Department of Signal Processing and Acoustics

Demand Response and Energy Portfolio Optimization for Smart Grid using Machine Learning and Cooperative Game Theory

Adriana Chiș

Aalto University

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Aalto University
School of Electrical Engineering
Department of Signal Processing and Acoustics
Signal Processing Group

Supervising professor
Prof. Visa Koivunen, Aalto University, Finland

Preliminary examiners
Assistant Prof. Vassilis Kekatos, Virginia Tech, USA
Dr. Iiro Harjunkoski, ABB Corporate Research, Germany

Opponents
Prof. Yih-Fang Huang, University of Notre Dame, USA
Dr. Iiro Harjunkoski, ABB Corporate Research, Germany

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Abstract

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Abstract
Widespread availability of electricity is a hallmark of civilization. A reliable electricity supply is fundamental for the social and technological development of the world. To cope with the growing electricity demand and other challenges associated with energy delivery today, technological advancements towards a modern updated power grid are needed. The development of a smart grid is a solution to enable a more stable, reliable, efficient, economical and sustainable energy generation, transmission, distribution and usage. One drawback of the traditional power grid is the mismatch between energy supply and demand. The solution to this problem is the deployment of a more flexible energy generation system, together with a balanced electricity consumption. This could be achieved by means of demand side management (DSM).
The focus of this thesis is to model efficient DSM methods for optimizing electricity consumption. In particular, price-based demand response (DR) methods that require the active participation of electricity users are developed. Price-based DR methods allow for energy users to optimize their energy consumption and reduce their costs. This occurs if they adjust and change their electricity consumption patterns in response to dynamic prices applied by utility companies. One problem tackled in this thesis is that of optimizing the charging of electric vehicles (EVs). More and more people are interested in purchasing EVs. The EVs however, will significantly increase their electricity consumption and cost. Using machine learning techniques, efficient methods that optimize the home charging of an EV and reduce the long term cost of charging for the owner are developed. The EV charging is scheduled by taking advantage of the time-varying electricity prices within a day, but also of the dynamic nature of prices on different days.
In the traditional power grid, the role of the energy consumers was that of price takers with no other involvement in the energy sector. The smart grid however, will support consumers also in owning renewable energy sources (RESs) and energy storing systems (ESSs). Local energy generation and ownership of ESSs opens opportunities for new energy strategies and markets. By enabling cooperation among energy producers and consumers, they would be able to manage and use their renewable energy resources and storage spaces more efficiently and reduce their electricity consumption costs even more. In this thesis, collaborative models for exchange and trade of energy within communities of households owning RESs and ESSs are developed. Using a mathematical model from cooperative game theory, the community energy portfolio optimization problem is formulated as a coalitional game for the households to minimize their costs, individually and collectively. Moreover, using a concept from microeconomics, a DSM method is also developed from the perspective of the utility company to balance the community's grid energy consumption.

Keywords Smart grids, demand side management, demand response, machine learning, game theory, electric vehicles, smart community

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Preface

The research work included in this doctoral dissertation has been carried out at the Department of Signal Processing and Acoustics from Aalto University, Finland. The completion of this work was possible due to the diligent supervision of Prof. Visa Koivunen to whom I would like to express my deepest gratitude for his trust and high quality research guidance.

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Last, but not least, I want to thank my wonderful parents Livia and Corneliu Chiş for the love and care that they have always shown to me. I couldn't have reached here without their support.

Espoo, August 12, 2018,

Adriana Chiş

Contents

List of Publications

This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.

I A. Chiş, J. Lundén and V. Koivunen. Scheduling of Plug-in Electric Vehicle Battery Charging with Price Prediction. In *Proc. of the 4th IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe) conference*, Copenhagen, Denmark, pp. 1-5, 6-9, Oct. 2013.

II A. Chiş, J. Lundén and V. Koivunen. Optimization of plug-in electric vehicle charging with forecasted price. In *Proc. of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Brisbane, QLD, Australia, pp. 2086 - 2089, 19 - 24, Apr. 2015.

III A. Chiş, J. Lundén and V. Koivunen. Reinforcement Learning-Based Plug-in Electric Vehicle Charging With Forecasted Price. *IEEE Transactions on Vehicular Technology*, vol 66, no. 5, pp. 3674 - 3684, May 2017.

IV A. Chiş and V. Koivunen. Collaborative Approach for Energy Cost Minimization in Smart Grid Communities. In *Proc. of the IEEE Global Conference On Signal And Information Processing (GlobalSIP)*, Montreal, Quebec, Canada, pp. 1115-1119 , 14 - 16, Nov. 2017.

V A. Chiş, J. Lundén and V. Koivunen. Coalitional Game Theoretic Optimization of Electricity Cost for Communities of Smart Households. In *Proc. of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, New-Orleans, LA, USA, pp. 4726 - 4729, 5 - 9, Mar. 2017.

VI A. Chiş and V. Koivunen. Coalitional game based cost optimization of energy portfolio in smart grid communities. *IEEE Transactions on Smart Grid*, to appear.

VII A. Chiş, J. Rajasekharan, J. Lundén and V. Koivunen. Demand Response for Renewable Energy Integration and Load Balancing in Smart Grid Communities. In *Proc. of the 24th European Signal Processing Conference (EUSIPCO)*, Budapest, Hungary, pp. 1423 - 1427, 29 Aug.-2 Sept., 2016.

List of Symbols

$a_{n/m}(t)$	Amount of energy exchanged by a household n or m with other households from the community in time-slot t
$b(t)$	Total amount of energy purchased by the community from the utility company/main power grid in time-slot t
$b_{n/m}(t)$	Amount of energy purchased by a household n or m from the utility company/main power grid in time-slot t
b_d^{init}	Initial state of charge of the EV's battery in day d
d	Daily time steps
e_d	MDP action in day d
$\mathcal{F}$	Set of transition samples
$g(t)$	Total amount of energy required by the community from the utility company/main power grid in time-slot t
$g_m(t)$	Amount of energy required by a household m from the utility company/main power grid in time-slot t
l	Index of a sample from a set
$\mathcal{M}$	Set of households owning RESs and/or ESSs and forming a coalition
m	Index of a household owning RESs and/or ESSs
$\mathcal{N}$	Set of all households in the community
n	Index of a household from the community
$\mathcal{P}$	Set of pure energy consuming households
p	Index of a pure energy consuming household
$r_m(t)$	Amount of energy charged/discharged to/from the ESS of household m in time-slot t
$s_m(t)$	Total amount of energy stored in the ESS of household m at the end of time-slot t
S_{ω_d,e_d}	Subset of transition samples
$\mathcal{T}$	Optimization time frame

T	Number of time slots in the optimization time frame
t	Discrete time steps
$u(t)$	Total energy demand of the community in time-slot t
$u_{n/m}(t)$	Energy demand of a household n or m in time-slot t
$\mathbf{x}_d$	MDP state in day d
β	Bandwidth of the kernel function
γ	Discount factor
Δ_d	Difference between the minimum hourly costs of charging the EV's battery of two consecutive days
ϵ_d	Amount of energy consumed by the EV in day d
$\lambda(t)$	Price for electricity sold by RESs and/or ESSs owning households to pure consuming households in time-slot t
$v(\mathcal{M})$	Characteristic function of the coalitional game
ϕ	Kernel function
$\Phi(v)$	Shapley value
$\Phi_m(v)$	Amount of payoff assigned by the Shapley value to household m
τ	Index of an algorithm iteration
$\xi(t)$	Electricity price per unit of energy applied by the utility company in time-slot t
ω_d	Index of a weekday
$\lVert \cdot \rVert$	Distance norm
$\lVert \cdot \rVert_1$	L_1 norm

List of Abbreviations

ADMM	Alternating direction method of multipliers
AMI	Advanced metering infrastructure
BNN	Bayesian neural network
CVXP	Convex programming
DES	Distributed energy systems
DP	Dynamic programming
DR	Demand response
DSM	Demand side management
EV	Electric vehicle
ESS	Energy storing system
GP	Geometric programming
HAN	Home area network
kWh	Kilowatt hour
LP	Linear programming
MDP	Markov decision process
MILP	Mixed integer linear program
MIQP	Mixed integer quadratic programming
MPC	Model predictive control
NBS	Nash bargaining solution
PAR	Peak-to-average ratio
PHEV	Plug-in electric vehicle
QO	Quadratic optimization
RES	Renewable energy source
RL	Reinforcement learning
RTP	Real time pricing
SARSA	State–action–reward–state–action algorithm

SDP	Stochastic dynamic programming
SLP	Stochastic linear program
SP	Stochastic programming
ToUP	Time of use pricing
V2G	Vehicle-to-grid

1. Introduction

1.1 Motivation

Widespread availability of electricity is a hallmark of civilization today. The traditional paradigm of electricity consumption involves large power stations that generate electricity and an electric grid to distribute the electricity to private, commercial and industrial customers. The current electricity grid is facing important challenges that must be addressed in the near future. One major concern is the growth of demand and the inadequacy of the current grid infrastructure to sustain this growth. The International Energy Outlook 2016 [1] estimates a world energy demand growth from 21.6 trillion kilowatt hour (kWh) in 2012 to 25.8 trillion kWh in 2020 and 36.5 trillion kWh by 2040. The aging of the power grid also represents a big concern. A major part of the power grid infrastructure existing today in the developed world dates back to the middle of the 20^{th} century. Therefore, it needs to be replaced by a modern and updated power grid that would be able to sustain the continuously growing energy requirements. Other potentially more important challenges are pollution and climate change caused by fossil fuel-based energy production. All these challenges call for a rapid renewal and upgrade process towards an advanced smart power grid.

The smart power grid may be characterized as a cyber-physical system [2] that is able to combine large and small-scale power system infrastructure elements together with cyber systems. These cyber systems would be composed of networked sensing, processing, optimization and control components connected by communications and information processing units. The main purpose of the smart grid is to enable a more stable, reliable, efficient, economical and sustainable energy generation, transmission, distribution and usage. The smart power grid has the aim to achieve other major goals, too. One is to ensure a balanced supply and demand. Electricity demand is typically fluctuating according to daily industrial, commercial and private consumer activities or due to emergency events. In the traditional power grid, extra power capacity needs to be built in order to deal with fluctuations in demand. In the smart power grid, however, a more flexible energy generation system will be deployed to satisfy the demand of electricity in real time. Another major goal of the smart grid is to allow energy consumers to have active participation in the power system. Automated and easy-to-access energy efficiency programs, in which customers may make own decisions on their energy consumption based on economical or other reasons, will also be deployed. Balancing supply and demand and enabling active customer participation in the power sector may be achieved by means of demand side management (DSM) [3]. DSM would give network operators greater flexibility in managing and controlling the power system. At the same time, it would also allow for end consumers to optimize their energy consumption and costs. Electricity consumers may significantly reduce their costs by adopting DSM methods that make use of dynamic pricing tariffs, also called price-based demand response (DR) methods [4]. The dynamic prices typically reflect the demand of electricity in the power network, i.e. they are low during the hours of the day with low electricity demand and high during peak hours. This pricing strategy, or other types of financial incentives, are applied by the utility companies and give consumers the opportunity to reduce their electricity bills if they adjust and change their electricity consumption patterns in response to these prices. For example, they may shift part of their electricity consumption from periods in which prices are high to periods in which the prices are low [4]. Hence, active participation of end energy consumers is required in order for these DR methods to be efficient. DR methods can be applied automatically at end consumers premises through installation of smart sensing and control devices. However, the consumers can also choose to individually follow the variation of electricity prices and manually turn on and off their home appliances based on current price.

Through deployment of DSM programs, the smart power grid will be able to integrate new emerging energy resources and solutions such as distributed energy sources (DESs), energy storage systems (ESSs), smart homes and buildings, automated real-time energy management programs. In addition to allowing customers to optimize their energy consumption, the smart grid will also support them in owning DESs such as renewable energy sources (RESs). Consequently, in addition to consuming energy, they would also produce their own energy. This will further encourage the development of local energy markets in which end energy consumers and producers can interact in order to find an optimal usage of their local energy generation.

1.2 Scope of the thesis

The main scope of this thesis is to develop new DSM methods, in particular price-based DR methods for optimizing the electricity consumption of end consumers with the purpose of reducing their electricity consumption costs. The developed methods stem from signal processing, optimization, machine learning and game theory. First, DR methods for optimizing the home charging of electric vehicles (EVs) are proposed. The EVs are an ecologically friendly alternative to conventional vehicles powered by internal combustion engines. However, the adoption of EVs would increase the electricity consumption on the power grid. The cost of energy consumption for the EVs' owners would increase significantly as well. One of the objectives of this thesis is to propose DR methods for optimizing the home EV charging. The methods facilitate saving energy costs and help in avoiding problems caused by plugging in more EVs to the power system. The proposed methods schedule the charging in response to the dynamic prices incurred by the utility company and reduce the long terms cost of electricity consumption for the owner.

Another objective of this thesis is to develop novel collaborative methods for optimizing energy portfolios within communities of smart households owning RESs and/or ESSs. The methods operate under DSM programs. Cooperative frameworks for optimizing energy portfolios may be employed at distribution level in order to optimize the electricity consumption, usage of energy storage space and usage of locally produced renewable energy. Households owning RESs and/or ESSs could individually optimize their electricity consumption and reduce their electricity consumption costs through DR methods. However, by cooperating and interacting with each other they would be able to manage and use their renewable energy resources and storage spaces even more efficiently and reduce their electricity consumption costs even more. Interactions among electricity end users owning RESs and/or ESSs may take place through exchange, transfer or share of electricity and also of information. Two-way energy flow and communications systems are needed to facilitate such interactions [5]. Enabling such interactions may also open opportunities for development of local energy markets [6]. Interactions among energy users may be classified as competitive or collaborative. In this thesis, collaborative models and methods for improving the efficiency of electricity usage and resource allocation within smart grid communities of households are proposed. These households equipped with renewable generation and storage facilities collaborate by exchanging and trading energy and sharing storage spaces with the goal of reducing the aggregate costs, or balance the load of the community on the power grid.

1.3 Contributions of the thesis

The main results of this doctoral dissertation have been published in seven peer-reviewed articles, out of which two are journal articles (Publications III and VI) and the remaining five are conference papers (Publications I, II, IV, VI and VII). The author of this dissertation was responsible for the theoretical studies, development of methods, computer simulation, and numerical results in all the publications (Publication I-Publication VII) included in this dissertation. The author of this dissertation was also mainly responsible for writing the articles. The co-authors provided important help in planning the research, steering the work through technical discussions, as well as revising the publications. A brief overview of the contributions of this thesis is given below.

- DR methods for optimizing the home charging of an EV with the purpose of reducing the long term cost of charging are proposed in Publications I, II and III. The local utility company uses a dynamic pricing scheme for charging their customers. The EV's charging is being optimized from the owner's perspective in order to reduce the charging cost. The proposed methods take advantage of the day to day and hour to hour variations of the dynamic prices. Using reinforcement learning (RL) techniques, in particular the state–action–reward–state–action algorithm (SARSA) with eligibility traces [7] in Publications I and a fitted-Q iteration-based [8] batch RL algorithm in Publications II and III, the EV's charging is scheduled based on daily charging decisions. These charging decisions are taken such that the charging costs are reduced while ensuring that the driving needs of the owner are satisfied. Heuristic methods are used in Publications I and II for defining the rewards employed in the proposed RL methods. These methods reward actions that charge the EV's battery at low costs while fulfilling the owner's driving needs. An optimal linear programming (LP) model is formulated and solved with the purpose of defining the reward values in Publication III. A Bayesian neural network (BNN)-based method for predicting electricity prices over a one day period is also proposed in Publication III. The obtained results show that the proposed methods may reduce the charging costs by 7-10% in comparison to a daily optimal charging method and by 40-50% in comparison to the conventional charging method.

- Collaborative models for exchanging or trading energy and sharing energy storage space in a community of residential households are proposed in Publications IV, V and VI. The community consists of households owning RESs and/or ESSs in Publication V. In Publications IV and VI, pure energy consuming households are included in the community model, too. The collaborative models work under DSM programs. The main goal is to minimize energy consumption and operational costs for the community of households. The collaboration is formulated using a coalitional game model in Publications V and VI. The coalitional games belong to the class of cooperative games. In a cooperative game theoretic model [9], players form coalitions with the purpose of jointly achieving payoffs. Providing a fair division of the cost savings among the participants in the coalition is another property of cooperative game theory. The households from the community owning RESs and/or ESSs form a coalition to exchange energy among themselves in Publication V and they also sell energy to pure consumers in Publications IV and VI. DR methods are formulated in Publications V and VI as constrained linear programs with the purpose of reducing the energy consumption cost (Publication V) and also operational costs (Publication VI) of the formed coalitions. The cost savings obtained by the coalition are divided among the participating households according to the Shapley value [10, 11]. Shapley value is a one-point payoff solution through which the overall cost savings obtained by the coalition are fairly divided among its members according to their individual contribution in achieving these cost savings. A DR method is formulated as a constrained linear program to optimize energy consumption, renewable energy allocation, storage usage, energy exchange and trade under different amounts of renewable energy production within the community in Publication IV. It is shown that in the considered scenarios the proposed methods reduce the cost for the households owning RESs and/or ESSs by 18% in comparison to optimizing their electricity consumption individually, hence, not collaborating. The pure consumers also obtain a 3% reduction in cost in comparison to buying all their needed energy from the utility company.

- A DSM method for households in a community to reduce the costs of consuming energy from main power grid and balance the load of the community on the grid is proposed in Publication VII. A local energy trading model is first formulated from the perspective of the households owning RESs. Renewable energy surplus may be sold to neighboring households in need of energy. The cost of energy bought by the community from the main power grid is reduced. A DSM problem is also formulated from the perspective of the utility company for balancing the community's energy consumption from the power grid. This problem is formulated as a geometric programming (GP)-based optimization using the Cobb-Douglas production function from microeconomics [12, 13]. The obtained results show that in the considered scenarios the proposed method reduces the community's costs for purchasing electricity from the main power grid by 10%. It also balances the profile of the energy consumed by the community from the power grid during a day, obtaining a peak-to-average ratio (PAR) close to unity.

1.4 Structure of the thesis

This thesis consists of five chapters and seven original publications. Chapter 2 introduces basic concepts of the smart grid and the related enabling technologies. Chapter 3 provides a survey on DSM methods for optimizing charging of EVs. The contributions of this thesis regarding DR methods for optimization of home charging of an EV are described. The goal is to reduce the long term charging cost for the EV's owner. A complete description of these methods is given in Publications I, II and III. DSM methods for exchange and trade of energy among energy consumers and producers at distribution level of the power grid are considered in Chapter 4. First, a survey on interactive methods for trading and exchanging energy that have the goal of reducing the costs related to energy consumption is given. The contributions of this thesis on collaborative methods for minimizing costs of a community of households are described. A complete description of the proposed methods is given in Publications IV, V and VI. The contributions of this thesis related to interactive DSM methods for reducing the consumption cost and balancing the load on the grid are presented in subsection 4.3. The method proposed in this thesis for reducing the cost and balancing the energy consumption of a community of households from the power grid is fully described in Publication VII. Finally, a summary of this work, concluding remarks and possible future work are discussed in Chapter 5. Publications I-VII containing detailed technical description and results of the developed methods are attached at the end of this dissertation.

2. Smart power systems

The deployment of a smart power grid implies a gradual upgrade process in the traditional power system. The upcoming changes towards a smart electric grid are expected to affect all energy sectors and all parties involved in the energy industry including generation, transmission, distribution, consumers, retailers, aggregators, utilities, municipalities and end consumers.

