_{v,h,\omega}$ overlaying $\rho_{v,h,\omega}$. For the sake of readability, empty columns 1-6 and 19-24 are not shown, however, dark shaded cells indicate disconnection and unavailability $\nu_{v,h,\omega}$, while the numbers inside the cells show the consumption $\rho_{v,h,\omega}$. Paying close attention to the details, it can be observed that the stylized mobility is constructed such that M1 and M3 represent the same high unavailability, while M2 and M4 show very high availability. Furthermore, the following holds:

$$\forall v, h: \qquad \nu_{v,h,M1} = \nu_{v,h,M3} \geq \nu_{v,h,M2} = \nu_{v,h,M4}. \tag{5.13}$$

Further differentiation within the subgroups of even and uneven mobility sub-scenarios is given by the amount of traveling or energy consumption:

$$\forall v, h: \qquad \rho_{v,h,M1} \geq \rho_{v,h,M3} \quad \text{and} \quad \rho_{v,h,M2} \geq \rho_{v,h,M4}. \tag{5.14}$$

The final set of scenarios could take the shape of different possible combinations. The detailed composition of the scenarios and their sub-scenarios, together with probabilities can be accessed in the supplemental material of Fig. D.5.

Vehicle Location and Network Pricing This case study also makes assumptions about vehicle location and network pricing. However, since it is not the focus of this case study and the same assumptions are made in the next case study, they are not detailed here. For further information please refer to the subsequent case study on charging with network use-of-system tariffs.

5.1.2.4 Anticipativity in Optimization Runs

All calculations were performed running MatLab© for handling input and output data. For comparison, the optimization problem was formulated and

Table 5.9: Case Study Problem Summary

Run	Obj. Fn. [€]	CPU Time [s]	Total Iterations	Equations	Non-Zeros	Real Variables
Base Run	0.59 80 15	0.343	1866	152 137	554 041	106 536
Run 1A	0.52 37 77	0.359	2036	178 633	607 033	106 536
Run 2A	0.52 37 78	0.328	2047	169 417	588 601	106 536
Run 1B	0.53 25 84	0.328	2018	172 297	594 361	106 536
Run 2B	0.53 28 82	0.343	2039	169 705	589 177	106 536

Table 5.10: Results: Stochastic Programming Metrics

Run	EVPI [€]	EVPI [%]	VSS [€]	VSS [%]
Run 1A	0.07 42 38	14.17	0.03 268	6.24
Run 2A	0.07 42 37	14.17	0.03 269	6.24
Run 1B	0.06 54 31	12.29	0.04 149	7.79
Run 2B	0.06 51 33	12.22	0.04 179	7.84

solved in GAMS© Build 24.0.1 employing the CPLEX™ 12.5.0 solver on a 64-bit MS Windows©7 machine with 8.00 GB RAM and an Intel© Core™ i7-3770 CPU clocked at 3.4 GHz.

To calculate the quality metrics introduced above, the simulation procedure consists of five runs with the following characteristics. The unconstrained base case does not take into account any of the information restrictions for stochastic programming, it is therefore equivalent to determining z_{pf}, i.e., the objective function value with perfect forecast. The four remaining runs are then including different information constraints as follows:

RUN 1A *Full Nonanticipativity:* all nonanticipativity constraints are fully binding. Hence, in the first stage decision for each hour, the program cannot differentiate between different scenarios. Hence, only one optimal energy quantity for the day-ahead market schedule is found. Only information constraint (5.9) is binding.

RUN 2A *Full Offer-curve Constraints*: the nonanticipativity constraints are relaxed to find multiple day-ahead pairs of price and optimal energy quantity. Only information constraint (5.10) is binding.

RUN 1B *Nonanticipativity but with Indicative Mobility Forecast:* similar to Run 3, but with aggregated information about $\alpha_{v,h,\omega}$ vehicle availability. It is not known how much is consumed in each hour. Only information constraint (5.11) is binding.

RUN 1B *Nonanticipativity but with Detailed Mobility Forecast on Hourly Consumption of each Vehicle:* similar to Run 4, but with perfect aggregated mobility forecast including both availability and consumption. Only information constraint (5.12) is binding.

Runs 1A and 2A take day-ahead market prices as the basis of information, while Runs 1B and 2B take data on PEV mobility as the basis of information.

5.1.2.5 Results

As a problem summary, Tab. 5.9 gives an overview of the case study results and shows the size of the problem in the different runs. On a high level valid for all runs, it can be observed that the problem is solved in very little time, i.e. roughly one third of a second. This is expected as the fleet of vehicles is very small and the problem is purely linear. Solver iterations do not significantly surpass the 2 000 mark. Furthermore, the linear characteristic of the formulation accords with the absence of any binary and integer variables. However, since wait-and-see decisions for state-of charge as well as charging and discharging are represented on a detailed vehicle basis, the amount of real variables, with ca. 100 000, is rather high for such a small case study. Adding to the problem of dimensionality is the inclusion of distribution network use-of-system prices for each node.

Furthermore the results regarding the stochastic programming quality metrics can be accessed in Tab. 5.10, where for all the runs, EVPI and VSS are listed. The detailed analysis in for the specific cases follows underneath.

The base run sets the benchmark to the result of which all following runs are measured against. The optimal objective function value is found at 0.59 80 15. Since it is the least constraint of all runs, it exhibits the smallest problem instance in terms of solver iterations, equations and non-zeros. There are no indications for the quality metrics, as the base run is needed to be the reference for computing the VSS and EVPI values of the other runs to follow.

Full Nonanticipativity Run 1 comes along with the biggest problem instance (178 633 equations and 607 033 non-zeros) compared to all others. It stands for the typical two-stage stochastic problem formulation in which no information about future outcomes are available at the first stage. Because the feasible region is so constraint, it shows the lowest objective function value with 0.52 37 77. It has hence an EVPI of 0.07 42 38, which - put in relation to the base run optimum of the objective function - amounts to a 14.17%. The VSS is similarly significant with 0.03 268 and 6.24%, respectively.

These results give rise to the main finding of this study: both quality metrics indicate an advantage of using the stochastic programming for the given problem. This suggests that with the combined uncertainty of market prices and fleet mobility, finding optimal day-ahead market schedules can justifiably be done well with the stochastic programming framework used in this thesis.

Full Offer-Curve Constraints Run 2 shows very little difference to the previous one. It appears that even though problem size decreases eminently, the solution shows almost no improvements at an objective function value of 0.52 37 78. Hence, EVPI and VSS are the same as in Run 1. The reason for this is assumed to lie in the structure of the day-ahead price scenarios and the aggregated availability and consumption of the vehicles. Since all three day-ahead sub-scenarios follow the same price profile only at different levels, the cost signals giving preference to one hour over another are the same. Also, each day-ahead market sub-scenario has the same sub-branches of mobility and balancing uncertainty, thus making it unprofitable to distinguish between price levels.

Nonanticipativity with Indicative Mobility Forecast Run 4 takes second rank in terms of constraints and non-zeros. Accordingly the objective function value amounts to 0.53 25 84, which implies an EVPI of 0.06 54 31, 12.29% respectively. Here the program is allowed to find a schedule that also alternates with the scenario counter. This means that in the given set up it is valuable to know whether there is more or less travel. This is even true although for instance consumption values still differ very much among scenarios with same travel. Thus it is possible to distinguish between scenarios of different unavailability, even though the amount of consumption that lies behind this disconnection is unknown to the program. The VSS of 0.04 149 or 7.79% still suggests that scheduling according to expected values of involved stochastic processes would lead to a significantly worse outcome.

Nonanticipativity with Detailed Mobility Forecast on Hourly Consumption of each Vehicle Finally, Run 5 resolves the uncertainty regarding mobility, which leads to a slightly better result than the previous run with the objective function value at optimum 0.53 28 82, which implies an EVPI of 0.06 54 31, 12.22%. The VSS of 0.04 179 or 7.84% still suggests that scheduling according to expected values of involved stochastic processes would lead to a significantly worse outcome.

5.1.2.6 Summarizing Notes: Uncertainty Matters

This section has provided a methodology how to assess the effect of different mobility forecasts for stochastic charge scheduling of aggregated PEV fleets. It was applied to a case with a very small fleet but this permits to easily follow the hourly implications for individual vehicles in detail. Different information constraints were used to show the impact on optimal scheduling and operational decisions for a retailer executing transactions in two consecutive markets under uncertainty in inputs regarding market prices and mobility.

The computation of typical quality metrics of stochastic programming, i.e., the expected value of perfect information and the value of the stochastic solution, has intended to quantify the above named effects of different information included at the first-stage scheduling. Furthermore, it has shed light on implications for the different sources of uncertainty: day ahead market prices, mobility, i.e., availability and consumption. Overall, the results are well aligned with the observed tendency in literature to account for uncertainty and support the use of stochastic optimization frameworks.

5.2 Coordinating PEVs for Efficient Network Use

*The following case study has been published in **[91]**.*

Electricity market signals are deemed efficient to allocate resources at the transmission system level, yet they may not always sufficiently represent the local network status of the distribution system. The illustrative case study in Chapter 2 has shown that high penetration levels of PEV may cause network reinforcement, which would have an impact on investment, operation and maintenance costs of the infrastructures. However, while long run marginal cost (LRMC) pricing for computing node dependent network UoS tariffs has been proposed for integrating distributed generation, it remains unexplored in the context of PEV charging.

Hence, this section as it applies the PEV energy retail problem with interactions in day-ahead and balancing markets from the aggregator's perspective, taking into account location dependent network UoS tariffs in the form of network capacity charges for peak demand.

In the DLC case, the retail tariff for the final customer is supposed fixed in the medium term, and these capacity charges are accounted as costs to the aggregator. By aligning the PEV charging schedule, in time and location, to the network signals, the aggregator can hence further minimize its perceived costs. Applied to a medium voltage system with urban characteristics and spatial PEV mobility, profit optimal charging schedules for the aggregator are found.

5.2.1 Pricing Network Capacity with DSO's LRMC

As it has been discussed in earlier sections, the operational operational challenge of a PEV Aggregator presents a combination of the multiple problems that are well known in electric power systems research: In particular it is similar to that of an electricity retailer [67], sometimes also referred to as supplier or marketer, and a large consumer with potential on-site generation [68]. If feeding back energy to the system is considered, too, the PEV retail problem shares characteristics with wind power producers [70], conventional power producers under resource unavailability [69], [135], as well as with energy storage system operators[71].

However, as it has been shown in the preceding case study, see Tab. 2.3, at the distribution level of electricity grids, the connection of high penetration levels of PEV potentially cause network reinforcements. This would have an impact on investment levels of DSOs and raise network operation and maintenance costs. For integrating distributed generation, long run marginal cost pricing for computing node dependent network UoS tariffs has been proposed [89], [90], but in the context of PEV charging this remains unexplored.

Assuming some degree of centralized control by an aggregation agent, the scheduling of charging PEV presumably provides high degrees of flexibility in terms of timing and location of the charging. Therefore, constrained by its unavailability due to driving and subsequent re-connection, the charging schedule of such a fleet of PEVs could efficiently react to a combination of market signals with UoS tariffs to avoid temporal simultaneity and local coincidence of charge [23].

Therefore, in the following case study, a model for optimal operational decisions of a PEV aggregator in the short-term is applied to a very specific set of numerical data. The objective is to analyze, how electricity price uncertainty and mobility-caused unavailability of the fleet in different locations affect the optimal market involvement and profit functions of this new agent when node dependent network UoS tariffs are considered.

Due to the above named characteristics, the coordination of charging a fleet of electric vehicles is an interesting topic as such, however it becomes even more challenging to see how both electricity market as well as network signals influence optimal outcomes. The proposed stochastic optimization methodology accounting for uncertainty of prices as well as fleet mobility is put into practice. The stylized case study is carried out to emphasize the value of the proposed model and its functionality.

5.2.1.1 Network Data of an Urban MV Feeder

For illustration purposes the same network as presented in [89] is chosen. Please see Fig. 5.13 for a graphical representation of the single MV feeder in an urban environment with the following characteristics: 17 load nodes with a total demand of 4 MW and 1 MVar, of which only the active part is considered here; all nodes have residential customers attached except for node $n = 1$ which is dominated by a commercial customer's load profile. The resulting node specific network UoS prices can be found in Tab. 5.11, taken from [89]. However, the original prices were divided by 5 (10) for the ON (OFF) -peak $C^{UoS}_{n,h\in\mathcal{H}^{on}}$ ($C^{UoS}_{n,h\in\mathcal{H}^{on}}$) period to account for the shorter time horizon of one day, making total market and grid prices approx. equal in magnitude. Also, for simplicity, all nodes are supposed to have a medium charging option, with connection capacity $\overline{P}_n$=7.2 kW. This is not withstanding the fact that in general the total capacity connected at each node is much larger than $\overline{P}_n$.

5.2.1.2 Stylized Day-Ahead and Balancing Prices

Many of the following parameters are shared with the previous case study in 5.1.2. Therefore, some references to illustrative tables and figures are pointing back to the previous section to avoid redundancy. Nevertheless, the text details all the necessary data.

Day-Ahead Market Price Scenarios The stylized day-ahead market price scenarios stay the same as before, constituted by three vectors of 24 hourly price elements are depicted in Fig. 5.11. Note that these are not generated by time series but manually constructed for illustration purposes. These are all

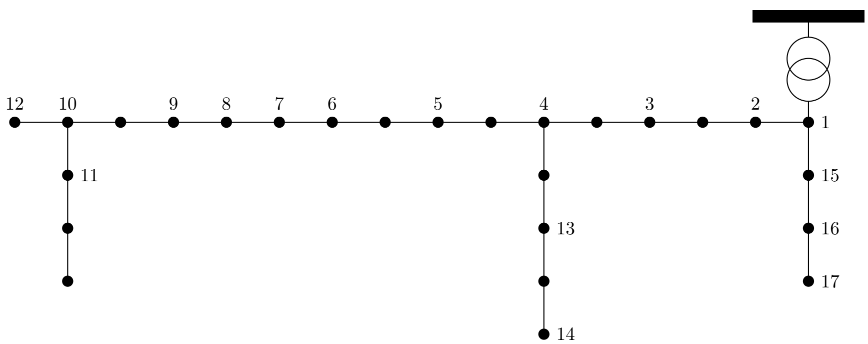


Figure 5.13: Network Topology of Urban MV Feeder as in [89]

Table 5.11: Network UoS Tariffs as Prices Related to the Used Capacity

Node n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
$C^{UoS}_{n,h\in\mathcal{H}^{on}}$ [€/kW$_{\text{max per day}}$]	0.388	0.438	0.470	0.504	0.536	0.556	0.586	0.602	0.616
$C^{UoS}_{n,h\in\mathcal{H}^{off}}$ [€/kW$_{\text{max per day}}$]	0.194	0.219	0.235	0.252	0.268	0.278	0.293	0.301	0.308

Node n	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
$C^{UoS}_{n,h\in\mathcal{H}^{on}}$ [€/kW$_{\text{max per day}}$]	0.640	0.678	0.618	0.522	0.532	0.514	0.538	0.624
$C^{UoS}_{n,h\in\mathcal{H}^{off}}$ [€/kW$_{\text{max per day}}$]	0.320	0.339	0.309	0.261	0.266	0.257	0.269	0.312

Table 5.12: Balancing Market Price Scenarios

Sub-Scenario # ω	**Probability** π_ω	ϱ_h^+	ϱ_h^-
B1	0.6	1.2	1
B2	0.4	1	0.9

following the same diurnal price profile with a high maximum price of approx. $\mathbb{E}\left\{\lambda^D\right\} + 20\%$ €/kWh occurring at night (21h), low minimum price of approx. $\mathbb{E}\left\{\lambda^D\right\} - 30\%$ €/kWh occurring during the early morning hours (3h), which can be regarded as representative for a typical market outcome in Spain.

Balancing Market Price Scenarios Unlike in the previous case study of section 5.1.2, suppose for simplicity that the balancing market outcome vectors $\varrho_h^+ = \lambda_h^+/\lambda_h^D$ and $\varrho_h^- = \lambda_h^-/\lambda_h^D$, can for all hours h conveniently be reduced to one scalar each for positive and negative deviation as depicted in Tab. 5.12. That is, for each hour, the system has the same probability ($\pi_{B1} = 0.6$) to deviate positively and the same to deviate negatively ($\pi_{B2} = 0.4$). In expectation terms, the system will deviate positively (supposed systematic imbalance) and the expected ratio of day ahead to balancing price is $\mathbb{E}\left[\varrho_{h,\omega}\right] = 1.075$, hence the expected absolute balancing price is $\mathbb{E}\left[\lambda_{h,\omega}^+\right] = 0.0602$.

Client Side Prices and Network Cost under DLC Because of the change in assumption for the balancing market prices, on the client side, the sales price component attributable to wholesale, excluding the tariff components related to using the network is now $\gamma^{\underline{\vee}} = 0.058$ €/kWh. The per energy unit basis component representing the network use-of-system prices $\vartheta^{\underline{\vee}} = \gamma^{\underline{\vee}} = 0.058$ €/kWh is set such that both components make up the same amount in the final customer bill.

The main assumption is that under DLC, the final customers are giving up control and therefore should not be held responsible for the timing of the charge. Therefore, the aggregator translates the capacity based network UoS charges into a flat rate volumetric energy component in the final bill of the customers. The aggregator therefore has a given revenue per energy supplied and optimizes its cost according to its use of the network. The final customers, given the flat rate energy component, are indifferent to the timing of the PEV charging, as long as their energy requirements are fulfilled.

Again, charging is turned off, hence $\gamma^{\overline{\wedge}}$ becomes irrelevant.

5.2.1.3 Characteristics of a Small PEV Fleet

Unavailability Scenarios The same small fleet of 5 vehicles is supposed. The unavailability and consumption patterns are the same as in Tab. 5.4 and Tab. 5.5, which show $\alpha_{v,h,\omega}$ and $\rho_{v,h,\omega}$, i.e., mobility sub-scenarios M1 and M2. These are equiprobable and hence occur both with a chance of 50%. Regardless

Table 5.13: Vehicle Home Nodes

Vehicle v	1	2	3	4	5
Home node n	17	11	4	10	14

of the scenario, the target SOC is higher than the initial SOC forcing the same net energy exchange over the course of the day for all vehicles. That is, initial as well as target SOCs are, in both mobility sub-scenarios at $\iota_v^{SOC} = 2$ kWh and $\phi_v^{SOC} = 4$ kWh, respectively.

Vehicle Location Vehicles have home nodes, to which they connect when available for charging. These are $n = (17, 11, 4, 10, 14)$ for $v = (1, 2, 3, 4, 5)$. These can be found in Tab. 5.13. In general, vehicles always connect to the home node, however the case study includes a variation (Run 3), for which in certain hours connected vehicles are located at node $n = 1$, being a charging station located on the premises of a commercial building. For simplicity these hours include all time of availability between first and last trip of the day.

5.2.1.4 PEV Charging with Market and Grid Signals

The results section has a two-fold objective. On the one hand, the model functionality is demonstrated, and on the other hand, the impact of network capacity charges on the profit optimal charging schedule is shown.

All calculations were performed running MatLab© for handling input and output data. For comparison, the optimization problem was formulated and solved in GAMS© Build 24.0.1 employing the CPLEX™ 12.5.0 solver on a 64-bit MS Windows©7 machine with 8.00 GB RAM and an Intel© Core™ i7-3770 CPU clocked at 3.4 GHz.

Simulation Procedure With the model defined in equations (4.1), (4.2), (4.6)-(4.10), (4.16), (4.17) and (4.19), the simulation procedure consists of three runs with the following characteristics. Run 1 - *Market Signals Only*: all constraints and variables concerning network UoS are excluded such that only the market signals determine the charging schedule, and hence $\kappa_\omega^{UoS} = 0$. Run 2 - *Alignment in time*: network constraints are considered as well as network charges, $\kappa_\omega^{UoS} > 0$. Run 3 - *Alignment by node*: ceteris paribus all vehicles departing from home are available at node 1 for charging during the day, i.e. between first and last trip, hence Run 3 is given through a varied vehicle-to-location incidence cube $\mathbf{A^n}_{v,h,\omega}$, not as an explicit constraint.

Charging Governed by Market Signals Only Fig. 5.14 illustrates profits in different markets and scenarios for Run 1, in which all network related constraints are yet inactive.

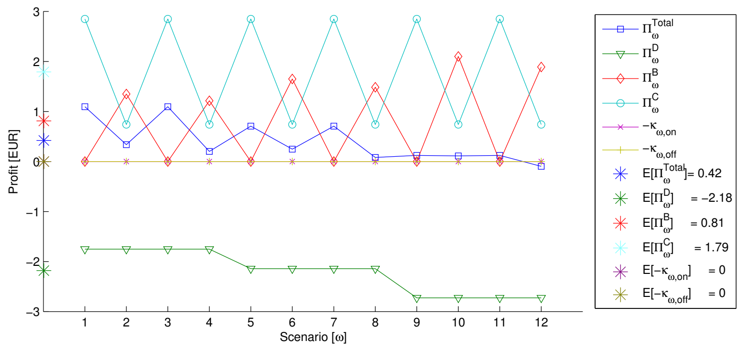


Figure 5.14: Run 1: Scenario Profits with Market Signals Only

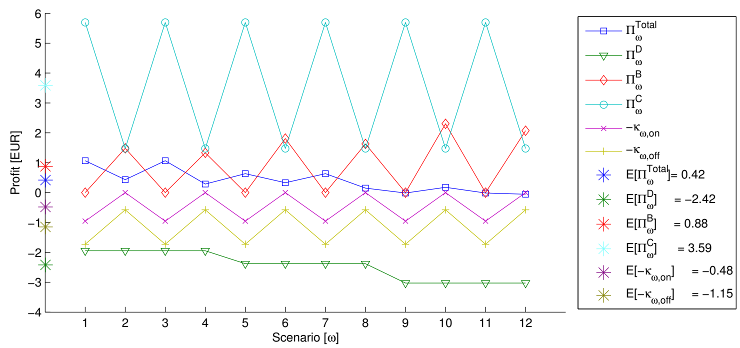


Figure 5.15: Run 2: Scenario Profits with Grid Signals

Day-ahead profit curve Π_ω^D: the nonanticipativity constraints (4.8) ensure that day-ahead market bids are coming in three different batches only. The involvement results in a negative profit because only buying positions are permitted with uni-directional charging, i.e. no discharging. With increasing scenario number, day-ahead prices become more expensive, thus resulting in higher costs.

Balancing profits Π_ω^B are alternating with the scenario number. Even scenarios with low mobility result in a positive profit, because sales are driven by negative balancing positions to get rid of the day-ahead energy which was scheduled for higher mean demand. Scenarios with odd numbers (high mobility) result in zero balancing requirement, because demand equals the day-ahead schedule. With an increase in scenario number, the differences between zero involvement and profits become greater as the net balancing prices are rising.

Client side revenues Π_ω^C are alternating with the scenario numbers because with a flat energy tariff they are merely driven by sales volume, which is determined by the mobility scenarios (high mobility equals high demand and vice versa). Costs for network use, both for ON- $\kappa_{\omega,on}^{UoS}$ and OFF-peak periods $\kappa_{\omega,on}^{UoS}$, are yet zero as they are turned off in Run 1.

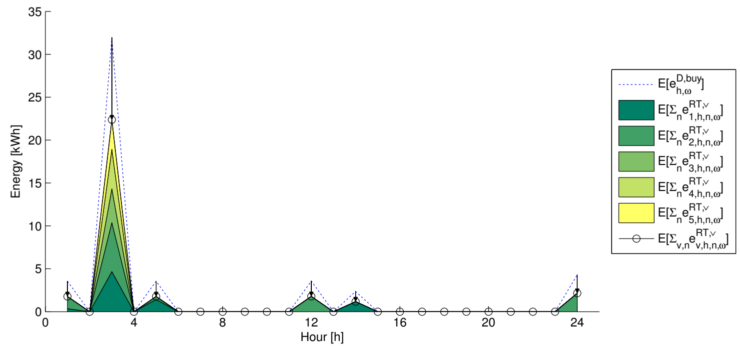


Figure 5.16: Run 1: Expected D and RT Charging, Market Signals Only

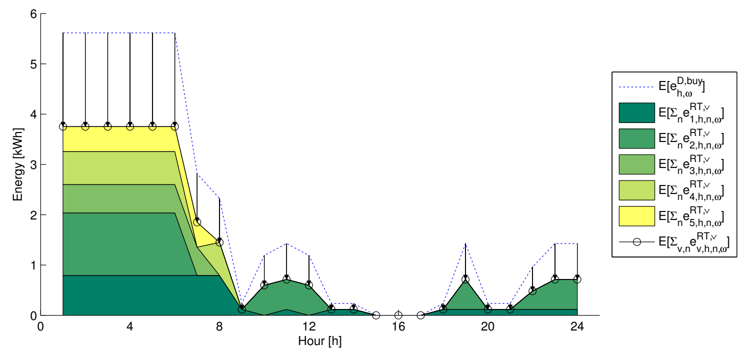


Figure 5.17: Run 2: Expected D and RT Charging with Grid Signals

Fig. 5.16 shows the individual and aggregated charging schedule of the PEVs with only market signals governing the optimal outcome. The expected charging $e^{D,\underline{\vee}}_{h,\omega}$ is aligned with the day-ahead λ^D (as well as balancing) market price profiles λ^B shown in Fig. 5.12. On an aggregated fleet level, the optimal charging occurs mainly in hours 1, 3, 5, 12, 14 and 24, which represent the signals provided by the market prices (local minima in diurnal price profile). The highest expected fleet consumption at $h = 3$ reaches up to 32 kWh in the day-ahead schedule (dashed line) and approx. 23 kWh including expected balancing and fleet mobility (solid line with circle marker). Underneath, lies a stacked area, which indicates the expected individual vehicle charging quantities for all hours of the optimization horizon.

