



HAL
open science

Coordination mechanisms for smart homes electric energy management through distributed resource scheduling with demand response programs

Berk Celik

► **To cite this version:**

Berk Celik. Coordination mechanisms for smart homes electric energy management through distributed resource scheduling with demand response programs. Electric power. Université Bourgogne Franche-Comté, 2017. English. NNT: 2017UBFCA013 . tel-01868463

HAL Id: tel-01868463

<https://theses.hal.science/tel-01868463>

Submitted on 5 Sep 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

SPIM

Thèse de Doctorat



école doctorale sciences pour l'ingénieur et microtechniques

UNIVERSITÉ DE TECHNOLOGIE BELFORT-MONTBÉLIARD

Coordination mechanisms for smart homes electric energy management through distributed resource scheduling with demand response programs

■ BERK CELIK

SPIM

Thèse de Doctorat



école doctorale sciences pour l'ingénieur et microtechniques
UNIVERSITÉ DE TECHNOLOGIE BELFORT-MONTBÉLIARD

N° 0 0 1

THÈSE présentée par

BERK CELIK

pour obtenir le

Grade de Docteur de

l'Université Bourgogne Franche-Comté

Spécialité : **Génie électrique**

Coordination mechanisms for smart homes electric energy management through distributed resource scheduling with demand response programs

Unité de Recherche :
FEMTO-ST

Soutenue publiquement le 29 septembre 2017 devant le Jury composé de :

MANUELA SECHILARIU	Rapporteuse	UTC, AVENUES
BRUNO FRANCOIS	Rapporteur	ÉCL, L2EP
STÉPHANE CAUX	Examineur	INPT – ENSEEIHT, LAPLACE
DELPHINE RIU	Examinatrice	INPG – ENSE3, G2ELAB
SIDDHARTH SURYANARAYANAN	Examineur	Colorado State University
ABDELLATIF MIRAQUI	Directeur de thèse	UTBM
ROBIN ROCHE	Co-encadrant	UTBM, FEMTO-ST
DAVID BOUQUAIN	Co-encadrant	UTBM, FEMTO-ST

ABSTRACT

Grid modernization through philosophies as the Smart Grid has the potential to help meet the expected world increasing demand and integrate new distributed generation resources at the same time. Using advanced communication and computing capabilities, the Smart Grid offers a new avenue of controlling end-user assets, including small units such as home appliances. However, with such strategies, decisions taken independently can cause undesired effects such as rebound peaks, contingencies, and instabilities in the network. Therefore, the interaction between the energy management actions of multiple smart homes is a challenging issue in the Smart Grid.

Under this purpose, in this work, the potential of coordination mechanisms established among residential customers at the neighborhood level is evaluated through three studies. Firstly, coordinative home energy management is presented, with the aim to increase local renewable energy usage in the neighborhood area by establishing energy trading among smart homes, which are compensated by incentives. The control algorithm is realized in both centralized and decentralized manners by deploying a multi-agent system, where neighborhood entities are modeled as agents. Simulations results show that both methods are effective on increasing local renewable energy usage and decreasing the daily electricity bills of customers. However, while the decentralized approach gives results in shorter time, the centralized approach shows a better performance regarding costs.

Secondly, two decentralized energy management algorithms are proposed for day-ahead energy management in the neighborhood area. A dynamic pricing model is used, where price is associated to the aggregated consumption and grid time-of-use scheme. The objective of the study is to establish a more advanced coordination mechanism (compared to previous work) with residual renewable energy is shared among smart homes. In this study, the performance of the algorithms is investigated with daily and annual analyses, with and without considering forecasting errors. According to simulations results, both coordinative control models show better performance compared to baseline and selfish (no coordination) control cases, even when considering forecasting errors.

Lastly, the impact of photovoltaic systems on a residential aggregator performance (in a centralized approach) is investigated in a neighborhood area. In the proposed model, the aggregator interacts with the spot market and the utility, and proposes a novel pricing scheme to influence customers to control their loads. Simulation results show that when the penetration level of residential photovoltaics (PV) is increased, the aggregator profit decreases due to self-consumption ability with PV in the neighborhood.