2.1 Smart grid definition

There is no single widely accepted definition of a smart grid. The development of the smart grid is an evolutionary process and its components and services will be slowly standardized over time. For example, the Smart Grids European Technology Platform gives the following definition [14]: *"A smart grid is an electricity network that can intelligently integrate the actions of all users connected to it - generators, consumers and those that do both - in order to efficiently deliver sustainable, economic and secure electricity supplies"*. In [15], the smart grid is defined as: *"The smart grid is an advanced digital, two-way power flow, power system capable of self-healing, and adaptive, resilient, and sustainable, with foresight for prediction under different uncertainties. It is equipped for interoperability with present and future standards of components, devices, and systems that are cyber - secured against malicious attack."* Regardless of the definitions of a smart grid given by various entities, it is commonly agreed that the future smart grid must comprise the following, but not only, key characteristics and features [14, 16]:

- It must accommodate different types of energy generation and storage facilities;
- It must accommodate active customer participation;
- It must enable new products, services and markets;
- It must enable bidirectional flow of information and power;
- It must provide energy efficiency, quality and reliability;

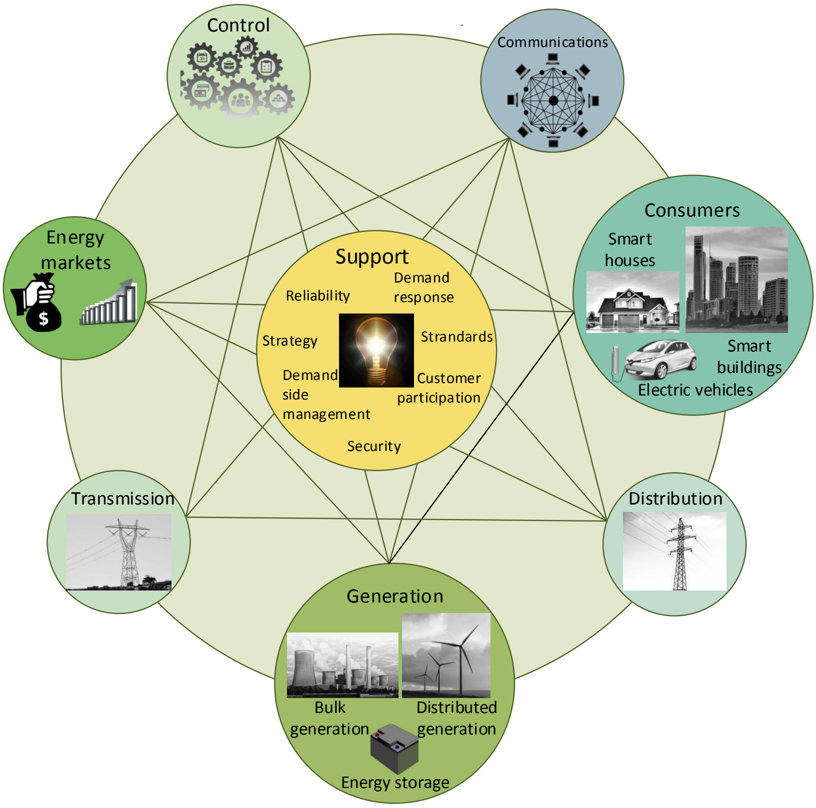

Figure 2.1. Smart grid architecture and main components. The smart power grid fuses traditional power grid components with innovative technologies and system facilities.

- It must present automatic self-healing properties, i.e. the ability to prevent, detect and repair system faults;
- It must be versatile and resilient to cyber attacks and natural disasters.

2.2 Smart grid components

The smart power grid will fuse components of the traditional power grid architecture with new system facilities and technologies, as shown in Figure 2.1. The most important innovative technologies that will enable the existence of smart electricity grid are the following:

Distributed energy sources (DES) and renewable energy sources (RESs): Conventional power plants will co-exist with distributed generators deployed at residential, commercial and industrial locations [17]. DES may refer to local dispatchable energy sources such as gas turbines, or internal combustion engines and non-dispatchable energy sources such as solar panels and wind turbines that produce electricity on site. The renewable energy is a free, clean and non-depletable source of energy. Therefore, RESs have become more and more popular in recent years. Installation of RESs provides an important and sustainable alternative to the conventional coal-based power generation. However, one major drawback of RESs is the highly intermittent nature of their power generation which depends on the weather and its continuous changes.

Energy storage systems (ESSs): ESSs represent a key component of the future smart grid. In order to compensate for the variability of the renewable energy generation, ESSs may be used in conjunction with RESs to store the renewable energy surplus at times when the renewable energy production is higher than the energy demand [18]. ESSs could be also used to facilitate the control, optimization, management and operation of energy flows within the power system, for example by storing energy at times of low demand and use that energy at times of high demand. This will ensure the reliability and stability of the grid and facilitate the optimization of energy consumption.

Microgrids: Microgrids are standalone systems composed of networks of small loads, DES and ESSs. They could be seen as miniature versions of the main power system. A microgrid is envisioned to be able to operate in an isolated mode, i.e. it could operate as an independent, self-sustainable system that fulfills its internal electricity requirements and also ensures self reliability and security. However, in most of the cases, the microgrids would operate in connection to the main power system to be able to fulfill their demands at times of insufficient renewable resources [19]. Due to their capability of disconnecting from the main power system and operate in islanded mode, the deployment of microgrids next to business centers, data centers, or hospitals would confer a high degree of reliability to these facilities, allowing them to function even in the most critical situations [20].

Bi-directional communications and flow of power: The operation of the power system would be controlled by the power system operators in close cooperation with the distributed facilities such as distributed independent RESs and ESSs, microgrids, or residences and business centers. In order to enable this joint operation of the power grid, the future smart grid must incorporate two-way communications and a bidirectional power flow systems. The communications system will support bidirectional flow of information between the entities operating the power grid, making it more secure and reliable. In order to ensure a resilient bidirectional flow of power within the power network, efficient grid monitoring and control over the network operation is also needed [21].

Active consumer participation: In the conventional power grid, the consumers are passive receivers of electricity and prices, without having active participation in controlling electricity in the power network. However, in the future, the consumers will represent an active component of the smart energy system [22]. By taking part in programs such as those for DSM and DR energy consumers may participate in the energy industry not only as energy buyers, but also as RESs and ESSs owners, as energy traders, or as control agents.

DSM programs: DSM programs include energy efficiency programs, load management [23] and DR methods [23, 24] which are implemented through modifying, modelling and predicting the electricity customers' demand patterns. One of the main goals of these programs is to reduce the PAR of the electricity demand on the grid. By using DSM programs [25] the end users may obtain benefits reflected in reduced costs and reliable electricity supply, while for the energy providers the benefits are accrued in a more efficient use of the supply capacity. Hence, unnecessary investments determined by the peak load periods which require extra generation capacity may be avoided.

Advanced metering infrastructure (AMI): The AMI is another key component of the smart grid. It is a system comprised of smart meters, sensors [26] and other monitoring devices, electric and electronic control equipment, smart communications equipment, real-time computational platforms, information processing units, etc. This system will be deployed at all levels of the power grid, facilitating the energy management and control operations that will make the grid more reliable, secure and efficient. It will also facilitate the implementation of real-time DSM programs [27]. The AMI together with the two-way communications system would enable data recording and information exchange among customers and utility companies or other grid operating entities. This will also enable the participation of customers in DR programs.

Home area network (HAN): A HAN represents an advanced metering system located inside electricity customers' homes. It is composed of smart home appliances, smart meters, sensors, energy management and control devices [28]. The HAN allows for efficient management of the home's electricity supply and demand through controlling smart appliances inside the house. The HAN may be connected to the utility company through the two-way communications link for exchanging information such as pricing data or customers' demand. However, the utility company would typically not have control over it.

Smart appliances: Smart appliances are appliances equipped with grid friendly controllers and have delayable loads. An appliance has a delayable load if its operation is flexible and can be scheduled to work over different periods of time [29]. Such appliances include, for example, washing machines, heaters, air conditioning systems, dryers. The grid friendly controller of a smart appliance would be an integral part of the HAN. This controller is able to control the load of the appliance by turning it on or off according to a pre-defined schedule, or in case of critical situations to avoid eventual power grid faults such as frequency fluctuations and abnormal levels of current and voltage, for example.

Electric vehicles (EVs): EVs can be considered a special category of smart appliances. But, their role in the deployment of a smart power grid may be much more significant than that. Integrating a large number of EVs into the power grid can be challenging. An EV would significantly increase the average energy consumption of a household and the penetration of high numbers of EVs in the power system can dramatically increase the load on the grid [30]. However, by exploiting their high potential for supporting DSM programs [31], the EVs can have important positive impacts over the power system. For example, the charging of the EVs's batteries can be easily maneuvered through intelligent programs that aim at flattening peak loads on the grid. Moreover, by enabling vehicle-to-grid (V2G) technologies [32], the discharge of batteries may also be controlled, and hence, EVs can be used as distributed storage units to store energy, or for providing ancillary services to the grid. Ancillary services represent services that support the continuous and secure flow of electricity within the power network such that the electricity demand over the grid is always satisfied [33]. In order to be able to obtain all these benefits, smart programs for integrating the EVs into the electric grid are needed.

Energy markets: Smart grid deployment is coupled with the liberalization of the electricity markets. Market competition, fair market rules, dynamic pricing and customer incentives are factors that will allow the smart grid to achieve maximum efficiency. Energy consumers may directly participate in the wholesale market by taking part in DSM programs, in particular in price-based DR programs that give financial incentives to energy consumers to change their energy usage patterns [34]. The need for integration of renewable energy resources may determine the formation of zonal energy markets, i.e. trade of electricity among power networks belonging to neighbouring geographical regions [35]. Moreover, the smart grid also involves active interactions among industrial, commercial or residential consumers equipped with renewable generation and energy storage systems. Such energy producers and consumers, i.e. prosumers, would be able to exchange and trade energy among themselves, thus forming local trading markets [36].

2.3 DSM methods

DSM methods refer to demand related policies that modify the energy usage patterns and amount of energy consumed by end consumers. DSM methods are designed to be applied to the general end electricity consumers such as commercial and industrial consumers, as well as residential energy users. In this thesis, the attention will be focused on DSM methods applied to end consumers at residential level. Due to the rigid and uncontrollable aspect of the residential demand, the residential sector is currently a major contributor to the volatility of the load on the power grid. In order to overcome this, DSM programs should be adopted by residential energy consumers.

A DSM program may have a variety of objectives. The most important ones are the following:

- Reducing the peak demand on the grid;
- Balancing generation and demand;
- Reducing the overall electricity consumption in the time of insufficient electricity capacity caused by high demand growth or high fuel cost.

Achieving the above objectives would result in many different benefits such as:

- Increasing the system reliability;
- Improving the efficiency of energy production and distribution;
- Mitigating electrical system emergencies;
- Reducing the number of blackouts;
- Reducing the dependency on expensive imports of fuel;
- Reducing the release of harmful emissions in the environment.

Although these positive effects enumerated above may affect more the production, generation and transmission side of the grid, end consumers would also benefit by receiving good quality electricity. However, the main reason that may drive consumers to participate in DSM programs is the opportunity of achieving significant reductions in the energy consumption cost. There are several categories of DSM programs. Some appeal to the rational behavior of energy consumers and try to educate energy consumers into reducing and modifying their energy consumption. However, the majority of DSM programs give financial incentives to energy consumers to change their energy consumption patterns. Hence, in this way the customers may get significant cost reductions for their energy consumption.

DSM methods include energy efficiency, peak load management methods and DR methods. These methods are closely related and dependent on each other. Hence, a clear distinction between them does not exist. Energy efficiency methods refer to any method for controlling, planning and scheduling of energy use that improves the efficiency of energy utilization by matching electricity supply with demand while maintaining a high quality of service. The most common methods for optimizing the energy use are the peak load management methods [37]. The main goal of load management techniques is reducing the peak loads on the power grid. This is mostly done by shifting part of the loads that are creating the peaks to periods of time with lower demand while trying also to avoid causing discomfort to the consumers. Load management methods can be broadly classified into two categories: direct load control and indirect load control methods [38]. Both types of load control techniques may use financial incentives to motivate customer participation.

Direct load control methods include techniques in which electricity consumers agree that, against a certain discount in their electricity bills, the utility companies, or grid operators may have direct control over the smart appliances located in their homes. The control is done through remote controllers installed on these devices within their HAN [39]. The utility companies may then interrupt the electricity supply to these appliances during peak demand periods. If adopted by many electricity consumers, these methods may reduce the periods of high demand and the need for investing on extra electricity production capacity to satisfy the high demand during the peak periods. This would save money for both utility companies and customers.

Indirect load control methods refer mostly to DR programs. DR programs give to the end customers, such as industrial, commercial and residential energy users, but also load aggregators, the possibility of actively participating in the operation of the smart power grid. DR provides techniques through which electricity consumers control their energy usage in response to dynamic pricing or other forms of financial incentives offered by the utility company [40]. These are called price-based DR methods. The benefits of the electricity consumers for using such programs are reflected in reductions in the electricity consumption cost, while the utility companies may have better control over the load dispatch and again avoid investing in extra electricity capacity. Some electricity pricing methods used for price-based DR methods are discussed next.

2.3.1 Electricity pricing methods

So far, electricity utility companies have had a monopoly status in providing energy in many regions. The mass-market end customers were charged with bulk costs for their electricity usage. Conventional electricity meters installed at residential or small business locations would register and accumulate the electricity usage over a certain period of time, for example during one month. These end customers are then charged with a constant price for each unit of consumed electricity. The most common electricity pricing methods used by utility companies in the traditional power grid are the following two:

Flat rates: All electricity consumed within a period of time, usually one month, is charged using same price per unit of energy.

Tiered rates: Tiered rating refers to users being charged with different prices per unit of consumed electricity, for example, depending on the season. The electricity consumed during winter would have a different price than that consumed in summer. Another way of applying tiered rating is based on different thresholds of consumption. The amount of electricity consumed up to one threshold would generally be charged at small rates, while the amount of consumed electricity exceeding the threshold would be charged at a high rate.

The smart power grid enables time-varying pricing [41]. Through an AMI and smart meters installed at residential locations, the utility companies are able to record the electricity usage of end users for short periods of time, for example on hourly basis, but sometimes even shorter time-steps. Then, a pricing method that reflects the real-time demand and market situation could be adopted. A few common types of time-varying pricing mechanisms are listed below.

Time of use pricing (ToUP): Different prices are applied during different periods of a day. The day is divided in several periods according to the demand of electricity in the system. As an example, electricity prices in a day may be divided according to a three-period time program: off-peak hours, when the demand is low, mid-peak hours, when the demand is moderate, and peak hours, when the demand is the highest within a day. This pricing mechanism can also be applied through simple day and night periods.

Real-time pricing (RTP): Is a pricing method in which the rates are applied on very short time intervals, for example, on hourly basis. In this case the prices vary the most within one day and reflect the real-time demand of electricity in the power system.

Critical peak pricing: High electricity prices may be applied by utility companies during some periods, for example over few hours, when a critical event may occur in the power system, or when very high wholesale market prices are expected. Such peak pricing periods may be caused by extreme weather conditions requiring lot of heating or air conditioning, or during a holiday such as Christmas, for example. In some cases the event may be anticipated and the time and duration of the price increase may be known in advance.

Variable peak pricing: Is a hybrid pricing scheme between time of use and real-time pricing. On-peak and off-peak periods may be established. The on-peak rates may follow, for example, the real-time pricing scheme in which the prices depend on the real-time market and grid conditions. The off-peak periods may have flat rates.

The time-varying pricing mechanisms described above may be classified as dynamic pricing methods. These techniques may be exploited by utility companies to give incentives for adoption of DR programs by mass energy consumers. However, in many cases ToUP is also considered in DR programs.

2.3.2 DR programs

As already mentioned earlier in this chapter, DR programs can be used by electric grid operators as a tool for balancing supply and demand. These programs enable efficient usage of the available electricity capacity and make the grid operation more sustainable and reliable. Important changes in the operation of the power network will occur together with the deployment of DR programs. One remarkable change is that energy consumers will have an active participation in the activity of the electric grid. However, this would not take place in a random manner, but controlled by the grid operators. In price-based DR programs, the utility companies can apply time-varying electricity prices which will be announced in advance to the consumers. Hence, the energy consumers will be given the possibility to modify their typical energy consumption patterns in response to time-varying prices [42]. Other types of financial incentives can also be offered by the utility companies and grid operators in order to persuade energy consumers to adopt DR programs. Such new pricing mechanisms aim at lowering electricity usage at time of high demand or when the reliability of the power system is jeopardized. As a consequence, the adoption of DR programs may have various beneficial outcomes for the end customers, utility companies and grid operators. The benefits for the consumers stand in lower energy prices and improved reliability of energy supply. The utility companies and grid operators could benefit, for example, by achievement of a flat demand profile. DR programs can provide a more efficient use of the energy generation capacity of power plants. DR programs can also partly facilitate the integration of renewable energy generation. At the transmission side, these programs may reduce the need for heavy investments in the transmission infrastructure. By expanding their services through innovative programs, the utility companies may increase customer satisfaction which may help in maintaining customers' loyalty. DR programs can be adopted and implemented by different energy consuming, or energy management entities in the power system including aggregators, retailers and end consumers. When participating in DR programs, end customers can change their electricity usage patterns using different approaches. Few examples are given below.

Load curtailment: Residential end customers may reduce their electricity usage by reducing the run time of some appliances such air conditioners and electric heaters, or by lowering the lighting levels at their homes [43]. This may, however, cause some discomfort for the customers.

Electricity consumption shifting: The electricity usage can be optimized and shifted from periods of high demand, and hence, high electricity prices to periods of low demand and electricity prices [44]. For example, the run time of smart appliances with interruptible and delayable loads may be delayed to periods of low electricity price rates.

Installation of ESSs: In order to avoid the discomfort of changing their regular consumption patterns or modifying the time of use of certain appliances, the energy consumers may also install ESSs [45]. Electricity may be drawn from the power grid at times when price is low, stored and then used at later times, without worrying about changing the actual consumption patterns.

Installation of DES: In order to reduce their dependence on electricity provided by the power grid, energy consumers may install own RESs [46], or dispatchable energy sources.

Energy sharing, exchange and trading: Installation of RESs and ESSs give the end consumers the benefit of being both energy producers and consumers, i.e. prosumers. Enabling energy exchange among prosumers opens the possibility for new appealing demand response solutions through energy interactions. Energy consumers and prosumers may interact by exchanging and sharing, in an optimized manner, the renewable energy production or storage spaces in order to obtain an improved utilization of electrical energy. Another form of interaction could be enabled through energy trading. Prosumers may form local markets in which they trade their renewable energy production or even their storage space with other prosumers, or with simple energy consumers against a price, with the aim of obtaining financial benefits. Energy sharing or trading may take place in a competitive manner, or in a collaborative manner. Energy interaction may reduce and balance the demand on the grid, bring higher electricity cost reductions for individuals or groups and improve the renewable energy integration as compared to DR programs individually applied by single prosumers. DR programs enabling energy sharing, exchange and trading may be applied at a microgrid level, over multiple microgrids, or over communities of households.

Successful deployment of DSM and DR programs relies on the development of robust and secure transmission, distribution and communications infrastructures that support smooth and reliable two-way power flow and two-way information flow within the power network. It also relies on the development of advanced control and market models for optimized operation of the power grid. Such highly efficient and reliable models could be developed if accurate knowledge of daily, hourly, or even minute wise consumption of electricity, electricity prices, weather information, renewable electricity production, etc., would be available in advance. In Chapters 3 and 4 of this thesis various DSM methods are proposed. In particular, the problem of smart charging of EVs with the goal of minimizing the charging cost for the owner is addressed in Chapter 3. Furthermore, methods for improving efficiency of energy consumption, minimizing costs and balancing the demand within smart grid communities of households through collaborative interactions are provided in Chapter 4.

3. Optimization of electric vehicle charging using DSM

Transportation sector is a major contributor to the increased amount of green house gas emissions in the atmosphere. A large proportion of the energy used in the transportation sector is produced using fossil fuel. In the fight against pollution, considerable efforts are put into the development of EVs and plug-in hybrid electric vehicles (PHEV). The EV industry has experienced significant progresses in recent years. Innovative research and development technologies have allowed not only for larger and larger battery pack sizes, which implicitly allow for longer driving ranges, but also for rapid cost declines. In some countries, also regulations on fossil fuel economy and other local measures such as limiting access of conventional vehicles to certain urban regions are stimulating the adoption of EVs. EVs and PHEVs provide and environmentally friendly and cost effective alternative to the conventional vehicles with internal combustion engines powered by fossil fuel. The EVs are powered entirely by electrical energy and incorporate rechargeable batteries. In the case of PHEVs, the driving power is split between an internal combustion engine and an electric engine. The EVs' and PHEVs' batteries can be charged externally with energy from the power grid, or even with green energy generated by RESs. The amount of carbon emissions produced by the EVs is marginal in comparison to conventional vehicles.

A massive adoption of EVs may bring a variety of benefits and new business opportunities in the power sector. However, integrating these vehicles into the power grid may also be challenging. Uncontrolled EV charging can significantly increase the load on the power system. This may further lead to faulty system operation and may jeopardize the reliability of the power grid [30]. Uncontrolled charging can also significantly increase the electricity cost for the EVs' owners. Controlled charging instead, could represent a tool for performing DSM and yield benefits to system operators and for the EVs' owners as well. EVs can be used as flexible loads for balancing the load on the grid. Some EVs may also support V2G technology, i.e. they may allow bidirectional charging and discharging of their batteries. In this case, the EVs could be used as mobile storage systems to store energy and also to provide ancillary services to the power grid. Through controlled charging enabled by DSM programs the electricity cost may also be significantly reduced for the owners.

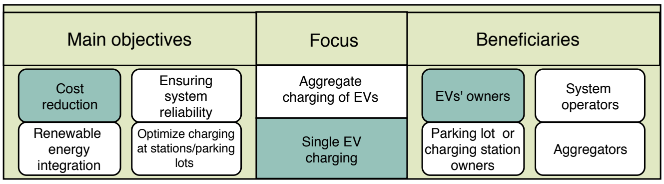

Figure 3.1. A broad classification of DSM techniques for optimizing EVs' charging.

In order to mitigate the negative effects of EVs' integration, a multitude of DSM methods, algorithms and techniques have been developed in recent years. The methods may have different objectives such as:

- Reducing the electricity consumption costs and other costs related to EVs' charging;
- Ensuring reliability of the power system: providing ancillary services and power regulation services;
- Balancing the load on the power grid;
- Improving integration of renewable energy;
- Optimizing charging at parking lots and charging stations: minimizing the charging time, maximizing the number of charged EVs, etc.;
- Satisfying the charging needs of the EV owners.