Fig. 5.18 presents the expected battery SOC for each vehicle $v \in \mathcal{V}$, consistent with the individual mobility schedules, i.e., availability and energy demand, indicated in Tab. 5.4 and 5.5. The expected SOC shows how the energy contained in the batteries $e^{SOC}_{v,h,\omega}$ evolves over time even though the total energy exchange (set by ι^{SOC}_v and ϕ^{SOC}_v) is equal for all the vehicles. It can be observed that charging occurs rather abruptly at once.

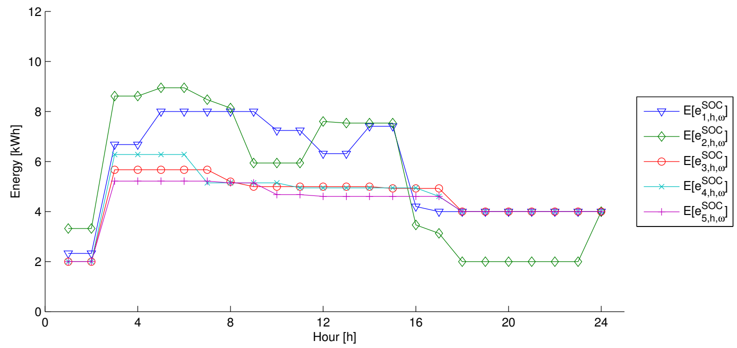


Figure 5.18: Run 1: Expected Battery State of Charge, Market Signals Only

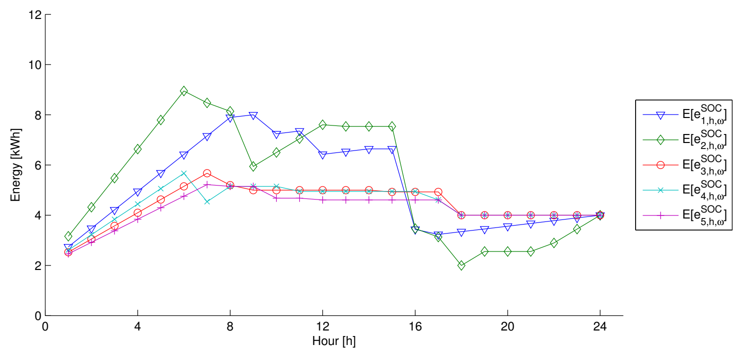


Figure 5.19: Run 2: Expected Battery State of Charge with Grid Signals

Charging with Grid Signals Fig. 5.15, 5.17 and 5.19 summarize the results of Run 2, where the objective function of the aggregator includes network signals in the form of capacity prices. Even though parameters C_n^{UoS} and $\vartheta^{\underline{\vee}}$ have been chosen such that the net expected profit remains unchanged (higher procurement costs day-ahead and additional network payments are compensated by the profits on the retail, client side), the network signals are taken into account and affect the outcome. In contrast to Run 1 a massive peak reduction is achieved, very likely alleviating punctual network saturation. In order to observe the substantial difference, please note the difference in scale between 5.17 and 5.16. Now, with network signals, the highest expected fleet consumption at $h = 3$ merely reaches approx. 5.6 kWh in the day-ahead schedule (dashed line) and approx. 3.8 kWh in real time. Effectively demand is spread out over time according to the two-step tariff of ON-peak and Off-peak hours. Hence, with grid signals the SOC changes from charging evolve much smoother over time.

Alignment by Network Node Fig. 5.20 compares the expected total charging per node for Run 2 and 3. It can be observed that in Run 2 all charging occurs at home nodes $n \in \{4, 10, 11, 14, 17\}$. In Run 3 on the other hand,

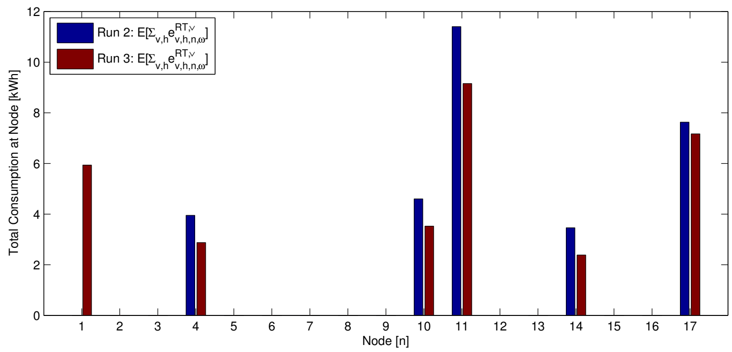


Figure 5.20: Expected Total Charging per Node

with the opportunity to charge at the node of the commercial center with lower network capacity charges prices for using the network, part of the charging is displaced to node $n = 1$.

The expected total profits do not increase significantly. On the contrary, the objective function slightly decreases by 7.14% to $\mathbb{E}\left[\Pi_\omega^{Total}\right] = 0.39$ because of higher network costs κ^{UoS}. This is because part of the charging still has to occur after the last trip at the home node. And since use $u_{n,\omega}$ is determined by maximum consumption, the difference in network prices $C^{UoS}_{n,h\in\mathcal{H}^{on}}$ between home node and commercial center does not offset the additional cost for using the extra node. However, if e.g. $\iota_v^{SOC} = \phi_v^{SOC} = 2$ and $\gamma^{\vee}_{-} = \vartheta^{\vee}_{-} = .064$, $\mathbb{E}\left[\Pi_\omega^{Total}\right]$ increases by 11.8% from 0.3998 in Run 2 to 0.4471 in Run 3.

In summary the network UoS charges seem to provide the right signals incentivizing the program to take into account time-of-use as well as location. With the given mobility, locational alignment of the charging can be observed at those nodes with more favorable capacity prices depending on target SOC and mobility need.

Problem Size Tab. 5.14 shows the size of the problem with and without network constraints. Accounting for network node specific capacity prices may cause increased complexity however computation time remains manageable in its purely linear nature.

5.2.2 Temporal and Spatial PEV Charging Alignment

This section has presented a case study of the retail problem of a PEV aggregator interacting with electricity markets as well as incorporating network prices. The demonstrated approach respects the unbundling of competitive retail and network operation of monopolist infrastructures. Serving as an optimization tool for accurate estimation of economic impacts, it uses well-known linear solving technology. In addition, realistic operational decisions for a retailer executing transactions in two consecutive markets are represented in the proposed model

Table 5.14: Case Study Problem Summary

	Run 1: Market Signals Only	Run 2: With Grid Signals
Obj. Fn. Value	0.418	0.418
CPU Time	0.093 s	0.172 s
Total Iterations	583	1 753
Equations	30 349	79 333
Non-Zeros	184 789	283 549
Real Variables	52 452	53 268
Binary Variables	0	0
Integer Variables	0	0

formulation. In addition, with the stochastic programming approach, uncertainty in the inputs regarding market prices and mobility can be accounted for.

The presented case allows for observing implications on optimal scheduling. Furthermore, the results have pointed at the fact that network capacity charges are an efficient instrument to account for local network situations in the charging schedules. The program schedules the PEV charging, both in alignment with time and by network node location, while maximizing the aggregator's profits.

Chapter 6

PEV Coordination with ILC

Similar in structure and function to the preceding chapter, via a set of carefully-selected, complementary case studies, this chapter applies the model for indirect load control and computes numerical results for further analysis.

6.1 PEV Coordination for ILC Market Participation

The following case study is published in [148].

6.1.1 The Shift Towards Distributed Decision Making

Before introducing the case study, the interested reader is referred to the appendix Chapter C, which provides a qualitative discussion of ILC versus DLC. To give an additional motivation for the case study, it seems pertinent to gain insights, how different charging algorithms can be classified in terms of their need for infrastructure and protocols. Are the proposed optimization problems feasible or could communication be a barrier to the realization of these? A priori, it seems reasonable to state the hypothesis that there are to some extent conceptual similarities between the PEV charging and other back-end communication needs in smart grid, see subsection 2.4.3.

6.1.1.1 Retail Alternatives of the Aggregator

The simulations carried out for the case study have a two-fold purpose. On the one hand, the case study presents the advantages of the proposed bi-level methodology in which the UL and LL have influence on each other as opposed to single agent decision making. Hence the procedures emphasize the differences between these two categorically different approaches. On the other hand, the case study compares different tariff alternatives of the aggregator. Hence the data used is given and the simulation procedure carried out has the following structure.

Retail Tariff Alternatives to the PEV Aggregator This analysis turns to the different aspects of reselling energy by looking at three alternative pricing schemes of the aggregator to the final customer, i.e. the PEV: dynamic hourly pricing, time-of-use tariff and a flat energy rate. In theory, under profit maximization it is of high interest to the aggregator to obtain a very flexible demand which can be scheduled according to varying market prices. The degree of competition will determine the benefit that the aggregator will pass on to the final customer by offering lower prices in resale to the final customers. The more flexible the tariff the more freedom to reflect the actual opportunity cost of the customers more appropriately and pass on part of the risk exposure to the final customers.

The electricity customer always reacts to the final price that he perceives. Beside the energy retail it is composed of net access fees, concession levies, apportionment from feed in tariffs for renewable energy and sales tax. These are all subject to country-specific regulation and, most importantly, not alterable by the PEVSA in its function of a retailer. Hence, the following schemes merely refer to the wholesale price plus the commercialization margin by the aggregator:

a. Dynamic Hourly Pricing

Under dynamic hourly pricing, the customer has access to hourly varying final customer prices according to the finalization of the day-ahead wholesale energy market price. In this case the aggregator would buy energy in the day-ahead market passing on the uncertainty stemming from market volatility by calculating a margin as a fix premium or a proportion of the final price while the electric vehicle as a final customer would be taking the decision of charge. Then, to the aggregator there still remains uncertainty from forecasting the timing and amount of consumption of the vehicles in order to minimize transaction in more costly balancing markets.

b. Time-of-Use Pricing

Under a time-of-use tariff, the customer is offered a flat rate for sub-intervals of the day, assuming that the vehicle does not give up any control over the charging process to the aggregator. The ex-ante calculation of the resale prices for these periods has to take into account a two-fold purchase risk for the time of their duration: volatility for the day-ahead market spot prices as well as the demand uncertainty and the arising costs of trading in balancing markets.

c. Flat Energy Rate

Flat energy rates are to date a very common final customer end price and basically constitute a single period version of the time-of-use pricing.

Depending on the tariff scheme, the arbitrage potential for the aggregator may vary. The following graphic presents the potential arbitrage for an aggregator on a typical day by visualizing the difference between set tariffs and wholesale market price.

As introduced in the mathematical formulation and outlined once again con-

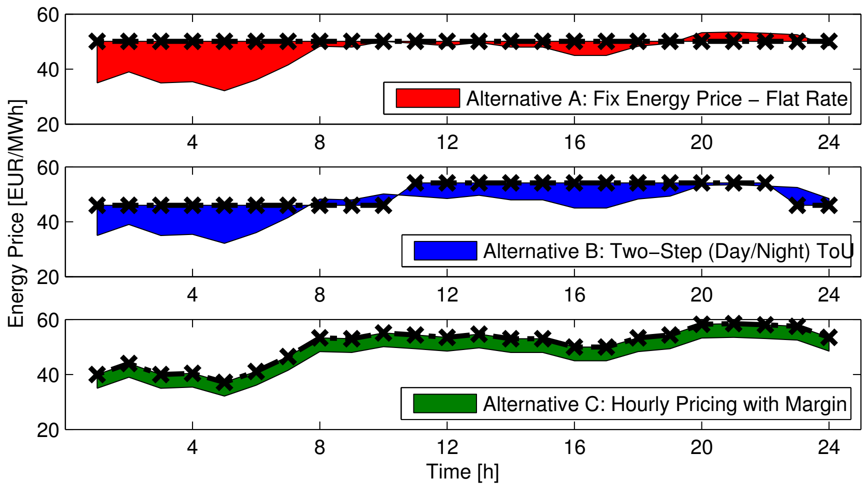


Figure 6.1: PEV Aggregators' Retail Tariff Alternatives

ceptually above, the relevant retail tariff options can all be summarized in the UL variable pertaining to the hourly retail price $\gamma_h^{\vee}$. Thus, with regard to the tariff choice, the PEV aggregator could set constraints on the shape of the hourly retail price curve. Given one of the following retail options, the aggregator can decide on the profit maximizing or benefit sharing equilibrium price level:

A. flat rate tariff,

B. time-of-use (TOU) (day-night, three-step, etc.),

C. hourly prices etc.

A conceptual visualization of these alternatives in terms of positive (profit) or negative (loss) price differences between market prices and final customer tariff is provided in Fig. 6.1. The shaded area indicates the positive (profit) or negative (loss) price differences between market prices and final customer tariff.

6.1.2 Case Study Data Description

Base Runs: Market Prices, PEV Data and Mobility The fleetsize is kept small with$|\mathcal{V}|=3$ representative vehicles, or vehicle clusters. The model horizon is reduced to$|\mathcal{H}|=6$ periods. Day-ahead electricity market prices are assumed to have the following profile: $\lambda_h^D=$ € [.020 .040 .030 .040 .050 .010] per kWh. The inputs regarding mobility are provided in Tab. 6.1, while initial and

Table 6.1: Stylized Mobility: Availability $\nu_{v,h}$ and Energy Requirement $\rho_{v,h}$

$\nu_{v,h}$	h					
v	1	0	1	0	1	1
	0	0	1	0	0	1
	1	0	1	1	0	1

$\rho_{v,h}$	h					
v	0	1	0	2	0	0
	2	1	0	2	3	0
	0	5	0	0	5	0

final SOCs are set to $\iota_v^{\text{SOC}} = \phi_v^{\text{SOC}}$= [9 8 7] kWh. The battery SOC of each vehicle is assumed to not exceed the battery capacity of $\overline{E} = 12$ kWh.

In the base run and if not indicated otherwise, the levels of discomfort of the vehicles are set to Λ_v= € [.001 .002 .003] per kWh. The cost of NSE for PEV mobility is Ξ_v = € [.09 .10 .11] per kWh. The on- and off-peak periods are $\mathcal{H}^{\text{on}} = \{2..5\}$ and $\mathcal{H}^{\text{off}} = \{1, 6\}$, respectively. The minimum price difference between retail prices under ToU is set at ϵ = € .02 per kWh.

Please note that the case study has been designed in such a stylized form with rather small data sets to ensure clarity of the model's functionality by being able to manually track results. Nevertheless, the proposed model could handle much more realistic case studies with larger problem instances similar to [72], [73].

Simulation Procedure First, the LL problem is solved isolated from the UL (Runs 1 - 6). By doing so, the detailed functioning of the linear formulation of the final customers decision making is illustrated. This will help to analyze the more complex interactions when considering the full bi-level structure. Then, both UL and LL problems are combined and solved simultaneously in the proposed MPEC formulation. In consecutive runs (I - IV and I,BS - IV,BS), first a single-level DLC reference case is solved and then the bi-level equilibrium points for the three different tariff alternatives are found without and with benefit sharing constraints.

6.1.2.1 Isolated LL: Optimization as LP

First, the LL problem given in (4.37)-(4.42) is solved isolated from the UL, with a fixed set of parameters. In 6 optimization runs, sensitivities on the relevant cost parameters of the LL objective function Λ_v and Ξ_v are carried out. Please note that this is equivalent to altering $\gamma_h^{\veebar}$, as the LL decisions merely depend on the relative weights of the respective cost terms in the objective function.

The reference schedule is determined by immediate charging: $\Sigma_v \check{\mathbf{E}}_{v,h}^{\text{RT},\veebar}$=[0 0 9.68 0 2.15 10.75] kWh. In the base case, the retail prices are set to $\gamma_h^{\veebar} = \lambda_h^D + .010$= € [.030 .050 .040 .050 .060 .020] per kWh. One after the other, never simultaneously, Λ_v is increased to the double and quadruple, while Ξ_v is reduced to $\frac{1}{3}$ and $\frac{1}{5}$ of the respective base values.

Run 2, is the actual base case run. Run 3 and 4 exhibit increasing cost and discomfort, due to higher weights on Λ_v. Run 7 and 8 present decreasing cost

Table 6.2: Overview of the Numerical Results for Isolated LL Optimization

Run:	**Specifics**	**Energy Cost** $\kappa_{PEV}^{LL} = \Sigma_{v,h} e_{v,h}^{\mathbf{RT}} \cdot \gamma_h$	**Discomfort:** $\Lambda_v \cdot t_v$	**SOCRedctn.:** $\Xi_v \cdot e_{v,h}^{\mathbf{DR}}$
1	ASAP	0.73118	0	0
2	Base	0.51518	0.04600	0
3	Λ_v= [.002 .004 .006]	0.55071	0.04938	0
4	Λ_v= [.004 .008 .012]	0.58718	0.05498	0
5	Ξ_v = [.030 .033 .036]	0.45910	0.04881	0.04347
6	Ξ_v = [.018 .020 .022]	0.21505	0.02581	0.22400

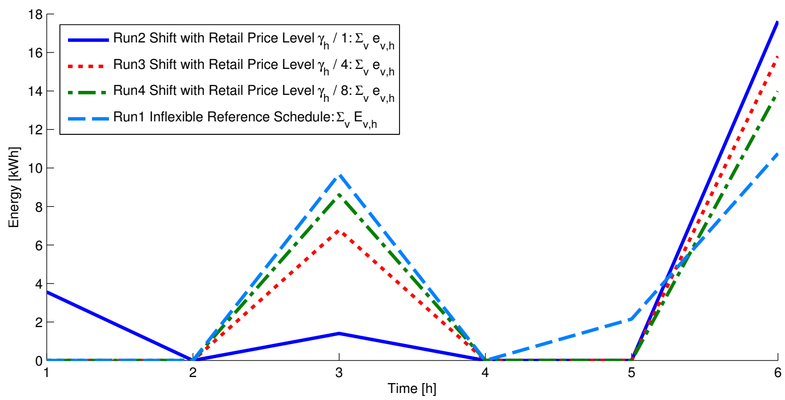


Figure 6.2: Lower level problem as LP: Retail Price Sensitivity

and discomfort as well as decreasing total energy demand, due to lower costs of non-supplied energy Ξ_v.

Tab. 6.2 summarizes the first results from the isolated LL optimization runs, by indicating the different terms of the LL objective function. Run 1 shows by far the worst hypothetical charging cost. These are computed ex-post, due to the fact that the reference schedule optimization (4.38)-(5.2) does not take into account cost.

For the interested reader, the supplemental Fig. D.6a and Fig. D.6b in the appendix show the results of these first LL isolated runs. In both figures the two extreme schedules are presented by the reference case (Run 1) and the base case (Run 2). The schedules obtained from the sensitivity Runs 3-6 tend to lie in between for most of the periods.

The effect of applying different levels of discomfort on the optimized charging schedule, seen in Fig. D.6a in the appendix, is in principle the same as applying different retail price levels: The higher the discomfort or the lower the retail price level, the more the charging schedule approaches the schedule of high convenience and low flexibility $\check{\mathbf{E}}_{v,h}^{\mathrm{RT},\veebar}$. The effect of decreasing the cost of non-supplied energy is contrary to the retail price and discomfort sensitivity, as shown in Fig. D.6b of the appendix: The lower cost of non-supplied energy, the lower the total consumption $\Sigma_{v,h} e_{v,h}^{\mathrm{RT}}$. Expensive consumption (cf. period 3) is reduced first, followed by inexpensive consumption (cf. period 1 and 6). Discomfort remains active and influencing (cf. period 6).

6.1.2.2 Combining UL with LL as MPEC

Tab. 6.3 provides a summary of the numerical results obtained in the combined optimization of UL and LL in an MPEC. On a more detailed level, Tab. 6.5 and 6.7 indicate charging schedules and monetary terms for selected runs. A total of 7 runs is carried out. The first run (I DLC) serves as a hypothetical reference case to compare the ILC runs (2-7) runs against it. First, the UL is given maximum freedom to maximize its profits under the three proposed tariff schemes (runs 2-4). Then, the UL is constraint by the budget of the LL, again under the three proposed tariff schemes (runs 5-7).

Under DLC with a flat rate (I), the retail price is exogenously set to γ_h =.06, resulting in a net profit of z_{UL} =1.0655 for the aggregator on the UL while the PEV on the LL pay $\kappa_{\text{PEV}}^{\text{LL}}$ =1.3548 and incur a discomfort of 0.046. Given the PEV availability and consumption, the UL can set the cost optimal schedule with regard to the market prices. This means, as much charging is moved to hour 6 as possible, see *Tab. 6.5* for $e_{v,h}^{\text{RT}}$ and *6.6* for $e_{v,h}^{SOC}$. As the aggregator is merely interested in its own profit, discomfort is not part of the UL objective under DLC but it can be calculated ex-post.

Under ILC with a flat rate (II), the UL sets the retail price as high as γ_h =.085 and thus earns z_{UL} =1.4072 from LL payments $\kappa_{\text{PEV}}^{\text{LL}}$ =1.9126. However, the schedule is completely unaligned with the market prices. The LL not receiving any other incentive from the UL, it represents the outcome with zero discomfort = 0, i.e. no deviations from the reference schedule.

ILC runs III and IV both show the same optimal schedule (and thus lower level discomfort) as in the DLC case, however the UL makes as much as z_{UL} =1.4322 and z_{UL} =1.4677 of profit, respectively. This is due to the high price levels of $\gamma_h^{\mathbf{off}}$ = .075 $\gamma_h^{\mathbf{on}}$ = .095 with ToU and the considerable margin of m = 0.065 with hourly prices.

Runs I - IV exhibit arguably high profits for the UL. But in the absence of any competition for the aggregator, these are quite plausible since the retail prices are still lower than the cost of non-supplied energy. Also, the relative distribution of weights on the cost terms of the LL objective function provides that the avoided LL costs from alignment to the retail prices are higher than the incurred discomfort.

However, there are a few remedies to show a different outcome with lower retail prices. Conceptually, these could be justified by simulating an increased level of competition for the PEV aggregator that would prevent it from having excessive benefits. Besides the ones already shown in the LL isolated runs, these remedies could be: a) setting an upper bound for prices and b) revenue caps to a reasonable profit margin, which both finally lead to benefit sharing of the UL to the LL.

To show the effect of benefit sharing constraints, 3 more cases are run, in which for each retail alternative II-IV the following has to hold on the UL:

$$\Sigma_h \Pi_h^{\text{C,ILC}} \leq (1 + \text{bs}) \cdot \Sigma_h \kappa_h^{\text{D,DLC}}, \tag{6.1}$$

Table 6.3: Result Overview: Combined UL-LL Optimization as MPEC

Run and Control Tariff Option Flexibility of Charging Schedule	I - DLC Flat Rate Maximal	II - ILC Flat Rate Minimal	III - ILC Time of Use Maximal	IV - ILC Hourly Prices Maximal
UL: Aggregator Profit z_{UL}	**1.0655**	**1.4072**	**1.4322**	**1.4677**
UL-LL: Retail Price γ_h, γ_h^{off}, γ_h^{on} or m	$\gamma_h = .06$	$\gamma_h = .085$	$\gamma_h^{\mathbf{off}} = .075$ $\gamma_h^{\mathbf{on}} = .095$	$m = 0.065$
LL: $\kappa_{PEV}^{LL} = \Sigma_{v,h} e_{v,h}^{\mathbf{RT}} \cdot \gamma_h$	**1.3548**	**1.9126**	**1.7216**	**1.7571**
LL: **Discomfort** $\Sigma_{v,h} \Lambda_v \cdot \left(t_{v,h}^{+} + t_{v,h}^{-}\right)$	**0.0460**	**0**	**0.0460**	**0.0460**
LL: **DR Cost** $\Sigma_{v,h} \Xi_v \cdot e_{v,h}^{\mathbf{DR}}$	**0**	**0**	**0**	**0**

Table 6.4: Combined Results with Benefit Sharing

Run and Control Tariff Option Flexibility of Charging Schedule	II - ILC,BS Flat Rate Minimal	III - ILC,BS Time of Use Maximal	IV - ILC,BS Hourly Prices Maximal
UL: Aggregator Profit z_{UL}	**-0.1195**	**0.0965**	**0.0965**
UL-LL: Retail Price γ_h, γ_h^{off}, γ_h^{on} or m	$\gamma_h = .017$	$\gamma_h^{\mathbf{off}} = .016$ $\gamma_h^{\mathbf{on}} = .036$	$m = 0.0043$
LL: $\kappa_{PEV}^{LL} = \Sigma_{v,h} e_{v,h}^{\mathbf{RT}} \cdot \gamma_h$	**0.3858**	**0.3858**	**0.3858**
LL: **Discomfort** $\Sigma_{v,h} \Lambda_v \cdot \left(t_{v,h}^{+} + t_{v,h}^{-}\right)$	**0**	**0.0460**	**0.0460**
LL: **DR Cost** $\Sigma_{v,h} \Xi_v \cdot e_{v,h}^{\mathbf{DR}}$	-	-	-

where bs stands for the percentage of revenues above the ideal day-ahead charging cost from the most efficient charging schedule. It could be set to $\frac{100}{|\mathcal{V}|}[\%]$. In this case, this means that the total revenue from retail on the LL (i.e. costs for electricity on the LL) should not exceed a level of 33.3% above the most efficient procurement cost from market purchases. In this way it would prevent the UL to use excessive market power, or it can be understood as a natural bound that would be consequential to an acceptable level of competition on the PEV aggregator business. The results for these revenue cap runs are given in *Tab. 6.4.*

Because of the constraint in (6.1), for the three BS runs the retail prices are reduced to γ_h=.017, γ_h^{off}=.016, γ_h^{on}=.036 and m=0.0043, respectively. For all runs, the LL electricity cost equals $\kappa_{\mathrm{PEV}}^{\mathrm{LL}}$ =0.3858 while incurring the known discomfort of 0.046 of the fully flexible schedule and zero discomfort of the inflexible one. However, the UL profits now vary significantly among the runs. In III,BS and IV,BS the profit is positive at around z_{UL} =0.1 because of the fully flexible schedule. In II,BS with the flat rate and the inflexible schedule the UL has a negative profit of the same magnitude. Thus, incentivizing flexibility on the LL can be decisive for the profit on the UL.