Overall, developed coordination mechanisms provide benefits to both the neighborhood (peak load reduction) and the home levels (daily costs). The vital outcome of this dissertation, no matter the type of the smart home (with/without generation and storage), all smart homes achieved to reduce their daily electricity bills, thus the participation of the end-users secured with the influence of the economical benefits. Moreover, the presented methods contribute to the reduction of carbon-dioxide emission in two ways: increasing

renewable energy utilization, and decreasing dependency on peaking generators.

Keywords: Smart grid, demand response, demand-side management, multiple households coordination, rebound peak, residential energy management

RÉSUMÉ

La modernisation des réseaux électriques via ce que l'appelle aujourd'hui les réseaux intelligents (ou *smart grids*) promet des avancées pour permettre de faire face à une augmentation de la demande mondiale ainsi que pour faciliter l'intégration des ressources décentralisées. Grâce à des moyens de communication et de calcul avancés, les *smart grids* offrent de nouvelles possibilités pour la gestion des ressources des consommateurs finaux, y compris pour de petits éléments comme de l'électroménager. Cependant, ce type de gestion basée sur des décisions prises indépendamment peuvent causer des perturbations tels qu'un rebond de consommation, ou des instabilités sur le réseau. La prise en compte des interactions entre les décisions de gestion énergétique de différentes maisons intelligentes est donc une problématique naissante dans les *smart grids*.

Cette thèse vise à évaluer l'impact potentiel de mécanismes de coordination entre consommateurs résidentiels au niveau de quartiers, et ce à travers trois études complémentaires. Tout d'abord, une première stratégie pour la gestion coordonnée de maisons est proposée avec l'objectif d'augmenter l'utilisation locale d'énergie renouvelable à travers la mise en place d'échanges d'énergie électrique entre voisins. Les participants reçoivent en échange une compensation financière. L'algorithme de gestion est étudié dans une configuration centralisée et une configuration décentralisée en faisant appel au concept de système multi-agents, chaque maison étant représentée par un agent. Les résultats de simulation montrent que les deux approches sont efficaces pour augmenter la consommation locale d'énergie renouvelable et réduire les coûts énergétiques journaliers des consommateurs. Bien que l'approche décentralisée retourne des résultats plus rapidement, l'approche centralisée a une meilleure performance concernant les coûts.

Dans une seconde étude, deux algorithmes de gestion énergétiques à J-1 sont proposés pour un quartier résidentiel. Un modèle de tarification dynamique est utilisé, où le prix dépend de la consommation agrégée du quartier ainsi que d'une forme de tarification heures creuses-heures pleines. L'objectif est ici de concevoir un mécanisme de coordination plus avancé (par rapport au précédent), en permettant des échanges d'énergie renouvelable résiduelle au sein du quartier. La performance des algorithmes est étudiée sur une période d'une journée puis d'une année, en prenant ou non en compte les erreurs de prévision. D'après les résultats de simulation, les deux algorithmes proposés montrent de meilleures performances que les méthodes de référence (sans contrôle, et algorithme égoïste), même en considérant les erreurs de prévision.

Enfin, dans une troisième étude, l'impact de l'introduction de production photovoltaïque résidentielle sur la performance d'un agrégateur est évaluée, dans une configuration centralisée. L'agrégateur interagit avec le marché spot et le gestionnaire de réseau, de façon à proposer un nouveau modèle de tarification permettant d'influencer les consommateurs à agir sur leur consommation. Les résultats de simulation montrent quand le taux de pénétration de photovoltaïque résidentiel augmente, le profit de l'agrégateur diminue, du fait de l'autoconsommation dans le quartier.

Dans l'ensemble, les mécanismes de coordination ont des avantages à la fois au niveau des quartiers (réduction du pic de demande) que des maisons individuelles (réduction des coûts énergétiques). Un des résultats importants de ce travail est que quel que soit le type de maison et sa configuration (avec ou sans production et stockage), tous les consommateurs peuvent réduire leur facture énergétique, ce qui permet d'assurer un niveau minimum de participation des consommateurs. De plus, les méthodes présentées contribuent à la réduction des émissions de dioxyde de carbone en permettant une meilleure utilisation locale des énergies renouvelables ainsi qu'en diminuant le recours à des générateurs de pointe.