In this chapter, a short overview on state-of-the-art DSM methods that employ minimizing the cost of EVs' charging is provided. The methods optimize the EVs' charging, but also the discharging, when V2G technology is used. Some policies focus only on minimizing the charging costs. However, besides cost reduction, many of the proposed methods aim at satisfying different constraints or achieve some other goals, too.

A broad classification of the methods existing in the literature for optimizing EVs' charging is shown in Figure 3.1. As already mentioned, one criterion for classification is the objective of the methods. The classification also divides the approaches into:

- DSM methods focused on optimizing the aggregate battery charging of a large number of vehicles;
- DSM methods dedicated for optimizing the charging of a single EV.

The methods may be designed to bring benefits for different entities such as:

- EVs' owners;
- Grid operators and utility companies;

- System aggregators;
- Parking lot or charging stations owners.

Besides the criteria for classification shown in Figure 3.1, there are other criteria and aspects which may influence the outcome of the proposed methods. These are:

- The electricity pricing scheme applied in the proposed methods;
- Electricity prices, demands, renewable energy production: known (deterministic), or known with uncertainty (stochastic);
- The period of operation: real-time, or finite time horizon ahead, such as day-ahead;
- Implementation mode: centralized, or distributed.

In the smart grid, the EVs' owners may reduce their cost or receive financial incentives by adopting price-based DR methods. Hence, the pricing mechanism employed in the proposed methods is very relevant. Price-based DR methods may employ different electricity pricing mechanisms: conventional dynamic pricing schemes such as RTP and ToUP, or pricing schemes individually customized by utility companies which depend, for example, on some events occurring in the power system. The EV charging may take place in real-time, or it can be scheduled in advance over a finite time period ahead. The optimization techniques may assume that the electricity prices and charging demands are fully known, or known with some uncertainty for the considered optimization time frame. If the knowledge of data such as electricity prices, or EVs' charging load is random then the data is considered stochastic.

An overview on relevant DSM methods employed for optimization of EVs' charging is presented further in this chapter. The methods are classified according to criteria given in Figure 3.1. However, the focus is on methods that employ cost reduction, or maximizing financial benefits. The overview is not complete and only the newest and most relevant problems and techniques have been considered. A survey on older methods and approaches for optimization of EVs' charging may be found in [47].

3.1 DSM methods for optimizing aggregate charging of EVs

A significant body of literature that addresses the problem of EV charging is focused on methods for controlling charging of large numbers of vehicles. The charging may occur at charging stations and parking lots, or at EV owners' home sites. These methods have the goal of maximizing financial benefits, or reducing the costs for the system operators, EV aggregators, charging stations or parking lot owners, but also for the EVs' owners. Many of the methods may also employ the EVs for providing ancillary services to the power grid and hence contribute to improving the reliability of the system, or use EVs in conjunction with RESs for improving integration of renewable energy into the power system. Since renewable energy is a free source of energy, charging the EVs' batteries with renewable energy can also reduce the cost of charging. Large penetration of EVs into the power system can also open various business opportunities such as the appearance of charging stations and parking lots that provide charging facilities. Moreover, the EVs could also be active components of energy markets. A survey on methods for aggregate EV charging is provided next.

3.1.1 Methods for ensuring power system reliability

A large penetration of EVs is expected to significantly increase the load on the grid, while random charging could also endanger the reliability of the power system through inducing frequency fluctuations, power network bus congestions, or voltage drops. By regulating their charging, EVs can however contribute to mitigating these power grid faults and actually help the power system to maintain its stability. Control centers could monitor the status of the power grid and send control signals towards the distribution level where the charging of EVs would be scheduled according to the received information [48]. EV service providers may make decisions upon pricing and electricity procurement in order to achieve multiple objectives such as securing their own profit, maximize satisfaction of customers and minimize the negative impact of EVs' penetration in the power system [49].

A method for optimizing the charging of EVs at residential locations is proposed in [50]. The goal is to shape the load on the grid to avoid distribution system overloading and to reduce the EVs owners' charging cost. The method simultaneously performs valley filling and minimization of the the charging cost. A constrained, double objective, quadratic optimization (QO) problem is formulated for coordinating the charging of the EVs. The first term of the objective function defines a valley filling problem that minimizes the gap between instantaneous system load and the average load of the households in the system. The second term minimizes the cost of electricity consumption over a fixed charging period. Two methods for solving the formulated problem are proposed. One method employs a static day-ahead scheduling of the charging. The second method employs a dynamic sliding window optimization. Standard LP and QO methods are employed to find the solutions to the proposed methods.

The ancillary services provided by the EVs can have even greater impact in maintaining the reliability of the grid when the vehicles are equipped with V2G technology. In order to avoid grid frequency fluctuations, EV aggregators could coordinate the charging and discharging of these vehicles directly at customer's residences or at charging stations [51]. When the EVs themselves are equipped with sensors that monitor the frequency status of the grid, frequency control schemes may be employed to control the individual charging of each EV, in a distributed fashion [52].

3.1.2 Methods for improving renewable energy integration

The problem of integrating renewable energy into the power grid is also a highly challenging problem. The benefits of green energy are indisputable, however, just as in the case of EVs, the penetration of renewable resources into the power system may jeopardize the stability of the grid. A large imbalance between generation and demand, frequency fluctuations, and other system faults may be induced. In this situation the EVs may again play an important role. The intermittent aspect of the RESs' output may be balanced by coordinating and synchronizing the charging of EVs with the renewable energy production [53, 54]. V2G technology may be used to provide ancillary services in a system with high penetration of renewable energy and overcome frequency fluctuations caused by intermittent feeding of renewable energy into the grid. For example, the electric grid frequency deviation may be used as a dynamic control signal for dictating the charging and discharging of EVs equipped with V2G technology [55]. EVs may be charged with renewable energy in order to reduce emissions of carbon into the atmosphere. Associating EVs with RESs may result also in electricity charging cost reduction as compared to fully charging the EVs with electricity from the main power grid. In [56], the problem of installing RESs and ESSs at parking lots offering EV charging services is studied. The goal of the problem is to optimize the charging of the EVs using the produced renewable energy such that the profits of the parking lots owners are maximized.

Optimization of EVs' charging may aim at maximizing the profit of buildings owning RESs. In [57], buildings own RESs and offer charging services for EVs. The EVs' owners receive financial incentives for buying green electricity from these buildings and not from the utility company. The renewable energy generation is considered to be free of cost, while the electricity purchased from the power grid is charged at ToUP tariffs. The EV charging problem is modeled as a stochastic finite-stage Markov decision process (MDP) with unknown transition probabilities. At each hourly time-step within a day, the system state of the MDP problem is described by the wind power generation amount of the building, the required charging load of the EVs, the remaining parking time or trip duration of the EVs and the EVs' location. The state variables are defined individually for each EV and building. The proposed method derives a charging policy according to a binary variable that indicates at every time-step if an EV will be selected for charge or not. The objective function of the optimization problem is modeled such that the expected profit of each building is maximized. The method also takes into account the random wind generation and the daily random travelling requirements of the EVs' owners. A method called distributed simulation-based policy improvement method is proposed to solve the stochastic MDP problem in a decentralized fashion.

Other methods that tackle the problem of using renewable energy for charging

EVs are proposed also in [58] and [59]. In [58], the employed model assumes a certain variance in the renewable energy generation and in the EVs' charging loads. A stochastic EV charging problem is formulated using a queuing model with the goal to efficiently integrate the renewable energy and reduce the cost of charging the EVs. A Lyapunov optimization-based method is used to solve for the optimal charging schedule. A method for integration of residential EVs in a power system with intermittent renewable energy is proposed in [59]. The EVs may act as storage systems and sell back electricity to the power grid. An optimization problem for minimizing the total cost of the customers is proposed and the solution is obtained through a distributed algorithm using the alternating direction method of multipliers (ADMM).

3.1.3 Methods for optimizing charging at stations and parking lots

Optimizing and scheduling the charging of PHEVs and EVs at charging stations equipped with RESs and ESSs is investigated in [60, 61]. A scheduling policy for charging PHEVs' batteries is modeled as a MDP in [60]. The goal is to minimize the charging cost under RTP, but also to allow the charging stations to serve as many vehicles as possible. Here, a battery replacement strategy is assumed, i.e. the PHEVs are equipped with standardized batteries which can be replaced at the charging station in order to reduce the waiting time of the customers. The MDP charging model for a single charging station is described using the following state variables: price level, number of batteries waiting for charging and number of active chargers. A charging policy must be found for a finite discretized period ahead. Two actions may be performed for each battery, namely charge the battery, or defer the charging. The state transitions at each time-step are dictated by a pre-defined transition probability matrix. A schedule for charging the batteries is found through a value iteration algorithm, such that the cost of charging and the number of batteries deferred from charging is minimized. Moreover, in [60] it is also considered that the public utility purchases power in a day-ahead market. Based on the MDP charging model for a single charging station, an algorithm is proposed to determine the distribution of power for multiple charging stations. The method takes into account the uncertainty of power demand and RESs generation. A multi-stage stochastic programming (SP) method is employed to solve the power supply problem and minimize the cost of the public utility.

In [61], a problem based on an infinite horizon MDP with unknown transition probabilities is formulated to determine the number of EVs to be served per-time-slot at a charging station equipped with RESs and an ESS. The main objective is to minimize the average waiting time of the EVs. However, reducing the long term cost of charging is also considered in the problem. The method assumes random renewable energy generation, random charging demands, time-varying electricity prices for electricity acquired from the power grid and uncertain arrival times of the EVs at the charging station. At any time-step, the MDP state of the system is described by the following variables: the length of the queue formed by the EVs' charging demands, the number of new charging demands, the renewable energy level in the storage, the electricity price. The optimal charging policy determines the number of charging demands to be served and the amount of renewable energy allocated from storage such that the length of the EVs' charging queue is minimized. A stochastic optimization problem is formulated to find the optimal charging policy. The problem is first written as a constrained MDP problem. Then, the problem is converted into an unconstrained MDP problem and solved by applying Lagrangian relaxation.

A real-time method for coordinating the EV charging at a parking station is proposed also in [62]. The arrival time of the EVs is again not known in advance. Differently from the method in [61], the goal here is to maximize the number of EVs being charged simultaneously while minimizing the cost of charging under dynamic pricing. An LP-based binary optimization method is proposed for solving the formulated problem. Other cost optimal methods for charging EVs at charging stations and parking lots assume stochastic arrival and also departure times of the EVs in [63], or assume random charging prices in [64].

In [65], a global optimization problem is proposed for scheduling the charging of a large number of EVs at distributed charging points. Uncertain arrival time of the EVs is again assumed. Some EVs in the system have V2G technology and may sell back stored energy to the grid. Electricity prices are modeled as a linear function of the system load. The objective function is formulated to minimize the total charging and discharging cost of the EVs in the system. A method for charging small groups of EVs in a distributed fashion is also proposed. The proposed optimization problems are convex and can solved through standard convex programming (CVXP) methods [66, 67].

Smart charging strategies can take advantage of RTP schemes in order to maximize the welfare of the whole system, electricity suppliers on one side and energy consumers on the other side [68]. However, in a system with multiple electricity suppliers, mechanisms for price regulation [68] may represent a key factor for maintaining a balance between supply and demand and maximizing the overall welfare of the system. Price regulation strategies may also be applied to control the V2G discharging activities [69]. The financial incentives offered for the V2G discharging services are controlled such that these services do not become an unfair competition for energy retailers.

3.1.4 Methods that model energy market strategies

DSM encourages the development of different strategies for energy markets. A market framework for direct load control is formulated in [70]. A pricing scheme is proposed to give incentives to the EV owners to allow the grid operator to control and postpone the charging of their EVs beyond their required charging deadline. Aggregators may also apply indirect load control [71]. For this, they need to take optimal decisions in determining the retail prices. The EVs owners react to the offered electricity prices and charge their vehicles in such a way that their cost savings are maximized.

A system aggregator buys electricity at RTP rates and sells it to EVs' owners by adding a markup price in [72]. A method that maximizes the revenues of the system aggregator is formulated. The method also considers satisfying customers' demands and lowering their costs. The revenue of the aggregator is defined by the difference between the retail price and the market wholesale price. In order to balance the load of the charged vehicles, the aggregators may adjust the charging amounts of the EVs or may temporarily adjust the charging prices. Two charging schemes are proposed. The first scheme is a static LP-based scheme that assumes that the EV charging task is known before the EVs are connected to the grid. The second is a dynamic, heuristic scheme in which the the charging task is assumed to be unknown beforehand. The charging tasks are individually planned for each EV when connected to the grid.

In the attempt to maximize their profits and minimize EVs' charging costs, the EV aggregators also have the possibility of participating in day-ahead electricity markets. In these markets, the aggregators are bidding for buying the amounts of energy to be consumed at each time-step of next day. Their goal is to buy energy at lowest possible price. The challenge for the aggregator is then to match the amounts of procured energy with the actual energy dispatch during the following day. An optimized distributed coordination scheme is proposed in [73] for an EV aggregator which participates in the day-ahead market. The goal of the aggregator is to coordinate the charging and discharging of a fleet of EVs which also offers V2G regulation services to the power grid.

An EV aggregator participates in a day-ahead market also in [74]. Based on forecasted day-ahead electricity prices and statistics regarding the driving activities of the EVs' owners, the aggregator decides the amount of energy to be purchased in each time-slot of the following day. A risk-aware day-ahead optimization method for charging of EVs in a residential area is proposed. The method schedules the EV charging to minimize the charging cost as well as the risk of load mismatch between the scheduled load and the actual driving activities. To model the random driving of the EVs, the charging loads are assumed to be discrete random variables. The day-ahead EV charging problem is formulated as a two-stage stochastic linear program (SLP) and it is solved by applying the L-shaped method [75] and importance sampling. Furthermore, a distributed real-time algorithm is proposed with the same goal of minimizing the charging cost and load mismatch. In the distributed method, each EV may optimize its own charging strategy using shadow prices computed and received from the aggregator.

A problem for coordinating the charging of a fleet of EVs by an aggregator participating in a day-ahead market is again formulated in [76]. A finite-time MDP is used to model the charging dynamics of each EV during a day. The day is discretized in time-slots. The arrival time of the EVs at the charging unit is not known in advance. Each EV stays connected to the charger for a period of time known only at arrival. The MDP states are defined by the amounts of energy already stored in each individual EV battery. The MDP actions choose the amounts of energy to be charged in each EV in each time-step. A batch RL approach is proposed to learn the daily collective charging behavior of the fleet of EVs. Based on this, a fitted Q-iteration algorithm is used to select discrete energy amounts be purchased in the day-ahead market. The goal is to minimize the expected cost of the purchase. The purchase is done according to the day-ahead prices which are assumed to be known. A heuristic online control algorithm is proposed to control the energy dispatch such that the amount of energy purchased by the aggregator in the day-ahead market is met in every time-step. This heuristic algorithm calculates the charging priority and the charging power of each EV.

Competitive market frameworks may be modeled for consumers who compete for allocation of cheap energy to charge their EVs [77]. Market strategies may also be developed for energy retailers and EV owners using hierarchical game theoretic frameworks [78]. In such frameworks, the retailers set the electricity prices with the goal of maximizing their profits. Then, the home consumers adjust their EVs charging schedule in response to the price announced by the retailers. Such approach is proposed in [79] to control the charging of a large number of EVs at a charging station. The EVs are considered flexible loads. The charging demands of the EVs are assumed known. A first proposed strategy employs a local controller to schedule the charging of EVs on behalf of their owners. A quadratic cost function is employed to define the aggregate cost of charging. Hence, the problem is modeled as a mixed integer quadratic programming (MIQP) that minimizes the total cost of charging during the scheduling horizon. Furthermore, a second control strategy is proposed for decentralized charging, such that each EV owner controls the charging individually. The decentralized problem is modeled as a leader-follower non-cooperative Stackelberg game in which the system controller decides the electricity prices and the total amount of energy capacity provided to the EVs. The EVs' owners choose their charging strategy in response to these values.

The charging strategies discussed so far include day-ahead, or real-time charging strategies. Typically these strategies have hourly or 15 minutes decision making time-steps. However, in a real-time communications environment this long time-slots may not be discretized densely enough to cope with the real-time market operations. More realistic operation schemes must be constructed for coordinating EV charging in real-time [80]. For an efficient integration of the EVs into to the power network the EV charging strategies must also be scalable to large number of vehicles. A scalable and computationally efficient EV charging protocol is proposed in [81]. The protocol coordinates the EV charging in a distributed fashion in order to obtain electricity cost reductions and ensure the reliability of the power network trough applying operational constrains on the distribution power network.

Table 3.1 presents a comparison of the features involved in the reviewed DSM

Table 3.1. A comparison regarding various features involved in DSM methods for optimizing aggregate charging of multiple EVs. The following notations are used: no.- number, dyn.- dynamic, optimiz.- optimization, time-var.- time-varying, DSBPI- distributed simulation-based policy improvement method, QuM- queuing model, SKB- Stackelberg, C- centralized, D- distributed. The column *Data* refers to knowledge of electricity prices, EV loads and driving patterns.

Method	*Beneficiary*	*Objective*	*Time horizon*	*Pricing method*	*Data*	*Solution*	*Implementation*	*V2G*
[50]	system operator, EV owners	load balancing, min cost	day-ahead, rolling horizon	fixed, ToUP	known	QO, LP	C	×
[57]	building aggregators	min cost	day-ahead	ToUP	stochastic EV loads	MDP, DSBPI	D	×
[58]	aggregator	min cost, renewable integration	real-time	RTP	stochastic EV loads	QuM, Lyapunov optimiz.	C	×
[59]	EV owners	min cost	day-ahead	base+ time-var.	known	ADMM	D	✓
[60]	parking operator	min cost, max no. EVs	day-ahead	fixed levels	stochastic demand	MDP, SP	C	✓
[61]	parking operator, EV owners	min wait time, min cost	real-time	time-var.	stochastic EV loads, arrival	MDP, Lagrange relaxation	C	×
[62]	parking operator, EV owners	min cost, max no. EVs	real-time	RTP	known	LP, convex relaxation	C	×
[65]	EV owners	min cost	day-ahead	fixed	known	CVXP	C	✓
[72]	aggregator, EV owners	min cost	day-ahead	RTP+ retail	stochastic EV loads, arrival	CVXP	C	×
[74]	aggregator, EV owners	min cost, min load mismatch	day-ahead, real-time	RTP	stochastic EV loads	SLP, L-shaped method	C, D	×
[76]	aggregator	min cost, min load mismatch	day-ahead, real-time	RTP	known	Heuristic algorithm, Fitted Q	C	×
[79]	station operator, EV owners	min cost	day-ahead, real-time	quadratic function	known	MIQP, SKB	C, D	×

methods for optimizing the aggregate charging of EVs. These methods may have different complex objectives. All methods however, have as one objective the reduction of the EVs' charging costs. The methods have individual features, specific to the approached problem. For example, some methods imply real-time operation. Other methods imply day-ahead scheduling. Some methods assume known electricity prices, EV charging loads and driving patterns, while some other methods assume stochastic EV charging loads and driving patterns. Except for [59] that optimizes the EVs' charging from the EV owners' perspective only, the remaining methods involve also the perspective of the system operator or aggregator when optimizing the charging. It can be observed that besides minimization of cost, other objectives are also included in the problem formulation such as: reducing the waiting time for charging, maximizing the number of vehicles charged simultaneously, minimizing the mismatch between the load scheduled in a day ahead market and actual load dispatch. Due to the lack of standardization, a clear and fair comparison of the performances of these methods is difficult to be made.

3.2 DSM methods for optimizing the charging of an individual EV

Coordinated charging over large numbe of EVs distributed across the power network could be quite a challenging task. DSM methods for optimizing the charging of individual EVs may have similar beneficial effects over the power network.

A dynamic programming (DP) technique is proposed in [82] to determine a day-ahead charging policy for minimizing the charging cost of a PHEV which provides regulatory services to the grid. The policy determines the amount of energy to be purchased from the power grid and charged into the PHEV's battery while taking into account the power regulation requirements. The proposed method needs to ensure full charge of the battery before the next day's trip. Day-ahead spot market pricing and the power required for a driving cycle are considered to be known in advance. The proposed method is modeled as a dynamic program and is solved using standard DP techniques. The method provides a daily cost reduction from 0.43$ to 0.2$, i.e. a 46% reduction over a charging strategy in which the electricity is charged at flat price.

Similarly to the method above, a grid-to-vehicle method for optimizing home charging of an EV is proposed in [83]. The EV provides ancillary services to the power grid. An hourly-based decision making policy is derived with the goal of minimizing the expected cost over the charging horizon. Fulfilling a regulation service commitment to the power grid is also required. The decision making policy is derived by modeling the charging problem as an MDP over a fixed horizon determined by the EV's pug-in duration. At the beginning of each hour, the electricity price, the regulation service price and the regulation signal provided by the system operator are assumed to be not known. The charging controller needs to choose the charging rate and the capacity for regulation before fully knowing these values. The hourly MDP state vector is composed by the following variables: the control signal for regulation, the price of the regulation capacity and the electricity price. The optimal charging policy minimizes the expected charging cost and charges the EV's battery as much as possible before the disconnection from the charger, while also satisfying the regulation service commitment. To cope with the uncertainty of the electricity prices and regulation signal, a backwards recursion-based stochastic dynamic programming (SDP) is proposed to solve the charging problem over a discrete set of possible states. Multiple charging trials are simulated. The reported results show that the proposed SDP method reduces the mean charging cost by 22% in comparison to a model predictive control (MPC) policy.