6.1.3 Endogenous Hourly Retail Prices

To complement existing single-level direct load control, this case study has applied the bi-level formulation for the decision making problem of a plug-in elec-

Table 6.5: Charging Schedules for Combined UL and LL Optimization

Runs	I, III and IV						II - Flat Rate					
$e_{v,h}^{\mathbf{RT}}$	**1**	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**4**	**5**	**6**
1	0	0	0	0	0	3.23	0	0	1.08	0	2.15	0
2	0	0	1.40	0	0	7.20	0	0	3.23	0	0	5.38
3	3.55	0	0	0	0	7.20	0	0	5.38	0	0	5.38

Table 6.6: Battery SOCs for different runs in the combined optimization

Runs	I, III and IV						II - Flat Rate					
$e_{v,h}^{\mathbf{SOC}}$	**1**	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**4**	**5**	**6**
1	9.0	8.0	8.0	6.0	6.0	9.0	9.0	8.0	9.0	7.0	9.0	9.0
2	6.0	5.0	6.3	4.3	1.3	8.0	6.0	5.0	8.0	6.0	3.0	8.0
3	10.3	5.3	5.3	5.3	0.3	7.0	7.0	2.0	7.0	7.0	2.0	7.0

tric vehicle aggregator given in the previous chapter. On the upper level this aggregator bids in electricity markets and finds the optimal retail price, while on the lower level the final customers optimize their charging subject to discomfort and considering demand response. The optimal charging schedule depends on the relative weights of electricity costs, discomfort and costs of non-supplied energy in the lower level objective function.

Results indicate that in the absence of any competition, the aggregator on the upper level intends to maximize its profit by increasing the retail prices until slightly below the cost of non-supplied energy to achieve high revenues but not lose the demand through fuel switching. Furthermore, it has been demonstrated how the indirect load control formulation finds the retail price endogenously as opposed to ex-ante fixing the profit under direct load control. Comparing different retail price alternatives, the upper level profit is maximized under hourly pricing, while time-of-use and flat rate options also provide high yields for the upper level. When simulating competition on the retail market by limiting the revenues of the upper level it can be shown that the PEV aggregator's profitability depends on providing the right price signals to the final customers, such that the most efficient charging schedule response is achieved.

Table 6.7: Procurement Costs and Client-Side Revenue

	$\kappa_h^{\mathbf{D}}$						$\Pi_h^{\mathbf{C}}$					
Runs	**1**	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**4**	**5**	**6**
I - DLC	-0.071	0	-0.042	0	0	-0.176	0.213	0	0.084	0	0	1.058
II - ILC Flat Rate	0	0	-0.290	0	-0.108	-0.108	0.000	0	0.627	0	0.139	0.697
III - ILC ToU	-0.071	0	-0.042	0	0	-0.176	0.209	0	0.110	0	0	1.036
IV - ILC Hourly Prices	-0.071	0	-0.042	0	0	-0.176	0.239	0	0.108	0	0	1.008

6.2 PEV Coordination for Efficient Network Use via ILC

*The following case study is published in **[149]**.*

This last case study joins many of the above treated aspects into one comprehensive analysis. Among others, this analysis, like previously carried out in **[149]**, studies the effects of DLC control architectures for the charging processes of PEV.

6.2.1 ILC Case Study Description with Affine Demand

The case study is divided in two parts. A) First, a small-scale example with detailed information on individual vehicles is detailed, illustrating the proposed model's functionality. In A.1), this example is first solved excluding network pricing as in (4.45.I)–(4.45.II), and then, in A.2), solved including capacity-based UoS network charges as in (4.45).III, (4.55) and (4.56). Another run, A.3) is added, in which the aggregator is supposed to compete with others for customers via the price interface.

B.) Further on, a large-scale case discusses scalability of the approach and associated computational burden.

Fleet-level sensitivity analysis relates to the aggregated affine demand, for which B.1) the threshold, i.e. the minimum possible willingness to pay is varied, B.2) the shape, i.e. relative dispersion of the fleet's willingness to pay distribution is altered, and B.3) the cost of minimum final SOC, i.e. energy anxiety is analyzed.[1]

6.2.1.1 Market Prices, PEV Data and Mobility

The inputs and parameter settings for the small scale example can be found in Tab. 6.8a and 6.8b. Day-ahead electricity market prices $\lambda_h^{\mathbf{D}}$ follow a typical day-ahead profile as happened for EPEX SPOT in Germany on April 11th, 2011, with early morning valley at $h = 4$, a low mid-day peak around noon and a high evening peak at $h = 20$. A graph of $\rho_{v,h}$ is provided in Fig. 6.3.

6.2.1.2 Large-Scale Fleet Parameters

The parameter settings relating to time horizon $|\mathcal{H}|$ and market prices $\lambda_h^{\mathbf{D}}$ remain the same as in the small-scale example. For all other settings on the LL including the mobility pattern of the PEV, a Monte-Carlo simulation is carried out. Probability distributions correspond to data provided in [23], [74] consistent

[1] The used notation for the Weibull distribution is as follows:

$$\sim Wei\,(b,\, c) + a, \tag{6.2}$$

where a is the left-hand side threshold, above which all other values lie, b is the shape parameter, and c is the scaling parameter.

Parameter	Value	Units
$\lvert\mathcal{H}\rvert$	24	hours
$\mathcal{H}^{\mathbf{on}}$	{7, ... , 22}	
$\mathcal{H}^{\mathbf{off}}$	{1, ..., 6}∪{23, 24}	
$\lvert\mathcal{V}\rvert$	3	vehicles
$\tilde{\lambda}^{\mathbf{D}}$	0.034	€ /kWh
$\frac{1}{\lvert\mathcal{H}\rvert}\sum_{h \in \mathcal{H}} \lambda_h^{\mathbf{D}}$	0.052	€/ kWh
$\mathbf{C}^{\mathbf{UoS,off}}$	0.04	€/ kW
$\mathbf{C}^{\mathbf{UoS,on}}$	0.08	€/ kW

(a) Price Data

Parameter	Value			Units
v	1	2	3	
$\overline{E}_v$	11.5	12	12.5	kWh
η_v	.94	.96	.98	-/-
$\overline{P}_v$	3.6	7.2	3.6	kW
Ξ_v	0.11	0.12	0.13	€ /kWh
$\sum_h \rho_{v,h}$	7.0	6.9	8.0	kWh
$\iota_v^{\mathbf{SOC}}$	9.0	10.0	10.5	kWh
$\phi_v^{\mathbf{SOC}}$	7.0	6.0	5.0	kWh
$\underline{D}_v$	5.5	3.2	2.6	kWh
$\overline{D}_v$	9.9	9.2	10.1	kWh
α_v	59.3	69.9	78.2	kWh^2 /€

(b) Individual Data for 3 Vehicles

Table 6.8: Input parameter settings

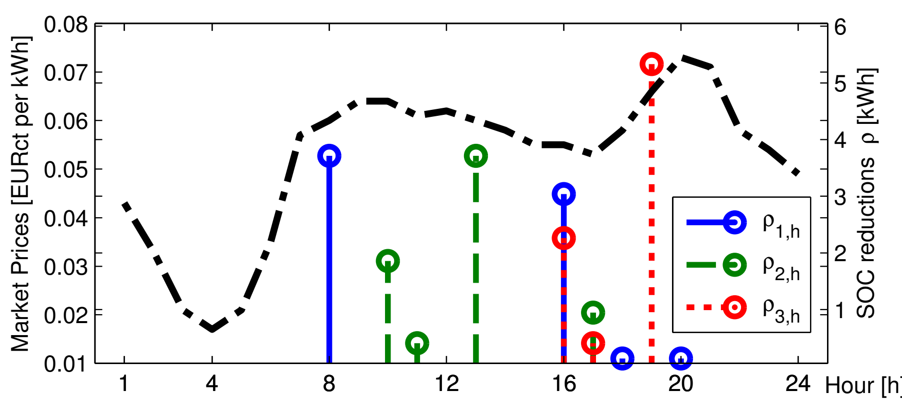


Figure 6.3: Small Case Input: SOC Reductions during Driving

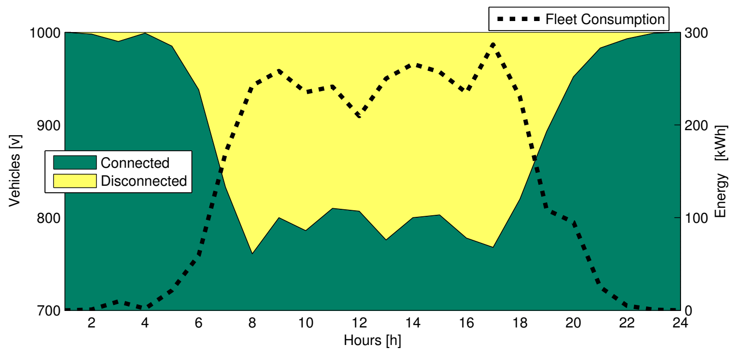


Figure 6.4: Large Case Input: Mobility

Table 6.9: Selected information for Monte-Carlo simulation

Parameter	Probability Distribution
η_v	$\min[\sim N\,(0.96,\,0.01),\,0.98]$
$\overline{P}_v =$	$x = [3.6\,7.2\,11\,22]$ kW,
$F^{-1}\,(\sim U\,[0,1])$	$F\,(x) = [0.45\,0.80\,.95\,1]$
$\iota_v^{\mathbf{SOC}}$	$\sim N\,(11,\,1)$
$\phi_v^{\mathbf{SOC}}$	$\iota_v^{\mathbf{SOC}} + 1$
$\overline{E}_v$	$\max[\phi_v^{\mathbf{SOC}} + 1, \sim N\,(11,\,1)]$
Ξ_v	$\sim Wei\,(0.1,\,1.8) + .0255$

with a large mobility survey from Germany, see Fig. 6.4. Statistical moments of the other key parameters are given in Tab. 6.9. Normal distributions are used where possible, i.e., for η_v, $\iota_v^{\mathbf{SOC}}$, $\phi_v^{\mathbf{SOC}}$ and $\overline{E}_v$. Different connection capacities $\overline{P}_v$ are modeled via a discrete cumulative probability function. The NSE cost, Ξ_v follows a generic Weibull distribution.

With the given information, the large-scale case conducts sensitivity analysis on the key parameters defining the LL demand reaction to UL price signals. Therefore, in three sets of sensitivity runs, both aggregated fleet demand $\sum_{v,h} e_{v,h}^{\mathbf{RT},\veebar}$, as well as UL profits $z_{\mathbf{UL}}$ are tracked for the feasible set of retail prices while varying input parameters $\tilde{\lambda}^{\mathbf{D}}$, Ξ_v and $\phi_v^{\mathbf{SOC}}$.

Computer Resources For comparisons of computational burden, used soft- and hardware is indicated. All calculations were performed running MatLab© for handling input and output data via GDX files. The optimization problem was formulated and solved in GAMS© Build 24.1.2 employing the CPLEX™ 12.5.1 solver for (MI)LPs, i.e. reformulated MPECs on a standard laptop 64-bit MS Windows©2003 Server machine with 32 GB RAM and an Intel© Xeon™ E-5520 CPU clocked at 2.26 GHz, with up to 16 threads in dynamic search and opportunistic parallel mode.

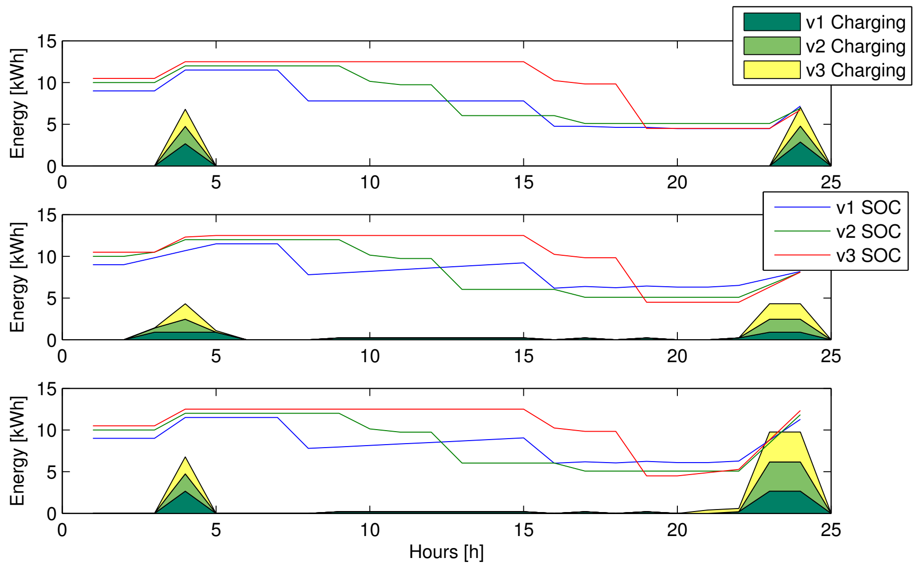


Figure 6.5: Numerical results: Detailed individual hourly scheduling

6.2.2 Numerical Results on an Hourly Basis

Results without Network Pricing A.1) Solving the problem with the given data, yet $\mathbf{C^{UoS,on}} = \mathbf{C^{UoS,off}} = 0$, leads to the numerical results illustrated in Fig. 6.5. Detailed hourly data for $e^{\mathbf{RT}}_{v,h}$ and $e^{\mathbf{SOC}}_{v,h} - e^{\mathbf{NSE}}_{v,h}$ are provided. It is profit-optimal for the aggregator to set a constant retail price margin of $m =$€ct 6 /kWh above the hourly market prices. With this retail price level, the LL cost-optimally consumes in $h = 4$. The retail price margin is sufficiently low, not causing any demand reduction below $\underline{D}_v$. In summary, it is profit-maximizing for the aggregator to increase prices slightly below the PEV fleet's conjunct willingness to pay, at which part of the demand would be lost.

The economics for UL and LL are recorded in Tab. 6.10. The detailed numerical data is provided as supplemental material in Tab. D.7a. It is shown that the margin leads to good profits for the UL, while the schedule is perfectly aligned with market prices, i.e. the aggregator can purchase the energy at minimal cost at the hours of lowest wholesale electricity market prices, given availability and the minimum final SOC requirements. The LL faces moderate charging cost, and does not have to afford any NSE.

Results with Network UoS Charges A.2) Including network UoS charges alters the optimal outcome for the UL. The UL does not remain indifferent, because even though (4.23)–(4.27) and (4.52) are not affected by $\mathbf{C^{UoS}}$, the lower level charging schedule is, and thus the UL economics. Taking into account the PEV fleet's cost incurred from using the network renders NSE comparatively more attractive at lower margins for the UL. Hence, the UL profit-optimal margin of $m =$€ct 4 /kWh, slightly lower than in A.1). Total energy consumption increases due to the decreased prices. Though, because of the network capacity pricing effect, $e^{\mathbf{RT}}_{v,h}$ is evenly distributed over more hours, as can be seen in Fig. 6.5. The detailed numerical data is provided as supplemental material in Tab. D.7b.

This smoothed consumption due to the network signals effectively means less alignment according to market signals and therefore higher procurement cost for the UL. This overcompensates the additional revenue from higher demand. The increase in LL cost is due to consuming more energy, higher average energy cost and additional network UoS payments. Nevertheless this would be an overall more efficient demand curve for the system. However, this conclusion is conditional on the main assumption of exogenous market outcomes, in which the aggregator as a price-taker has no means to influence the results of the market clearing. If the market share and power of the aggregator would be sufficiently high, then there could be an interest in smoothing its demand curve to avoid price spikes.

Budget constraints as a proxy for competition A.3) The numerical results show that the profit-optimal solution includes rather high retail prices, even though the LL reacts to these prices via demand reductions designated through $\mathbf{h^2}$ of (4.52). These prices are to some extent unrealistic, yet insightful, because they are reminding of the fact that profit maximizing monopolistic behavior of the UL may lead to undesirable outcomes for the demand side on the LL. In reality, such high prices are generally avoided through adequate levels of competition on the retail market, i.e. the aggregator would have to contend for customers by offering reasonably low prices for his services. With the given model, such prices can be proxied via including an upper bound on the disposable budget: $\sum_{v,h} \gamma^{\vee}_h \cdot e^{\mathbf{RT}}_{v,h} \leq \overline{\mathbf{B}} =$ €1.5. This arguably takes away a valuable proposition of the bi-level structure, which endogenously finds the profit-optimal price level, because the feasible region for retail prices is further constrained. Nevertheless, it shows the model's capability to represent the realistic decision making of both UL and LL in a competitive retail market setting with network UoS tariffs.

To this end, the following parameter changes are carried out before the model is re-run: PEV, knowing that there is competition on retail prices, could signal higher willingness to pay without fear to be taken advantage of, thus Ξ_v is significantly increased to € 1.5 /kWh approximating the marginal price of the next best alternative, such as, e.g, gasoline. Furthermore, it is assumed that under competition, the total profits of the aggregator cannot be higher $z_{\mathbf{UL}} \leq$€ 0.2 (0.03 /kWh), however this might not be binding if the budget constraint is more restricting.

This leads to the results as shown in Tab. 6.10 and Fig. 6.5. The detailed numerical data is provided as supplemental material in D.7c. Competition curtails the profits to the same level as before, even though LL willingness to pay would yield a profit optimum much higher. Thus the resulting margin leads to high

Table 6.10: Small Case Study Results: Run A.1-3)

Variable	Outcome A.1)		Outcome A.2)		Outcome A.3)		Units
m	0.06		0.04		0.01		€ /kWh
$z_{\mathbf{UL}}$	0.79	(0.057)	0.68	(0.039)	0.2	(0.007)	€ (€ /kWh)
$\kappa^{\mathbf{D}}$	-0.46	(-0.033)	-0.7	(-0.040)	-1.29	(-0.070)	€ (€ /kWh)
$\Pi^{\mathbf{C}}$	1.25	(0.091)	1.38	(0.079)	1.5	(0.082)	€ (€ /kWh)
$z_{\mathbf{LL}}$	1.25	(0.091)	2.14	(0.122)	3.02	(0.164)	€ (€ /kWh)
$\sum_{v,h} e^{\mathbf{NSE}}_{v,h} \cdot \Xi_v$	0	0	0	0	0	0	€ (€ /kWh)
$e_v^{\mathbf{UoS,off},\veebar} \cdot \mathbf{C}^{\mathbf{UoS,off}}$	-	-	0.76	(0.043)	1.52	(0.052)	€ (€ /kWh)

demand, which almost fully charges the batteries by the end of the optimization horizon. This charging is, however, smoothly spread out over the off-peak and on-peak hours, to avoid sharp load spikes at the hours of low prices.

The ILC scheduling with hourly varying prices is valuable to the final customers. By explicitly pricing the deviations between a preferred schedule of biggest comfort and flat energy prices, [148] shows that the comparative value lies in the range of 10-12% in cost savings. To indicate how much money can be counted towards the implementation of this approach, in the following, an illustrative approximation of this value is provided. In Run A.3), the three vehicles pay € 2.91 or if all energy and network capacity costs were evenly spread out € 0.1 per kWh: vehicle 1 incurs € 0.99, vehicle 2 € 0.91 and vehicle 3 € 1.01. Supposing a distance of 14 200 km per year as traveled by the average vehicle in Germany 2011, and all inefficiencies accounted, a PEV consumes around 0.35 kWh per km. A 12% comparative annual cost avoided would then be around € 60. Consequently, the net present value of a constant cash flow of € 60 over a supposed vehicle life time of 12 years discounted at 8% p.a. is approximately € 450.

6.2.2.1 Aggregated Fleet Scheduling with ILC

Computational Characteristics In large-scale mixed-integer programming, computational tractability tends to be an issue. To this end, Tab. 6.11 indicates the key computational characteristics when using the proposed model to solve the scheduling problem for fleets of $|\mathcal{V}| = [10, 100, 1000]$ vehicles. It appears that even though PEV batteries and charging are modeled at an individual level, the proposed formulation remains tractable. Equations, non-zeros in the coefficient matrix and continuous real variables increase almost linearly with fleet size. For the constant and relatively low amount of binary variables, the largely scaled linear sub-problems can be solved with reasonable efficiency.

Numerical Summary The optimal solution for the run with 1000 vehicles leads to an UL profit of $z_{\mathbf{UL}} = €\,123.97$, at a margin $m = €\,0.062$/kWh and a total energy consumed of $\sum_{v,h} e^{\mathbf{RT},\veebar}_{v,h} = 1996.29$ kWh.

Table 6.11: Large-Scale Summary - Computational Characteristics

$\lvert\mathcal{V}\rvert$	Solve Time [s]	# Iterations	Equations	Non-Zeros	Real Vars.	Binary Vars.
10	9.8	776 856	2 654	16 565	2 888	12
100	671	1 904 814	25 964	164 334	28 538	12
1000	8 464	2 103 393	259 064	1 641 991	285 038	12

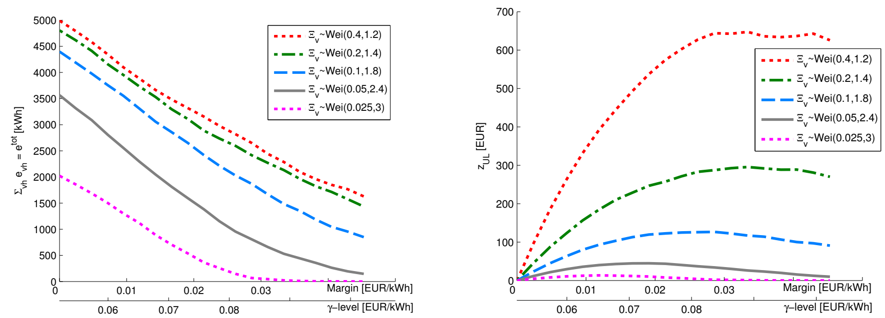
Sensitivity Analysis The following analysis makes it possible to visualize the functional relationship between aggregated affine demand and the possible retail price signals, see Fig. 6.6a, as well as the complete shape of the feasible region of the UL profits, depicted in Fig. 6.6a. It indicates how sensitive the above mentioned results are to the key parameters chosen. Without this analysis, it would be difficult to imagine the functional shape of the feasible region that the aggregator is given to choose from, as the outcome of the optimization problem would only yield on point, i.e., the one with the maximum profit of the objective function, on the curves given.

Varying the Weibull distribution parameters changes the steepness of the aggregated demand slope, as dispersion of $\Xi_v - \tilde{\lambda}^{\mathbf{D}}$ is reduced. $\Xi_v - \tilde{\lambda}^{\mathbf{D}}$is the difference between the lowest feasible retail price reference that is still plausible for the aggregator, and the upper willingness to pay of the final customers. This difference provides the range in which a given vehicle will consume energy from the aggregator. The dispersion of this difference among the different individual PEV in the fleet population contributes to the shape of the aggregated affine fleet demand. The more dispersed, the less steep this aggregated affine fleet demand. Consequently, the profit-optimal margin gets larger, and total UL profits increase significantly. And vise versa: the less dispersed, the more steep and the lower the total UL profits.

Besides the steepness, the statistical moment of expectation of the willingness to pay Ξ_v plays an additional role. Given a lowest feasible retail price, the smaller the average willingness to pay happens to be, the earlier demand drops. To the extreme that even at zero margin the PEVs do not consume their minimum demand any more.

Since Ξ_v does not have an hourly index, i.e. willingness to pay is not time dependent, the difference in hourly market prices leads to kinks in UL profits and LL demand, however the distribution of the parameters among vehicles somoothens out the curves.

The same observation holds for the variation on the left-hand side of the affine demand by setting different values of $\tilde{\lambda}^{\mathbf{D}}$. In the sensitivity runs for the willingness to pay, a steeper affine demand of the aggregation is achieved, while the profit-optimal margin moves to the right less than in the former sensitivity. This can be taken as a proxy fora range anxiety cost function. The more the PEV is adverse to low final SOCs, the less flexible is its charging schedule and thus the range anxiety becomes a cost.



(a) Affine Fleet Demand (b) UL Profit Region

Figure 6.6: Sensitivity Analysis for Varying Ξ_v Distributions

However, the sensitivity of the minimum final SOC proves to be the least constructive. No valid change in both outcome variables can be observed, when increasing the preferences of the final customers to end up with higher energy stored by the end of the time horizon. For supplemental graphics, please refer to Fig. D.7 and Fig. D.8.

6.2.3 Final Remarks on ILC Scheduling

By means of a mathematical problem with equilibrium constraints, this final case study has demonstrated the use of a methodology to assess the decision making of a plug-in electric vehicle aggregator exercising indirect load control over a fleet of vehicles to determine profit-optimal retail prices. This client-side reaction to the aggregator's prices is individually given for each vehicle, depending on local preferences and physical characteristics.