Mots-clés : Réseau intelligent, effacement diffus, gestion de la demande, maison intelligente, quartier intelligent, gestion de l'énergie résidentielle

ACKNOWLEDGMENTS

This work would not have been possible without the support and helps of many researchers, colleagues and friends.

I would like to thank, firstly, Prof. Manuela Sechilariu and Prof. Bruno Francois for accepting to review this dissertation, despite their very busy schedules, and for their helpful comments. I would also like to thank Prof. Stéphane Caux, Prof. Delphine Riu, and Prof. Siddharth Suryanarayanan for accepting to participate in my defense.

I would like express my sincere appreciations to the director of my thesis, Prof. Abdellatif Miroui for selecting me for this Ph.D. position and giving me the opportunity to accomplish this doctoral research. Then, I would like to thank my co-supervisors Dr. David Bouquain and Dr. Robin Roche for their guidance and support throughout the years of my Ph.D. studies. I would especially like to thank and present my deepest gratitude to Dr. Robin Roche, for his encouragement, understanding, his valuable advices, and last but not least for having trusted me during the last three years.

I would also address special thanks to Prof. Siddharth Suryanarayanan for inviting me to Colorado State University, USA, and giving me this great opportunity to work with him and the members of the Advanced Power Engineering Laboratory (APEL). I owe enormous gratitude to him for providing me with his complementary and invaluable expertise. It has been a fantastic experience where I learnt a lot, and that helped me achieve my goals. I must also thank Prof. Howard Jay Siegel and Prof. Anthony A. Maciejewski for their valuable contributions and suggestions to my doctoral research, and the members of APEL: Ms. Swagata Sharma, Mr. Fathalla Eldali, Mr. Rahul G.Kadavil, Mr. Turki Alaqeel and Mr. Sulaiman Almohaimed for their warm welcome and help.

During the three years of my doctoral studies, many researchers I met and worked with generously shared their expertise and friendship with me. I thank them all: Prof. Timothy Hansen, Prof. Fei Gao, Dr. Damien Paire, Dr. Alexandre Ravey, Dr. Daniela Chrenko, Dr. Yiming Wu, Dr. Nanfang Yang, Mr. Bei Li, Ms. Citlalli Gamez, and all the engineers, technicians.

I appreciate the financial support of UTBM for funding me during my doctoral research, and the Electrical and Computer Engineering Department of Colorado State University for hiring me as a non-student employee to help co-fund my extensional stay.

Finally, I express my deepest gratitude to my best friends: Nuri, Umut, Ihsan, Kerem and Mustafa, who have never withheld their great support and left me alone in this difficult journey. My warmest gratitude should also be expressed to my parents and my precious little sister Ipek for being supportive of me through all these years. I owe an enormous amount to my parents for their constant encouragement to push onwards and to give the best of myself. I may certainly not have continued this far on my studies without their endless motivation.

ACRONYMS

<i>ADHDP</i>	Action dependent heuristic dynamic programming
<i>AS</i>	Ancillary services
<i>AMI</i>	Advanced metering infrastructure
<i>ANFIS</i>	Adaptive neural fuzzy inference system
<i>CES</i>	Community energy storage
<i>CIP</i>	Customer incentive pricing
<i>CM</i>	Capacity market
<i>CPP</i>	Critical peak price
<i>CO₂</i>	Carbon-dioxide
<i>DB</i>	Demand bidding
<i>DER</i>	Distributed energy resources
<i>DG</i>	Distributed generation
<i>DLC</i>	Direct load control
<i>DM</i>	Decision-making
<i>DSM</i>	Demand-side management
<i>DR</i>	Demand response
<i>EDR</i>	Emergency demand response
<i>EV</i>	Electric vehicle
<i>FERC</i>	Federal energy regulatory commission
<i>FIT</i>	Feed-in-tariff
<i>GA</i>	Genetic algorithm
<i>GUI</i>	Graphical User Interface
<i>GT</i>	Game theory
<i>HAN</i>	Home area network
<i>HEMS</i>	Home energy management system
<i>HPC</i>	High performance computing
<i>HVAC</i>	Heating-ventilation-air-conditioners
<i>IBR</i>	Incremental block rate
<i>I/C</i>	Interruptible/curtailable
<i>ICT</i>	Information and communication technology
<i>JADE</i>	JAVA agent development
<i>IBP</i>	Incentive-based programs
<i>LSE</i>	Load serving entity
<i>MAS</i>	Multi-agent system
<i>MG</i>	Microgrid
<i>MINLP</i>	Mixed-integer nonlinear program
<i>MPI</i>	Message passing interface
<i>NAN</i>	Neighborhood area network
<i>OA</i>	Omnipath Architecture
<i>Open-MP</i>	Open-multi processing
<i>PAR</i>	Peak-to-average ratio