Another decision making algorithm for optimizing the home charging of an EV is proposed in [84]. The proposed algorithm chooses the amount of energy to be charged in the EV's battery with the purpose of minimizing the charging cost and satisfying the driving needs of the owner. The problem assumes that the daily driving patterns of the EV's owner are stochastic. An inhomogeneous Markov model is employed to characterize the stochastic driving habits of the owner within a day. The time horizon is discretized in time-steps of one minute. The state of the MDP model describes the use of the vehicle in every time-step as driving or not driving. The transition probabilities of the MDP model are determined by fitting data resulted from previous driving experiences to the model. An optimal EV charging problem is then formulated as an SDP problem in which minute wise charging decisions are taken over a 48-hours time horizon. The electricity prices over 48 hours are assumed known. The formulated problem maximizes the revenue at the end of the optimization horizon. This revenue is defined by the negative cost of charging the vehicle. A penalty is incurred when the driving needs of the owner are not respected. The optimal charging solution is obtained using a backward induction-based SDP method. Simulations are performed using true pricing data for 65 days. Depending on the incurred penalty for not respecting the charging needs, the proposed method reduces the average daily cost by 12-24% in comparison to a heuristic method called low price charging method. In the low price charging method the EV is charged either when the price is in the lowest 20%-quantile of the price distribution within 24-hours, or when the state-of-charge of the battery goes below 50%.

Smart home EV charging for households owning photovoltaic renewable generation systems is investigated in [85]. A two stage algorithm for scheduling the EV charging is proposed. A time series model first predicts the generation output of the photovoltaic system and the EV's electricity consumption based on historical data. Using the predicted data and known electricity prices an optimization problem is proposed to schedule the EV charging. The schedule implies choosing the optimal energy amount per-time-slot to be consumed under ToUP such that the cost of charging is minimized over a fixed period ahead. The optimization problem is casted as a mixed integer linear program (MILP). The proposed method achieves cost savings of 6% in comparison to the case when the EV is charged immediately after being parked. Cost savings of 15.2% are achieved in comparison to the case when the EV is charged immediately after lunchtime.

Controlled charging of EVs found at different locations within the distribution level of the grid can be considered for balancing the load on the grid too [86]. Different perspectives on PHEV charging are considered in [87] and [88]. In [87], an online energy management framework has been developed for controlling the power of a PHEV with the purpose of minimizing the total fuel consumption. A method based on an evolutionary algorithm is proposed to predict the power demand of the vehicle at each time-step. The method optimizes the control of the power split between the internal combustion engine and the electric engine. A Q-learning-based RL method is employed in [88] to find an optimal energy control scheme for a hybrid electric tracked vehicle (HETV) while driving. The control problem proposed here chooses the split of power between the battery pack and the engine generator set which represent the power sources of a HETV. The objective is to minimize the real-time fuel consumption under different driving patterns.

3.2.1 Optimizing the home charging of an EV using forecasted electricity prices

The contribution of this thesis on smart charging methods for scheduling the charging of an EV have the goal of reducing the long term cost of charging an EV at home and are presented in Publications I, II and III. The proposed methods fall in the category of price-based DR methods. The formulated problems are modeled as an infinite horizon MDP with unknown transition probabilities. Plug-in and plug-out times of the EV as well as the day-ahead prices of electricity are assumed to be known. These electricity prices follow a RTP scheme. An estimate of the daily consumption of the vehicle is also considered known. However, in a real scenario the driver will not travel a fixed distance on daily basis. Therefore, in order to make the charging more robust to fluctuations in true consumption, an additional uniform random variation between 0 and ± 20 % of the estimated consumption is added to this consumption value. The daily consumption, including this additional random component, is denoted by ϵ_d. The related state-of-the-art methods for optimizing EV charging optimize the EV charging either by scheduling the charging based on hourly time-steps, or the scheduling time-step is discretized even further. The MDP models in Publications I, II and III are defined differently, based on discrete daily time-steps: $d = 1\ldots$. The proposed methods explore the day-to-day fluctuations of electricity prices and make daily charging decisions to reduce the long term cost of charging for the EV owner. One day is discretized in time slots $t = 1,\ldots,T$. The methods assume known day-ahead electricity prices, $\boldsymbol{\xi}_d = [\xi_d(t), t = 1,\ldots,T]$, while electricity prices for the second day ahead, $\boldsymbol{\xi}_{d+1} = [\xi_{d+1}(t), t = 1,\ldots,T]$, are predicted using a BNN-based method. The proposed methods make use of historical electricity prices and explore possible past charging experiences in order to learn an optimized charging policy that reduces the long term cost of charging for the EV owner. The best charging policy is obtained by optimizing for the infinite-horizon expected discounted reward:

$$J(\mathbf{x}_d) = \mathbb{E}\left\{\sum_{d=1}^{\infty} \gamma^{d-1} r(\mathbf{x}_d, e_d)|\mathbf{x}_1\right\}, \tag{3.1}$$

where γ is the discount factor, $0 \le \gamma \le 1$, and $r(\mathbf{x}_d, e_d)$ is the immediate reward for taking action e_d when the system is in state $\mathbf{x}_d$. $\mathbf{x}_1$ is the initial state of the system when the optimization begins.

It is difficult to analytically determine the optimal charging policy since electricity prices are not know for long term period in advance. In order to determine an optimized charging policy, the state-action-value function, $Q(\mathbf{x}_d, e_d)$, or Q-function, is found by learning state-action pairs that maximize the expected reward, or minimize and expected penalty. These are learned by iteratively updating the Q-function through exploring possible charging situations using available historical data and employing a RL technique. The best action for each new, unseen state, $\mathbf{x}_{\text{new}}$, is the one that minimizes, or maximizes the Q-function value for that particular state:

$$e_{\text{new}} = \min_{e_d}/\max_{e_d} Q(\mathbf{x}_{\text{new}}, e_d), \tag{3.2}$$

In Publication I, the battery capacity is discretized into equally sized levels. The states of the MDP problem are composed of three discrete variables: $\mathbf{x}_d = [\omega_d, b_d^{\text{init}}, \Delta_d]$, where ω_d is the index corresponding to the day of the week and b_d^{init} is a discrete variable associated with a battery level showing the state-of-charge of the EV battery at the beginning of the day. Δ_d is a variable indicating the difference between the minimum hourly costs of charging during day d and $d+1$, respectively, while the EV is parked at home. This value is also discretized into several levels of costs. The action e_d is defined by an operation that chooses the number of battery levels to be charged within day d. Hence, the action space is discrete, too. In Publication I a penalty term $r(\mathbf{x}_d, e_d)$ is defined instead of a reward. Hence, in this problem, the optimal charging policy is the one that minimizes the expected penalty value in the state-action-value function, $Q(\mathbf{x}_d, e_d)$. Fixed penalty values $r(\mathbf{x}_d, e_d)$ are heuristically defined for each possible action given the value of the discrete variable Δ_d and the value of the consumption ϵ_d. These values penalize charging high amounts of energy in day d if the price of electricity during the current day d is higher than the price in the following day $d+1$. The proposed method makes sure that the driving constraints of the EV owner are satisfied. In each state, an action is chosen using an ε-greedy method. Then, the state-action-value function is found using the offline SARSA RL algorithm with eligibility traces. The employed algorithm is described in detail in Publication I. The optimum charging action for new states is the one that minimizes state-action-value function (3.2). The chosen amount of energy is optimally charged at minimum price during the hours when the EV is parked at home. The proposed charging method reduces the cost of charging by 7% in comparison to a smart strategy that optimally charges daily at minimum price. It also reduces costs by 40% in comparison to the conventional, non-optimized charging strategy.

In Publications II and III, the MDP actions still represent discrete values indicating the amount of energy to be charged in the battery, however, the state space of the MDP includes continuous variables. A fitted Q-iteration batch RL algorithm is employed to solve the EV charging problem.

In Publication II, the states of the MDP are composed of same three variables as in Publication I, $\mathbf{x}_d = [\omega_d, b_d^{\text{init}}, \Delta_d]$. The difference is that the variable showing the initial state-of-charge of the EV battery, b_d^{init}, and the variable showing the difference between the minimum hourly charging costs in two consecutive days, defined as:

$$\Delta_d = \min_{t\in\mathbf{h_d}} \boldsymbol{\xi}_d(t) c_{\text{rate}} - \min_{t\in\mathbf{h}_{d+1}} \boldsymbol{\xi}_{d+1}(t) c_{\text{rate}}, \tag{3.3}$$

are continuous variables. In (3.3), c_{rate} represents the hourly charging rate, $\mathbf{h}_d$ and $\mathbf{h}_{d+1}$ are sets showing the hours of days d and $d+1$ when the vehicle is connected to the charger at home, while t is the hourly time index. In this problem, the reward values, $r(\mathbf{x}_d, e_d)$, are heuristically designed based on the value of variables Δ_d and b_d^{init} and the value of the daily charging demand ϵ_d defined by the driving needs of the EV owner. These values are designed such that they reward the actions of charging high amounts of energy when the prices are low and also ensure that the battery is sufficiently charged such that the driving consumption needs are satisfied.

The state space of the MDP problem in Publication III includes a fourth continuous variable: $\xi_{d_{\min}} = \min_{t\in\mathbf{h_d}} \boldsymbol{\xi}_d(t)$, which represents the minimum hourly price of electricity during the interval of hours when the EV is parked at home. Also, Δ_d is defined as:

$$\Delta_d = O_d^{\text{cost}}(\epsilon_d) - O_{d+1}^{\text{cost}}(\epsilon_d), \tag{3.4}$$

where $O_d^{\text{cost}}(\epsilon_d)$ denotes the optimal cost for charging the amount of energy ϵ_d during day d and $O_{d+1}^{\text{cost}}(\epsilon_d)$ is the optimal cost for charging the amount of energy ϵ_d during day $d+1$. The state space of the MDP problem is: $\mathbf{x}_d = [\omega_d, b_d^{\text{init}}, \Delta_d, \xi_{d_{\min}}]$. The action space is discretized in levels of 1kWh. Again, the action e_d chooses a number of battery levels indicating the amount of energy to be charged.

In Publication III, the reward values $r(\mathbf{x}_d, e_d)$ are found using a rolling horizon LP-based optimization method. The proposed LP optimization method determines the optimal charging amount in possible charging situations simulated using a known set of historical data. This historical data contains the electricity prices over the past 182 days and the estimated charging loads ϵ_d of the EV for every day of the week. The LP optimization is applied over a time frame of 14 consecutive days, but only the optimal charging value for the first day, e_d^{opt}, is recorded. Hence, the update of the rolling horizon optimization occurs in time steps of one day. The reward corresponding to the optimal action $e_d = e_d^{\text{opt}}$ is set to be equal to the value of the optimal cost for charging the amount of energy defined by e_d^{opt} within day d, $O_d^{\text{cost}}(e_d^{\text{opt}})$. The reward for the remaining possible actions is a penalized cost value:

$$r(\mathbf{x}_d, e_d) = \begin{cases} O_d^{\text{cost}}(e_d^{\text{opt}}), & \text{if } e_d = e_d^{\text{opt}}, \\ O_d^{\text{cost}}(e_d^{\text{opt}}) + \text{Penalty}, & \text{otherwise.} \end{cases} \tag{3.5}$$

A method for predicting the electricity prices $\boldsymbol{\xi}_{d+1}$ for the second day ahead employing a Bayesian neural network (BNN) [89] is proposed and presented in Publication III. The input vector fed to the BNN consists of 9 relevant features used for the predictive Bayesian inference. These features are:

- A value {1, ...,7} indicating the index of the day of the week for which the electricity price is being predicted;
- A flag {0,1} indicating whether the day of the week is a working day or weekend;
- A value {1, ...,24} showing the corresponding hour of the day;
- The hourly local marginal electricity prices from one day before;
- The hourly local marginal electricity prices from the same day of the week before;
- The hourly system load from one day before;
- The hourly system load from the same day of the week before;
- The average hourly local marginal electricity price from the day before;
- The average hourly system load from the day before.

Price forecasting is a highly explored research topic. Important scientific progresses are made and advanced methods for accurate prediction of electricity prices are proposed [90, 91, 92]. For a detailed description of the proposed methods for price prediction and definition of reward values, please check Publications I, II and III.

In Publications II and III, for learning the Q-function, a batch of transition samples are collected by simulating possible charging scenarios and the available set of historical data. This batch of transition samples is of form:

$$\mathcal{F} = \left\{ (\mathbf{x}_d^{(l)}, e_d^{(l)}, \mathbf{x}_{d+1}^{(l)}, r(\mathbf{x}_d, e_d)^{(l)}) | l = 1, ..., |\mathcal{F}| \right\}, \tag{3.6}$$

where $|\mathcal{F}|$ is the cardinality of the set $\mathcal{F}$ and l is used to denote the index of a sample. Each sample is composed by a four touple: the state $\mathbf{x}_d^{(l)}$, an action $e_d^{(l)}$ taken in that state, the next state $\mathbf{x}_{d+1}^{(l)}$ in which the system reaches after taking the action and the corresponding reward $r(\mathbf{x}_d, e_d)^{(l)}$. In order to learn the state-action-value function $Q(\mathbf{x}_d, e_d)$ the set of transition samples $\mathcal{F}$ is divided into equally sized subsets of samples according the day of the week ω_d and action $_d$: $S_{\omega_d, e_d} = \left\{ (\mathbf{x}_d^{(l)}, e_d^{(l)}, r(\mathbf{x}_d, e_d)^{(l)}, \mathbf{x}_{d+1}^{(l)}) | l = 1, ..., m| \right\}$. Hence, each subset

S_{ω_d,e_d} represents a collection of m state transition samples in which action e_d was taken.

The state-action-value function is found using the fitted Q-iteration batch RL algorithm presented in Algorithm 1. In order to run the fitted-Q iteration algorithm for the cost of charging to be minimized, the reward values are all inversed as follows: $r(\mathbf{x}_d, e_d) = -r(\mathbf{x}_d, e_d) + \max_{r(\mathbf{x}_d,e_d)} \mathcal{F} + \min_{r(\mathbf{x}_d,e_d)} \mathcal{F}$, i.e. the new reward value is the negative value of the initial reward to which the minimum and maximum reward values from the set $\mathcal{F}$ was added.

Algorithm 1 Fitted Q-iteration algorithm with kernel approximation of the state-action-value

Input: Subsets of samples S_{ω_d,e_d}, discount factor γ

Initialize Q function: $\hat{Q}^{(1)}_{\omega_d}(\mathbf{x}^{(l)}_{d+1}, e_d) = 0; l = 1,\dots,m$

repeat at every iteration $\tau = 1,2,\dots$

for every action e_d **do**

for $l = 1,\dots,m$ **do**

$$\hat{Q}^{(\tau+1)}_{\omega_d}(\mathbf{x}^{(l)}_{d+1}, e_d) = \sum_{\mathbf{x}^{(l')}_d \in S_{\omega_d,e_d}} \kappa(\mathbf{x}^{(l')}_d, \mathbf{x}^{(l)}_{d+1})[r(\mathbf{x}_d, e_d)^{(l')} + \gamma \max_{e_d} \hat{Q}^{(\tau)}_{\omega_d}(\mathbf{x}^{(l)}_{d+1}, e_d)]$$

end for

end for

until $|\sum_{e_d} \sum_{l=1}^{m} (\hat{Q}^{(\tau+1)}_{\omega_d}(\mathbf{x}^{(l)}_{d+1}, e_d) - \hat{Q}^{(\tau)}_{\omega_d}(\mathbf{x}^{(l)}_{d+1}, e_d))| \simeq 0$

Output: $\hat{Q}_{\omega_d}(\mathbf{x}^{(l)}_{d+1}, e_d)$

In the proposed batch fitted-Q iteration algorithm, the Q-function update employs a kernel averaging regression operator to fit the Q state-action-value function to the data:

$$\kappa(\mathbf{x}_d, \mathbf{x}_{d+1}) = \frac{\phi\left(\frac{\|\mathbf{x}_d - \mathbf{x}_{d+1}\|}{\beta}\right)}{\sum_{\mathbf{x}_d \in S_{\omega_d,e_d}} \phi\left(\frac{\|\mathbf{x}_d - \mathbf{x}_{d+1}\|}{\beta}\right)}, \tag{3.7}$$

where ϕ represents the kernel function, β is a *bandwidth* parameter that controls the smoothness of the kernel function and $\|\cdot\|$ can be any suitable distance norm. In Publication III, the chosen distance norm is the L_1 *norm*, $\|\cdot\|_1$, while the kernel function is the Gaussian kernel:

$$\phi\left(\frac{\|\mathbf{x}_d - \mathbf{x}_{d+1}\|}{\beta}\right) = \frac{1}{\sqrt{2\pi}\beta} \mathrm{e}^{\frac{-\|\mathbf{x}_d - \mathbf{x}_{d+1}\|_1^2}{2\beta^2}}. \tag{3.8}$$

When the learning stage is terminated, the state-action values $\hat{Q}_{\omega_d}(\mathbf{x}_{\text{new}}, e_d)$ for every possible action e_d in new, unseen charging states $\mathbf{x}_d = \mathbf{x}_{\text{new}}$ can be obtained using the following formulation:

$$\hat{Q}_{\omega_d}(\mathbf{x}_{\text{new}}, e_d) = \sum_{\mathbf{x}_d^{(l)} \in S_{\omega_d, e_d}} \kappa(\mathbf{x}_d^{(l)}, \mathbf{x}_{\text{new}})[r(\mathbf{x}_d, e_d)^{(l)} + \gamma \max_{e_d} \hat{Q}_{\omega_d}^{(\tau)}(\mathbf{x}_{d+1}^{(l)}, e_d)]. \tag{3.9}$$

The optimum charging action is the one that maximizes $\hat{Q}_{\omega_d}(\mathbf{x}_{\text{new}}, e_d)$. In Algorithm 1, the notation l' is used to refer to indexes of state components $\mathbf{x}_d$ in a data subset S_{ω_d, e_d}. Also $\hat{Q}_{\omega_d}(\mathbf{x}_{d+1}^{(l)}, e_d)$ denotes the Q-function computed using the proposed method. The daily charging is scheduled using a LP method to occur during the hours with minimum price while the EV is parked at home.

In Publication III, the construction of the sample set $\mathcal{F}$ used in simulation for training the proposed fitted Q-iteration algorithm had a duration of 1 h 8 minutes and 43 seconds. The simulation was performed in Matlab [93] on a conventional desktop computer. The construction process of the sample set can be performed offline using the historical set of data samples. The fitted Q-iteration algorithm was trained separately for each week day. The overall training time of the algorithm was 22 minutes and 30 seconds.

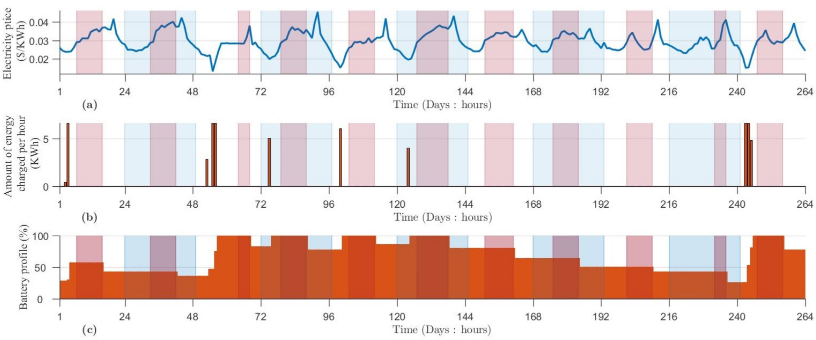

Figure 3.2. An example of charging pattern obtained by the proposed method over 11 consecutive days showing: the hourly price of electricity (a), the amount of energy chosen to be charged during each hour of these days (b) and the charge level of the battery (c). The highlighted regions in each sub-figure indicate the hours of the day when the car is not at home. The method chooses to charge a high amount of energy during the days when the price is low and not to charge at all when the prices are high. Copyright 2017 IEEE.