In two sub-case-studies with up to 1000 vehicles, the optimal energy quantities and economics for both aggregator on the upper level and final customers on the lower level have been obtained. The study shows, how capacity based use-of-system network tariffs influence the decentralized PEV charging schedules, which are equal to those under DLC.

Furthermore, the case study points out that aggregators with full information on local vehicle characteristics can strategically leverage the advantage of a bi-level leader to receive excessive profits. This is grounded on the proposed model's characteristics not explicitly representing aspects of aggregator competition and PEV selecting aggregator's in a functional retail market. Nevertheless, it serves as a basis for analyzing the strategic interactions in a two-agent leader-follower game. The insights gained with this model are transferable for the design of and indeed motivate the necessity of retail equilibrium models. As a quick remedy, the case study emulates aggregator competition on the retail market by the concept of a disposable budget. Finally, the case study presents a manifold sensitivity analysis highlighting the impact of key parameters on the aggregated LL demand response and profitability of the aggregator.

It has to be noted, that the success of the proposed ILC scheduling would depend on the aggregator's forecasting ability of the PEVs optimization problems in detail and the goodness of its estimates regarding, e.g. PEV energy requirements, driving patterns, and other locally available preferences. Nevertheless, the ILC case study and the model it is based on arguably have some drawbacks and limitations. Indeed the following points may not have been addressed to the utmost potential:

- on the wholesale side, the aggregator is competing against other demand-side participants for the cost optimal purchases of electricity

- on the client-side retail market, the aggregator is competing for final customers against other agents

- the PEV's problem to select the most competitive aggregator for their energy purchases.

Nevertheless, in spite of these shortcomings, it is deemed a research work that merits some interest because it sheds light on neglected parts of the aggregator's problems, in particular, modeling the retail side with ILC, which is more standard to the reality of suppliers today, than any DLC formulation could provide. In particular, it is important to note that the conclusions drawn from this model are independent of these structural limitations of the MPEC bi-level formulation.

6.3 Comparing the two ILC Case Studies

Up to this point, this section has provided two ILC case studies, which can be compared according to the functions they serve in highlighting different aspects of the proposed model. Both modeling approaches, and thus the way they highlight case studies, have advantages and disadvantages.

The case study presented in Section 6.1 treats the subject of PEV coordinating purely by market signals, or prices referring to the wholesale components of the final customer's bill. It presents the main proof of concept that it is possible to model ILC in a bi-level structure, decomposing the decision making of the aggregator on the UL and the final customers on the LL. Furthermore, it is capable to show that under the right retail pricing scheme, ILC may hold the same scheduling outcome in terms of energy charging quantities as DLC models. Another noteworthy advantage of the first ILC case study is the clear distinguishing of UL and LL by first solving only the LL in isolated model runs and providing sensitivity analysis for all the cost parameters of the LL objective function. Finally, the same case study shows the implications of modeling the discomfort incurred by the PEV when deviating from a reference charging schedule. This makes it possible to compare the flat rate energy retail pricing scheme with other time differentiating tariffs under ILC.

The main disadvantage of the first case study alludes to the same model functionality of explicitly modeling the LL deviations from the reference schedule: the penalization in the objective function requires the modeler to come up with concrete prices. This is obviously a soft science and objective justifications for the choice of any specific set of parameters is difficult to provide. Finally, the last drawback of the first ILC case study pertains to the implementation of the approach. It is formulated as an MCP and solved with a NLP solver, i.e., PATH, although it is unlikely that there are any KKT stationarity points that do not provide global optimality, it cannot be mathematically proven that the found optima are necessarily global. Non-exhaustive search heuristics by repetitively randomizing initial solutions have to be carried out to ensure that the joint bi-level structure yields sufficiently satisfying results, i.e., that with high levels of confidence the found solutions are likely to be global optima.

The second ILC case study as provided in Section 6.2 contains some pronounced differences compared to the former. Besides modeling the market interactions of the UL, passing on retail price signals pertaining to the wholesale components of the total bill of the final customer, the second case study also includes network UoS pricing. This changes the behavior of the final customers and the lever that the UL has over the LL. The signal given by the aggregators' retail prices are somewhat diluted by the additional network cost information. Furthermore, the second ILC case study provides a representation of a larger fleet, discussing scalability of the approach and fleet level effects. Sensitivity analysis is carried out for the combined optimization of UL and LL together, but with a focus on the UL.

The second case study only models one pricing scheme, hourly prices with a constant margin above wholesale realizations, as it is deemed the most efficient signal among the three alternatives previously analyzed in the preceding ILC case study. Hence, no comparison among different retailing alternatives can be provided with the second case study. In terms of implementation, the discretization of retail prices provides a global answer to the bi-level problem. Optimality is guaranteed via the CPLEX solver. However, unfortunately, due to linear modeling choice in the explicit demand reduction, the LL total demand simply depends on the average of the price over the considered time horizon. This has multiple limitations. First, a given PEV is not connected at all times, so the prices at certain hours could in reality be irrelevant for it. Second, its energy needs might be higher at certain hours, so the prices at those hours could have a higher weight in its decisions. The point is that the average price is not necessarily directly related to the average cost of a PEV.

In summary, both ILC studies complement each other in the insights that they provide. The difference in characteristics gives rise to many aspects of modeling and implementation decisions that can be made along the way and enrich the scientific debate on ILC.

Chapter 7

Contributions, Conclusions and Future Work

This final chapter marks the closure of this dissertation. It concludes the research carried out within this thesis by summarizing its main contributions and results, deriving conclusions from it and pointing to possible paths of future work. Section 7.1 starts by reporting the main contributions of this thesis in a concise but interconnected matter. Proceeding, Section 7.2 formulates a comprehensive answer to the research question formulated and the general research objectives derived in the Introduction of Chapter 1, as well as the specific research objectives deduced at the end of the literature review in Chapter 3. Finally, taking the main limitations of the developed approach as a starting point, Section 7.3 indicates the research lines pertaining to future work.

7.1 Main Contributions

The contributions of this thesis compared to the state-of-the-art prior to the respective publications of the results are listed underneath, point by point. However, please consider that the whole is bigger than the sum of all its parts, i.e., that each contribution becomes most meaningful when put into the context of the other parts complementing it:

- This thesis has contributed by outlining the relevant parameters of a **regulatory framework** governing the efficient integration of PEV in modern electric power systems. It has highlighted that coordination algorithms striving for validity in fully unbundled power systems, such as, e.g., aligned with European Directives, should note of the specific regulatory settings that different power systems agents are subject to. In such a setting, *aggregators are competitive market agents* at the interface of wholesale and retail electricity markets. Here, competitiveness refers to the fact that an aggregator carries out transactions in a market place according to its business model. Distributors, i.e., *network infrastructure operators*, on the other hand, are *fully regulated entities, acting in natural monopolies*, whose decisions are therefore subject to diametrically different objectives. Furthermore, the thesis has alluded to one way of classifying charging modes by the characteristics: *location and access to the charging point*, the *intermediary agents* involved in facilitating the final products as well as the *level of sophistication in communication, control and optimization strategies* over the battery charging process.

- A **two-stage stochastic linear program for the PEV aggregator**'s day-ahead and balancing decisions with **direct load control** over a large fleet of PEV has been proposed, while accounting for risk via a CVaR term in the objective function. The model includes *uncertainty in* both market prices as well as *PEV mobility parameters.* Furthermore, it presents calculations of two metrics named *expected value of flexibility* and *expected value of aggregation*; the former quantifies the value associated with the flexible timing of the charging and the latter measures the benefits from jointly scheduling larger PEV fleets to reduce the costs of uncertainty. The proposed scheme obtains PEV charging schedules at the *level of individual vehicles* with moderate computation time when applying scenario-reduction techniques. To model the uncertainty in PEV mobility, i.e. availability to the power system and energy requirements, a discrete-time, agent-based Monte-Carlo simulation of PEV mobility was used, including various variance reduction techniques. To depict forecasting behavior of the aggregator, SARIMA and GARCH models for day-ahead and balancing prices have been identified and their parameters estimated.
- An extension of the above DLC model has been used to calculate **standard stochastic programming metrics** for a stylized case with a fleet of 5 electric vehicles. The effect of including different information constraints regarding market prices and mobility forecasts is used to obtain the *value of the stochastic solution* and the *expected value of private information* for the given application.
- Set in an existing, real medium voltage distribution network with urban characteristics and spatial PEV mobility, **network UoS tariffs for capacity have been applied** to the retail problem of scheduling PEV charging by an aggregator. This is done to enhance the above DLC coordination model and to *overcome the lack of regulatory rigor* used in a substantial share of the PEV coordination literature. UoS tariffs based on *DSO's long run marginal cost* have been proposed as a means of interaction between the aggregator as a market agent and the DSO being the regulated network operator. These are deemed to sufficiently account for the local situation of the network and serve as a capacity signal for *smoothing effects on the PEV load*.
- A second set of models has been elaborated, conceptually presenting a formulation of the PEV aggregator's problem with particular focus on the

retail interface with the final customers. It affords a *decentralized* optimization of charging costs as well as aggregator profits, in which final customers decide on their charging schedule, depending on the *endogenously determined* and *profit-optimal prices* of the aggregator. These decisions respect a *potential discomfort* that may arise when PEV users have to *deviate from their preferred charging schedule.* Methodologically, this has been achieved by applying **complementarity modeling**, which by itself is well known from other electricity market problems. Thereby the main assumption of centrally coordinated direct load control for optimal charging schedules has been relaxed to present **indirect load control**. To this end, the proposed formulation is a bi-level optimization problem given by an **MPEC**, in which 1) the upper level *decisions on retail tariffs* and optimal bidding in electricity markets are subject to 2) the lower level *client-side optimization of PEV charging schedules.*

- Again for the sake of regulatory rigor, the same capacity based *network UoS tariffs* have been applied to the bi-level retail problem of scheduling PEVs via prices. The **efficient modeling of this MPEC** problem in the PEV framework *avoids non-linearity with the help of the strong duality-theorem* and achieves computationally efficient solutions by *discretizing bi-linear terms employing only few integer variables.* Demand side reductions are modeled via an *affine demand with constant profit margin*, for the aggregator using hourly time-discriminating prices. A qualitative discussion of issues regarding the aggregator's role and added value of its services to power systems, as well as points to issues that could arise under a monopolistic market of retail for PEV.

7.2 Conclusions with Respect to the Defined Research Objective

The question underlying the research carried out in the context of this thesis has been:

In the presence of resource scarcity, how should PEVs be advisably coordinated, providing benefits to electric power systems?

The most relevant power system resources represented in this context have been electricity generation, network capacity, as well as flexibility to respond to unforeseen imbalances. Ideally, the coordination of PEV charging should take into account all the above, even more so in the case of scarcity in any of the above named resources. The power system generation side can be well represented by wholesale energy markets. Prices in power spot exchanges are deemed an efficient signal to allocate the available resources. PEVs aligning their charging schedule according to day-ahead electricity market prices are a first step. In a second step, uncertainty should be managed because it is costly. Laws of physics mandate to balance power system generation and demand at all times. Yet, generator ramping limits make short-term changes in output more costly than scheduling generation ahead of time. Finally, network capacity, especially in distribution networks may also be limited. PEV charging schedules are inherently flexible, having the potential to react to short-term signals and adjust previously committed schedules at very little cost. However, stochastic processes presenting uncertainty in prices and mobility parameters of a fleet, may also cause costs. Aggregation of larger fleets may alleviate parts of this, because they reduce the relative forecasting errors. Furthermore, peaks in PEV consumption could congest networks and create a need for costly reinforcements. An ideal PEV coordination approach should take into account cost causality principles and if given the right degrees of freedom, smoothen demand over time and space. However, ideal charging methods cannot override existing regulatory frameworks that specifically define the roles of different power system agents. It is therefore deemed crucial to properly distinguish the modeling of competitive market agents as well as network operators acting in natural infrastructure monopolies.

From these basic insights, the main research objective has been derived: to propose models for decision making of existing and future power system agents that can influence the total system efficiency, while charging plug-in electric vehicles. The specific objectives cascading down from the main research objective relate to the development and application of models that describe the optimal decision making of plug-in electric vehicle aggregators exercising direct as well as indirect load control over the charging schedule while participating in day-ahead electricity markets. In both models, the goal is then to include an adequate representation of the distribution network usage that is aligned with the long run marginal cost of the distribution system operator.

To tackle the topic even more precisely, the main research objectives were decomposed further into specific research questions. The most relevant actors, whose decision making is most decisive for PEV coordination have been identified. The PEV aggregator focuses on the fleet management of PEV for electricity market participation, while the distribution system operator is involved when PEVs are efficiently charged for their capacity use in distribution networks.

Research sub-question 1a): In a given market price and mobility scenario, what is the profit maximizing charging schedule of electric vehicles? A detailed analysis of each scenario requires care and specifically designed tools. Using the optimization programs developed in this thesis, a PEV aggregator can optimally determine its involvement in day-ahead electricity markets. The buying and selling positions taken in different hours depend on the charging and discharging variables, which are imposed by the PEV energy requirement and constrained to the availability of the aggregated fleet of vehicles. Given this feasible region, in principle, the program will find low price hours for purchases and high price hours for discharges. The profit of the aggregator then mainly depends on the arbitrage between different instants in time and thus market prices, as well as retail prices agreed with the final customers. Such decision making is, for the most cases, likely to decrease net social cost and drive the system towards a more efficient outcome, utilizing less expensive generation resources.

Research sub-question 1b): How do market prices, mobility behavior representation, retail tariffs/pricing schemes as well as storage parameters impact the profitability? Market prices and their variability do have a pronounced effect on the profitability of the PEV aggregator's business model. As alluded in the answer to research sub-question 1a) the aggregator is looking for both, arbitrage between hours, as well as for a margin over the retail interface. Furthermore, it is of high importance to account for shorter term markets, such as intra-day, adjustment and balancing markets. This thesis has considered one particular occurrence of imbalance settlement systems, a two-price system, in which imbalances are essentially penalized if they contribute to the system imbalance. Balancing responsible parties in such a system cannot get better off compared to their day-ahead commitments, in case they decrease the system imbalance. Under such a system, deviations from the day-ahead schedules can be very costly and uncertainty must be managed accordingly.

Retail tariffs and pricing schemes directly influence the profitability as they determine the amount of revenue that can be obtained from the aggregator. In the presented DLC models, revenues are flat rate volumetric energy tariffs that are exogenously set. Profits can therefore be accordingly calibrated. In the presented ILC models however, the final customers react to the retail prices given to the PEVs with potential demand reductions.

Storage parameters, in particular inefficiencies for the energy transfer are of less importance. They play into the energy balances and increase the amount of money exchanged for the same net energy charged or discharged, and thus add precision and detail to the economic approximations, however, they do not substantially alter the conclusions that can be drawn from the numerical results. The size, i.e. the energy capacity of the battery also does not play a very crucial role.

Research sub-question 1c): What is the value of flexibility exhibited by a fleet of vehicles scheduling their charging according to wholesale electricity market prices. Within this thesis, the aggregator's value of flexibility of a PEV fleet is defined as the economic benefit of aligning the PEV schedule with market prices. To estimate this value of flexibility, first, the optimal objective function value in the original formulation with DLC is opposed to that of a schedule over which the aggregator cannot exercise control. Their relative difference makes up this value. In the large-scale DLC case study with 1000 vehicles, 200 initial, and 100 reduced scenarios for market prices and mobility, the expected value of PEV flexibility under direct load control by the aggregator has been found to be substantial. It lies in the range of 33%. However, how this benefit would be shared is not answered by the DLC study. It could mean that either the aggregator's profits increase by this amount, or to incentivize the PEV participation in a DLC scheme these profits could be passed on to the final customers through tariff reduction.

Research sub-question 1d): If uncertainty in the input data is considered, what are appropriate measures to hedge against the risk exposure? Considering uncertainty via a finite set of possible future realizations of the stochastic processes involved permits the use of stochastic decision making frameworks. With linear programming methods, it is possible to formulate the deterministic equivalent of a two-stage decision sequence, with here-and-now variables as well as wait-and-see variables. Nonanticipativity restrictions constrain the former to account for the limited foresight available at the first stage decisions. Many risk measures can be applied. The conditional value at risk is a coherent risk measure that can be included in such stochastic linear programs as an additional, scalably weighted term to the expected profit in the objective function. Given a confidence level α, it enables the control of the expected value of the lowest (1-α)-quantile scenarios of the profit distribution. Increasing the level of risk-aversion of the PEV aggregator comes at the cost of lower expected profits in the objective function. The case studies in this thesis have shown that hedging against adverse lower-tail profits can be achieved, as well as strategies of reaching outcome distributions with lower risk can be found. The PEV aggregator may, e.g., reduce specific hourly day-ahead positions and strongly (slightly) increase (decrease) positive (negative) balancing.

Research sub-question 1e): To what extent does the size of the fleet impact the aggregator's economics? The size of the aggregator's fleet impacts its economics because of the relative forecasting error and the associated cost under the above mentioned imbalance penalization scheme. To analyze how much the stochasticity of a single PEV's mobility influences the economics of the charging schedule in the day-ahead planning, a disaggregation technique has been applied, in which the problem is solved with varying aggregation sizes of parallel sub-fleets. It turns out that the confidence with which day-ahead forecasts of vehicle mobility, i.e., energy demand and unavailability, can be carried out increases with the fleet size. Hence, a larger fleet incurs lower imbalance settlement fees as compared to the same fleet broken up in smaller sub-fleets. In effect, the more vehicles are controlled by the same entity, the better the individual vehicles compensate for the uncertainty in mobility of the others within the same aggregation. This expected value of PEV aggregation has been found to lie in the range of 19% comparing the scheduling of 250 four-vehicle big sub-fleets with the scheduling of one fleet of 1000 vehicles.

Research sub-question 1f): How can different controlled charging schemes, i.e. ILC and DLC, be mathematically represented in the decision making optimization of the PEV aggregator? The DLC approach is rather common in literature and involves the assumption that all decision variables, notably the charging and resulting SOCs of the vehicles are under control of the PEV aggregator. This essentially means that the aggregator can directly determine power set points and optimal energy quantities to be charged. All constraints are directly incurred by the aggregator. Representing ILC schemes, on the contrary, involves the conceptual decomposition of the problem ownership into two levels, and defining the information exchanged at their interface. While the PEVs receive retail prices from the aggregator within a given pricing scheme constraint, the aggregator incurs the demand reaction to these price signals. This thesis has indicated that the bi-level structure common in complementarity modeling for electricity markets can be a suitable framework for the given problem structure.

Research sub-question 2a): What is the effect of pricing distribution system capacity by means of network UoS charges both in DLC and ILC models? Although it is widely accepted that electricity market signals are deemed efficient to allocate resources at the transmission system level, using uniform, zonal or locational marginal pricing, they may yet not always sufficiently represent the local network status of the distribution system at sub-transmission levels. Furthermore, high penetration levels of PEV potentially cause network reinforcement, which would have an impact on investment, operation and maintenance costs of the DSO, who in turn translates these via the grid fees to the final customers. This is an undesirable charging outcome, as without coordination taking into account networks, the total system efficiency is at danger. Therefore, this thesis has used relatively unexplored long run marginal cost pricing for computing node dependent network UoS tariffs. Both under DLC and under ILC, as shown by representative case studies, the charging schedules are generally smoothened. Peak reductions are achieved, very likely alleviating punctual network saturation.

Research sub-question 2b): Including network topology in the above PEV aggregator model, represented by locational capacity prices, how are charging schedules changing their alignment from market signals? Ideally, mathematical formulations for PEV charge scheduling would take into account capacity-based network UoS prices that are dependent on each network node at MV level. The basic idea of these prices is grounded on the fact that the use of the system is less costly at a point of supply where there tends to be spare capacity compared to another point, where the network tends to be saturated. This is common ground in distributed generation, as it sends a locational signal to investors of distributed energy resources, promoting locations where it is overall less costly to connect and use the network. Given an appropriate infrastructure, the batteries of PEVs presumably present a certain degree of freedom not only regarding the timing of charging, but also the location. Therefore, the same principle could be applied to the scheduling of controlled PEV charging.

It must be noted that, indeed, if all vehicles received the same price signal and there were sufficient PEV penetration in the local network, congestion could arise. Nevertheless, a remedy to congestion could in fact be an appropriate UoS pricing of the network, not only differentiating between different nodes, but also including time discrimination in the access tariff as this would treat vehicles at different locations individually. PEV penetration is a slow process and as such it can be well included in the planning processes of network operators including both, the tariff design in the short- to medium term, as well as investment decisions for reinforcement in congested areas. In principle, the pricing of UoS based on capacity is already an effective tool to make use of the system. However additionally, it sends a signal to the users that is well aligned with the long run marginal cost of operating the network. If the lack of spare capacity is more prominent in certain parts of the grids, the higher capacity prices give a strong signal, always relative to the other components of the final customer bill, such as the wholesale parts, to the PEV to smoothen the charging curve. If the danger of congestion prevails, the UoS revenues should permit the grid operator to reinforce the network by upgrading lines and transformer capacity.

The case studies show implications on optimal scheduling with UoS. The results have pointed at the fact that capacity network charges are an efficient instrument to account for local network situations in the charging schedules. Including UoS in the proposed models schedules the PEV charging in alignment with time and by network node location.

General Policy Recommendations Even though this thesis did not explicitly set out to provide policy recommendations, but rather contribute on a technical modeling level, some general policy recommendations are not left unmentioned. The EU has set ambitions targets for the decarbonization of both the electricity sector and transport systems. The electrification of personalized mobility appears to be a promising pathway for these aims. Information and communication technologies as well as the corresponding standards seem ready and applicable to achieve an efficient use of the resources for when PEV penetration levels rise. However, the regulatory frameworks should enable all market players and system operators to fully reap the given potential. It seems recommendable to revisit the regulation of distribution grids for a future world of smart grids. Significant efforts should be undertaken to precisely define the roles of future distribution system operators, transmission system operators and market participants such as PEV aggregators.

In particular, this thesis has shown that the application of capacity-based pricing for the use of networks could help to drive the system operation towards higher overall efficiency. Volumetric energy charges seem less appropriate in a capacity-driven system, which is mainly based on fixed capital costs. Therefore, pricing schemes similar to the here-applied use-of-system network fees should be encouraged by legislation and enacted through regulation. Ideally, the legal framework of the European Union would seize the opportunity to harmonize the variety of diverging solutions that are being undertaken in many different places with the intention to apply only the best proven practices. More European integration of short-term intraday and balancing markets would be desirable. Similar to what has been achieved by day-ahead markets would be desirable. Electricity markets should have the lowest possible barriers, justified ideally only by transaction costs, to incentivize a broad range of actors both on the supply and demand side for the highest flexibility. This includes lower regulatory entry hurdles and less discriminatory rules for aggregator participation. Variations in wholesale prices can drive the operation schedules PEV storage units and should therefore be visible to the optimization algorithms with as little distortion as possible.

PEVs are a powerful integrator to link wholesale and retail markets via dedicated supplier-aggregators. PEVs are also helpful in showing a way towards decentralized generation schemes, where market roles change. Ideally, there would be electricity market places that promote the final customers to engage with the energy system to spark a transition towards a sustainable future.

7.3 Future Work

Naturally, the research work presented in this thesis has its limitations. A large share of these shortcomings automatically translates into future research lines, dedicated to improving or extending the developed tools for further functionality. The main strands identified are mentioned in the following:

Risk Management Scenario-based linear stochastic programming has inherent disadvantages compared to deterministic scheduling, because each stochastic process considered multiplies the amount of scenarios needed to represent such a range of outcomes. The limits of the proposed DLC approach with the regard to computational tractability have been shown. It is likely that to solve even larger problem instances of the given formulation, the application of decomposition techniques to parallelize the solving algorithms for multi-cluster high performance computing is promising.

Information Constraints For the stochastic DLC scheduling with risk management, a hedging strategy was shown, which included a shift of demand from the day-ahead to the balancing market. However, this may be partly due to the assumption of perfect foresight in the second stage of the model. To alleviate this assumption, future research lines could involve extending this formulation to a multi-stage stochastic program. A first step would be to include the knowledge on balancing prices after taking balancing decisions etc.

Spatial UoS DLC Scheduling Future work on spatial UoS DLC scheduling is equally manifold. This thesis merely includes a stylized case study that shows the functionality of the proposed PEV aggregator model as well as advantages of the pricing methodology. In the future, it could be interesting to apply this approach to a case with realistic mobility, big scale, real medium to low voltage networks and using time series models for generating market price (day-ahead and balancing) scenarios. Furthermore, a risk aversion measure could be included.

Bi-level Programming for ILC Also for the ILC, future work includes further analysis of scalability. Bender's type decomposition techniques seem a-priori promising candidates to achieve even better computational performance.

Furthermore, under ILC, it should be pointed out that the developed mathematical formulation does not explicitly model the aspects of aggregator competition and PEV selecting aggregator's in a functional retail market. Notwithstanding, it can, as mentioned in multiple instance of the manuscript, serve as a basis for analyzing the strategic interactions in a two-agent leader-follower game. The insights gained with this model are transferable for the design of retail equilibrium models and indeed motivate the necessity of these. So far, competition can merely be emulated in the form of a quick remedy, and the next step in research could naturally be an EPEC, where the retail market equilibrium outcomes can be approximated. In fact, mathematically speaking, the building blocks for an EPEC are partially shared by its underlying MPECs. To explain this, please consider the following: EPECs are essentially a means to represent types of mathematical programs that are useful for modeling such games when there is more than one leader, and one wants to find an equilibrium among these and the shared lower level. In game theoretic terms, the problem is to obtain a Nash equilibrium among multiple leaders of a Stackelberg leader-follower problem, where there is a shared single follower. A Stackelberg game represents a situation of asymmetric information in which the leaders correctly anticipate the reaction of the follower to the leaders' decisions, but the followers take the leaders' decisions as exogenous, naively acting as if they had no influence over the leaders' doings. The followers' reactions could be captured, as in the MPEC presented in this paper. In this regard, this thesis presents the first step towards a more exhaustive treatment of electricity retail market equilibria with PEV.