<i>PBP</i>	Price-based programs
<i>PCC</i>	Point of common coupling
<i>PDC</i>	Peak demand charge
<i>PHEV</i>	Plug-in hybrid vehicles
<i>PSO</i>	Particle swarm optimization
<i>PV</i>	Photovoltaic
<i>RES</i>	Renewable energy sources
<i>SGRA</i>	Smart grid resource allocation
<i>SM</i>	Success Metric
<i>SMAPE</i>	Symmetrical mean absolute percentage error
<i>RTP</i>	Real-time price
<i>SCADA</i>	Supervisory control and data acquisition
<i>SG</i>	Smart Grid
<i>TCP/IP</i>	Transmission control protocol/Internet protocol
<i>T & D</i>	Transmission and distribution
<i>THA</i>	Two-horizon algorithm
<i>TOU</i>	Time-of-use

CONTENTS

I	Introduction	1
1	Demand-Side Management in the Smart Grid	3
1.1	Concept of smart grid	4
1.2	Electric energy management	5
1.2.1	Demand side management	5
1.2.2	Demand response	7
1.3	Flexibility of demand-side resources	8
1.3.1	Residential sector	9
1.3.2	Commercial sector	11
1.3.3	Industrial sector	12
1.3.4	Transportation sector	12
1.4	Problem statement	13
1.5	Organization of the dissertation	14
2	State-of-the-Art Review	17
2.1	Load modeling techniques	17
2.1.1	Top-down approaches	17
2.1.2	Bottom-up approaches	18
2.2	Home energy management in the residential sector	18
2.2.1	Incentive-based single home energy management	19
2.2.2	Price-based single home energy management	19
2.3	Neighborhood energy management	21
2.3.1	Concept of neighborhood area	21
2.3.1.1	Neighborhood area structure	22
2.3.1.2	Role of entities	22
2.3.2	Coordination structure and objectives	23
2.3.2.1	Centralized coordination	23
2.3.2.2	Decentralized coordination	25
2.3.3	Coordination techniques	29

CONTENTS

2.3.3.1	Multi-agent systems	29
2.3.3.2	Game-theoretic approaches	31
2.3.3.3	Optimization techniques	33
2.4	Overview of the state-of-the-art	34
II	Coordination Mechanisms	39
3	Incentive-Based Renewable Energy Trading Among Smart Homes	41
3.1	System model	42
3.1.1	Home energy system	42
3.1.1.1	Consumption model	43
3.1.1.2	PV generation model	44
3.1.1.3	Energy storage model	45
3.1.2	Neighborhood area	45
3.1.3	Electricity pricing: neighborhood incentive model	46
3.2	Problem formulation	47
3.2.1	Baseline scenario	47
3.2.2	Selfish scenario	48
3.2.3	Decentralized coordination	50
3.2.4	Centralized coordination	57
3.3	Simulation setup	58
3.3.1	Simulation parameters	59
3.3.2	Co-simulation platform	60
3.4	Performance evaluation	61
3.4.1	Cost and computation time analysis	61
3.4.2	Power and energy analysis	62
3.4.3	Scalability analysis	67
3.5	Conclusion	67
4	Dynamic Pricing-Based Decentralized Home Energy Sharing Coordination	69
4.1	System model	70
4.1.1	Home energy system	70
4.1.2	Forecasting error model	74
4.1.3	Electricity pricing: dynamic model	75
4.2	Problem formulation	77