Figure 3.2 shows an example of a charging pattern obtained by using the proposed method over 11 consecutive days. It can be observed that the charging occurs during those days and hours when the prices are lowest. A comparison between the cumulative charging costs over 110 consecutive days of the proposed charging strategy and other three charging strategies is shown in Figure 3.3. The conventional method simulates the traditional charging behavior in which drivers charge the EV's battery when it is almost empty without considering the cost. Also the charged amount is a random value between the amount of energy needed for the next trip and full capacity of the battery. The daily optimal charging method is a smart deterministic charging method in which the exact daily consumption is considered to be known at the beginning of the day and

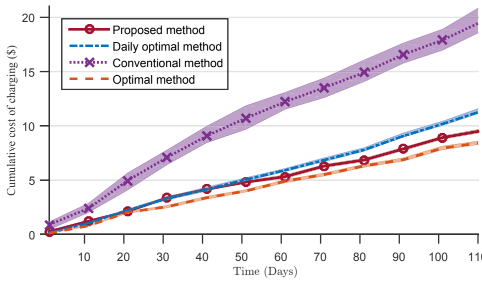

Figure 3.3. Comparison between cumulative charging costs of the proposed fitted-Q iteration-based charging strategy and other three charging strategies. The average cost values and the variance bounds on randomized consumption are presented. The proposed method reduces the costs of charging by roughly 50% when compared to the conventional charging method and by roughly 10% when compared to a daily optimal charging strategy. To reach the global optimal solution the cost should be further reduced by 8%. Copyright 2017 IEEE.

the battery is charged with that amount of energy such that the electricity cost is minimized. Finally, the optimal charging method is a fully deterministic method in which the price of electricity and the exact daily consumption of the EV are known in advance for the whole time frame of 110 days. Figure 3.3 shows the average cost values and the variance intervals for 50 different car usage realizations. This variance is caused by the random component added to the EV consumption ϵ_d, as explained in the beginning of this section. In Publication III, in the considered scenarios, the fitted-Q RL-based method proposed for EV charging reduces the cost of charging by 10% in comparison to daily optimal charging and by 50% in comparison to the conventional charging strategy.

A comparison regarding various features involved in DSM methods for optimizing single EV charging is presented in Table 3.2. Some of the features are specific to a single method. Hence, a clear one to one comparison among these methods cannot be made. These methods optimize the EV charging for the benefit of the EV owners only. The optimization method proposed in [87] optimizes the battery charging of a hybrid vehicle with the purpose or reducing the fuel consumption. A quantitative comparison on the performance of the reviewed DSM methods is presented in Table 3.3. Again, it is difficult to compare these methods due to the lack of standardization and different benchmarks used in each method. The time period over which the results are computed is important for the reported results, too. In [83] for example, simulations are performed over a time span of 12 hours and the reported results show a 22% improvement in terms of charging costs in comparison to a MPC approach. In [82, 85] results are reported for simulations performed over 24 hours. These results may be, however, specific to the particular set of prices and the charging load for the considered day and do not guarantee that the value of the cost reduction will stay the same if the methods are applied for longer time periods. In [84], costs are calculated over 65 days and the daily average cost reduction is of 12-24% in comparison to a heuristic low price charging scheme which is not an optimal

Table 3.2. A comparison regarding various features involved in DSM methods for optimizing the charging of an EV. The following notation is used: time-var.- time-varying, P-Publication. The column *Data* refers to knowledge of electricity prices, EV loads and driving patterns.

Method	*Beneficiary*	*Objective*	*Time horizon*	*Pricing method*	*Data*	*Solution*	*V2G*
[82]	PHEV owner	min cost	day-ahead, rolling horizon	RTP	known	DP	×
[83]	EV owner	min cost, regulation	real-time	RTP based	stochastic price	MDP, SDP	×
[84]	EV owner	min cost	real-time	time-var.	stochastic EV arrival, departure	MDP, SDP	✓
[85]	EV owner	min cost	day-ahead	ToUP	predicted EV loads	MILP	×
[87]	EV owner	min fuel use	rolling horizon	×	known	Evolutionary algorithm	×
P I	EV owner	min cost	day-ahead	RTP	known+ predicted price	MDP, SARSA	×
P II, P III	EV owner	min cost	day-ahead	RTP	known+ predicted price	MDP, Fitted-Q	×

Table 3.3. A comparison regarding performance of DSM methods for optimized charging of an EV. The following notations are used: LPC-low price charging method, P-Publication.

Method	[82]	[83]	[84]	[85]	P I	P II	P III
Cost reduction	46%	22%	12-24% daily average	6%, 15.2%	7%, 40%	8%, 40%	10%, 50%
Comparison benchmark	flat price charging method	MPC	LPC	charge after parking, charge after lunch	daily optimal, conventional	daily optimal, conventional	daily optimal, conventional
Measurement period	1 day	12 hours	65 days	1 day	224 days	224 days	110 days

charging method. An observation that must be made is that in the reviewed articles the word stochastic is used in different ways. In some cases, the word stochastic is used for totally random processes, for example, the EV's charging load is considered a random variable. In some other cases instead, the term stochastic is used to refer to a deterministic value to which a random component is added. This is also the case of the methods proposed in Publications I, II and III, where the EV's daily consumption is considered known and a random component is added to this value. However, in Table 3.2 the proposed methods were not classified as stochastic.

In Publications I, II and III the results are reported for very long time spans, 224 days in Publications I and II and 110 days in Publication III. The comparison benchmarks are the daily optimal and conventional charging methods. The methods proposed in this thesis for optimizing the EV charging reduce the long term cost of charging. The results in Publications I, II and III show that the proposed DSM methods reduce the cost of charging at the end of the 224-days and 110-days periods. The cost is reduced by 7-10% in comparison to the daily optimal charging method and by 40-50% in comparison to the conventional, non-optimized method for charging the battery.

3.3 Discussion

A massive penetration of EVs into the transportation systems and consequently into the power network could cause a multitude of negative effects on the electric grid which must not be neglected. It is obvious that the penetration of EVs into the power system must be accompanied by methods for optimizing their charging. These methods help in maintaining control over the load levels on the grid, and hence improve the reliability of the power system and reduce unnecessary investments in energy production. The EVs' charging can be controlled in various of ways. DSM methods combine the efforts of power system operators with the active participation of EV owners for jointly reducing and optimizing the electricity consumption and cost for charging these vehicles. Among the existing DSM methods, the price-based DR methods are the most appealing to the consumers. Cost reduction drives consumers to participate in energy efficiency programs. In these methods, the utility companies design the electricity tariffs with the goal of balancing the demand and matching the demand with the supply. These tariffs are typically defined using time-varying dynamic pricing schemes with the intention to influence the energy consumption patterns of the consumers.

In this chapter, DR methods for EV charging optimization were reviewed and discussed. In the first part of this chapter, an overview on methods involving coordinated charging of large numbers of EVs is presented. The negative effects of the EVs' incursion into the power system could be avoided by simultaneously optimizing and coordinating the charging of large numbers of EVs. Moreover, the benefits of using the EVs' batteries as flexible loads or as dynamic energy storage systems, enabled through V2G technology, could be maximized through DR methods. State-of-the-art methods on aggregate EVs' charging propose programs that bring benefits for parking lot and charging station owners, system operators, EV aggregators and EVs' owners as well.

In the second part of this chapter a review on state-of-the-art methods designed for single EV charging is presented. In this case, the EV owners are the price takers and the proposed methods are focused mostly on minimizing the their charging cost only. The reviewed methods consider different strategies and assumptions in the proposed charging scenarios. Hence, a fair one to one comparison on the performances of these methods may not be feasible. The state-of-the-art methods for single EV charging optimize and schedule the charging based on hourly or even minute wise control actions. In Publications I, II and III, however, decisions made on daily basis are combined with hourly scheduling of an EV's charging in order to reduce the long term cost of charging for the owner. The EV's daily plug-in and plug-out times to the charger are assumed known in the proposed methods. The daily EV consumption values are also assumed known, but a random component that accounts for eventual fluctuations in consumption is included. Modeling the daily charging patterns and consumption of EVs is a different research topic that is already tackled in literature [94]. The contributions of this thesis on optimizing the EV charging focuses on choosing the amount of energy to be charged daily, based on the variations in electricity prices between consecutive days, and optimally schedules the charging within a day. Taking in consideration the variability of electricity prices over periods longer than 24 hours may result in significant cost reductions as demonstrated in Publications I, II and III. The proposed methods do not only consider the hour to hour fluctuations of electricity prices, but also the day to day fluctuations of electricity prices. In [84], the charging is scheduled at one minute time-steps considering perfect knowledge of electricity prices over 48-hours. The methods proposed in Publications I, II and III consider known day-ahead electricity prices and predicted electricity prices for the second day-ahead. The hour to hour, day to day, or season to season fluctuations of electricity prices are strongly dependent on the fluctuations of the demand of electricity on the power grid. This demand is further influenced by diverse external factors such as season, temperature and weather, day of the week, holiday periods etc. Some of these external factors and past electricity pricing data are taken in consideration in Publication III and a BNN-based method is proposed for price prediction. The method is used to predict prices for the second day ahead. Depending on the variations between known day-ahead electricity prices and predicted priced for the following day ahead, the proposed EV charging methods choose the amount of energy to be charged within a day. The methods may choose to charge the EV's battery, if in the present day the price of electricity is lower than the price in the following day. Otherwise, if the state-of-charge of the battery is sufficient and the driving needs do not require immediate charging, the methods may choose not to charge energy into the battery in the present day and wait until the following day to take another decision. Once a charging decision is taken, the charging takes place during the hours with minimum price when the EV is connected to the smart charger. The RL-based decision making methods take optimized decisions on the daily EV charging amounts, the methods employing discrete actions. However, in order to take optimal decisions, a method employing continuous action values would be needed. This may be studied in future work. By using the proposed EV charging methods the cost of charging may be reduced by 10% in comparison to the optimal daily charging strategy and by 50% over the conventional method, in the considered scenarios.

The methods developed in this thesis assume day-ahead knowledge of driving patterns for scheduling the EV's energy consumption and also an accurate estimation of the EV's consumption. Predicting with high accuracy an EV's daily driving patters and consumption remains a challenging task and can represent a another challenging topic for future work. Another fact that must be considered when using price based DR methods, like the ones proposed in this thesis, is that when used by a large number of EV users, combined shifting of electricity usage may result in formation of other peaks and fluctuations in electricity demand. Consequently, methods for preventing such effects and intelligently coordinating the home charging of very large numbers of EVs are further needed.

4. Energy cost and portfolio optimization in smart grid

Since the birth of commercial electricity, fossil fuel has been used as power resource to supply our electricity demand. Continuous exploitation and utilization of fossil fuel is not only leading towards an early shortage of this resource, but it is also partly causing one of the biggest world crisis, that of pollution and global warming. In the attempt to make our electricity system more sustainable, alternative energy sources together with efficient methods for utilization of this energy are being explored. Among the alternative energy sources, the RESs seem to be the most prevalent, particularly due to their significantly reduced carbon emissions in comparison to conventional energy sources. In order to ensure a reliable and greener energy supply, the new, modernized power grid has to have the ability of combining conventional methods for power generation together with alternative methods such those based on renewable power generation. Together with the widespread adoption of the RESs, the modernized power grid will also be forced to adopt innovative technologies and programs like those for DSM to enable optimal utilization of these renewable resources.

Small scale installation of RESs encourages also the appearance of a new type of end customer, namely the prosumer. In the traditional power grid, the role of the end customer is that of price taker, with no involvement in the energy sector. The flow of power is occurring only one way, from generation towards load. However, in the modernized power grid, the prosumer will be a new type of end consumer, one that not only consumes energy, but one that also owns RESs and/or ESSs and is able to feed power back into the power network. End energy consumers may choose to install RESs due to various reasons: to protect the environment and reduce pollution, make their homes go off-grid and hence secure themselves from eventual power cuts or from unpredicted increases in prices on behalf of the utility company. The perpetual reduction in the cost of electricity is an important reason for installation of RESs, too. Renewable energy is a free source of energy, but installation of RESs comes with a significant capital cost. There is also a cost associated with maintaining them. However, these investment costs are expected to be paid back in time. There are numerous benefits resulting from installation of renewable sources, but their intermittent nature and dependence on weather patterns can make a complete reliance on the renewable resources a difficult task. Energy consumers may still need to rely on energy delivered by the power grid in times when their renewable energy production is insufficient to fulfill their energy demands. Not only deficit of renewable energy production can be a problem, but also, in times of abundant production, the energy surplus may be wasted. Installation of ESSs may accommodate the surplus of renewable energy production such that it may be used later, during times of deficit. The ESSs may be also used to perform DR and hence enable ESSs owners to participate in DSM programs.

Local energy generation and ownership of ESSs opens opportunities for new energy strategies and markets. Active interactions among energy entities at the distribution level of the power grid are steered by the desire of achieving minimal costs and having a sustainable local energy supply. Such entities may be consumers, prosumers, microgrids, independent RESs, or ESSs, etc. In the context of the smart power grid, interactions among energy entities may refer to a variety of actions, such as exchange, share and trade of energy, information and of other resources. For example, in order to make their renewable energy supply more reliable and minimize their operational costs, entities at the distribution level of the grid may decide to share or trade their resources by creating local energy markets. Bidirectional power flow and information flow establish the basis for interactions in the energy sector. What is yet not clear, is how these interactions should be operated. Proper frameworks should be designed to define infrastructure requirements, operational rules and pricing schemes related to energy interactions. Interactions at distribution level should also be included in DSM programs to ensure optimal energy consumption and smart allocation of resources and costs.

A brief overview of state-of-the-art DSM methods and frameworks that enable interactions among distribution system entities is given in this chapter. There are several criteria according to which these interactions can be classified. One of these criteria is the objective of the methods. According to their objective, the methods may be broadly classified in:

- Methods driven by cost reduction or monetary revenue maximization;
- Methods for load balancing;
- Methods that ensure the sustainability of the electricity supply;
- Methods that minimize the discomfort of energy users, etc.

Reduction in consumption cost can be achieved through price based DR programs. These programs are mainly adopted by end consumers. Utility companies and load aggregators however, may as well aim at increasing their financial profits, but also at balancing the load on the grid. Some of the methods proposed in the literature focus on achieving only one of these objectives. However, other methods may have mixed objective. Another criterion for classification is the manner through which these interactions occur. Hence, state-of-the-art methods may be classified in:

- Competitive methods for energy trading and sharing;
- Collaborative methods for energy trading and sharing.

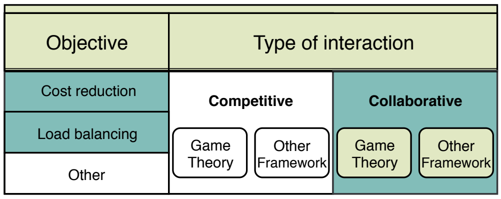

Figure 4.1. Criteria for classifying DSM methods employing interactions at distribution level of the smart power grid.

Besides the above mentioned criteria for classification, there are other criteria and aspects that must be taken into consideration:

- The pricing scheme applied in the proposed methods;
- Electricity prices, demands, renewable energy production: known (deterministic), or known with uncertainty (stochastic);
- The period of operation: real-time, or finite time horizon ahead, such as day-ahead;
- Implementation mode: centralized, or distributed.

A survey on DSM methods employed for enabling interactions among smart grid entities at the distribution level of the smart power grid is provided in this chapter. The survey is not complete and only the newest and most relevant problems and techniques have been considered. The survey is structured according to the objectives driving the interactions and the type of interaction employed by the method, as shown in Figure 4.1. Competitive and collaborative types of interactions may be further divided according to the mathematical model of the interactive process. Thus, the methods may be classified as model free methods, following an own set of rules for modeling the interactions, and game theory-based methods. The system setup, the employed strategies and other factors influencing the interactions are discussed. Note that this survey is not complete, but focuses on the most relevant methods complying to the criteria of classification given in Figure 4.1. The other criteria for classification mentioned above shall also be considered. The pricing scheme applied in the proposed methods is very relevant. The methods may adopt a pricing method derived from, or identical to that applied by the utility company in the region. Internal pricing methods for the local energy trade can also be used. The electricity prices are in many cases assumed to be given in advance for the operational time frame. In a similar way, the electricity load may be assumed to be known in advance for the considered time frame of operation. The proposed methods may be working in real-time, or they may schedule the control operations in advance over a finite time period. Also the proposed methods may be implemented in a centralized fashion, i.e. controlled by an operator or system controller, or in a distributed fashion. Most of the reviewed state-of-the-art methods imply financially driven interactions. The main focus in these methods is achieving cost savings in consuming, storing, trading energy and also in exchanging information. The interacting entities can be competitors or collaborators. Consequently, the employed methods may be further divided into competitive or collaborative methods for achieving financial revenues.

4.1 Competitive methods for energy cost minimization

Interactions among power grid entities become competitive when each participant in such competition desires to buy energy at lowest price possible, or sell energy at high price. Both cases lead to gaining financial revenues. In order to obtain these gains, a participant continuously tries to improve his strategy over the ones of his competitors. Hence, the approach is selfish since the participants are focused on maximizing their personal financial gains. Energy retailers and sellers are competing not only against each other, but also with the energy consumers buying energy from them. Many of the state-of-art-methods modeling competitive situations among players in the energy sector are non-cooperative game-theoretical methods [95, 96, 97].

Non-cooperative game theory [98] models competitive structures that focus on individual players, their strategies and how these strategies may influence their revenues or payoffs. These strategic non-cooperative games aim at maximizing the utilities of each participant given the actions of all the other participants in the game. To learn more about non-cooperative game theoretic methods in smart grids we refer the reader to the survey in [99].

In the traditional energy industry, competition occurs among the big market players such as energy producers, transmission system operators, distribution system operators and utility companies. In smart grid, however, competition may occur also among smaller players such as end consumers, prosumers, microgrids, etc. Interactions and energy trading among energy users at distribution level are studied in [100]. The energy users are divided in two categories: passive energy consumers and active energy users. The passive energy users only consume energy and do not have the means to actively participate in DSM. The active energy users on the other hand, own dispatchable energy sources and/or ESSs. Hence, they are able to participate in DSM programs. A DSM method employing a non-cooperative game model among the active energy users is proposed with the goal of minimizing costs within the system. The costs to be minimized include: the cost of energy purchased from the main power grid and the energy production cost. The central operator coordinating the day-ahead optimization process aims at minimizing the cumulative costs of all energy users, both active and traditional users. Under this objective, the active users are competing among themselves to minimize their individual costs by finding optimal dispathcable energy generation and storage scheduling strategies. A proximal decomposition algorithm (PDA) is proposed to solve the non-cooperative game in a distributed manner such that the game reaches Nash equilibrium [100].

Distributed storage units may compete against each other for selling stored energy to other energy consumers in the power system. In [101], such interactions and trading decisions among storage units are studied. These interactions among the storage units, representing the sellers, and consumers, representing the buyers, are modeled by means of a non-cooperative game. In this game, the storage units strategically decide the amounts of energy to sell in order to maximize their financial benefits. A bidding occurs between buyers and sellers. Based on the bidded amounts of energy, a double auction mechanism is employed to determine the actual buyers and sellers that will participate in the trading process. The trading price and amounts of energy to be traded between sellers and buyers are also decided. An algorithm based on the double auction market mechanism is proposed to solve the non-cooperative game [101]. It is shown that the proposed non-cooperative game always reaches Nash equilibrium.

Allocation of renewable energy may also be a reason for competition. Residential households are competing against each other for allocation of renewable energy and to reduce their costs in [102]. The households belong to a microgrid which owns RESs. The microgrid serves the residential energy consumers who own smart home appliances and EVs. A real-time renewable electricity allocation framework is modeled using a non-cooperative game model among the households. The home consumers determine strategies to optimally schedule their smart home appliances. These strategies also include the charging and discharging of their EVs which are used as electricity storage systems. The stored energy can be also sold back to the microgrid. The proposed game is controlled by the microgrid and allows consumers to compete and minimize their costs under the constraint that the overall social welfare of the microgrid is maximized. The renewable electricity allocation game is played over discrete time-steps and a distributed real-time allocation method is proposed for solving it. The game converges to Nash equilibrium.

In other scenarios, households own RESs but do not have sufficient energy storage space to store the surplus of energy. Such problem is considered in [103] where a competitive model for energy trading and DR in a neighbourhood of households is proposed. The participating households own RESs but not storage systems. Instead, they may exchange energy with a community storage controlled by an operator. At each time-step, both the energy users and the storage system exchange energy with the main power grid too. In order to increase its own financial profit, the storage operator purchases energy from the main power grid and sells it later, at a different price, to those households with shortage of renewable energy or back to the power grid. The residential energy users also aim at reducing their costs, so they also trade energy either with the community storage or with the main power grid. A competitive model is framed as a Stackelberg game between the community storage operator and the energy consumers in the neighbourhood. The storage operator is the leader of the game while the households are the followers. In the first stage of the game, the storage operator optimizes the energy portfolio within the neighbourhood. The optimal aggregate energy amount to be traded in each time-step among the storage and residential energy users is found. In the second stage, the energy users compete for the allocation of the energy scheduled by the storage. A two step iterative algorithm is proposed to solve the Stackelberg game such that the solution reaches Stackelberg equilibrium. By participating in the proposed Stackelberg game, the energy users obtain an average cost reduction of 29.4% in comparison with trading energy with the main power grid only [103]. In a similar framework, microgrids participate in a competitive market controlled by a distributor that collects the surplus of energy from different providers and allocates the energy to consumers in [104].