Appendix

Appendix A

Mathematical Foundation

A.1 Complementarity Modeling for Bi-level Programs

A.1.1 KKT Conditions

A.1.1.1 For the LL with Reference Schedule

To combine both UL and LL formulations in one problem, the Karush-Kuhn-Tucker (KKT) conditions of the LL problem are formulated. To this end, the partial derivative of the Lagrangian form of (4.45) is taken with respect to each of the primal decision variables, which at the optimum have to fulfill the first order condition:

$$\nabla \mathcal{L}\begin{pmatrix}\vdots\end{pmatrix} = \nabla \mathbf{f}\begin{pmatrix}\vdots\end{pmatrix} + \theta^{\intercal}\cdot\nabla \mathbf{g}\begin{pmatrix}\vdots\end{pmatrix} + \mu^{\intercal}\cdot\nabla \mathbf{h}\begin{pmatrix}\vdots\end{pmatrix} = 0. \tag{A.1}$$

The stationarity components of the objective function in vector form are then

$$\nabla \mathbf{f}\begin{pmatrix}\vdots\end{pmatrix} = \begin{pmatrix}\gamma_{\overline{h}}^{\vee} \\ 0 \\ \Lambda_v \cdot |\mathcal{H}| \\ \Lambda_v \cdot |\mathcal{H}| \\ \Xi_v \cdot |\mathcal{H}|\end{pmatrix}, \tag{A.2}$$

$$\theta_{v,h}^{\mathbf{g}_1}\cdot\nabla \mathbf{g}_1\begin{pmatrix}\vdots\end{pmatrix} = \theta_{v,h}^{\mathbf{g}_1}\cdot\begin{pmatrix}-1 \\ 0 \\ 0 \\ 0 \\ 0\end{pmatrix}, \tag{A.3}$$

$$\theta^{\mathbf{g}_2}_{v,h} \cdot \nabla \mathbf{g}_2 \begin{pmatrix} \vdots \end{pmatrix} = \theta^{\mathbf{g}_2}_{v,h} \cdot \begin{pmatrix} 0 \\ -1 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \tag{A.4}$$

$$\mu^{\mathbf{h}_1}_{v,h} \cdot \nabla \mathbf{h}_1 \begin{pmatrix} \vdots \end{pmatrix} = \mu^{\mathbf{h}_1}_{v,h} \cdot \begin{pmatrix} -\eta^{\underline{\vee}} \\ 1 \\ 0 \\ 0 \\ -1 \end{pmatrix} + \mu^{\mathbf{h}_1}_{v,h-1} \cdot \underbrace{\begin{pmatrix} 0 \\ -1 \\ 0 \\ 0 \\ 0 \end{pmatrix}}_{h \in \{2..|\mathcal{H}|\}}, \tag{A.5}$$

$$\mu^{\mathbf{h}_2}_{v,h} \cdot \nabla \mathbf{h}_2 \begin{pmatrix} \vdots \end{pmatrix} = \mu^{\mathbf{h}_2}_{v,h} \cdot \begin{pmatrix} -1 \\ 0 \\ -1 \\ 1 \\ 0 \end{pmatrix}, \tag{A.6}$$

$$\mu^{\mathbf{h}_3}_{v,h} \cdot \nabla \mathbf{h}_3 \begin{pmatrix} \vdots \end{pmatrix} = \mu^{\mathbf{h}_3}_{v,h} \cdot \underbrace{\begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}}_{h \in \{|\mathcal{H}|\}}. \tag{A.7}$$

with $\begin{pmatrix} \vdots \end{pmatrix} = \left(\bar{e}^{\mathrm{RT},\underline{\vee}}_{v,h},\, \bar{e}^{\mathrm{SOC}}_{v,h},\, \bar{t}^{+}_{v,h},\, \bar{t}^{-}_{v,h},\, \bar{e}^{\mathrm{DR}}_{v,h} \right)^{\intercal}$. The constraints relating to the KKT-stationarity are thus:

$$\begin{aligned}
&\forall v,h\colon\quad \gamma^{\underline{\vee}}_{h} - \theta^{\mathbf{g}_1}_{v,h} - \mu^{\mathbf{h}_1}_{v,h} \cdot \eta^{\underline{\vee}}_{v} - \mu^{\mathbf{h}_2}_{v,h} && -\theta^{\mathbf{g}_3}_{v,h} = 0, && \text{(A.8)}\\
&\forall v,h\colon\quad -\theta^{\mathbf{g}_2}_{v,h} + \mu^{\mathbf{h}_1}_{v,h} - \underbrace{\mu^{\mathbf{h}_1}_{v,h-1}}_{h \in \{2..|\mathcal{H}|\}} + \underbrace{\mu^{\mathbf{h}_3}_{v,h}}_{h \in \{|\mathcal{H}|\}} && -\theta^{\mathbf{g}_4}_{v,h} = 0, && \text{(A.9)}\\
&\forall v,h\colon\quad \Lambda_v - \mu^{\mathbf{h}_2}_{v,h} && -\theta^{\mathbf{g}_5}_{v,h} = 0, && \text{(A.10)}\\
&\forall v,h\colon\quad \Lambda_v + \mu^{\mathbf{h}_2}_{v,h} && -\theta^{\mathbf{g}_6}_{v,h} = 0, && \text{(A.11)}\\
&\forall v,h\colon\quad \Xi_v - \mu^{\mathbf{h}_1}_{v,h} && -\theta^{\mathbf{g}_7}_{v,h} = 0. && \text{(A.12)}
\end{aligned}$$

KKT feasibility and complementarity of the inequalities is described by the following:

$$\forall v,h\colon 0 \le \theta^{\mathbf{g}_1}_{v,h} \perp \mathbf{g}_1 = \bar{e}^{\text{RT},\veebar}_{v,h} - \nu_{v,h}\overline{P}_v \ge 0,^{*} \tag{A.13}$$

$$\forall v,h\colon 0 \le \theta^{\mathbf{g}_2}_{v,h} \perp \mathbf{g}_2 = \bar{e}^{\text{SOC}}_{v,h} - \overline{E}_v \ge 0, \tag{A.14}$$

$$\forall v,h\colon 0 \le \theta^{\mathbf{g}_3}_{v,h} \perp \mathbf{g}_3 = e^{\text{RT},\veebar}_{v,h} \ge 0, \tag{A.15}$$

$$\forall v,h\colon 0 \le \theta^{\mathbf{g}_4}_{v,h} \perp \mathbf{g}_4 = e^{\text{SOC}}_{v,h} \ge 0, \tag{A.16}$$

$$\forall v,h\colon 0 \le \theta^{\mathbf{g}_5}_{v,h} \perp \mathbf{g}_5 = t^{+}_{v,h} \ge 0, \tag{A.17}$$

$$\forall v,h\colon 0 \le \theta^{\mathbf{g}_6}_{v,h} \perp \mathbf{g}_6 = t^{-}_{v,h} \ge 0, \tag{A.18}$$

$$\forall v,h\colon 0 \le \theta^{\mathbf{g}_7}_{v,h} \perp \mathbf{g}_7 = e^{\text{DR}}_{v,h} \ge 0, \tag{A.19}$$

Remaining essentially unchanged are the equality constraints regarding feasibility in the KKT optimum :

$$\begin{aligned}\forall v,h\colon \mathbf{h^1} = & -e^{\text{RT},\veebar}_{v,h}\cdot\eta^{\veebar}_{v} - e^{\text{SOC}}_{v,h-1} - e^{\text{DR}}_{v,h} + \rho_{v,h} \\ & + \underbrace{e^{\text{SOC}}_{v,h}}_{h\in\{2..|\mathcal{H}|\}} + \underbrace{\iota^{\text{SOC}}_{v}}_{h=1} = 0,\end{aligned} \tag{A.20}$$

$$\forall v,h\colon \mathbf{h}_2 = -e^{\text{RT},\veebar}_{v,h} - t^{+}_{v,h} + t^{-}_{v,h} + \check{\mathbf{E}}^{\text{RT},\veebar}_{v,h} = 0, \tag{A.21}$$

$$\forall v,h\in\{|\mathcal{H}|\}\colon \mathbf{h}_3 = e^{\text{SOC}}_{v,h} - \phi^{\text{SOC}}_{v} = 0. \tag{A.22}$$

A.1.1.2 For the Daily Affine Demand

In the LL formulation with daily affine demand, the constraints relating to the KKT-stationarity are:

$$\begin{aligned}\forall v,h\colon \quad & \gamma^{\veebar}_{h} + \mu^{\mathbf{g^1}}_{v,h} + \theta^{\mathbf{h^1}}_{v,h}\cdot\eta^{\veebar}_{v} + \theta^{\mathbf{h^2}}_{v,h} - \theta^{\mathbf{h^3}}_{v} \\ & - \mu^{\mathbf{g^3}}_{v,h} + \mu^{\mathbf{g^5}}_{v,h\in|\mathcal{H}^{\mathbf{on}}|} + \mu^{\mathbf{g^6}}_{v,h\in|\mathcal{H}^{\mathbf{off}}|} - \mu^{\mathbf{g^7}}_{v,h} = 0,\end{aligned} \tag{A.23}$$

$$\forall v,h\colon \quad \mu^{\mathbf{g^2}}_{v,h} - \theta^{\mathbf{h^1}}_{v,h} + \underbrace{\theta^{\mathbf{h^1}}_{v,h+1}}_{h\in\{2..|\mathcal{H}|\}} - \mu^{\mathbf{g^8}}_{v,h} = 0, \tag{A.24}$$

$$\forall v,h\colon \quad \Lambda^{+}_{v} + \theta^{\mathbf{h^2}}_{v,h} - \mu^{\mathbf{g^9}}_{v,h} = 0, \tag{A.25}$$

$$\forall v,h\colon \quad \Lambda^{-}_{v} - \theta^{\mathbf{h^2}}_{v,h} - \mu^{\mathbf{g^{10}}}_{v,h} = 0, \tag{A.26}$$

$$\forall v,h\colon \quad \Xi_v + \theta^{\mathbf{h^1}}_{v,h} - \theta^{\mathbf{h^3}}_{v} - \mu^{\mathbf{g^3}}_{v,h} + \mu^{\mathbf{g^4}}_{v,h} - \mu^{\mathbf{g^{11}}}_{v,h} = 0, \tag{A.27}$$

$$\forall v\colon \quad \mathbf{C^{UoS,on}} - \sum_{h\in|\mathcal{H}^{\mathbf{on}}|} \mu^{\mathbf{g^5}}_{v,h} = 0, \tag{A.28}$$

$$\forall v\colon \quad \mathbf{C^{UoS,off}} - \sum_{h\in|\mathcal{H}^{\mathbf{off}}|} \mu^{\mathbf{g^6}}_{v,h} = 0 \tag{A.29}$$

Appendix B

Time Series Model Estimation

B.1 Forecasting Day-Ahead Market Spot Prices

B.1.1 Data Analysis for Model Identification

According to a famous quote, model identification is necessarily inexact, because it is not easy to mathematically describe the real world [140].

Stabilization of Variance - Box-Cox Transformation

Since the original time series contains negative values as depicted in Tab. B.1, a logarithm or Box-Cox transformation for further variance stabilization is a priori not possible. Hence, a shift-parameter a is applied such that $\dot{y}_t = y_t + c$, with $a = |\min_t \{y_t\}| + 1$. For the given time series, it is set to $a = |y_{7994}| + 1 = 37.82$. Following,

$$\dot{y}_t^{(\lambda)} = \frac{\dot{y}_t^{\lambda} - 1}{\lambda}, \text{ with } \lambda : \quad \max_{\lambda} L^{(\lambda)} = -\frac{n}{2} \ln\left(\hat{\sigma}^2_{(\lambda)}\right) + (\lambda - 1) \sum_{i=1}^{n} \ln\left(\dot{y}_i\right), \tag{B.1}$$

where λ is the optimal parameter value determined by maximising the natural log-likelihood function $L^{(\lambda)}$, in which $\hat{\sigma}^2_{(\lambda)}$ is the estimate of the least squares variance using the transformed variable $\dot{y}_t^{(\lambda)}$. For the given time series, such a transformation with $\lambda = 1.9188$ is performed. The mean stabilizing effect can be assessed by studying the following.

Fig. B.1 illustrates the effect of the Box-Cox transformation on the original data series (left side figures). The upper diagrams produce histograms of the

t	122	123	148	150	151	4696	4697	7900	7902	7903	7944
y_t	-10.02	-10.04	-0.10	-0.04	-10.10	-0.02	-0.59	-0.10	-0.07	-9.30	-36.82

Table B.1: Negative Outliers of Original EPEX Time Series

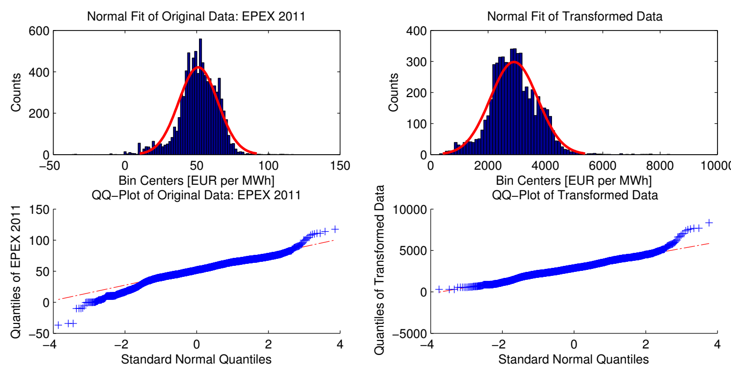


Figure B.1: Assessing the Effects of Transforming the Series

values in the vector data using the number of bins equal to the square root of the number of elements in the series data, then superimpose a fitted normal distribution. The lower, quantile-quantile plots display the sample quantiles of the series data versus theoretical quantiles from a normal distribution. After applying the transformation, the new series (right side figures) has a distribution that is slightly closer to normality as compared to its distribution prior to the transformation.

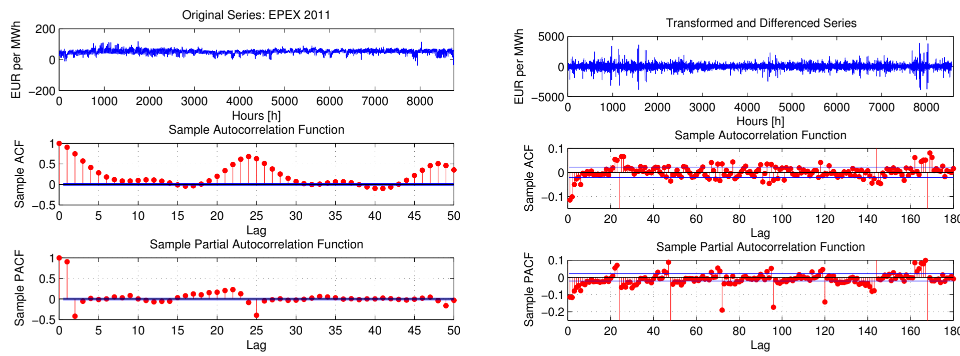
Sample and Partial Autocorrelation Function Analysis

Following the standard methodology described in [140] and [139], the sample auto-correlation function (ACF) as well as the sample partial auto-correlation (PACF) functions are plotted for the first 50 lags in Fig. B.2a. Tentatively, normal and seasonal differencing of order $d = 1$ and $D = 1$, respectively, with $(1 - B)$, $\left(1 - B^{24}\right)$ and $\left(1 - B^{168}\right)$ seems promising to take care of the significant components of the respective lags in the PACF and should provide a suitable stabilization of the mean. Fig. B.2b shows the differenced series. A statistical test, known as KPSS, of the differenced series was performed to check trend stationarity. The null hypothesis that the univariate time series y is trend stationary was not rejected. The series was thus found to not be a nonstationary unit-root process.

With both ACF and PACF of the differenced series tailing off after lags 6 and 8, respectively, suggests a mixed ARMA process as a conjunction of exponentials and damped sine waves after the first $q - p$ lags.

Model Identification

Further on, it will be assumed that mean and variance of the differenced and transformed series $\dot{y}_t^{(\lambda)}\,(1 - B)\left(1 - B^{24}\right)\left(1 - B^{168}\right)$ are sufficiently stable to continue with the parameter estimation of various ARMA models. In particular, the resulting $\text{SARIMA}(1,1,2)_{24,168}$, $\text{SARIMA}(2,1,1)_{24,168}$, and $\text{SARIMA}(1,1,1)_{24,168}$



(a) Sample ACF and PACF of the Original Series (b) Sample ACF and PACF of the Transformed and Differenced Series

Figure B.2: Principal Tools of Model Identification - Differencing

are estimated and compared to each other. Further on, they will be referred to as Model A, B and C, respectively.

B.1.2 SARIMA Model Parameter Estimation for *EPEX*

For all models the first 6000 observations are taken for training the model, i.e. for the parameter estimation, though, out of these 6000, the first 200 are taken as pre-sample data. The rest of the observations, i.e. 6001-8760 are taken for model validation purposes in a rather strict way. That is, all models are estimated and validated using a forecasting horizon of 1 hour in the training period.

Preliminary Residual Analysis

After the successful convergence of the estimation algorithm, the normalized residuals are inferred from the respective model fits using the data from the training period. These normalized residuals are checked for normality and auto-correlation. First, normality checks are performed by means of qq-plots as in Fig. B.3, in which the residuals exhibit sufficient normality. Then, ACF and PACF of the residuals are plotted. Even though the null hypothesis of the Ljung-Box portmanteau test **box1970distribution** for a series of residuals exhibiting no autocorrelation for a fixed number of lags, against the alternative that some autocorrelation coefficient is nonzero cannot be rejected for any of the estimated models, the respective auto-correlation plots of Fig. B.4 show significance in less than 5% of the lags.

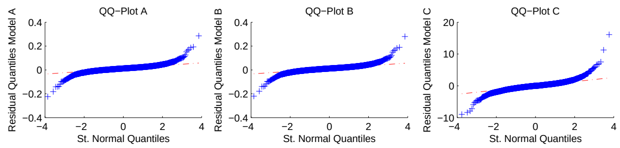


Figure B.3: Residual Analysis: QQ-Plots

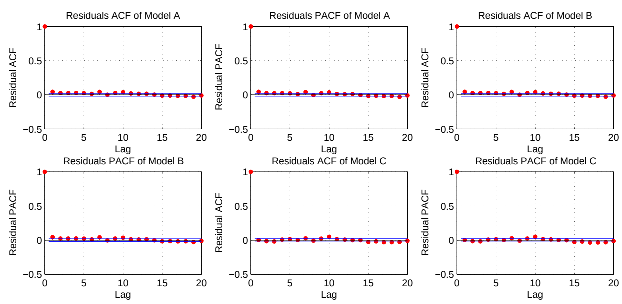


Figure B.4: Residual Analysis: ACF and PACF

Model	Specification	AR	MA	SAR	SMA	Constant	Variance
A	$\text{SARIMA}(1,1,2)_{24,168}$	$\phi_1 = .8149$ $\phi_2 = -.0201$	$\theta_1 = -.9840$	$\Phi_1 = .0255$	$\Theta_{24} = .2175$ $\Theta_{168} = -.6093$	$c_A = -0.0267$	$\sigma_A^2 = 56704$
B	$\text{SARIMA}(2,1,1)_{24,168}$	$\phi_1 = .7936$	$\theta_1 = -.7746$ $\theta_2 = -.2064$	$\Phi_1 = -.1619$	$\Theta_{24} = .2175$ $\Theta_{168} = -.6093$	$c_B = -0.0319$	$\sigma_B^2 = 56694$
C	$\text{SARIMA}(1,1,1)_{24,168}$	$\phi_1 = .7893$	$\theta_1 = -.9840$	$\Phi_1 = .0505$	$\Theta_{24} = .2176$ $\Theta_{168} = -.6093$	$c_C = -0.0267$	$\sigma_C^2 = 56704$

Table B.2: Maximum Likelihood Estimation Results: Model Parameters

Model Parameters

The result of the maximum likelihood estimation process can be viewed in Tab. B.2, where the parameters are indicated in the multiplicative format as introduced in equation (4.71). The result provides that seasonal moving average, constant and variance parameters are very similar in all models A, B, and C. Accordingly, it is expected that the forecasting performance will only differ insignificantly, yet one model must be chosen and hence further indicators are employed.

Model Comparison and Selection

Initially, the forecasting performance is assessed using visualization of forecast versus validation signal. Subtracting the latter from the former gives the forecast error. Fig. B.5a, Fig. B.5b and Fig. B.5c show both plots for models A, B and C, with zoom at different sub-axes, respectively. From the sheer graphic analysis the forecasting performance of all three models seems almost similar and therefore it is not possible to make out the best candidate at human eyesight. It inevitably appears reasonable to employ quantitative statistics.

Thus, the different models are compared using the following statistics:

1. R^2: Coefficient of determination, which is often used in the context of regression models, whose main purpose is the prediction of future outcomes on the basis of other related information.

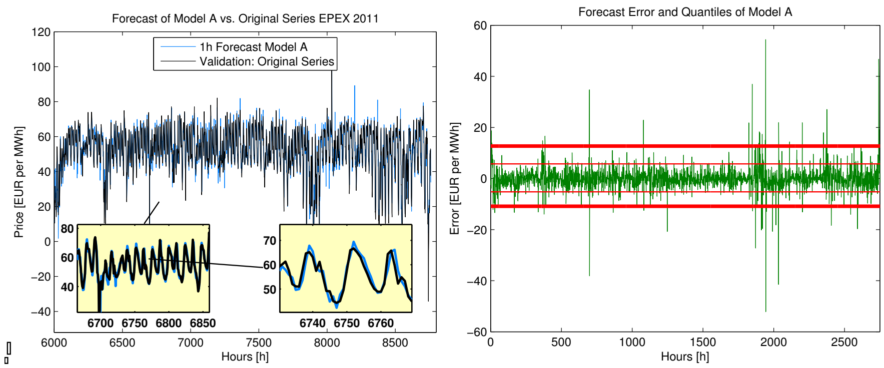
2. MAPE: Mean absolute percentage error, defined as $\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\dot{y}_t - f_t}{\dot{y}_t}\right|$, where $\dot{y}_t$ is the actual value and f_t is the forecast value.

3. MAE: Mean absolute error, defined as $\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|f_t - \dot{y}_t| = \frac{1}{n}\sum_{t=1}^{n}|e_t|$.

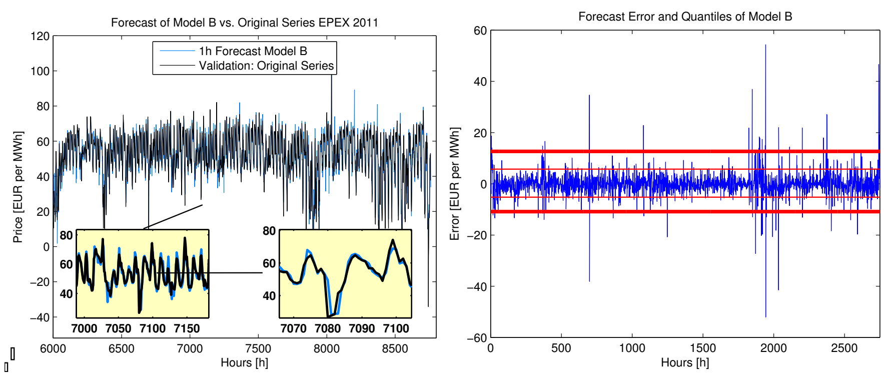
4. AIC: Akaike Information Criterion as a measure of the relative goodness of fit of the model. The AIC is defined as $AIC = 2k - 2\ln(L)$ where k is the number of parameters in the model, and L is the maximized value of the likelihood function for the estimated model.

5. SBC: Bayesian Information Criterion or Schwarz Criterion, which is a criterion for model selection among a finite set of models. It is defined as $-2 \cdot \ln p(\dot{y}_t|k) \approx \text{SBC} = -2 \cdot \ln L + k\ln(n)$, where $p(y_t|k)$ is the probability of the observed data given the number of parameters; or, the likelihood of the parameters given the dataset, n is the number of observations in the dataset, k is the number of parameters to be estimated. It is based, in part, on the likelihood function L, and it is closely related to the AIC.

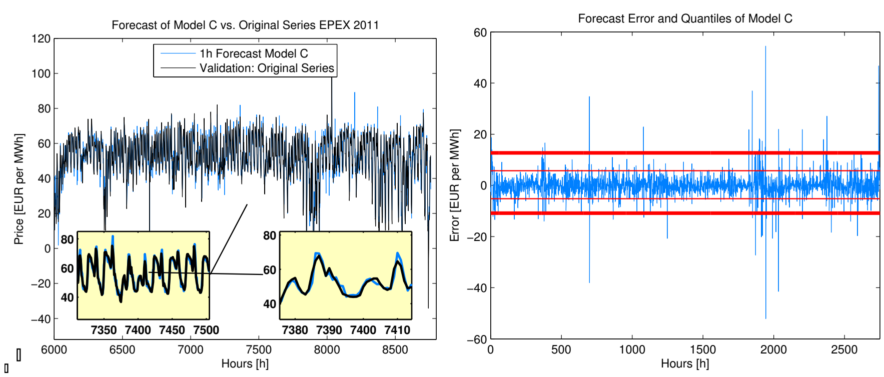
While statistics 1.-3. are calculated using the validation period, 4. and 5. are inherent to the log-likelihood estimation performed on the training period. Tab. B.3 provides a summary of the statistics for the given models. Based on information criteria, i.e. the lower the better, of the training period, model B is most suitable regarding AIC, while C has a better SBC. In the validation



(a) Model A - SARIMA$(1,1,2)_{24,168}$



(b) Model B - SARIMA$(2,1,1)_{24,168}$



(c) Model C - SARIMA$(1,1,1)_{24,168}$

Figure B.5: Forecasting Performance Assessment and Comparison

Model	Specification	R^2 [%]	MAPE [%]	MAE	AIC	SBC
		Validation (1h horizon)			Training	
A	$\text{SARIMA}(1,1,2)_{24,168}$	89.17514	0.419306	2.60199	83212.50500	85238.16620
B	$\text{SARIMA}(2,1,1)_{24,168}$	89.18141	0.418951	2.60123	83210.47487	85236.13607
C	$\text{SARIMA}(1,1,1)_{24,168}$	89.17508	0.419182	2.60215	83210.63556	85230.37378

Table B.3: Comparing Forecasting Performance of Different Models

period however, model B has the best fit in terms of highest determination coefficient R^2, as well as lowest forecasting errors measured MAPE and MAE. In summary model B, $\text{SARIMA}(2,1,1)_{24,168}$ is chosen as the best candidate of all three models.

B.1.3 Scenario Generation

Using random perturbations, model B is used to predict 1000 sample paths, i.e. equiprobable scenarios, over a 24 hour horizon. This horizon is chosen to replicate real conditions, in which rolling forecasts are performed according to the typical day-ahead market clearing in the EEX of 12-36 hours ahead, while price for the coming 12 hours are already determined by the previous clearing. To achieve a high range of prices, this simulation is repeated three times for starting hours 6000, 7200 and 8400, referring to different conditions in the system. These correspond to day 251, 301 and 351 of the year, or Sunday September 8th, Monday October 28th and Tuesday December 17th, respectively. This way both week-end as well as week days are covered. From the training period the observed series and inferred residuals are used as pre-sample data in case of the simulation at hour 6000. For 7200 and 8400 only observed series data, but no inferred residuals are used. The results of the three simulations can be assessed in Fig. B.6, in which the observed data of the original series is sequenced by the sample paths. The mean and the 95-percentile regions are plotted in addition. For a more detailed visualization of randomly selected specific paths that the scenario generation algorithm finds at the different time steps, please refer to Fig. **??** of the supplemental figures in the appendix.

For a realistic scenario generation of prices for a given day, the starting period should be 1am of a given day, such that the 24 hours are be used as scenarios with a reasonable degree of uncertainty for the day-ahead decision making of a market participant.

B.2 Forecasting Real Time Balancing Prices

The construction of time series models that capture the characteristics of real time balancing prices, in principle, requires the same steps as carried out for day-ahead spot prices. One simple difference may present, which series is taken as a point of departure. The reBAP is a single price system but the scenarios

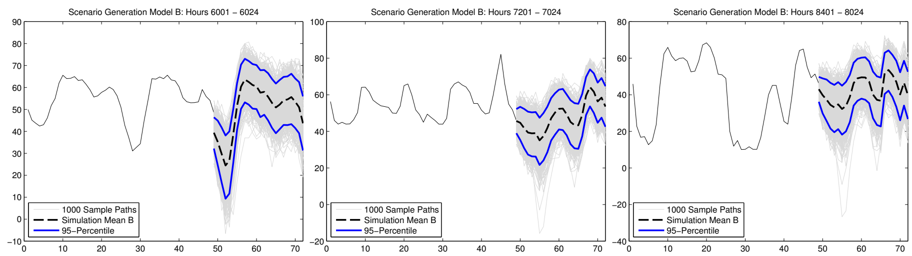
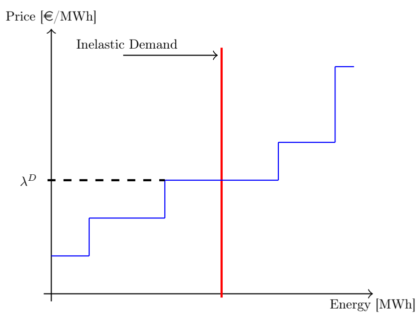
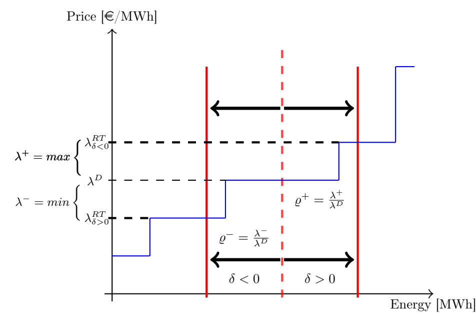


Figure B.6: Scenario Generation: Model B - SARIMA$(2,1,1)_{24,168}$



(a) Day-Ahead Price Formation



(b) Imbalance Price Formation

Figure B.7: Balancing Market Mechanisms in a Two-Price-System

generated are needed in another form. Therefore, before going into the details of SARIMA model estimation, as an introduction, a methodology is given, how to emulate two price systems from single price system data in case the underlying stochastic programming model requires this.

B.2.1 Balancing Market Mechanisms in a Two-Price-System

The market mechanisms that drive the formation of the prices are illustrated in Fig. B.7. It is depicted how the day-ahead market price is found in equilibrium of marginal production cost curve on the generation side crossing with the (here supposed inelastic) demand. Under unaltered generation conditions in real time, if ceteris paribus only the demand side deviates from the original day-ahead schedule, the formation of RT prices for both upward and downward deviation are shown. However, please note that this represents the case for marginal pricing and not for average pricing such as for the reBAP.

B.2.2 Time Series vs. Other Models for Real Time Prices

The above derived construction of a two-price system based on a single real-time balancing price makes it by definition impossible to reconstruct situations in which there exist simultaneous occurrences of λ^+ and λ^-. No matter which representation, of the time series λ^{RT} is chosen later, only one SARIMA model needs to be fit directly to forecast λ^{RT}. are other approaches to do this of course. In some two-price-systems, such as NordPool, in certain periods, the simultaneous occurrence of λ^+ and λ^- is possible. However, in these systems the balancing price calculation methodology is not based on netting all deviation energy and allocating an average price to the result, like for the reBAP. There is good literature on the subject, such as [144], which uses a combination of two different stochastic processes, one from a SARIMA time series model, and another from a Markov chain to model NordPool balancing prices. The advantage lies in its capability to derive simultaneous λ^+ and λ^- occurrences.

Essentially, the interaction of the different stochastic processes and its effects on replicating realistic scenarios may motivate even further research. Here only SARIMA time series models are applied.

B.2.3 Data Analysis for Model Identification

Stabilization of Variance

The original reBAP time series contains many negative values as depicted in Fig. 4.7. Hence, a normalization to values in the interval between 1 and 2, using the formula:

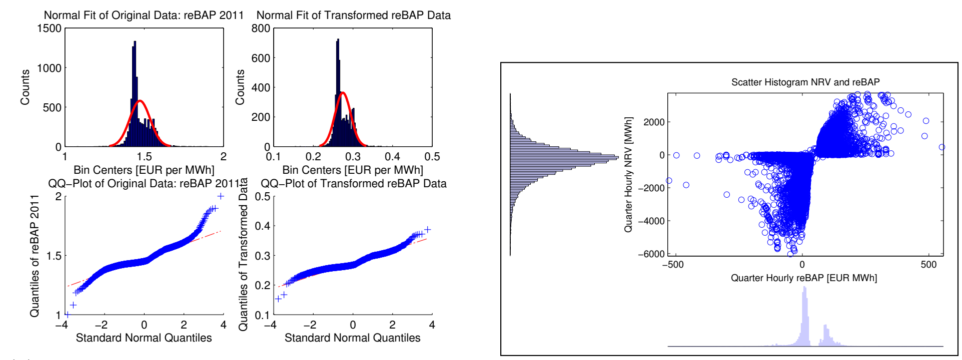
$$\dot{y}_{norm,t} = \frac{y_t - \min_t \{y_t\}}{\max_t \{y_t\} - \min_t \{y_t\}} + 1$$

is applied. Then, Box-Cox transformation with parameter $\lambda = -1.8842$ for further variance stabilization is carried out.

The mean stabilizing effect can be assessed in Fig. B.8. In the upper two histograms of Fig. B.8a, it can be observed that the hourly aggregated price data. This, at first guess, should not lie in the physical nature of power systems, where slight positive deviations should be as common as negative ones when forecasting techniques imply white-noise distributions of error terms. The bi-modality is further shown in the sub figure scatter plot of NRV versus reBAP on a quarter hourly granularity, which also includes histograms on both axes. From there it becomes evident that even though the net power system deviations (NRV) follow a slightly skewed normal distribution, with overall uni-modularly, whereas there is a double peak in the empirical distribution of the reBAP. It seems possible that this distortion is invoked by the average pricing methodology, in which both positive and negative deviations are netted, such that only the larger deviation is allocated with all the costs. To avoid the resulting price being almost infinity with the net deviation tending to zero, a price cap exists.

Sample and Partial Autocorrelation

ACF as well as the sample partial auto-correlation PACF functions are plotted for the first 50 lags in Fig. B.9a. Tentatively, normal differencing of order $d = 1$,



(a) Histogram and Normality Plots of the Normalized Original versus Transformed Series

(b) Histogram-Scatter Plots of System Deviation and Price

Figure B.8: Assessing the Effects of Transforming the Series

seems promising to take care of the significant components of the respective lags in the PACF and should provide a suitable stabilization of the mean. Fig. B.9b shows the transformed and differenced series. A simple statistical test of the differenced series was performed to check trend stationarity. With both ACF and PACF of the differenced series tailing off after lags 3 and 24, respectively, suggests a mixed ARIMA process as a conjunction of exponentials and damped sine waves after the first $q - p$ lags.

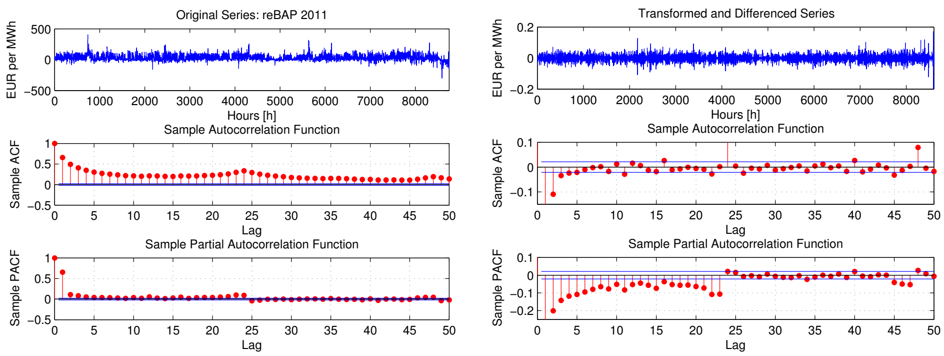
Model Identification

Further on, it will be assumed that mean and variance of the differenced and transformed series $\dot{y}_t^{(\lambda)}(1 - B)$ are sufficiently stable to continue with the parameter estimation of various ARMA models. In particular, the resulting ARIMA$(1, 1, 2)$, ARIMA$(2, 1, 1)$, and ARIMA$(2, 1, 2)$ are estimated and compared to each other. Further on, they will be referred to as Model D, E and F, respectively.

B.2.4 ARIMA Model Parameter Estimation for reBAP

Preliminary Residual Analysis

After the successful convergence of the estimation algorithm, the normalized residuals are inferred from the respective model fits using the data from the training period. These normalized residuals are checked for normality and autocorrelation. First, normality checks are performed by means of qq-plots as in Fig. B.10, in which the residuals exhibit sufficient normality. Then, ACF and PACF of the residuals are plotted. Even though the null hypothesis of the Ljung-Box portmanteau test that a series of residuals exhibits no autocorrelation for a fixed number of lags, against the alternative that some autocorrelation coefficient is nonzero cannot be rejected for any of the estimated models, the



(a) Sample ACF and PACF of the Original Series (b) Sample ACF and PACF of the Transformed and Differenced Series

Figure B.9: Principal Tools of Model Identification - Differencing

Model	Specification	AR	MA	Constant	Variance
D	ARIMA$(1,1,2)$	$\phi_1 = .51182$ $\phi_2 = .06283$	$\theta_1 = -.95523$	$c_D = 1.649 \cdot 10^6$	$\sigma_D^2 = .22024 \cdot 10^{-3}$
E	ARIMA$(2,1,1)$	$\phi_1 = .62192$	$\theta_1 = -1.06347$ $\theta_2 = .104016$	$c_E = 1.604 \cdot 10^6$	$\sigma_E^2 = .220352 \cdot 10^{-3}$
F	ARIMA$(2,1,2)$	$\phi_1 = .356942$ $\phi_2 = .141935$	$\theta_1 = -.796435$ $\theta_2 = -.151239$	$c_F = 1.732 \cdot 10^6$	$\sigma_F^2 = .220198 \cdot 10^{-3}$

Table B.4: Maximum Likelihood Estimation Results: Model Parameters

respective auto-correlation plots of Fig. B.11 show significance in less than 5% of the lags.

Model Parameters

The result of the maximum likelihood estimation process can be viewed in Tab. B.4, where the parameters are indicated in the multiplicative format as introduced in equation (4.71). Here, no seasonal AR and MA terms are included. The result provides that, constant and variance parameters are very similar in all models D, E, and F. Accordingly, it is expected that the forecasting performance might only differ insignificantly, yet one model must be chosen and hence further indicators are employed.

Model Comparison and Selection

Initially, the forecasting performance is assessed using visualization of forecast versus validation signal. Subtracting the latter from the former gives the forecast error. Fig. B.12a, Fig. B.12b and Fig. B.12c show both plots for models D,

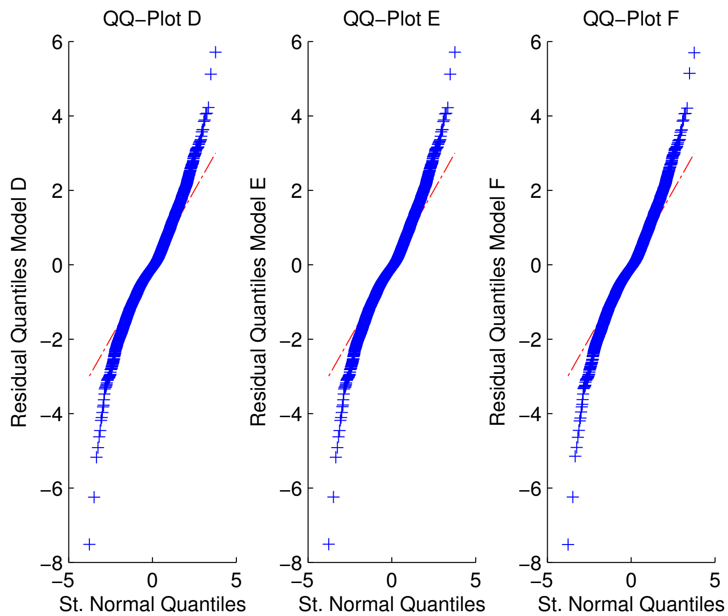


Figure B.10: Residual Analysis - QQ-Plots for the Three Models

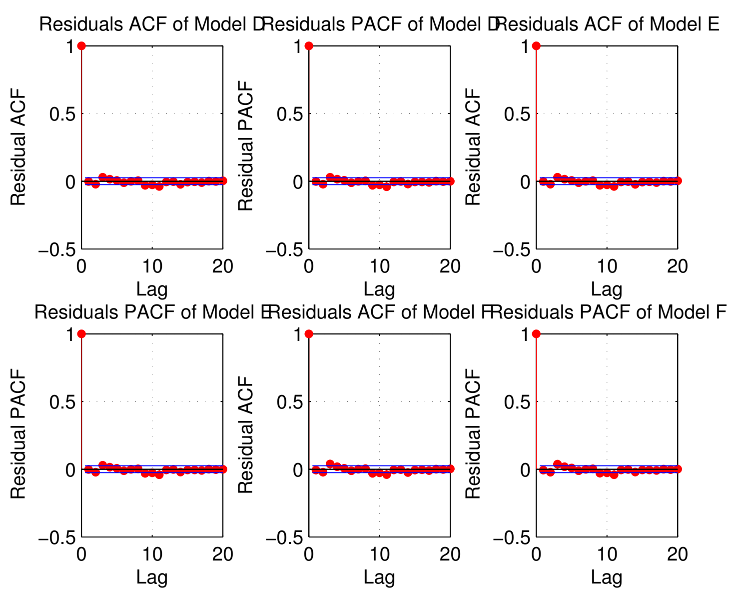


Figure B.11: Residual Analysis - ACF and PACF

Model	Specification	R^2 [%]	MAPE [%]	MAE	AIC	SBC
		Validation (1h horizon)			Training	
D	ARIMA(1, 1, 2)	40.0970	3.3128	24.0422	-33571.65	-33542.04
E	ARIMA(2, 1, 1)	40.1024	3.3127	24.0390	-33573.468	-33543.85
F	ARIMA(2, 1, 2)	40.1264	3.3205	24.0343	-33565.266	-33529.73

Table B.5: Comparing Forecasting Performance of Different Models

E and F, with zooms at different sub-axes, respectively. From the sheer graphic analysis the forecasting performance of all three models seems significantly similar and therefore it is not possible to make out the best candidate at human eyesight. It appears inevitably reasonable to employ quantitative statistics.

Thus, the different models are compared using the same statistics as introduced above for the day-ahead market prices. Tab. B.5 provides a summary of the statistics for the given models. Based on information criteria, i.e. the lower the better, of the training period, model E is most suitable regarding AIC and SBC. In the validation period however, model B has only the second best fit in terms of highest determination coefficient R^2, yet lowest forecasting errors measured MAPE and MAE. In summary model E, ARIMA$(2, 1, 1)$ is chosen as the best candidate of all three models.

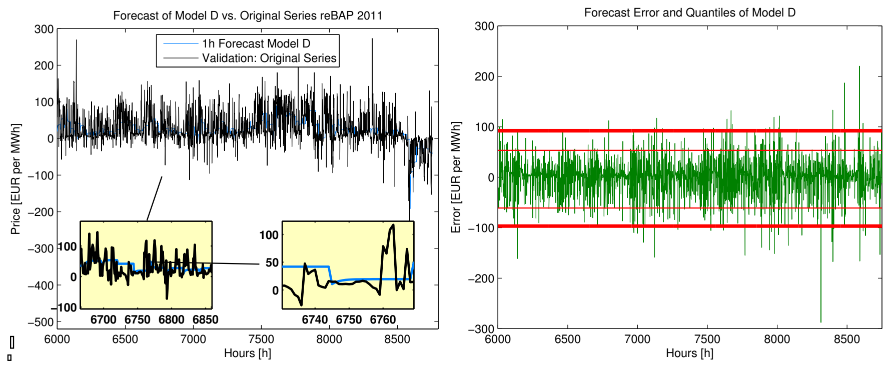
B.2.5 Scenario Generation

Using random perturbations, model E is used to predict 1000 sample paths, i.e. equiprobable scenarios, over a 1 hour horizon. This horizon is chosen to replicate presumed conditions, in which rolling forecasts are performed every hour to update real time behavior as much as possible. As with day-ahead prices, to achieve a high range of reBAP prices, this simulation is repeated three times for starting hours 6000, 7200 and 8400, according to the scenarios generated above. The results of the three simulations can be assessed in Fig. B.13, in which the observed data of the original series is sequenced by the sample paths. The mean and the 95-percentile regions are plotted in addition.

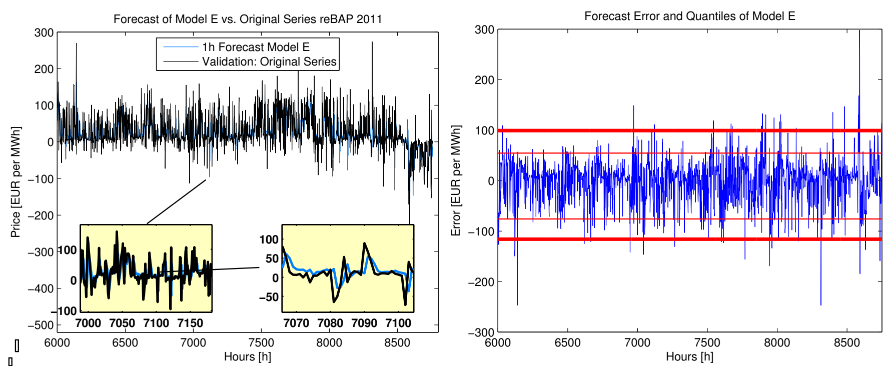
For a realistic scenario generation of prices for a given day, the starting period should be 1am of a given day, such that the 24 hours are be used as scenarios with a reasonable degree of uncertainty for the day-ahead decision making of a market participant.

B.3 Summary

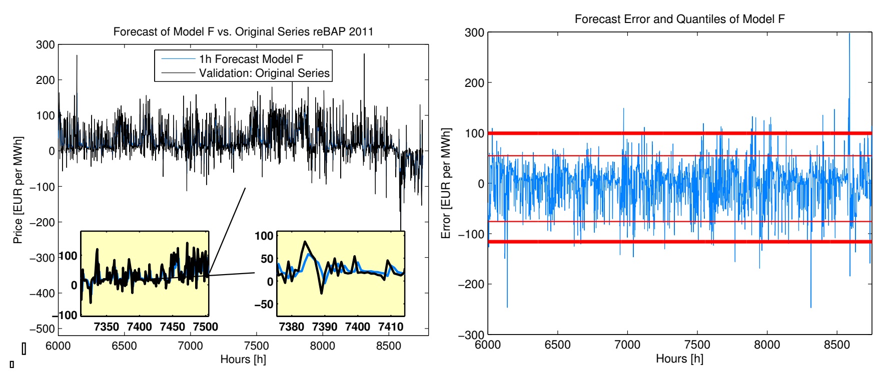
This appendix has identified, estimated and selected two time series models for describing German electricity market data. These models can be used to feed input about the uncertainty spanning the realization of possible day-ahead prices and imbalance settlement fees into scenario based stochastic programs.



(a) Model D - SARIMA$(1, 1, 2)_{24,168}$



(b) Model E - SARIMA$(2, 1, 1)_{24,168}$



(c) Model F - SARIMA$(2, 1, 2)_{24,168}$

Figure B.12: Forecasting Performance Assessment and Comparison

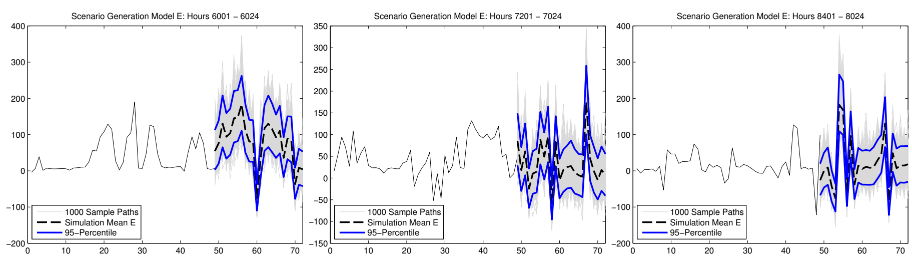


Figure B.13: Simulation for Scenario Generation: Model E - ARIMA$(2, 1, 1)$

Appendix C

Requirements of ILC vs. DLC

C.1 Data Requirements of CCO Approaches

General Insights Comparing ILC and DLC may not be important, if carrying out DLC for very large fleets is intractable from the optimization problem. However since one of the thesis objectives is to propose mathematical programs that tackle this challenge, for this section, the working assumption is that there is no problem in implementing and performing such large scale optimization instances. The discussion focuses on comparing the implications of communication alternatives and not whether these options are actually real alternatives. Once this is determined, the constraining system component, or bottleneck, appears to be situated on the PEVSA side of the communication network, since at this end signals from many parallel PEV could potentially arrive simultaneously. Furthermore, regardless of ILC and DLC, the communication network is not the binding constraint, it rather depends on the communication protocol that is being used on the network.

In addition, it can be assumed that the answer to the question lies in the V2G back-end technology; ILC poses a similar problem as in any other smart grid appliances such as studied in various research projects with collaboration on an international scale [84]. The cost of the communication network boils down to estimating the amount of information that needs to be exchanged, as well as the communication technology used: possible candidates are Power-line communication (PLC) for the public realm, where charging points with large capacities are directly communicated with the substation, Digital Subscriber Line technologies (xDSL) for use in home charging modes or simple wireless technologies such as General Packet Radio Service (GPRS) for any type of situation where no existing physical communication layer exists. It appears that charging control would be *reliable* even if realized with low bit rates in GPRS.

For a full cost comparison, the following points would have to be clarified: 1) amount of data exchanged, 2) timing and frequency of communication, 3) mapping of these to the bit space, 4) use-case distinction, and 5) prices for communication network capacity by technology.

For the approximation of cost, a small numerical example is constructed based on the time granularity, horizon and other general assumptions made in previous case studies: the fleet size amounts to 1000 vehicles, an entire day, i.e. a 24 hour horizon is considered hourly periods, both for energy and capacity pricing. Any data point is assumed to be encoded in an 8bit mapping. Furthermore, this estimation exercise does not claim to be meticulously exact to every detail, on the contrary, it merely serves as a coarse approximation and, as such, does not include data needed for encryption or for communication set-up sequences or for specific headers, which communicate the coding of the bit sequences to follow.