When participating in a competitive market, the subjectivity of the market players has an important role. Their feeling and fears about taking the right decision might considerably change the outcome of the competition. The subjectivity of microgrids when taking decisions related to energy trading is analyzed through prospect theory in [105]. The energy exchange among microgrids is formulated as a prospect theory-based non-cooperative static game. The microgrids trade energy among themselves at a predefined local price with the scope of maximizing their utilities. They can also trade energy with a power plant to which they are connected via the main power grid. The utility of a microgrid depends on the cost of traded energy and the amount of stored energy. In order to encourage the energy exchange among the microgrids, the local selling price is designed to be lower than the price of energy sold by the power plant. The local buying price is higher than the price at which the power plant buys energy. Nash equilibrium is derived for each pair of microgrids exchanging energy in the proposed static game.

Similarly to [105], the subjectivity of participants in an energy market is studied using prospect theory also in [106]. An electricity company trades energy with energy prosumers by employing a single-leader multi-follower Stackelberg game. The electricity company aims at maximizing its utility and first announces the buying/selling price. Prosumers also want to maximize their utilities. Hence, in response to the prices announced by the utility company, they play a non-cooperative game through which each prosumer strategically decides his bidding amount of electricity. The utility of the prosumers consists of the financial profit of the trade plus a possible future financial benefit associated with the unsold electricity. The utiltiy of the electricity company is represented by the money earned through selling electricity. The future price of electricity is considered not known so it is modeled as a random variable. The solution of the proposed game is obtained using a distributed learning algorithm. A similar approach that involves a game among multiple leaders and multiple followers is proposed also in [107].

Another type of market formulation is proposed in [108] where the energy is traded between a group of customers and a group of microgrids. This is modeled as a multi-leader multi-follower Stackelberg game. Differently from the methods in [106] and [107], here the customers are the leaders of the game, while the microgrids are the followers. At each time-step, each customer first chooses a microgrid from which he intends to buy electricity and announces the amount of electricity to be bought from that microgrid. In response to the total amount of energy requested from each microgrid by the customers, the microgrids establish

Table 4.1. A comparison regarding various features involved in DSM methods for competitive interactions at distribution level. The following notations are used: A-users - active users, P-users - passive consumers, S-hous - smart households, uGs- microgrids, Pros- prosumers, S-cons - smart consumers, ITER- iterative algorithm, NONC- non-cooperative, SKB- Stackelberg, DAMA- double action market-based algorithm, DEMANDS- distributed energy management algorithm, DLA- distributed learning algorithm, DRTA- distributed real time allocation method, NE- Nash equilibrium, PDA- proximal decomposition algorithm C- centralized, D- distributed. The row *Known data* refers to knowledge of electricity prices and demands.

Method	[100]	[101]	[102]	[103]	[105]	[106]	[108]
Entities	A-users P-users	ESSs	S-hous	ESS S-cons	uGs	P-comp Pros	S-cons uGs
Local generation	dispatchable	×	shared RESs	RESs	RESs	RESs	RESs
Grid interaction	buy	×	buy+ sell	buy+ sell	buy+ sell	buy+ sell	×
ESSs	✓	✓	EVs	shared ESS	✓	✓	✓
Load shifting	×	×	✓	×	×	×	×
Time horizon	day-ahead	single time	real-time	day-ahead	real-time	real-time	day-ahead
Known data	✓	✓	✓	✓	✓	stochastic prices	✓
Grid price	RTP	×	ToUP	RTP	×	fairness pricing method	×
Internal price	×	✓	✓	✓	✓	×	✓
Game	NONC	NONC	NONC	SKB	Prospect NONC static	Prospect SKB	SKB
Solution	PDA	DAMA	DRTA	ITER	NE derivation	DLA	DEMANDS
Perspective	D	C	D	C	C	D	D

the selling price. This is done according to a dynamic pricing model. The game is played in iterative stages until it reaches equilibrium. In [108], both the customers and the microgrids have the intention to maximize their individual utilities. The utilities of the customers are represented by the fulfillment of consuming the desired amount of energy while paying as little money as possible. The utilities of the microgrids are defined by the amounts of money earned by selling energy. A distributed energy management algorithm (DEMANDS) is proposed to solve the proposed game.

Table 4.1 gives an overview on the characteristics and features employed in the reviewed competitive DSM methods. It can be observed that the employed methods possess many similarities. For example, besides the method in [101] where a competitive method is proposed among independent storage units, all other methods employ some form or local energy production and ESSs. Another observation is that competitive methods for energy interactions are modeled using either non-cooperative games, or using leader-follower Stackelberg games. The methods have many differences and some features are specific to single methods. Consequently, it is difficult to compare them. This can be observed also in Table 4.2 where the performances of the methods are presented. In [105, 106] the performance is discussed from prospect theoretic point of view with respect to subjectivity of the players. Hence, these methods were not included in Table 4.2. The methods not only employ different features, but also their performances are compared to different benchmarks. Hence, once again it can be stated that a fair comparison cannot be made. However, it can be observed that all methods report results for simulations performed over maximum 1 day period. These results may be specific to that 24-hours set of prices and load profile considered in that particular simulation. It is not certified that the reported cost reductions will remain the same if the methods are applied for longer time periods.

Table 4.2. A comparison regarding performance of DSM methods for competitive interactions at distribution level.

Method	[100]	[101]	[102]	[103]	[108]
Performance	cost reduction	profit increase	cost reduction	cost reduction	profit increase
Value	20.7%	73-234.4%	29.4-81%	29.4%	14.6% average/uG
Comparison benchmark	no optimization	conventional solution	unregulated scheduling	grid trade	optimal RTP algorithm
Measurement period	1 day	1 day	1 day	1 day	1 day

4.2 Collaborative methods for cost minimization

The energy consumers and producers in a smart grid may collaborate instead of competing. While competition means improving yourself in order to win over others, collaboration implies joining forces with others for achieving a common goal. In this case, the goal is that of minimizing costs, or achieving financial revenues. In this section, the collaborative methods for cost minimization within smart power grid are divided into two sub-categories: model free methods, using own model for the collaboration, or methods employing cooperative game theoretic models.

4.2.1 Model free methods for collaboration

Microgrids are local energy systems operating over limited geographical areas, or sometimes over single buildings. These mini power systems comprise own renewable power generation, storage and loads and aim at having sustainable, cheap, secure and efficient energy delivery. The microgrids may be equipped with different types of RESs and their operators may decide upon the capacity of renewable energy equipment to be installed. Collaborative planning of renewable energy equipment and generation in a system of interconnected microgrids is proposed in [109]. The installation of the renewable energy equipment comes against a cost. A collaborative problem formulation is proposed for minimization of the microgrids' aggregate cost consisting of the cost for renewable energy installation and the system operation cost. The investment costs for the installed renewable generation is shared among the microgrids using the Nash bargaining solution (NBS) such that each microgrid obtains a cost reduction as compared to an individual, non-cooperative optimization scheme.

Microgrids that serve multiple energy consumers cooperate by trading energy to jointly minimize their energy consumption cost in [110]. The problem formulation takes into account the discomfort of the energy consumers for using their smart appliances at different times than the desired ones. The goal is to schedule the elastic loads and storage and optimize the amounts of generated renewable energy, energy consumed from or sold to the main power grid and energy traded among the microgrids. The cost to be minimized consists of the cost of energy exchanged with the main power grid, the cost of storage operation and a cost associated with the users' discomfort. The cost for the energy traded among the microgrids is calculated using NBS. An algorithm based on ADMM is designed to find the solution in a distributed fashion. The results show that through the proposed method the microgids obtain an overall cost reduction of 13.2% in comparison to the non-cooperative optimization solution in which the microgrids optimize their energy consumption individually.

The methods proposed in [109, 110] assume that the microgrids can adjust their local renewable power generation, whereas many other DSM methods assume that the renewable power generation is completely known or it presents a certain variability. In order to minimize the aggregate cost of consuming electricity from the main power grid, two microgrids equipped with RESs and ESSs cooperate by exchanging energy among themselves in [111]. A convex optimization problem is derived considering that electricity prices, loads and renewable energy production are known ahead for the optimization period. An off-line Lagrange duality-based method is employed to solve this problem in a distributed fashion. In addition, the same problem is proposed to be solved in real-time by two online algorithms, assuming stochastic loads and stochastic renewable energy production for the two microgrids.

An MPC-based method is proposed in [112] for energy management in urban districts with multiple microgrids. A distributed three-step MPC method is formulated. In the first step, the microgrids individually compute their optimal energy plans. Based on these plans, a global optimization method that minimizes even further the system cost is formulated in the second steps. Then in the third step, an iterative power re-distribution optimization is formulated for coordinating the microgrids according to the global solution. The method controls the flexible loads, heating systems, local energy generation and the energy exchange among the microgrids and with the main power grid in order to minimize the cost. Constraints on the thermal comfort of the buildings are also considered. Each optimization problem, at each of the three steps, is formulated as a MILP. The proposed MPC-based problem is solved over a rolling time horizon that considers at each new step updated forecasts of electricity prices, weather and heating requirements. Depending on the number of microgrids in the network, the performed experimental results show that the MPC-based method may obtain overall cost reductions between 13.8% and 51% for the network of microgrids. The comparison benchmark is the individual energy management solution.

Cooperation for supporting sustainability of electricity supply is even more essential when the participants are not connected to a permanent source of electricity. In [113], cooperation among islanded microgrids is studied. The micgrogrids are equipped with local energy generators and are not connected to the main power network, hence they depend only on own energy sources. It is assumed that the microgrids are not equipped with ESSs. The microgrids decide to cooperate by trading energy among themselves in order to optimize the utilization of their energy resources and reduce their costs. Each microgrid has a cost associated with its own energy generation. The distribution network operator applies a price per each unit of energy transferred among the microgrids, price which is common for all microgrids. A method for calculating the optimal amounts of energy to be transferred from one microgrid to another is proposed such that the their energy production and transfer costs are minimized. A two-step iterative algorithm based on the Lagrange dual decomposition method is proposed for solving the optimization problem in a distributed manner.

Cooperation between one macrogrid and multiple microgrids is investigated in [114]. The macrogrid is supported by conventional power sources, while the microgrids own DES and ESSs. The macrogrid and microgrids exchange energy such that the macrogrid transfers energy to and from the microgrids, while the microgrids may also transfer energy among themselves.

Similar DSM collaborative frameworks as those for employed for microgrids may be applied also in case of collaborative DSM programs for residential households. Households may also be equipped with small scale RESs, ESSs and smart control meters and can actually function as minigrids for optimizing their own consumption individually. A dynamic model for determining internal trading prices is proposed in [115] for peer-to-peer energy trading among neighbouring prosumers. The prosumers can buy and sell electricity from and to their peers and trade with the utility company. The purpose is to reduce their cost and their inconvenience for shifting their loads. The energy traded with the utility company is charged at fixed rates. The approach proposed for determining internal pricing takes into account the ratio between the amount of energy supplied by the prosumers and their energy demand. It also takes into account the electricity prices offered by the utility company. Based on this internal pricing mechanism, a distributed iterative algorithm is proposed to minimize the electricity cost of each prosumer. The cost consists of the electricity consumption cost and a cost measuring the inconvenience of the prosumers for load shifting. The proposed method optimizes the power consumption profile of each prosumer.

An energy management strategy using a shared ESS is proposed to control the energy operations within a microgrid of households in [116]. The households are individually equipped with RESs. Their energy consumption relies on their own renewable energy production and on the main power grid with which the microgrid interacts through buying and selling energy. The prices for purchasing energy from the main power grid are higher than the prices for selling back energy to the grid. The proposed energy management approach optimizes the energy stored in the shared ESS and the energy purchased or sold to the main power grid by the microgrid of households. The goal is to minimize the cost of purchasing electricity, maximize the cost of selling electricity from and to the main power grid and extend the lifetime of the ESS. An MPC algorithm is employed to solve the proposed problem.

A framework for a coordinated energy control in a neighbourhood of households is proposed also in [117]. The households individually own RESs, ESSs and EVs with V2G technology. The households can trade energy with the power grid and also with the neighbouring houses. Within the neighbourhood, the cost of buying electricity is assumed to be equal to the cost of selling electricity. An optimization problem is formulated for minimizing the total energy procurement cost of the households. The energy exchange among the households and between the households and power grid is optimized. Moreover, the approach optimizes the charging and discharging of the ESSs and of the EVs such that the electricity demand of each household is satisfied. The method also ensures that the neighbourhood transformer is equally used by all households. A two-step coordination strategy is proposed for solving the cost minimization problem.

A similar method for energy sharing among cooperative households in a community is proposed in [118]. The households are all equipped with RESs and ESSs, but they can also draw energy from the main power grid if necessary. The difference here is that randomized hourly statistics for the renewable energy generation, energy demand and electricity prices are assumed. A stochastic optimization problem is formulated for the households to share their surplus of energy with the purpose of minimizing the overall cost of the community for purchasing energy from the grid and for charging and discharging the ESSs. An online algorithm based on Lyapunov optimization is proposed to solve the cooperative energy sharing problem and minimize the time averaged cost. Again a Nash bargaining theory-based method is applied to divide the revenues of the cooperation among the residential households. The proposed method achieves a 12% reduction is cost in comparison to a non-cooperative benchmark solution.

A cooperative DSM method for minimizing the aggregate costs of all energy users, active and passive ones is proposed [100]. The costs to be minimized includes the cost for the energy procurement from the main power grid and the distributed energy production cost. The cost is minimized by adjusting the amount of dispatchable energy generation and by scheduling the storage in a day-ahead optimization process. A distributed dynamic pricing algorithm is employed to solve the cooperative problem in a distributed fashion.

4.2.2 Developed collaborative methods for optimizing energy portfolio within a smart grid community

The contributions of this thesis on cooperative DSM methods for smart grids are described in Publications IV, V and investigated in detail in Publication VI. Collaborative DR methods for aggregate optimization of energy consumption within a smart community of residential households are proposed with the goal of minimizing electricity cost. In Publication V, the collaborative optimization includes only households that own RESs and/or ESSs and share energy among each other in order to minimize their cost of consuming energy from the power grid. In Publications IV and VI, pure energy consuming households are also included in the DSM model for energy consumption optimization. Moreover, operational costs are also considered in the formulated problems. The set of households in the community is denoted by $\mathcal{N}$. This set is divided in a subset of households owning RESs and/or ESSs, $\mathcal{M}$, and a subset of pure energy consuming households, $\mathcal{P}$, $\mathcal{N} = \mathcal{M} \cup \mathcal{P}$, that do not own such facilities. It is assumed that the households in this smart community are equipped with smart energy management meters that can predict with accuracy their energy demand profiles, $\mathbf{u}_n = [u_n(t), t = 1, \ldots, T]$, $n \in \mathcal{N}$, and their renewable energy production profiles, $\mathbf{w}_m = [w_m(t), t = 1, \ldots, T]$, $m \in \mathcal{M}$, for a finite period ahead, $\mathcal{T}$. A collaborative model through which these residential households reduce their costs is proposed. The RESs and /or ESSs owning households also have the possibility to optimize their costs individually using DR methods, by using their available storage spaces and renewable energy production. However, in these frameworks, the RESs and/or ESSs owning households may minimize their costs even more by sharing their renewable energy production and storage spaces. Moreover, they may sell excess renewable energy and demand response services to pure energy consumers at a price lower than that offered by the utility company. It is shown in Publication VI that by including pure consumers in the collaborative framework, the RESs and ESSs owners may further reduce their costs in comparison to only exchanging energy and sharing storage space among themselves. The pure consumers can also achieve cost reductions. In case of insufficient renewable energy production within the smart grid community, the households may buy energy from the utility company: $\mathbf{b}_n = [b_n(t), t = 1, \ldots, T]$, $n \in \mathcal{N}$. The electricity prices offered by the utility company: $\boldsymbol{\xi} = [\xi(t), t = 1, \ldots, T]$, follow the day-ahead hourly market pricing scheme. Let $\mathbf{a}_n = [a_n(t), t = 1, \ldots, T]$, $n \in \mathcal{N}$ be the amounts of energy exchanged by the households at each time-slot. This energy is shared among the RESs and/or ESSs owning households free of charge. No internal prices are considered for the energy exchanged among the RESs and/or ESSs owners. Instead, internal pricing tariffs, denoted by $\boldsymbol{\lambda} = [\lambda(t), t = 1, \ldots, T]$, are assumed for the energy sold by these RESs and/or ESSs owners to the pure consumers. These prices are lower than the hourly prices per unit of energy applied by the local utility company. Consequently, the pure consuming households also reduce their costs by simply buying a part of the electricity needed to fulfill their demand at a cheaper price than that offered by the utility company. The collaborative method for energy optimization is modeled as a cost minimization problem with the following objective:

$$\min_{\{\mathbf{b}_n, \mathbf{r}_m, \mathbf{s}_m, \mathbf{a}_n\}_{m=1,n=1}^{M\;\;N}} \quad c_{\mathcal{M}}^{\text{community}} + \sigma \sum_{m=1}^{M} \sum_{t=1}^{T} [b_m(t) + w_m(t) - u_m(t) - a_m(t) - r_m(t)], \quad (4.1)$$

where

$$c_{\mathcal{M}}^{\text{community}} = \sum_{m=1}^{M} C_m^{\text{grid}} + \sum_{m=1}^{M} C_m^{\text{storage}} + \sum_{m=1}^{M} C_m^{\text{operation}} - \sum_{p=1}^{P} C_p^{\text{purchase}} \quad (4.2)$$

is the aggregate cost of electricity consumption for the community consisting of the following therms: $C_m^{\text{grid}} = \sum_{t=1}^{T} \xi(t) b_m(t)$, $\forall\ m \in \mathcal{M}$- cost of buying electricity from the power grid by the RESs and/or ESSs owners; $C_m^{\text{storage}} = \pi \sum_{t=1}^{T} |r_m(t)|$, $\forall\ m \in \mathcal{M}$- cost that accounts for storage degradation when charging and discharging an ESS; $C_m^{\text{operation}} = \tau \sum_{t=1}^{T} |a_m(t)|$, $\forall\ m \in \mathcal{M}$- cost of energy transfer operation; $C_p^{\text{purchase}} = \sum_{t=1}^{T} \lambda(t)[-a_p(t)]$, $\forall\ p \in \mathcal{P}$- cost of energy sold by the RESs and/or ESSs owning households to pure consumers. $|\cdot|$ denotes the absolute value. Moreover, the objective function of the proposed problem includes also the following term: $\sigma \sum_{m=1}^{M} \sum_{t=1}^{T} [b_m(t) + w_m(t) - u_m(t) - a_m(t) - r_m(t)]$ representing a penalty term which forces the amount of surplus renewable energy that exceeds the demand of the community users within period $\mathcal{T}$, i.e. the amount of renewable energy that is not consumed, to be stored in the ESSs for it to be consumed during following period. In expression (4.1), $r_m(t)$ represents the amount of energy charged or discharged in time-slot t from the ESS belonging to household m, while $\mathbf{s}_m = [s_m(t), t = 1,\ldots,T], m \in \mathcal{M}$ is the set of total energy amounts stored in the ESS at the end of each time-slot. The collaborative cost minimization problem is modeled as a constrained optimization problem that may be solved through standard LP methods. A 24-h example of prices, electricity demands, storage, electricity exchange and grid consumption profiles of the proposed DSM collaborative method for a smart grid community is shown in Figure 4.2.

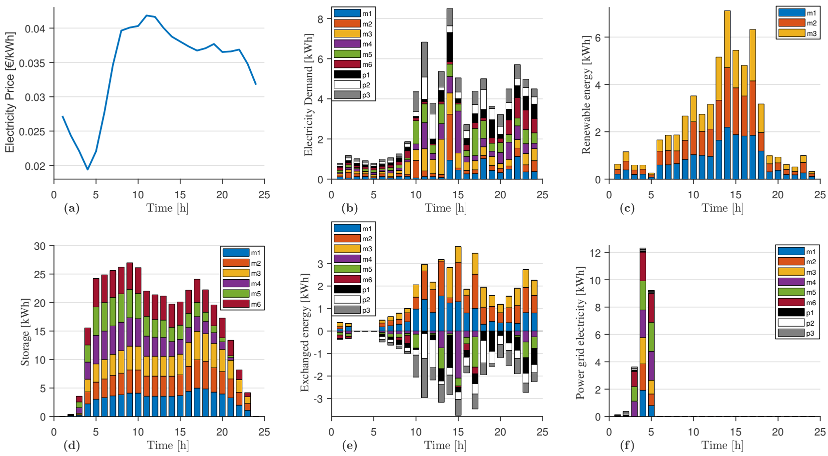

Figure 4.2. (a) 24-hours utility company electricity price. (b) 24-hours electricity demand of the households. (c) 24-hours renewable energy production of households owning RESs. (d) 24-hours ESSs profiles. (e) 24-hours amounts of electricity exchange among all households in the community. The positive blocks show amounts of energy provided by some households, whereas the negative blocks show amounts of energy received by the other households. (f) Electricity purchased from the utility company by the households. RES and ESS owning households buy energy from the utility during the hours when the price is low. Copyright 2017 IEEE

In Figure 4.3 it is shown that, at the end of a 31-days period, the proposed method may reduce the cumulative consumption cost for the RESs and/or ESSs owners by 18% in comparison to the individual cost optimization, while the consumption cost for the sole energy consumers may be reduced by 3%. The pure consumers buy part of their needed electricity from the RESs and/or ESSs owners for a 10% discount in price in comparison to the price offered by the utility company.