ILC: 1) Amount, 2) Timing and Frequency of Data: Under the ILC assumption, the functions carried out by the PEVSA are essentially the same as known from traditional retailers, i.e., market bids have to be determined, retail prices have to be set up and the reactions to price signals have to be forecast on the basis of past data. Hence the following data exchange can be foreseen:

- **PEVSA $\Rightarrow$ PEV:** The main data exchanged are prices. In the given decision framework, the PEVSA sends **one vector of 24 hours** once per day, day-ahead γ_h.
  - If balancing is considered, additionally 24 times per day one hour-ahead updated pricing: $\gamma_h^{\mathbf{D}}$, $\gamma_h^{\mathbf{B}}$a total of **two vectors of 24 hours**
- **PEV $\Rightarrow$ PEVSA:** any given time ex-post: Daily: **24 hourly data points** for the consumption per vehicle $e_{v,h}^{\mathbf{RT},\veebar}$
  - If balancing is considered, i.e. market design framework 2), additionally the PEV needs to commit to a preliminary day-ahead schedule, which would have to be submitted as **one vector of 24 hours** once per day, day-ahead $e_{v,h}^{\mathbf{D}\veebar}$.

ILC: 3) Bit space mapping: This would lead to the following estimation of minimum required bits. A total of approximately 768 bit per day, which are composed of:

- Prices day-ahead: once per day, 1000 vehicles x 24 data points x 8 bits per data point = 192 kbit per day
  - With market design 2), pre-schedule commitment day-ahead: once per day, 1000 vehicles x 24 data points x 8 bits per data point = 192 kbit per day
  - With market design 2), hour-ahead prices : 24 times per day, 1000 vehicles x 1 data point x 8 bits per data point = 192 kbit per day

Vehicles [h]	1	...	7	8	9	10	11	12	13	14	15	16	17	18	...	24
1		...				1.52		1.86				6.41	0.45		...	
2		...			4.39							8.00	0.68	2.26	...	
3		...		0.95	0.45						0.14			1.86	...	
4		...	2.26				0.45						0.68	1.22	...	
5		...		0.14		0.95		0.14						1.22	...	

Hours $h \in \mathcal{H}$ [h]

(a) Upon Connection

Vehicles [h]	1	...	7	8	9	10	11	12	13	14	15	16	17	18	...	24
1		...				1.52		1.86				6.41	0.45		...	
2		...			4.39							8.00	0.68	2.26	...	
3		...		0.95	0.45						0.14			1.86	...	
4		...	2.26				0.45						0.68	1.22	...	
5		...		0.14		0.95		0.14						1.22	...	

Hours $h \in \mathcal{H}$ [h]

(b) During Connection

Table C.1: DLC Data Exchange Occasions

- Ex-post: Once per day, 1000 vehicles x 24 data points per day x 8 bits per data point = 192 kbit per day

DLC: 1) Amount, 2) Timing and Frequency of Data: In the DLC case, not only two directions, but also four different occasions are distinguished, at which data needs to be exchanged. In Tab. C.1, the occasions that occur during the course of a day are highlighted in an overlay to the input representation table that showed the high mobility sub-scenario from **??**.

Once at some undefined point in time prior to day-ahead, i.e., at the time of establishing the contractual relationship between PEVSA and PEV, at least the following information has to be exchanged:

- **PEVSA** $\Rightarrow$ **PEV:** flat rate energy-based retail price γ_h,
- **PEV** $\Rightarrow$ **PEVSA:** battery size via. upper and lower SOC bounds $\overline{E}_v$, $\underline{E}_v$,
- **PEV** $\Rightarrow$ **PEVSA:** maximum (dis-)charge rates $\overline{P}_v^{\vee}$, $\overline{P}_v^{\wedge}$ and
- **PEV** $\Rightarrow$ **PEVSA:** energy exchange efficiencies $\eta_v^{\vee}$, $\eta_v^{\wedge}$.

Note that efficiencies are not necessary if they are included in the energy requirements. Also, note that this one-time communication at the establishment of contracts would save resources compared to other charging models, in which, e.g., maximum discharge rates, in the form of currents supported on each phase are communicated at each connection [41], see following paragraph.

Each time upon connection, i.e. right in between a period of disconnection and connection, as illustrated in Tab. C.1 a) by red dotted ovals, on average up to 3-5 times per day:

- **PEV ⇔ PEVSA:** identification, authentication and authorization v,
- **PEV ⇒ PEVSA:** current SOC $e^{\mathbf{SOC}}_{v,h}$,
- **PEV ⇒ PEVSA:** hour of disconnection or duration of charge t and
- **PEV ⇒ PEVSA:** amount of energy required during connection $e^{\mathbf{SOC}}_{v,h+t} - e^{\mathbf{SOC}}_{v,h}$.

During the time of connection, as illustrated in Tab. C.1 b) by blue dashed rectangles, on average 22 to maximally 24 hours per day:

- **PEVSA ⇒ PEV:** charging set point $e^{\mathbf{RT},\veebar}_{v,h}$.

Like in the ILC case, at any given time ex-post, e.g., daily, the metering data has to be transmitted:

- **PEV ⇒ PEVSA** 24 hourly data points for the consumption per vehicle $e^{\mathbf{RT},\veebar}_{v,h}$

DLC: 3) Bit space mapping: From the above mentioned estimation regarding amount, timing and frequency of data, the bit space mapping consistently derives as follows.

A total of approximately **680 kbit per day** would have to be transmitted, splitting up in:

- Before day-ahead: 1000 vehicles x 7 data points x 8 bits per data point = 56 kbit once for establishing the contract,
- Upon connection in the worst case: 5 times per day x 1000 vehicles x 6 data points x 8 bits per data point = 240 kbit per day,
- During connection and controlled charging, hour-ahead: 24 times per day, 1000 vehicles x 1 data point x 8 bits per data point = 192 kbit per day and
- Ex-post: Once per day, 1000 vehicles x 24 data points per day x 8 bits per data point = 192 kbit per day.

4) ILC and DLC Use-case distinction There is not fundamental difference in use-cases evoked by the prevalent communication architecture. Both ILC and DLC could by used in any use case. However, different use cases may render different communication technology to be the cheapest option. Despite the plurality of the different charging modes outlined in Chapter 2, for the sake of simplicity in this rough estimation, it is assumed that there are mainly two use-cases that are fundamentally different: home charging with existing xDSL, street charging with PLC for dedicated charging stations with multiple PEVs and high contracted DSO capacity. GPRS is only employed in cases where no communication infrastructure exists yet.

5) Prices for communication network capacity by technology For both charging controls, ILC and DLC, the amount of data calculated is relatively small. Also, the difference between ILC and DLC is almost negligible. In fact, the amount of data and difference between ILC and DLC are so small that it appears not necessary to carry out a full price comparison. For comparison, common data exchange rates are indicated: GPRS provides moderate speed operation at 56-114 kbit/s; xDSL operates in the range of 256kbit/s to 100 Mbit/s; and finally PLC can typically handle up to 576 kbit/s. To put these numbers into the right perspective, even if the daily amounts of data had to be transmitted at once, which is not the case, they could be handled by the slowest GPRS standard in a matter of seconds.

C.2 Qualitative Notes on CCO Modes

From this rough estimation, a few insights may be gained. Qualitative conclusions are drawn as follows:

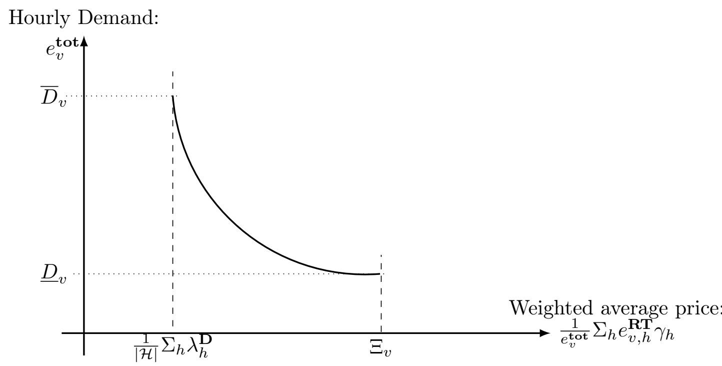
- The standardization process for coordinated charging communications is far advanced, the necessary technology is developed and has reached the market already. The existing technology with regards to communication protocols makes both ILC and DLC possible and likely to co-exist.

- In an hourly resolution model the amount of data needed to carry out both ILC and DLC is insignificantly small and therefore negligible. Even if daily amounts of data had to be transmitted at once, which is not the case here, they could be handled by the slowest among the considered communication technologies in under a minute. Even if there were no communication infrastructures like PLC and xDSL available at any of the charging points, the cost of GPRS communication would not appear to be prohibitively high.

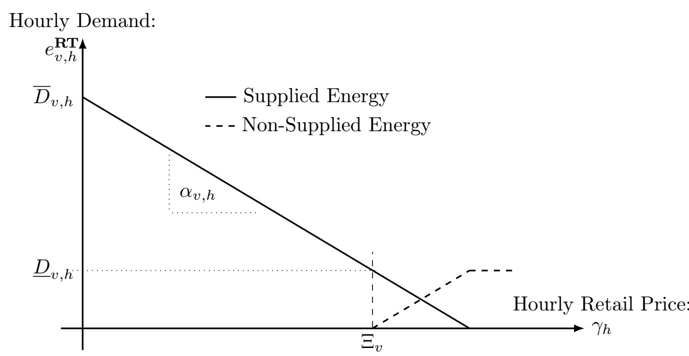
- Furthermore, the differences in data requirements between ILC and DLC are surprisingly low. With the given assumptions of the optimization problems presented in this thesis, in particular the hourly resolution, on a day to day basis DLC does not need much more data exchange than ILC. Furthermore with ILC, to consider both day-ahead and balancing prices for the retail would require an extra schedule to be committed from the PEV to the PEVSA, but this additional data would in total not be very important.

Appendix D

Supplemental Figures and Material



(a) Budget Constraint



(b) Hourly Affine Demand

Figure D.1: Alternative LL Demand Reactions Representations

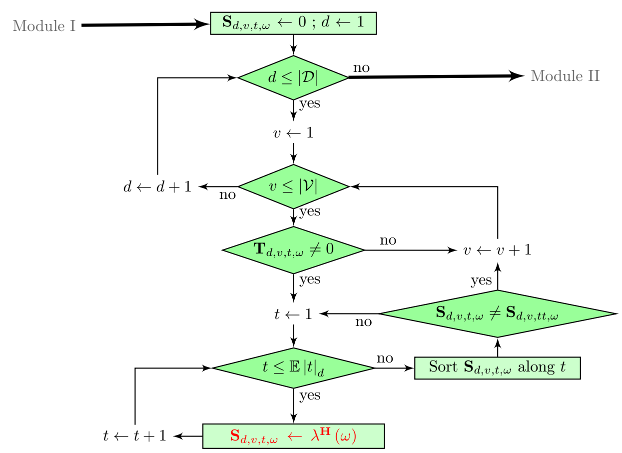


Figure D.2: Detailed Flow Chart for Module II of the Algorithm

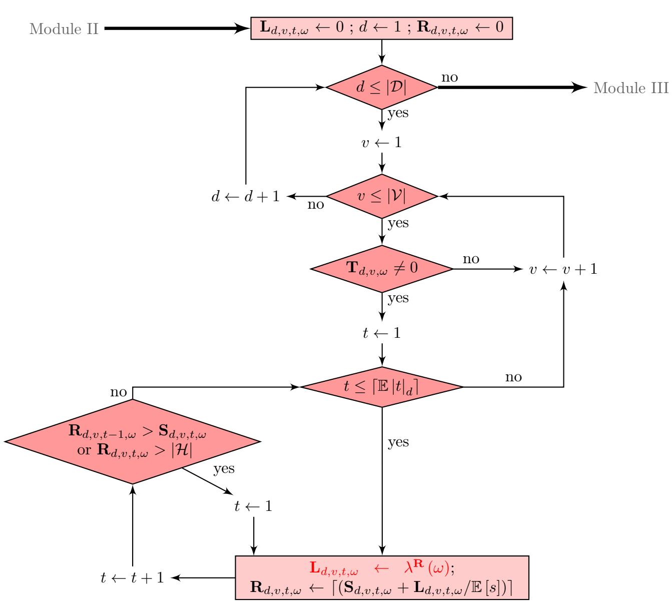


Figure D.3: Detailed Flow Chart for Module III of the Algorithm

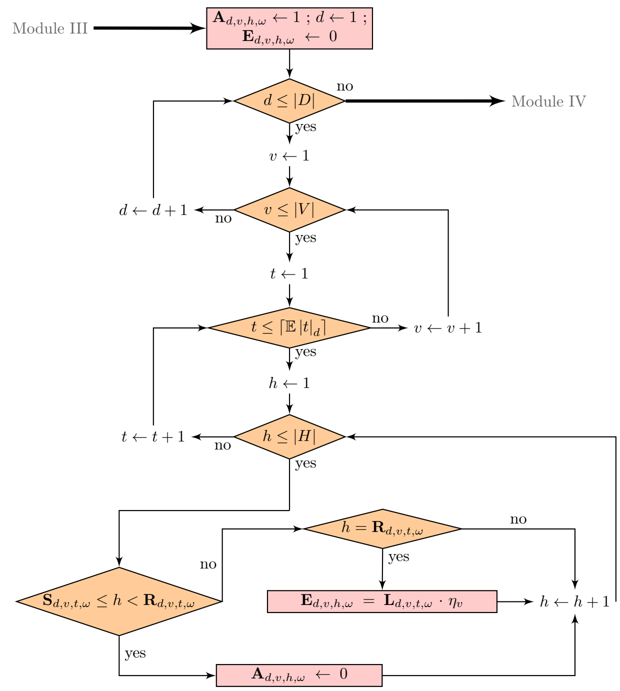


Figure D.4: Detailed Flow Chart for Module IV of the Algorithm

Table D.1: Travel Probability π_d^{travel} [23], [65], [66]

π_d^{travel}	Monday	Weekday	Friday	Saturday	Sunday
Travel	0.6273	0.6586	0.6494	0.5499	0.4066
No Travel	0.3727	0.3414	0.3506	0.4501	0.5934

Table D.2: Expected Trips of Moving Vehicles [23], [65], [66]

	Monday	Weekday	Friday	Saturday	Sunday
ntr_d^{avg}	3.95044	3.96463	4.21066	3.59744	2.8098

Table D.3: Trip Start Hour Probability $\pi_{d,t}^{startH}$ [23], [65], [66]

Hour h	Monday	Weekday	Friday	Saturday	Sunday
1	1.212E-03	1.893E-03	4.088E-03	6.031E-03	2.429E-03
2	1.943E-04	1.192E-03	3.262E-03	2.838E-03	1.242E-03
3	1.170E-03	6.696E-04	1.499E-03	2.889E-03	1.277E-03
4	7.647E-04	1.353E-03	2.873E-03	1.976E-03	4.130E-03
5	3.080E-03	5.862E-03	5.984E-03	1.384E-03	2.979E-03
6	1.815E-02	2.242E-02	1.717E-02	5.854E-03	5.785E-03
7	4.940E-02	5.141E-02	4.212E-02	1.305E-02	6.236E-03
8	7.007E-02	7.309E-02	6.572E-02	2.744E-02	1.827E-02
9	6.028E-02	5.966E-02	6.199E-02	6.892E-02	4.338E-02
10	6.578E-02	5.658E-02	6.035E-02	1.143E-01	6.801E-02
11	6.034E-02	5.627E-02	6.190E-02	1.199E-01	6.865E-02
12	5.684E-02	6.026E-02	5.716E-02	1.029E-01	8.973E-02
13	6.083E-02	6.525E-02	6.572E-02	9.099E-02	7.824E-02
14	5.863E-02	5.981E-02	6.860E-02	7.072E-02	8.667E-02
15	5.943E-02	6.264E-02	7.702E-02	6.825E-02	9.260E-02
16	7.976E-02	7.260E-02	8.355E-02	6.136E-02	7.352E-02
17	8.835E-02	9.267E-02	8.378E-02	4.296E-02	7.509E-02
18	8.757E-02	8.735E-02	7.397E-02	4.405E-02	7.987E-02
19	6.572E-02	6.392E-02	5.592E-02	4.967E-02	7.215E-02
20	4.480E-02	4.105E-02	4.199E-02	4.056E-02	4.310E-02
21	2.593E-02	2.561E-02	2.393E-02	2.076E-02	3.257E-02
22	2.365E-02	1.963E-02	1.802E-02	1.402E-02	2.713E-02
23	1.339E-02	1.379E-02	1.568E-02	1.801E-02	2.092E-02
24	4.665E-03	5.006E-03	7.723E-03	1.118E-02	6.036E-03

Table D.4: Trip Range Probability $\pi_{d,l}^{range}$ [23], [65], [66]

Trip Length l	Monday	Weekday	Friday	Saturday	Sunday
1	2.292E-01	2.111E-01	2.246E-01	2.111E-01	2.002E-01
3	1.780E-01	1.783E-01	1.671E-01	1.783E-01	1.594E-01
5	9.996E-02	1.214E-01	1.175E-01	1.214E-01	1.187E-01
7	9.172E-02	8.147E-02	9.230E-02	8.147E-02	7.652E-02
9	5.679E-02	6.149E-02	6.245E-02	6.149E-02	5.714E-02
11.25	3.471E-02	4.829E-02	4.989E-02	4.829E-02	5.119E-02
13.75	6.441E-02	6.157E-02	4.999E-02	6.157E-02	6.202E-02
16.75	4.989E-02	3.950E-02	4.922E-02	3.950E-02	4.632E-02
19.25	3.439E-02	3.239E-02	3.018E-02	3.239E-02	4.356E-02
22.5	4.960E-02	5.075E-02	6.141E-02	5.075E-02	4.582E-02
27.5	3.443E-02	3.424E-02	2.369E-02	3.424E-02	4.061E-02
32.5	2.629E-02	2.515E-02	1.459E-02	2.515E-02	1.440E-02
37.5	1.196E-02	1.275E-02	1.933E-02	1.275E-02	6.620E-03
42.5	3.388E-03	8.547E-03	5.700E-03	8.547E-03	4.698E-03
47.5	1.165E-02	8.524E-03	4.608E-03	8.524E-03	7.927E-03
55	3.345E-03	7.677E-03	1.040E-02	7.677E-03	1.322E-02
65	4.005E-03	4.359E-03	3.662E-03	4.359E-03	9.155E-03
85	7.168E-03	5.143E-03	4.981E-03	5.143E-03	1.643E-02
125	3.588E-03	2.987E-03	4.433E-03	2.987E-03	8.458E-03
225	4.340E-03	2.402E-03	1.996E-03	2.402E-03	1.255E-02
400	1.233E-03	2.056E-03	1.907E-03	2.056E-03	5.082E-03

Table D.5: Scenario Probabilities for Second DLC Case Study

Scenario ω	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Probability π_ω	0.03	0.03	0.02	0.02	0.09	0.09	0.06	0.06	0.03	0.03	0.02	0.02
Day-Ahead	D1	D1	D1	D1	D2	D2	D2	D2	D3	D3	D3	D3
Balancing	B1	B1	B2	B2	B1	B1	B2	B2	B1	B1	B2	B2
Mobility	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2

Scenario ω	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Probability π_ω	0.03	0.03	0.02	0.02	0.09	0.09	0.06	0.06	0.03	0.03	0.02	0.02
Day-Ahead	D1	D1	D1	D1	D2	D2	D2	D2	D3	D3	D3	D3
Balancing	B1	B1	B2	B2	B1	B1	B2	B2	B1	B1	B2	B2
Mobility	M3	M4	M3	M4	M3	M4	M3	M4	M3	M4	M3	M4

Table D.6: Scenario Probabilities for Third DLC Case Study

Scenario ω	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Probability π_ω	0.06	0.06	0.04	0.04	0.18	0.18	0.12	0.12	0.06	0.06	0.04	0.04
Day-Ahead	D1	D1	D1	D1	D2	D2	D2	D2	D3	D3	D3	D3
Balancing	B1	B1	B2	B2	B1	B1	B2	B2	B1	B1	B2	B2
Mobility	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2

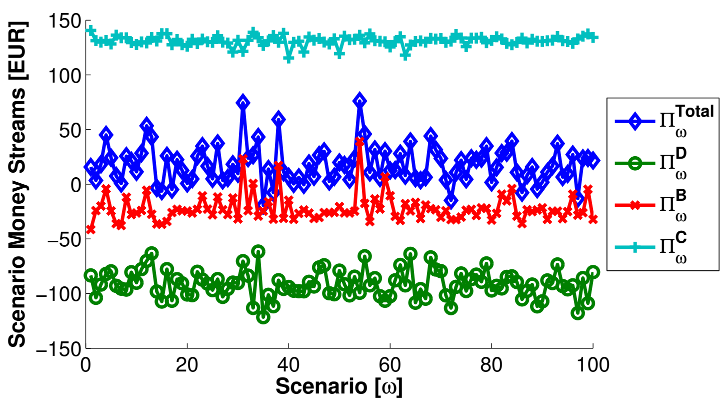
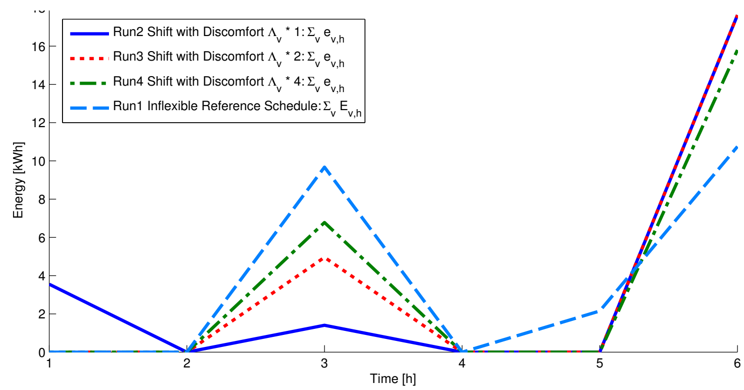
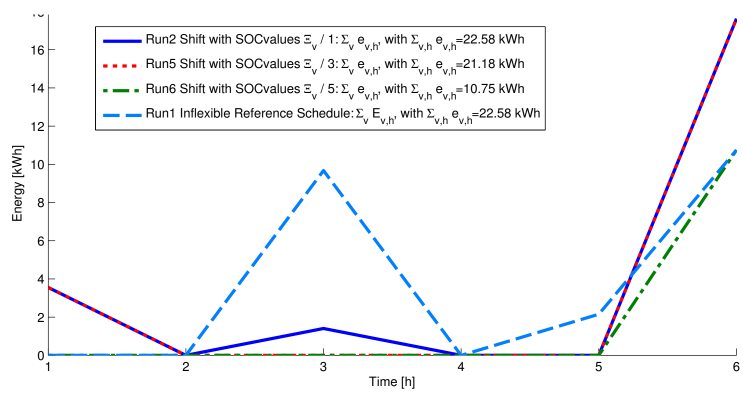


Figure D.5: Variability of Objective Function in Reduced Scenario Set

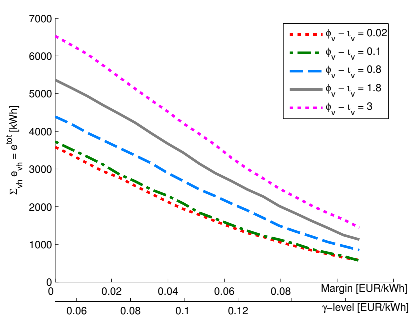


(a) Run 3 & 4 of lower level problem as isolated LP: Discomfort Sensitivity

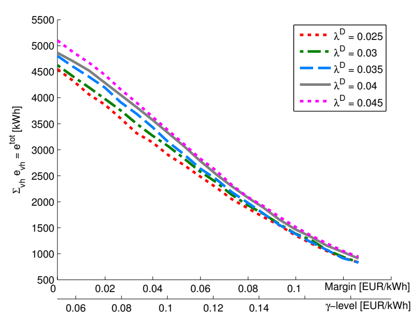


(b) Run 5 & 6 of lower level problem as isolated LP: Sensitivity on the NSE cost

Figure D.6: Varying the Cost Terms in $z_{\mathbf{LL}}$



(a) Varying $\phi_v^{\mathbf{SOC}}$



(b) Varying $\tilde{\lambda}^{\mathbf{D}}$

Figure D.7: Sensitivity Analysis Affine Fleet Demand

h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	$\sum_h$
$e_{1,h}^{\mathbf{RT}}$				2.66																				2.87	6.48
$e_{2,h}^{\mathbf{RT}}$				2.08																				1.89	4.4
$e_{3,h}^{\mathbf{RT}}$				2.04																				2.27	4.12
$\sum_v e_{v,h}^{\mathbf{RT}}$				6.78																				7.03	15
$e_{1,h}^{\mathbf{SOC}}$	9	9	9	11.5	11.5	11.5	11.5	7.79	7.79	7.79	7.79	7.79	7.79	7.79	7.79	4.75	4.75	4.62	4.62	4.48	4.48	4.48	4.48	7.18	
$e_{2,h}^{\mathbf{SOC}}$	10	10	10	12	12	12	12	12	12	10.14	9.74	9.74	6.03	6.03	6.03	6.03	5.08	5.08	5.08	5.08	5.08	5.08	5.08	6.9	
$e_{3,h}^{\mathbf{SOC}}$	10.5	10.5	10.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	10.24	9.83	9.83	4.5	4.5	4.5	4.5	4.5	6.72	
$\sum_v e_{v,h}^{\mathbf{SOC}}$	29.5	29.5	29.5	36	36	36	36	32.29	32.29	30.43	30.03	30.03	26.31	26.31	26.31	21.02	19.66	19.53	14.2	14.06	14.06	14.06	14.06	20.79	