Publication IV investigates possible cost reductions obtained by the community for different amounts of renewable energy production. Depending on the amount of produced renewable energy, cost reductions of 12-50% are obtained for the smart collaborative households owning RESs and/or ESSs, while 7-8% reduction in cost is obtained for pure energy consumers. For a detailed description of the proposed methods please see Publications IV, V and VI.

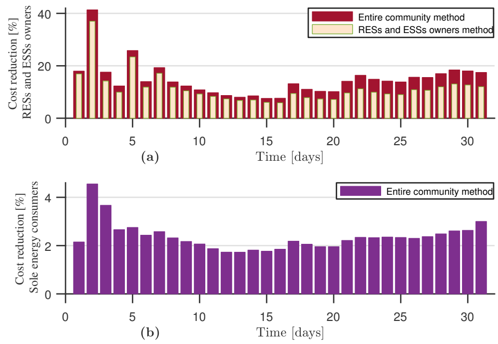

Figure 4.3. (a) 31-days cumulative percentage of cost reduction obtained by RESs and/or ESSs owners in comparison to individual cost minimization. Their cost reduction varies between 6% and 37% in the case when only RESs and ESSs owners participate in the proposed DSM program and between 7.5% and 41% in the case when sole energy consumers are included in the DSM program. At the end of 31-days period their cost reduction is of 12% and 18%, respectively. (b) 31-days cumulative percentage of cost reduction obtained by the sole consumers when they participate in the DSM program in comparison to buying all needed electricity from the power grid. Their daily cost reduction varies between 1.8% and 4.5%. At the end of the 31-days period their cost reduction is of 3%

In Publications V and VI, the interactions among residential households from a smart grid community are modeled through a coalitional game theory-based framework. A short overview and the contributions of this thesis on cooperative interactions among smart grid entities, framed by means of cooperative game theory, are presented further.

4.2.3 Collaborative methods based on cooperative game theory

Cooperative games [9] focus on coalitions that players may form in order to jointly achieve payoffs. In cooperative game-based frameworks it is not necessary to define precise structures for forming strategies for bargaining and negotiation, as non-cooperative games require. Instead, it is sufficient to specify what can the formed coalitions achieve as an overall profit. Coalitional games [119] are typically described in terms of the characteristic function of the game specifying the outcome resulted from the formation of the coalitional group. Compared to the model free collaborative methods described earlier in this chapter, the cooperative game-based frameworks provide, on one hand, means for the cooperative members to form coalitions, and on the other hand describe also ways through which the resulted profit may be divided among the members of the coalition in a fair manner. An extended introduction to coalitional game theory can be found in [11]. Also a survey on game theory-based methods for smart grid may be found in [120].

Cooperation between microgrids is modeled as a coalition formation game in [121]. The microgrids are equipped with RESs and ESSs. Each microgrid is serving a group of customers. The microgrids are connected to the main power grid with which they can exchange energy. The proposed coalition formation game implies that multiple coalitions may be formed among the whole set of microgrids, such that those microgrids that have an energy surplus can transfer or sell energy to those microgrids in need of additional energy. Within each coalition, a coalitional game with transferable utility is played. The value function of a coalition is defined by the total cost incurred for the power losses occurring over the distribution lines within the network of microgrids in the coalition. The aim of the coalitional game is to minimize this cost. A two stage distributed algorithm is proposed for solving the coalitional formation game. The first stage represents the coalition formation stage in which the microgrids are grouped into coalitions. Then, in the second stage, the power transfer occurs among the members of the same coalition such that the value function of the coalition, reflected by the power losses, is minimized. The revenues resulted from the coalitional game are distributed among the members of each coalition using a proportional payoff division method.

Energy cooperation among a group of nanogrids and a shared facility controller is studied in [122]. The nanogrids, which can be some households, are equipped with RESs and ESSs for serving their own demands. They may also buy electricity from the main power grid. The group of nanogrids have an agreement with a shared facility controller to transfer to it a certain amount of energy surplus at every time-step. The functionality of the shared facility controller depends on energy provided by the main power grid and the nanogrids. The nanogrids receive a financial reward for the amount of energy transferred to the facility controller, but also a financial penalty if they are not able to provide the entire contracted amount. A canonical coalitional game is formulated among the group of nanogrids. The nanogrids form a coalition to provide the contracted amount of energy to the facility controller. The value of the coalition is defined by the reward received for the power transfer which has to be maximized. The distribution of the overall reward among the coalition members is done according to a proportional payoff division scheme. According to this scheme, the reward of each member of the coalition is proportional to their contributions to the aggregate energy amount provided to the facility controller.

A system composed of a macrogrid, an aggregator, several renewable energy prosumers and conventional electricity consumers is considered in [123]. The aggregator trades electricity with the prosumers and with the main power grid and sells electricity to the conventional consumers. A contract-based framework is proposed to establish the trading rules and prices for the energy trade among aggregator, prosumers and consumers, respectively. The amounts of electricity sold and traded by the aggregator are optimized such that the aggregator is maximizing its contract-based profit. In order to satisfy their demands, the prosumers also trade energy among themselves against a price determined by a smart agent. The prosumers play a coalitional game through which they want to achieve profits by trading energy with the aggregator. All prosumers in the system participate in the coalitional game by forming a grand coalition. The achieved profit is distributed in a fair manner among the members of the grand coalition using a method based on asymptotic Shapley value. An optimal energy allocation algorithm to schedule the power allocation in case of the contract-based method is proposed. The method proposed in [123] is lacking of a clear description. The method has many adjustable parameters and requires multiple intermediate steps which may make it impractical. Moreover, quantitative results on the performance of the method are not given.

In Publication V and Publication VI, the interactions among residential households from a smart grid community are modeled using coalitional game theory. The coalition is formed by smart households owning RESs and/or ESSs, denoted by set $\mathcal{M}$, that collaborate by sharing their renewable energy resources and storage spaces. In Publication VI these households may also sell energy to pure energy consumers. The coalition is formed at all times by all the residences in the set $\mathcal{M}$, hence by the grand coalition. It is shown, by means of coalitional game theory, that these households may reduce their costs of electricity consumption both jointly and individually as compared to the individual cost optimization. Let c_m^{indiv} be the cost incurred by the households $m \in \mathcal{M}$ through the individual optimization. The characteristic function of the proposed coalitional game, $v(\mathcal{M})$, describes the aggregate cost savings achieved by the coalition. This function is defined as the amount of cost savings obtained by the coalitional group in the collaborative scenarios with respect to the total electricity cost that the members of the coalitional group would pay in the case of performing individual cost optimization:

$$v(\mathcal{M}) = \sum_{m=1}^{M} c_m^{\text{indiv}} - c_{\mathcal{M}}^{\text{community}}. \tag{4.3}$$

Here $c_{\mathcal{M}}^{\text{community}}$ is the joint electricity consumption cost of the coalition of households computed using the formulation in (4.2). A method to distribute the revenue of the coalition of households among its members has to be defined. There are a variety of approaches for achieving fairness such as nucleolus, egalitarian, NBS and Shapley value [119, 11]. In this work, the amount of cost savings obtained by the coalition is divided among its members using the Shapley value [10, 11]. The Shapley value is a one-point payoff solution through which the worth of the coalition is distributed among the players according to the average marginal contribution that each player is bringing to the coalitional game and hence, to the cost savings. The Shapley value, $\Phi(v)$, assigns to each player $m \in \mathcal{M}$ a payoff $\Phi_m(v)$ given by the following expression:

$$\Phi_m(v) = \sum_{\mathcal{G} \subseteq \mathcal{M} \setminus \{m\}} \frac{G!(M-G-1)!}{M!} [v(\mathcal{G} \cup \{m\}) - v(\mathcal{G})], \tag{4.4}$$

where $\mathcal{G}$ denotes any non-empty subset of households from the set $\mathcal{M}$ that may form a coalitional group, $\mathcal{G} \subseteq \mathcal{M}$. The cardinalities of the sets $\mathcal{M}$ and $\mathcal{G}$ are denoted by M and G, respectively. Shapley value leads to a fair solution since the payoff earned by each player is calculated based his contribution to the overall

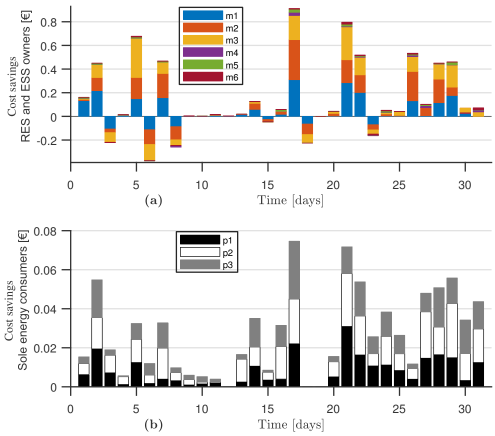

Figure 4.4. (a) The daily amount of cost savings achieved by the RESs and ESSs owning households in the collaborative DSM program which includes also the sole energy consumers. The blocks composing a bar show the payoffs received the households from the coalition as distributed by the Shapley value method. (b) The daily cost savings achieved by the sole energy consumming households through participating in the DSM program. Copyright 2017 IEEE

obtained savings. The cost savings obtained by the coalition and the distribution of these savings among its members can be observed in Figure 4.4. In few days, the collaborative method may not work as good as the individual cost optimization solution used as benchmark for comparison. However, over longer time periods, such as 31 days, the collaborative method achieves significant cost reductions. It can also be observed that the households owning RESs receive much higher payoffs than the rest.

Table 4.3 gives characteristics and features of DSM methods employing collaboration at distribution level. Only the most relevant methods on collaborative energy interactions are included in this table. The methods have some similarities. For example, all methods employ RESs and ESSs. The methods however, have some differences in their problem formulation and their respective system setup. Different types of entities are employed in the collaboration: microgrids [110, 111, 112], prosumers [115], smart residential households [116, 117]. In Publication V, only smart residential households are included in the community model, whereas pure consumers are also included in the methods proposed in Publications IV and VI. A collaborative optimization approach considering active and passive energy users is introduced in [100]. Except for the objective function which minimizes the aggregate cost of energy users, the system model of the collaborative method in [100] is the same as the one for the non-cooperative method already presented in Table 4.1. Hence, it was not included again here. Also, unlike the methods proposed in this thesis, the methods in [100] involve controlling dispatchable energy sources for satisfying the demand. The methods reviewed in Table 4.3 employ different kind of interactions with the main power grid. Some only buy electricity from the power grid, but other methods also sell

Table 4.3. A comparison regarding various features involved in DSM methods for collaborative interactions at distribution level. The following notations are used: S-cons - smart consumers, P-cons - pure consumers, S-hous - smart households, uGs- microgrids, Pros- prosumers, Aggr- aggregator, time-var.- time-varying, COAL- coalitional, ASV- asymptotic Shapley value, CS- coordination strategy, DIS-IT- distributed iterative algorithm, OEA- optimal energy allocation algorithm, ONL- online algorithm, NBS- Nash bargaining solution, S-logic- heuristic supervision logic, SV- Shapley value, C- centralized, D- distributed, P- Publication. The row *Data* refers to knowledge of electricity prices and demands.

Method	[110]	[111]	[112]	[115]	[116]	[117]	P IV	[123]	P V	P VI
Entities	uGs	uGs	uGs	Pros	S-hous	S-hous	S-hous P-cons	Aggr Pros	S-hous	S-hous P-cons
RESs	✓	✓	✓	✓	✓	✓	✓	S-hous	✓	S-hous
Grid interaction	buy+ sell	buy	buy+ sell	buy+ sell	buy+ sell	buy+ sell	buy	buy+ sell	buy	buy
ESSs	✓	✓	✓	×	common	✓	S-hous	×	✓	S-hous
Load shifting	✓	×	×	✓	×	×	×	×	×	×
Time horizon	day-ahead	real-time	rolling horizon	day-ahead	rolling horizon	real-time	day-ahead	real-time	day-ahead	day-ahead
Grid price	RTP	RTP	RTP	fixed	time-var.	ToUP	RTP	RTP	RTP	RTP
Internal price	×	×	×	✓	×	✓	✓	✓	×	✓
Data	✓	stochastic demands	✓	✓	✓	✓	✓	✓	✓	✓
Game	×	×	×	×	×	×	×	Pros COAL	COAL	COAL
Solution	ADMM NBS	ONL	MPC	DIS-IT	MPC	CS	LP	OEA ASV	LP SV	LP SV
Perspective	D	D	D	D	C	C	C	C	C	C

back electricity to the power grid. Different pricing schemes are considered for energy purchased from the power grid. Moreover, some methods also consider internal pricing for energy traded among the collaborative entities. Real-time optimization is considered in some cases. Other methods employ day-ahead optimization and hence, scheduling the energy related events for this entire period. Once again it can be seen that a clear distinction and classification of the methods cannot be made. This can be observed also from the performances reported by the reviewed methods which are summarized in Table 4.4. Quantitative results on cost reduction are not reported in [117] and [123]. Consequently, these methods could not be included in the table. The best performance on cost reduction is reported in [112]. Differently from the methods proposed in Publications IV, V and VI, the method in [112] proposes an MPC-based method for energy management within systems of networked microgrids. MPC is frequently used in various DR methods such as those for microgrid energy planning [124], or controlling industrial loads [125]. The MPC-based techniques provide

Table 4.4. A comparison regarding cost reduction of DSM methods for collaborative interactions at distribution level. The following notations are used optimiz.- optimization, NONC-non-cooperative, P- Publication.

Method	[110]	[111]	[112]	[115]	[116]	P IV	P V	P VI
Cost reduction value	13.2%	4.7-6.1% cost increase	13.8-51%	5%	25% /kWh	12-50% S-hous, 7-8% P-cons	18%	18% S-hous, 3% P-cons
Comparison benchmark	NONC optimiz.	offline algorithm	individual optimiz	grid trade	S-logic	individual optimiz., grid consumption	individual optimiz.	individual optimiz., grid consumption
Simulation period	1 day	1 week	1 day	1 day	1 year	31 days	31 days	31 days

frameworks for constrained dynamic optimization and typically involve a rolling horizon optimization time frames. One advantage of such techniques is that they may capture more accurately the changes in time of the renewable energy production or demand, for example. This may be due to the fact that in each new optimization, or control step, updated forecasts of the employed data are considered. Due to this re-computation of the optimization or control process the MPC-based methods are, however, computationally more heavy. Thus, they may not be applicable for very complex problems that require long computation time. Single day cost reductions between 13.8% and 51% for the cooperating, networked microgrids are reported in [112]. For the considered day, the cost savings of 13.8% are obtained in case of a network of five microgrids, while the 51% cost savings are obtained in case of a network of fifteen microgrids. It results that the cost savings increase with the number of cooperating microgrids. In [116] the system cost is analyzed with respect to the number of wind turbines installed in the system. Also, the benchmark method used for comparison is a heuristic supervision logic method (S-logic) which is a not an optimal method. For a high number of turbines installed in the system the method provides an annual average cost reduction of 25% per 1kWh of consumed energy in comparison to S-logic. In [111], the proposed method presents an increase in costs in comparison to the offline benchmark solution, in a simulation performed over a one week period. The method in [110] achieves an aggregate cost reduction of 13.2% over a single day, in comparison to the non-cooperative, individual optimization benchmark method. In Publications IV, V and VI cost reductions are reported over a 31-days period. The non-collaborative, individual optimization is used as benchmark. In the scenarios considered in Publications V and VI, cost reductions of 18% are reported at the end of the 31-days period for the smart households owning RESs and/or ESSs. Note that even though Publications V and VI report same results for the smart household's cost reduction, the problems have different formulations. A 3% cost reduction is obtained by the pure consumers in Publication VI. Cost reduction values are reported for different amounts of renewable energy production in the community in Publication IV. Cost reductions of 12-50% and 7-8% are obtained for the smart collaborative households and pure energy consumers, respectively. The higher is the amount of produced renewable energy, the bigger is the reduction in cost also.

4.3 Methods for load balancing

Besides reducing costs, or achieving financial gains, another objective that drives interactions at distribution level is that of load balancing. Load balancing is usually sought by system operators, load aggregators, or utility companies that have the goal of matching supply and demand and cut the peaks in electricity consumption. These peaks are causing increases in electricity prices and require extra energy generation capacity. Load balancing does not imply discarding utilization of certain electricity consumables, but shifting part of the load from hours of high demand to hours of lower demand and hence, obtain a more flat profile of energy consumption. Methods for load balancing may also be identified with methods for peak shaving, valley filling, or load flattening, all basically having the same purpose. An extended overview on cooperative methods for energy consumption balancing and cost minimization can be found in [13]. In this thesis, this overview is updated by adding more recent methods considering interactive methods for load balancing and cost minimization.

One way of achieving load balancing is through price-based DR. All the price-based DR problems implicitly perform load balancing as well [100, 103], even though many of the state-of-the-art price-based DR methods are focusing on reporting only the cost reductions obtained by the consumers, i.e. the price takers. A price-based DR method that takes in consideration also load balancing is presented in [126]. The interactions among community energy aggregators and smart community households are studied through a two-level market model in order to minimize costs and balance the demand. The energy aggregators compete for buying energy from utility companies at low prices in order to satisfy the electricity demands of their respective communities. The smart households in the communities own smart appliances and they also compete against each other to schedule their smart appliances to work when the price is low. The interactions among aggregators and those among households are modeled as competitive games. It is shown that through proper dynamic pricing, the proposed framework not only reduces the electricity costs of the consumers but also balances the overall demand.

Other methods for load balancing may combine price-based DR with utilization of ESSs by varying the demand through charging and discharging the storage. Load balancing is achieved through interactions among utility company and residential consumers also in [127]. The utility company aims at reducing the mismatch between supply and demand, i.e. balance the electricity demand, by setting the price of sold energy as an increasing function of the demand. The residential electricity users own ESSs and want to minimize their cost. They can schedule the usage of their appliances either by using electricity directly from the power grid, or by using stored energy. A competition among residential energy users arises for consuming energy at the lowest price offered by the utility. The interactions among utility company and electricity users are modeled as a leader-follower Stackelberg game in which the utility company is the leader that establishes the prices, while the residential users are the followers that schedule their appliances such that the cost of energy purchased from the utility company is minimized. A distributed iterative entropic algorithm is proposed to solve the leader-follower game. This is a two step algorithm. In the first step, the electricity users receive prices from the utility company and optimize their electricity consumption. In the second step, the utility company receives the demand requests from the consumers and uses these demands to recalculate prices. These two steps are repeated until Stackelberg equilibrium is reached. The performance of the proposed game is discussed also in terms of achieved energy consumption balance. It is shown that the proposed game balances the consumption of electricity, achieving a pear-to-average ratio (PAR) of 1.3.

Battery storage is used also in [128] for providing peak shaving, frequency regulation and cost reduction for commercial energy users. The optimization of battery usage is done according to a price-based method. The electricity bill for the consumers consist of the cost of actual energy charged and a penalty for causing a peak in demand. The battery owners could also benefit financially by providing frequency regulation services to the grid against a certain incentive price. A joint optimization problem is formulated for minimizing the next day's cost which includes the energy consumption cost, peak demand penalties, battery degradation and operation costs as well as frequency regulation incentives. A multiple linear regression model is employed in order to predict the system's load for the day ahead. Similarly to the method in [128], another method that uses ESSs to achieve peak demand shaving while taking in consideration ESSs' constrains is proposed also in [129].

Energy consumption must be shaped for balancing supply and demand also in case of energy systems where renewable energy is utilized. Methods through which residential households owning RESs and ESSs can optimize their electricity usage and cooperate with the purpose to reduce the instability produced on the distribution grid by the renewable energy integration and balance the energy consumption are studied in [130]. First, a simple rule-based control approach is proposed for the households to independently decide their batteries' charge and discharge profiles. A distributed method is also proposed for the households, using own microcontrollers, to optimize and balance their renewable energy production profiles. A distributed hierarchical control method is proposed to allow the households to cooperate by buying and selling electricity among themselves, but also with the the main power grid. The purpose is of minimizing their costs and balance the electricity usage of the system. An iterative negotiation strategy controlled by a central market controller is proposed to determine the buying and selling prices within the system.

A method for load balancing in a residential area with EVs, ESSs and RESs is studied also in [131]. Residential energy users interact among themselves and with the system operator in a day-ahead market framework. The residences first predict and individually flatten their day-ahead demand profiles through a non-cooperative mixed strategy game. The system operator then plans the day-ahead purchase of electricity according to the aggregate demand profile of the residential electricity users.