(a) Run A.1): Charging Schedule and SOC less NSE

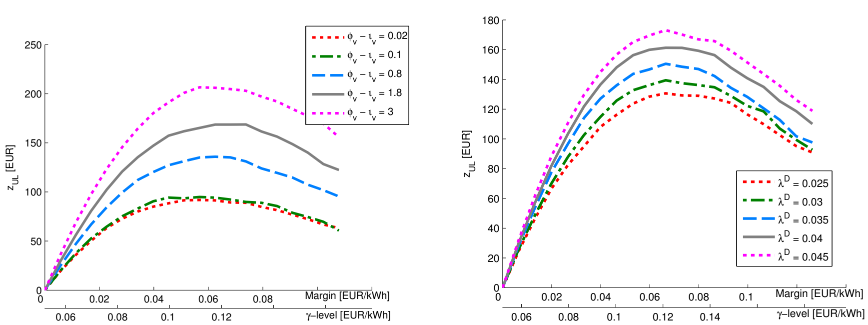
h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	$\sum_h$
$e_{1,h}^{\mathbf{RT}}$			0.89	0.89	0.89				0.22	0.22	0.22	0.22	0.22	0.22	0.22		0.22		0.22			0.22	0.89	0.89	7.31
$e_{2,h}^{\mathbf{RT}}$			0.51	1.57																			1.57	1.57	5.54
$e_{3,h}^{\mathbf{RT}}$				1.84	0.2																		1.84	1.84	5.55
$\sum_v e_{v,h}^{\mathbf{RT}}$			1.39	4.3	1.09				0.22	0.22	0.22	0.22	0.22	0.22	0.22		0.22		0.22			0.22	4.3	4.3	18.39
$e_{1,h}^{\mathbf{SOC}}$	9	9	9.83	10.67	11.5	11.5	11.5	7.79	7.99	8.19	8.4	8.6	8.8	9.01	9.21	6.17	6.38	6.24	6.44	6.31	6.31	6.51	7.35	8.18	-
$e_{2,h}^{\mathbf{SOC}}$	10	10	10.49	12	12	12	12	12	12	10.14	9.74	9.74	6.03	6.03	6.03	6.03	5.08	5.08	5.08	5.08	5.08	5.08	6.59	8.11	-
$e_{3,h}^{\mathbf{SOC}}$	10.5	10.5	10.5	12.3	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	10.24	9.83	9.83	4.5	4.5	4.5	4.5	6.3	8.1	-
$\sum_v e_{v,h}^{\mathbf{SOC}}$	29.5	29.5	30.82	34.97	36	36	36	32.29	32.49	30.84	30.64	30.84	27.33	27.53	27.74	22.44	21.29	21.16	16.03	15.89	15.89	16.09	20.24	24.38	-

(b) Run A.2): Charging Schedule and SOC less NSE

h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	$\sum_h$
$e_{1,h}^{\mathbf{RT}}$				2.66					0.19	0.19	0.19	0.19	0.19	0.19	0.19		0.19		0.19			0.19	2.66	2.66	9.89
$e_{2,h}^{\mathbf{RT}}$				2.08																			3.51	3.51	9.11
$e_{3,h}^{\mathbf{RT}}$				2.04																	0.4	0.4	3.6	3.6	10.04
$\sum_v e_{v,h}^{\mathbf{RT}}$				6.78					0.19	0.19	0.19	0.19	0.19	0.19	0.19		0.19		0.19		0.4	0.59	9.77	9.77	29.05
$e_{1,h}^{\mathbf{SOC}}$	9	9	9	11.5	11.5	11.5	11.5	7.79	7.97	8.15	8.33	8.51	8.69	8.87	9.05	6.01	6.19	6.06	6.24	6.1	6.1	6.28	8.78	11.28	-
$e_{2,h}^{\mathbf{SOC}}$	10	10	10	12	12	12	12	12	12	10.14	9.74	9.74	6.03	6.03	6.03	6.03	5.08	5.08	5.08	5.08	5.08	5.08	8.45	11.83	-
$e_{3,h}^{\mathbf{SOC}}$	10.5	10.5	10.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	10.24	9.83	9.83	4.5	4.5	4.89	5.28	8.81	12.34	-
$\sum_v e_{v,h}^{\mathbf{SOC}}$	29.5	29.5	29.5	36	36	36	36	32.29	32.47	30.79	30.57	30.75	27.21	27.39	27.57	22.28	21.11	20.97	15.82	15.68	16.07	16.65	26.05	35.45	-

(c) Run A.3): Charging Schedule and SOC less NSE

Table D.7: Numerical Results with Details on Hourly Resolution



(a) Varying $\phi_v^{\mathbf{SOC}}$ (b) Varying $\tilde{\lambda}^{\mathbf{D}}$

Figure D.8: Sensitivity Analysis on UL Profit Region

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Attributions

This thesis was devised with the open source document preparation system LyX (Build 2.0.6), which itself is built upon the LaTeX (MikTex Build 2.9) typesetting system using Donald Knuth's TeX macro language.

The main set of computational tools employed in the presented research is the numerical decision support system jointly designated as PEVAG. These decision support models have been developed for this thesis and are documented mainly in Chapters 4, 5 and 6, as well as in the associated publications. Model code and all input parameters are freely available under CreativeCommons (CC) BY-SA 3.0 license, allowing free copies and redistribution of the material in any medium or format, as well as remixing, transforming, and building upon the material for any purpose, even commercially. The code can be requested directly from the author via email. PEVAG is formulated and implemented in the *General Algebraic Modeling System* (GAMS©) Build 23.7 - 24.1.2. For handling input and output data, all calculations were performed running MatLab©. The optimization problems was for the most part solved with the CPLEX™ 12.5.1 solver for LPs, PATH 24.1.2 r40979 for generic NLPs and NLPEC 1.6 for non-linearized MPECs of PEVAG-ILC.

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Extended Summary

Introduction and Problem Statement

What would our modern societies be like, if there wasn't widespread access to electricity and how would we live without motorized mobility?

It appears rather difficult to imagine contemporary societies of developed countries without power systems as the backbone enhancing social welfare, economic prosperity and ultimately well-being to its human constituents. There is little doubt that also the transportation sector is an essential constituent to modern life.

However, to mitigate adverse climatological effects of emitting greenhouse gases, a rigorous de-carbonization of both industries has been set on the political agenda in many parts of the world. To this end, electrifying personal vehicles is believed to contribute to an affordable and reliable energy model that provides tolerable environmental impact.

The latest sales statistics suggest that the overall penetration and its rate of change still remain very low. Nevertheless, what the future holds is uncertain and may include some surprises. What is well known at this point is that plug-in electric vehicles (PEVs) are likely to exhibit a plurality of benefits and co-benefits to modern society. They are understood as an option for increased energy efficiency, and present a strategic development option to reduce geopolitical exposure from importing primary energy carriers. Most importantly for the context of this thesis, they constitute an inherently flexible electricity demand. This means that as a mobile storage technology, in principle, PEVs promise to facilitate, among others, the integration of the quickly growing variable renewable energy sources. Yet, a doubt remains:

How exactly should PEVs be coordinated, such that they provide benefits to electric power systems in the presence of resource scarcity?

The main objective of this research is to propose decision support tools that may improve the total system efficiency through PEV charging. To achieve this, the thesis document sets out to establish detailed understanding of the regulatory framework governing vertically unbundled power systems with high levels of PEV integration. In the first set of qualitative chapters, the most relevant existing and future agents are identified and their respective objective functions are described.

These are first and foremost, PEVs that service the mobility needs of final customers, who drive to and connect at different supply points of the power system, requiring variable amounts of energy. Second, medium and low voltage distributions system operators are directly affected in their tasks of long-term network expansion planning, mid-term tariff design and short-term operation of the grid in secure conditions, such as voltage stability and keeping currents within thermally dictated limits. Finally, an aggregation agent as the interface to the wholesale electricity generators is envisaged to be in charge of procuring energy in electricity markets, exposed to uncertainty in prices, fleet availability and demand requirements. This aggregator could coordinate the PEV charging either with direct load control (DLC), i.e., sending power set points to the individual vehicles, or with indirect load control (ILC), i.e., by sending retail price signals.

Research Methods

The thesis makes use of both qualitative and quantitative methods to attain its objectives. In Part I it first creates a common ground of conceptual ideas, general electric power system framework assumptions and qualitative discussions on existing work of PEV integration. Part II then presents quantitative modeling, which substantiates the methodology, points to specific assumptions for the proposed decision making tools and finally puts forward a thorough analysis of an aggregator's economics with a discussion of numerical results.

Contributing to the technical literature this thesis on the one hand proposes a two-stage stochastic linear program for the PEV aggregator's day-ahead and balancing decisions with DLC over a large fleet of PEVs, while accounting for the conditional value at risk in the objective function. On the other hand, it puts forward a formulation of ILC coordination as a bi-level optimization problem given by mathematical programming with equilibrium constraints, in which 1) the upper level decisions on retail tariffs and optimal bidding in electricity markets are subject to 2) the lower level client-side optimization of PEV charging schedules. These decisions may respect a potential discomfort that could arise when PEV users have to deviate from their preferred charging schedule. Set in an existing, real medium voltage distribution network with urban characteristics and spatial PEV mobility, network use-of-system tariffs for capacity have been applied to both DLC and ILC scheduling by a PEV aggregator.

It should be noted that from a regulatory perspective within the framework of the European Union, the regulated activities carried out by a network operator in its natural monopoly are strictly unbundled from those of the competitive aggregator agent. Thus, in the context of this thesis, it is assumed that all tasks of the distribution system operation can be boiled down to a simplified calculation of network use-of-system (UoS) fees, which are input to the optimization models presented here. The UoS fees are incurred either by the aggregator exercising DLC or by the PEVs receiving price signals under ILC.

The thesis develops simulation algorithms as well as optimization models employing state of the art software technology, e.g., MatLab© for handling input output data, GAMS© and CPLEX™ for optimization.

Discussion of Numerical Results and Conclusion

Regulation Matters In its qualitative analysis, this thesis has first an foremost highlighted that coordination algorithms striving for validity in fully unbundled power systems, such as, e.g., aligned with European Directives, should note of the specific regulatory settings that different power systems agents are subject to. In such a setting, aggregators are competitive market agents at the interface of wholesale and retail electricity markets. Distributors, i.e., network infrastructure operators, on the other hand, are fully regulated entities, acting in natural monopolies, whose decisions are therefore subject to diametrically different objectives.

Optimal PEV Coordination Furthermore, the use of quantitative tools has lead to a number of results. Considering uncertainty, a detailed analysis of each scenario requires care and specifically designed tools. Using the optimization programs developed in this thesis, a PEV aggregator can optimally determine its involvement in day-ahead electricity markets. The buying and selling positions taken in different hours depend on the charging and discharging variables, which are imposed by the PEV energy requirement and constrained to the availability of the aggregated fleet of vehicles. Given this feasible region, in principle, the program will find low price hours for purchases and high price hours for discharges. The profit of the aggregator then mainly depends on the arbitrage between different instants in time and thus market prices, as well as retail prices agreed with the finals customers. Such decision making is, for the most cases, likely to decrease net social cost and drive the system towards a more efficient outcome, utilizing less expensive generation resources.

The Value of PEV Flexibility Within this thesis, however, the problem owner is the PEV aggregator, whose value of flexibility of a PEV fleet is defined as the economic benefit of aligning the total schedule schedule with market prices. To estimate this value of flexibility, first, the optimal objective function value in the original formulation with DLC is opposed to that of a schedule over which the aggregator cannot exercise control. Their relative difference make up this value. In a large-scale DLC case study with 1000 vehicles, 200 initial, and 100 reduced scenarios for market prices and mobility, the expected value of PEV flexibility under DLC by the aggregator has been found to be substantial. It lies in the range of 33%. However, how this benefit would be shared is not answered by the DLC study. It could mean that either the aggregator's profits increase by this amount, or to incentivize the PEV participation in a DLC scheme these profits could be passed on to the final customers through tariff reduction.

The Value of PEV Aggregation Another central analysis of this thesis revolves around the aggregation of fleets under uncertainty. It is found that the size of the aggregator's fleet impacts its economics because of the relative forecasting error and the associated cost under the above mentioned imbalance penalization scheme. To analyze how much the stochasticity of a single PEV's mobility influences the economics of the charging schedule in the day-ahead planning, a disaggregation technique is applied, in which the problem is solved with varying aggregation sizes of parallel sub-fleets. It turns out that the confidence with which day-ahead forecasts of vehicle mobility, i.e., energy demand and unavailability, can be carried out increases with the fleet size. Hence, a larger fleet incurs lower imbalance settlement fees as compared to the same fleet broken up in smaller sub-fleets. In effect, the more vehicles are controlled by the same entity, the better the individual vehicles compensate for the uncertainty in mobility of the others within the same aggregation. This expected value of PEV aggregation has been found to lie in the range of 19% comparing the scheduling of 250 four-vehicle big sub-fleets with the scheduling of one fleet of 1000 vehicles.

Efficient Network Signals Through Capacity Use-Of-System Tariffs Although it is widely accepted that electricity market signals are deemed efficient to allocate resources at the transmission system level, using uniform, zonal or locational marginal pricing, they may yet not always sufficiently represent the local network status of the distribution system at sub-transmission levels. Furthermore, high penetration levels of PEV potentially cause network reinforcement, which would have an impact on investment, operation and maintenance costs of the distribution system operator, who in turn translates these into higher system costs via the grid fees to the final customers. This is an undesirable charging outcome, as without coordination taking into account networks, the total system efficiency is at danger. Therefore, this thesis has used relatively unexplored long run marginal cost pricing for computing node dependent network UoS tariffs. Both under DLC and under ILC, as shown by representative case studies, the charging schedules are generally smoothened. Peak reductions are achieved, very likely alleviating punctual network saturation.

The case studies provided in this thesis allow for observing implications on optimal PEV coordination with UoS. The results have pointed at the fact that capacity network charges are an efficient instrument to account for local network situations in the charging schedules. Including UoS in the proposed models helps to schedule the PEV charging both in alignment with time and by network node location.

Full List of Candidate's Publications

with Relevance for the Thesis Topic

Peer Reviewed Journals

With JCR Impact Factor

[A1] **Ilan Momber**, Sonja Wogrin, and Tomás Gómez, "Retail pricing: A bi-level program for PEV aggregator decisions using indirect load control," *IEEE Transactions on Power Systems*, Accepted for future publication. In Press, 2014.

[A2] **Ilan Momber**, Afzal Siddiqui, Tomás Gómez, and Lennart Söder, "Risk averse scheduling by a PEV aggregator under uncertainty," *IEEE Transactions on Power Systems*, vol. 30, no. 2, pp. 882 - 891, Jul. 2014.

[A3] **Ilan Momber**, Germán Morales-España, Andrés Ramos, and Tomás Gómez, "PEV storage in multibus scheduling problems," *IEEE Transactions on Smart Grids*, vol. 5, no. 2, pp. 1079 – 1087, Mar. 2014.

[A4] S. Beer, T. Gomez, D. Dallinger, **I. Momber**, C. Marnay, M. Stadler, and J. Lai, "An economic analysis of used electric vehicle batteries integrated into commercial building microgrids," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 517–525, Mar. 2012.

[A5] T. Gómez, **I. Momber**, M. Rivier, and Á. Sánchez-Miralles, "Regulatory framework and business models for charging PEVs: infrastructure, agents, and commercial relationships," *Energy Policy*, vol. 39, pp. 6360–6375, Oct. 2011.

Pending:

[A6] **Ilan Momber** and Tomás Gómez, "PEV aggregation as a resource for electric power systems: A literature review and outlook," Working Paper Submitted for Journal Publication, 2013.

Peer Reviewed Conferences

With Proceedings

[B1] **Ilan Momber**, Sonja Wogrin, and Tomás Gómez, "An MPEC for electricity retail alternatives of plugin electric vehicle (PEV) aggregators," in *18th Power Systems Computation Conference (PSCC)*. Wroclaw, Poland: IEEE, Aug. 2014.

[B2] **Ilan Momber** and Tomás Gómez, "The effect of mobility forecasts for stochastic charge scheduling of aggregated PEV," in *4th European Innovative Smart Grid Technologies (ISGT)*. Copenhagen, Denmark: IEEE, Oct. 2013.

[B3] **I. Momber**, T. Gómez, and L. Söder, "PEV fleet scheduling with electricity market and grid signals," in *10th International Conference on the European Energy Market (EEM)*. Stockholm, Sweden: IEEE, May 2013.

[B4] **I. Momber**, T. Gómez San Román, M. Rivier Abbad, and C. Mateo, "Benefits of EV supplier aggregators and distribution system operators from applying smart charging of plug-in electric vehicles," in *CIGRÉ International Symposium on the Electric Power System of the Future*, Bologna, Italy, Sep. 2011.

[B5] M. Stadler, **I. Momber**, O. Mégel, T. Gómez, C. Marnay, S. Beer, J. Lai, V. Battaglia, "The added economic and environmental value of plug-in electric vehicles connected to commercial building micro-grids", *2nd European Conference SmartGrids & E-Mobility*. ISBN: 978-3-941785-14-4, pp. 5-13, Brussels, Belgium, Oct. 2010.

[B6] **I. Momber**, T. Gomez, G. Venkataramanan, M. Stadler, S. Beer, J. Lai, C. Marnay, and V. Battaglia, "Plug-in electric vehicle interactions with a small office building: An economic analysis using DER-CAM," in *2010 IEEE Power and Energy Society General Meeting*, Minneapolis, USA, Jul. 2010.

Without Proceedings

[C1] **Ilan Momber**, Sonja Wogrin and Tomás Gómez, "Modeling Decisions of Plug-in Electric Vehicle Aggregators: An MPEC Approach," in *INFORMS Annual Meeting*, San Francisco, USA, Nov. 2014.

[C2] **Ilan Momber**, Sonja Wogrin and Tomás Gómez, "Indirect Load Control Approaches for Plug-in Electric Vehicle (PEV) Aggregators," in *20th Conference of the International Federation of Operational Research Societies (IFORS)*, Barcelona, Spain, Jul. 2014.

[C3] **Ilan Momber**, Afzal Siddiqui, and Tomás Gómez, "Plug-in electric vehicle participation in electricity markets a stochastic optimization approach," in *9th International Conference on Computational Management Science (CMS)*. London, UK: Imperial College, Apr. 2012.

[C4] **Ilan Momber**, Afzal Siddiqui, and Tomás Gómez, "Stochastic Plug-in electric vehicle participation in electricity markets," in *14th Young Energy Economists & Engineers Seminar (YEEES)*, WIP | TU Berlin, Germany, Apr. 2012.

Book Chapters

[D1] **I. Momber**, T. Gómez, and M. Rivier, "Regulatory Framework and Business Models Integrating Electric Vehicles in Power Systems," in Book: *EV Integration into Modern Power Networks*, ISBN: 978-1-4614-0133-9, 1st ed., R. Garcia-Valle and J. A. Peças Lopes, Eds. New York: *Springer*, 2013.

Technical Reports

[E1] **I. Momber**, T. Gómez San Román, M. Rivier Abbad, and R. Cossent, "New actors and business models for the integration of electric vehicles," *FP7 Project Deliverable MERGE* WP D5.1, Feb. 2011.

[E2] **I. Momber**, M. Rivier, R. Cossent, J. T. Saraiva, K. Kanellopoulos, and P. Andrianesis, "Identification of Regulatory Issues Regarding Market Design and Network Regulation to Efficiently Integrate Electric Vehicles in Electricity Grids," *FP7 Project Deliverable MERGE* WP D5.2, Oct. 2011.

[E3] M. Rivier, **I. Momber**, C. Batlle, P. Rodilla, A. G. Bordagaray, V. Alimisis, J. T. Saraiva, N. Harziargyriou, K. Kanellopoulos, and A. F. Raab, "Scenarios and Roadmap for Deployment of EV in Three European Regions: Recommendations for Policy Makers and Regulators," *FP7 Project Deliverable MERGE WP5* D5.3, Jan. 2012.

Invited Talks and Presentations

[F1] **Ilan Momber**, "PEV Coordination Through Market Prices and Network Use-of-System Charges - Invited Brown Bag Lunch Talk," *Lawrence Berkeley National Laboratory*, Berkeley, CA, USA, Aug. 2014.

[F2] ——, "PEV Coordination Through Market Prices and Network Use-of-System Charges - Invited Brown Bag Lunch Talk," *National Renewable Energy Laboratory*, Denver, CO, USA, Aug. 2014.

[F3] **Ilan Momber**, Germán Morales-España, Andrés Ramos, and Tomás Gómez, "PEV storage in multibus scheduling problems,", in *2014 IEEE Power and Energy Society General Meeting*, Washington D.C., USA, Jul. 2014.

[F4] **Ilan Momber**, "The PEVAG Model: PEV Coordination Through Market Prices and Network Use-of-System Charges - Invited Talk at Seminar for MIT Utility-of-the-Future Project," *Institute for Research in Technology (IIT)*, Madrid, Jun. 2014.

[F5] ——, "Stochastic PEV participation in electricity markets - invited seminar presentation," Engineering Department, Cambridge University, May 2012.

[F6] ——, "Electric Energy Systems - *University Enterprise Training Partnership (EES-UETP)* Course Lecture on Regulatory Framework and Business Models for Efficient Integration of EV," Porto Portugal, Oct. 2011.

Voluntarily Served as a Peer-Reviewer for:

Scientific Journals

- International Journal of Electrical Power & Energy Systems, Imprint: *Elsevier*, ISSN: 0142-0615
- Applied Energy, Imprint: *Elsevier*, ISSN: 0306-2619
- Transactions on Smart Grid, Imprint: *IEEE*, ISSN: 1949-3053
- Energies – Open Access Energy Research, Engineering and Policy Journal, Imprint: *MDPI*, ISSN: 1996-1073
- Sustainable Energy, Grids and Networks (SEGAN), Imprint: *Elsevier*, ISSN: 2352-4677

Scientific Conferences

- Electric Vehicle Symposium & Exhibition, *World Electric Vehicle Association (WEVA)*
- International Conference on the European Energy Market (EEM), *IEEE*
- PES Innovative Smart Grid Technologies (ISGT) Europe, *IEEE*
- PowerTech, *IEEE*

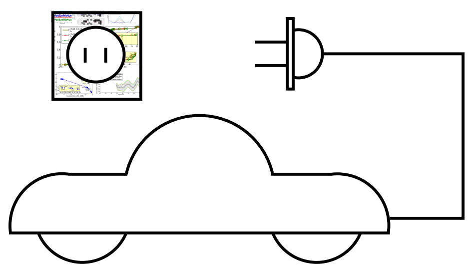
Candidate's Curriculum Vitae

Ilan Momber was born on February 23rd 1985 in the free city of West-Berlin, Federal Republic of Germany. He completed his pre-university education with an honorary diploma from *Centennial High School* in Pueblo, Colorado, U.S.A., in 2002, and concluded it with the matriculation exam (Abitur), from Askanische Oberschule (Gymnasium), Berlin-Tempelhof, in 2004.

After moving to the city of Karlsruhe in south-western Germany for his undergraduate studies, where he started appreciating the constituting principles of mathematics and engineering, he decided to re-locate to the Rhône-Alpes Region of France, to join the *Ecole Nationale Supérieure de Genié Industriel (ENSGI)*, in Grenoble. There, he was given the opportunity to make first contact with power systems, while interning in the production planning department of a *Siemens Transmission & Distribution* factory, manufacturing 72-145 kV gas-insulated substation equipment.

However, the pivotal experience drawing him into power systems research, was during his Diplomarbeit (final project, equivalent to an M.Sc. thesis), on the topic of "Integrating Plug-In Electric Vehicles in Microgrids", which he developed in cooperation between *Fraunhofer Institute for Systems and Innovation Research (FhG ISI)*, Karlsruhe and the *Lawrence Berkeley National Laboratory*, Berkeley, California. His research granted him the degree of Business & Industrial Engineering from the Karlsruhe Institute of Technology (KIT), in 2010 and encouraged him to pursue post-graduate studies in academia within the SETS Joint Doctorate at *Universidad Pontificia Comilas (UPCO)* in Madrid, Spain, as well as *Kungliga Tekniska Högskolan (KTH)* in Stockholm, Sweden. Between working in UPCO's *Instituto de Investigación Tecnológica (IIT)*, and KTH's *Electric Power Systems Department*, he spent half a year at the *Department of Statistical Science of University College London (UCL)*, UK, to deepen his understanding of stochastic optimization and econometrics.

Ilan's interests include regulation, technical and economic modeling of power systems with particular focus on plug-in electric vehicles and distributed generation. Besides work, he founded Fru-IIT, a group of ca. 20 co-workers joining their purchasing power and appreciation for vitamins to deliver more than 600 kg of fresh *fruiit* during the first 7 months of 2014 right to the office desks of IIT. He considers himself very fortunate to have lived in 5 different European countries and experienced the rich diversity of their cultures. By now, he naturally feels to be a true European. His ambition is to continue his dedication to a career in energy and power systems, relocating to the political capital of the EU, Brussels, where after too many years of long-distance he finally joins his dearly beloved girl friend, Anne-Sophie. He works as a Senior Research Associate at the Energy Centre of Vlerick Business School.



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