Optimal energy consumption models using storage systems are proposed in [132] and [133] for minimizing electricity costs of residential energy users and balance the load on the power grid in the benefit of the utility company. In [132], an energy optimization model for a single household is provided. Two different energy optimization problems are tackled here. The first problem takes advantage of the time-varying market energy price and optimizes the household's electricity consumption and battery storage usage such that the household's energy consumption cost is minimized while fulfilling the energy demand. In this approach, the ESS of the household is used to store energy during hours when the prices are low and consume it when the price is high. Hence, the grid consumption profile is not uniform. In the second problem formulation, energy consumption balance and cost reduction are considered. For balancing the grid energy consumption while also reducing the cost, the objective function is modeled using the Cobb-Douglas production function from microeconomics [12]. Simulation results show that the cost minimization problem may achieve a 12% reduction in cost, while the second problem provides a balanced energy consumption while also reducing cost by about 8%.

The same principle for load balancing and cost reduction is proposed also in [133]. A cooperative model is proposed in which households from a community are served by same utility company and share a common community energy storage. The goal is again load balancing and cost reduction. A method to fairly allocate the stored energy among the cooperative households is proposed based on Shapley value. The stored energy is allocated to the community households in a proportion equal to the contribution of each household to the uniformity of the community's load profile.

In this thesis, the contribution related to collaborative methods for energy balancing using ESSs extends the work in [132, 133]. In Publication VII, a method for efficient integration of renewable energy resources and balancing the energy purchased from the power grid by a community of households is proposed. The community model is very similar to that in Publications IV, V and VI. In the smart grid community, some of the households, $\mathcal{M}$, produce renewable energy and own ESSs as well, while the remaining households are pure consumers. It is assumed that the households in the community are equipped with smart energy-management meters that can accurately predict their energy demand profiles and their renewable energy production profiles for a finite time period, $\mathcal{T}$, ahead. The aggregate energy demand of the community is: $\mathbf{u} = [u(t), t = 1, \ldots, T]$, while the renewable energy production profiles are again denoted by $\mathbf{w}_m = [w_m(t), t = 1, \ldots, T], m \in \mathcal{M}$. Each renewable energy producing household stores in its ESS in each time-slot total amounts of renewable energy: $\mathbf{s}_m = [s_m(t), t = 1, \ldots, T], m \in \mathcal{M}$. These amounts are delimited by the capacity of the storage, C_m. Day-ahead hourly market prices are considered for energy purchased from the utility company: $\boldsymbol{\xi} = [\xi(t), t = 1, \ldots, T]$. The proposed method is divided in two stages: one for renewable energy allocation within community and one for balancing the energy purchased from the power grid.

An off-line algorithm for scheduling the integration and allocation of the renewable resources produced within the smart grid community is proposed in the first stage. The algorithm calculates for each time-slot the amount of own produced renewable energy that should be consumed by each RES owning household to satisfy its current demand and the amount of renewable energy that must be saved in each household's ESS for meeting the demand of that household later within period $\mathcal{T}$. The remaining per-time-slot surplus of renewable energy, not needed for the household's own consumption in period $\mathcal{T}$, may be sold away to other households from the community which are in need of energy. In Publication VII, internal prices related to the amounts of energy exchanged among households are not considered. The method proposed in Publication VII focuses strictly on cost reductions achieved by the community with respect to the energy consumed from the power grid. However, in order to have a trade which is fair to all the RESs owning households, it is considered that each RES owner can give away to others only a limited amount of his surplus of renewable energy in each time-slot. The amount of renewable energy that one household may give away in a time-slot should be proportional to the overall renewable energy available within the community in that time-slot. This will make sure that in case of a financial trade in which a renewable energy producer may sell his energy surplus at a certain price, the possible financial benefit obtained in each time-slot by the producer is proportional to the ratio between his renewable energy production and the renewable energy produced by the other households in the community. Hence, for obtaining a fair allocation of the renewable energy within the community, the total energy demand of the community at every time-slot is first reallocated to each RES owners only as:

$$\mu_m(t) = \left[\frac{w_m(t) + s_m(t-1)}{\sum_{m \in \mathcal{M}} (w_m(t) + s_m(t-1))} \right] u(t), \tag{4.5}$$

where $\mu_m(t)$ is the energy demand of household $m \in \mathcal{M}$ after the reallocation of the community demand and $s_m(t-1)$ is the renewable energy amount existing in the storage m at the end of previous time-slot. The difference between the available renewable energy supplies of a household $m \in \mathcal{M}$ and the energy demand at time-slot t is:

$$\Omega_m(t) = w_m(t) + s_m(t-1) - \mu_m(t), t = 1, \ldots, T. \tag{4.6}$$

The energy required by a RES owner m from the main power grid, at each time-slot, $g_m(t)$, in order to fulfill the new demand is:

$$g_m(t) = |\min\{\Omega_m(t), 0\}|, t = 1, \ldots, T, \tag{4.7}$$

where $|\cdot|$ denoted the absolute value. The total amount of renewable energy stored at the end of a time-slot in an ESS is given by:

$$s_m(t) = \min\{\max\{\Omega_m(t), 0\}, C_m\}, t = 1, \ldots, T. \tag{4.8}$$

A heuristic algorithm is proposed for computing the allocation and trade of renewable energy. The amount of energy needed by the community from the main power grid is also computed using this algorithm. The detailed description of the proposed algorithm for renewable energy integration and allocation can be found in Publication VII.

After the allocation of renewable energy, the set of aggregate amounts of energy that the community still requires from the power grid for fulfilling the demand in period $\mathcal{T}$ is: $\mathbf{g} = [g(t), t = 1, \ldots, T]$. This energy demand may be highly variable in time. In order to obtain balanced grid consumption over time period $\mathcal{T}$ for the community, in the second stage of the proposed method, a GP-based optimization method is used. This optimization is formulated using the Cobb-Douglas production function [134] for modeling the objective function:

$$\max_{b} \prod_{t=1}^{T} b^{\alpha_t}(t), \tag{4.9}$$

where $\mathbf{b} = [b(t), t = 1, \ldots, T]$ is the balanced energy consumed from the power grid for the community and $\alpha_t = \frac{\sum_{j=1, j \neq t}^{T} \xi(j) g(j)}{(T-1)\sum_{t=1}^{T} \xi(t) g(t)}$, with $\sum_{t=1}^{T} \alpha_t = 1$, represents the elasticity parameter of the Cobb-Douglas production function. This method makes use of the available ESSs in order to control the consumption and have a constant energy consumption level from the power grid, achieving a very low PAR. Moreover, it will also reduce the cost of electricity consumption from the power grid. It can be seen in Figure 4.5 that the GP-based method balances the load by reducing the PAR values by 52% and may provide a also a cost reduction of 4%. In the considered scenarios, the overall reduction in cost resulted through the method proposed in Publication VII for the energy consumed from the power grid by the community is about 10.5%.

Local interactions at distribution level may not only occur with the goal of minimizing costs or balance the supply and demand. There may be other reasons for the cooperation. For example in [135], households own RESs and ESSs and operate in an isolated mode, disconnected from the main power grid. The households decide to cooperate in order to minimize their energy delivery interruptions and maximize the usage of the available energy generation. Self sustainability in a community of energy prosumers may be achieved by establishing a market within the community network in which individual actions and interactions among the network's members are driven by the individual comfort and benefits

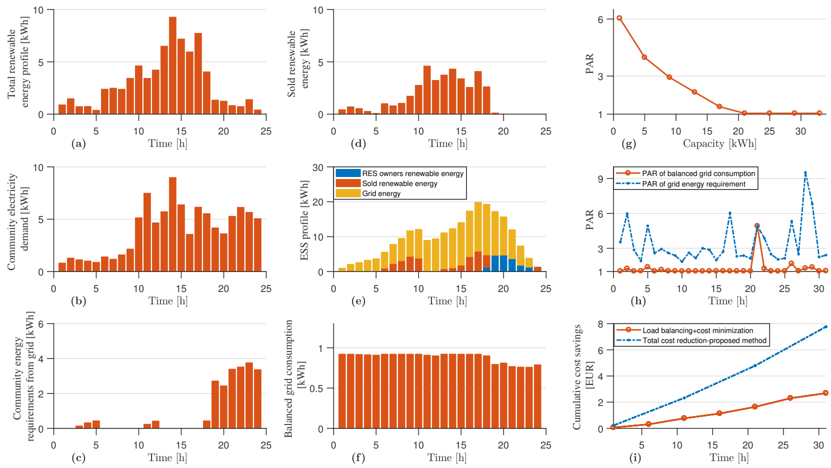

Figure 4.5. Renewable energy integration, load balancing and cost reduction. (a): the community's 24-hour wind energy production profile. (b): the total energy demand of the community. (c): the profile of the required grid energy. (d): the total amount of renewable energy sold per time-slot. (e): the community's total ESS profile including wind energy and grid energy stored for load balancing purpose. (f): the balanced grid consumption profile. (g): the variation of the PAR as a function of total capacity C_m. For capacity above 22kWh the PAR values are 1.04. (h): the PAR values of the grid demand and of the balanced consumption for 31 days. (i): the cumulative cost savings over 31 days. Copyright 2016 IEEE.

of the members [136]. A communications network between the smart meters of agents (prosumers and distributors) is employed in [137] to directly exchange control signals. Based on this communications network, a control method for energy transfers between microgrids of prosumers and distributors is proposed. In order to integrate small scale energy markets into the power system, such as those formed within communities of households or microgrids, coordination between big market players and and the small scale energy markets at the distribution level is needed. Along with this, complex market strategies among players at different energy system levels need to be conceived [138, 139].

4.4 Discussion

In order to protect the environment and reduce pollution, prevent interruptions in power delivery and reduce costs, more and more RESs and ESSs are being locally installed at distribution level. Local interactions in terms of exchanging and transferring energy among the entities owning RESs and ESSs are required for a better usage of resources. The energy transfer may take place free of charge or may occur through trading energy for a price. Moreover, the entities can share information, storage space and other resources. Facilitated by modern two-way communications and power flow network, and functioning under control of DSM programs, energy sharing and trading among end energy users may bring various benefits to those who adopt them. Trading and sharing energy and storage space may provide a more sustainable and reliable local power delivery through a better integration of renewable resources, reduce the need of individually owned ESSs with large capacities and have a more balanced energy consumption from the power grid. These may also result in significant cost reductions as demonstrated in Publications IV, V, VI and VII.

In this chapter, state-of-the-art DSM methods that enable trading and sharing of energy and storage space among power grid entities at distribution level have been presented and discussed. First, methods driven by financial benefits were reviewed. These methods were further divided into two main categories: competitive methods and collaborative methods. The competitive methods focus on selfishly increasing financial benefits for each compeating entity. This occurs for example if the entity sells its surplus of renewable energy production at higher price than the others, buys larger amounts of electricity at cheaper price, or receives a larger share of renewable energy or storage space if these resources are commonly owned with others. Most state-of-the-art DSM methods for competitive settings are formulated using non-cooperative or Stackelberg game models.

Energy consumers or producers may also achieve financial and other benefits by collaborating, instead of competing. In collaborative settings, the participating entities are non-selfish and work together to achieve a common goal such as reducing energy cost. DSM methods for collaborative interactions are formulated either by establishing own set of rules defining the grounds for collaboration, or are modeled through cooperative game theory. The cooperation may take place in terms of exchanging and sharing energy, energy storage space and sometimes information too.

Collaborative frameworks for energy trading and sharing within a smart grid community have been proposed in Publications IV, V and VI with the purpose of minimizing electricity consumption costs. The community may include different types of households: households owning ESSs only, RESs and ESSs owners and pure consumers too, unlike other methods in literature. It is assumed that households are equipped with smart meters that can record their electricity demands and renewable energy production over time and accurately predict these values for the day ahead. Renewable energy is considered a free source of energy. Hence, energy sharing among households owning RESs and/or ESSs was assumed in Publication V with the aim of minimizing cost of purchasing electricity from the main power grid. In Publications IV and VI, smart households owning RESs and ESSs also sell energy to pure consumers at a lower price than that offered by the utility company. The focus in Publications IV and VI is on optimizing consumption and operational costs for RESs and ESSs owners. However, the pure energy consuming households also reduce their cost. Compared to state-of-the-art methods reporting single day simulation results, the studies in Publications IV, V and VI report simulation results for 31 consecutive days. It is shown that in few days the collaborative method does not work as good as the individual cost optimization solution used as benchmark for comparison. However, over longer time periods such as 31 days, the collaborative method achieves significant cost reductions. The smart households owning RESs and ESSs may achieve a cost reduction of 18% in comparison to individually optimizing their costs. By buying a part of their needed electricity from the renewable energy producing households at a cheaper price than that offered by the utility company, the pure consumers also reduced their cost by 3%, in the considered scenarios. This occurs when RESs and ESSs owners sell energy to pure consumers for a 10% discount in price compared to the utility company's price. The proposed methods may be improved if optimal local prices for energy traded among energy producers and consumers are determined. Finding such optimal pricing methods may be a topic for future research. The collaborative methods in Publications V and VI are modeled using coalitional game theory. In the proposed coalitional game models, all households owning RESs and/or ESSs participate in the game at all times. In this way, no discrimination may occur by excluding any community members. This coalitional model was considered to be the most suitable for modeling collaboration within residential communities. The obtained cost savings are distributed among the members of the grand coalition using the Shapley value. Shapley value is a method for fair revenue division. It allocates the savings among coalitional members according to the contribution of each member in obtaining these savings. In this way every participant receives a share of the benefit and have an incentive to participate in the coalitional game. The Shapley value method may be, however, a computationally heavy method for very large communities of households. The computational time for calculating the Shapley value increases exponentially with the number of players participating in the coalition. For example, when calculating the Shapley value for a group of M players, the LP optimization is computed a number of $2^M - 1$ times. Hence, the computational time may become very large on a conventional desktop computer. However, distributed computing systems, or cloud computing platforms shall be employed in the smart grid architecture. Thus, the computational time of such methods should be reduced considerably using such technologies. The proposed methods are solved in a centralized fashion by a control unit managing the flow of power and information within the community and between the community and utility company. Developing methods for ensuring security and privacy of public utilities could be a topic for future work.

In the second part of this chapter, methods that aim at balancing the energy consumption are reviewed. Price-based DR methods that shift the loads from times when the price is high to times of low price, not only reduce the costs of consumption, but inherently also balance the profile of the electricity consumption. Another way to balance the load is through scheduling the charging and discharging of ESSs. Local energy trading in a smart grid community is studied in Publication VII for allocating renewable energy. Also a method for balancing the profile of energy consumed by the community from the power grid is proposed. Internal prices for the energy trade are not considered here. The proposed method achieves balanced energy consumption profiles with PARs close to unity.

The methods proposed in this thesis for collaborative sharing and trading of energy require full knowledge of the renewable energy production and electricity demand over the considered optimization time frame. Achieving this knowledge may be a challenging task. Smart meters installed at home sites may record data on energy demand and renewable energy production and machine learning, signal processing, or advanced time series analysis methods may be employed to predict these values for a finite period ahead. Advanced methods for accurate prediction of residential electricity demand and renewable generation already exist [140, 141, 142, 143]. However, this is still an active topic for research and may represent a challenging topic for future work. Designing local energy market models is also in early stage of studies and development. Thorough research and development of regulations, standards and protocols are yet needed for a successful deployment of energy markets.

5. Summary

The smart power grid is envisioned as a complex cyber-physical system of distributed, but cooperating components. The physical system of the smart grid combines conventional power network infrastructure components such as power plants, transmission and distribution networks with modern power network components such as RESs, ESSs, smart controllable appliances and EVs. The physical system would be coupled with a cyber system consisting of sensing, optimization and control elements dispersed at different levels of the physical power network. This cyber system measures and monitors the status of the power network, controls it's operation and ensures a high quality power delivery to the end consumers. The operation of the cyber system relies on the existence of two-way communications and power flow network and smart data processing and optimization technologies. DSM will also be a fundamental component of the smart power grid. It facilitates achieving energy efficiency and smart use of power system resources and assets. DSM provides flexibility and resiliency to the power system and ensures efficient power delivery while minimizing costs. In order to obtain these benefits, DSM methods combine participation of end consumers and demand management policies to flatten the peaks in energy consumption, match generation and demand and overall provide a more balanced load on the grid.

The focus of this thesis is to develop DR methods that involve the active participation of end consumers. Price-based DR methods, a category of DSM methods that use dynamic prices to give consumers the possibility to reduce their electricity consumption cost, are proposed. This happens provided that they modify their consumption patters in response to these dynamic prices. Methods that schedule the home charging of EVs in order to minimize the charging costs are developed. The EVs are an environmentally friendly alternative to conventional vehicles powered by fossil fuel, hence more and more people are considering to purchase EVs. The EVs however, will significantly increase their electricity consumption and cost. The proposed EV charging methods take advantage of the time-varying electricity prices within a day, but also of the dynamic nature of prices on consecutive days. Day-ahead electricity prices are commonly known while a method using a BNN is employed to predict electricity prices for the second day ahead. Given known day-ahead electricity prices and predicted electricity prices for the second day ahead, the proposed methods schedule the charging of the EV's battery such that the long term cost of charging is reduced for the owner, while the owner's driving needs are also fulfilled. Using an infinite horizon MDP model with unknown state transition probabilities the EV charging problem is formulated to take daily decisions on the amounts of energy to be charged in the EV's battery. The EV charging problem is solved using SARSA and batch fitted-Q iteration RL algorithms. Optimal schedule for the charging of the EV within a day is found by using standard LP methods. The proposed approach on EV charging may reduce the owner's long term cost of charging by 10% in comparison to the optimal daily charging method and by 50% in comparison to the conventional, not optimized charging method.

Enabling local interactions such as energy exchange and trade, share of energy storage capacity and information among energy producers and consumers at the distribution level of the grid may also bring important benefits to the power system. The power system becomes more flexible and the need for power plants to generate extra power capacity during consumption peaks may be reduced. Through energy exchange and trade, on site energy supplies such as those from RESs would become more sustainable. The interacting participants may benefit by reducing their costs related to energy consumption too. DSM methods that exploit the bidirectional power flow are developed in this thesis. They facilitate exchanging energy within communities of households owning RESs and/or ESSs. A price-based DR method is proposed to minimize cost of consumed energy and other energy related operational costs in a community of households owning RESs and/or ESSs. In order to minimize their costs, the households owning RESs and/or ESSs exchange energy among themselves and share their energy storage spaces. They also sell energy to pure consumers. The cost minimization problem is formulated as a linear program solved in a centralized fashion. Using a mathematical model from cooperative game theory, the problem of exchanging and trading energy in the community is formulated as a coalitional game such that each participating household may reduce their costs. The payoff that each household receives is proportional to the households' contribution to the overall cost savings obtained by the community. In the considered scenarios, the households forming the coalition may reduce their overall cost by 18% in comparison to not collaborating and optimizing their energy consumption individually. The pure energy consuming households also reduce their costs by buying part of their needed energy from the RESs and ESSs owning households at a discounted price (10% in our studies) in comparison to electricity prices offered by utility company. By finding methods to define and compute optimal trading prices, the developed methods may reduce the costs even further. Developing optimal pricing methods in also very important in designing efficient energy market models. Investigating optimal and regularized trading prices in local energy markets may represent a challenging topic for future work.

Besides reducing costs related to energy consumption, balancing load on the grid is another important goal of DSM. A DSM method to minimize electricity cost and balance the energy consumed by a community of households from the main power grid is proposed. The method facilitates integration of renewable energy produced by households owning RESs. For the energy required from the main power grid, the method uses the ESSs within the community to charge them with energy drawn from the grid during hours of the day with low electricity prices and use that energy during peak price hours. By using mathematical formulation stemming from microeconomy, the load balancing problem is written in the form of a GP-based optimization method. The method schedules the community's energy consumption from the power grid and provides an energy consumption profile with a PAR close to unity.

The DSM methods developed in this thesis are designed to work in an automatic manner, controlled by smart meters and central control units, without the need of end consumers to manually control their appliances. Hence, the developed methods are applicable in smart grids where an AMI is deployed and in case of households equipped with HANs. The methods proposed for optimizing the EV's home charging may be implemented at end customers' homes. The methods proposed for collaborative energy exchange and trade within communities of households are designed to be controlled by a central control unit. It remains to be studied whether centralized or decentralized control over residential loads is more effective and secure. Decentralized DSM methods are generally believed to make the power system more resilient to cyber attacks. In distributed methods, the end consumers do not need to share private information on their electricity consumption with a central operator either. Centralized control on the other hand, provides optimal results on aggregate load management and requires less infrastructure development. Moreover, a central operating system may be, in some cases, better at following the best practices in security than individual home owners.

The DSM methods developed in this thesis assume day-ahead knowledge of information for scheduling the energy consumption. While daily electricity prices are generally announced one day ahead by the utility companies, achieving full knowledge of renewable energy production and electricity demands over 24-hours period, or predicting EV's daily driving patters with high accuracy remains a challenging task. Developing methods that can reliably predict the renewable energy generation, driving patterns of EVs, electricity demands and prices over long time periods is an active topic of research and can represent a challenging topic for future work. Furthermore, the DSM methods proposed in this thesis may be improved by taking into account the variability of the electricity demand, renewable energy generation and of EV's driving patterns. Finding efficient solutions that solve the resulting DSM problems can also be a challenging task for future work. Designing local energy market models is also in early stage of studies and development. Deployment of such energy markets rely on the development of a complex power grid architecture and infrastructure, but also of regulations, standards and protocols.

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