4.3	Coordination mechanisms	80
4.3.1	Group-based coordination	80
4.3.2	Turn-based algorithm	81
4.3.3	Convergence	83
4.4	Performance evaluation	83
4.4.1	Daily simulation results	85
4.4.2	Annual simulation results	86
4.4.3	Scalability analysis	89
4.5	Conclusion	89
5	Aggregator-Based Asset Control with Residential PV Generation	91
5.1	System model	92
5.1.1	Smart home	92
5.1.2	Electricity network	92
5.2	Problem formulation	93
5.2.1	SGRA without considering residential PV generation	96
5.2.2	SGRA with considering residential PV generation	96
5.3	Parallel processing methods	100
5.3.1	Parallel processing with OpenMP	101
5.3.2	Parallel processing with MPI	102
5.3.3	Parallel processing with OpenMP/MPI	103
5.3.4	Performance of parallel processing techniques	104
5.4	Performance evaluation	106
5.4.1	Daily results of SGRA with/without PV	107
5.4.2	Weekly results of SGRA with/without PV	113
5.4.3	Scalability analysis	113
5.5	Conclusion	115
III	Conclusions	119
6	Conclusion	121
6.1	Contributions	121
6.2	Summary of Works	122
6.3	Future Works	123
	List of Figures	139

CONTENTS

List of Tables	143
IV Appendices	145
A Publications	147



INTRODUCTION

DEMAND-SIDE MANAGEMENT IN THE SMART GRID

The philosophy of the Smart Grid (SG) has emerged with the rapid modernization of the conventional electricity grid, by integration of many features from the fields of information and communication technology (ICT). The SG offers innovative power engineering solutions for sustainable energy management through integrated sensor, monitor, communication and automation technologies. An official definition of the SG by the European Technology Platform of Smart Grids is as follows: “a smart grid is an electricity network that can intelligently integrate actions of all users connected to it—generators, consumers and those that assume both roles— in order to efficiently deliver sustainable, economic and secure electricity supplies” [151].

To integrate SG features into the current electric grid, it has become necessary to gather information from all parts of the grid, process large amount data to determine efficient and reliable control strategies, and perform these actions in real time. Furthermore, the SG vision includes active end-user participation, which means that customers must have the ability to play a role in electricity markets and control operations through the ICT infrastructure.

Additionally, the SG vision contains new challenges to address issues such as global warming, increasing demand and energy prices, depletion of carbon-based fuel resources, and human health and safety concerns. It is thus a necessary concept to enable modified economic, social and environmental policies that could provide short-term and long-term benefits [148, 148]. To deal with these novel challenges, the SG enables to adapt new types of sources in the current electricity network, and offers opportunities for realizing a sustainable and reliable energy future [152].

SG systems are considered as the future of power systems, in that their features can contribute to resolve the above issues. However, the SG is a generic subject for power engineers, that contains a wide-range of topics. Thus, the implementation of the SG and its various applications into the current electricity network became popular and attracted significant attention by the power engineering community over the last few years. In this chapter, the concept of SG is briefly introduced for the residential, commercial, industrial and transportation sectors. Parts of this chapter are adapted from a published article [145].

1.1/ CONCEPT OF SMART GRID

Developments in ICT, control, communication, and associated applications have provided new tools for modernizing the traditional electricity grid. The evolution of the SG heralds a more interactive, distributed, and flexible role for the end-user in the day-to-day operations of the infrastructure. Consumers are provided access to near real-time information and can benefit from technologies such as two-way communication, distributed generation (DG) and controllable loads, thus changing from passive to active participants in the SG [92].

Electricity grid operators respond to the changing demand of consumers by adjusting generation and ensuring that transmission and distribution (T&D) assets are carrying no more than their rated value, efficiently and reliably. Historically, generation capacity was built to accommodate consumption peaks, i.e., the highest demand. But such peaks tend to increase over the years, for example due to population increase and the introduction of new consumption habits and devices (such as the personal computer in the 1990s and the projected electric vehicles growth in the coming decades). Although the increased electricity demand can be met by central bulk generation plants, the T&D system must be upgraded—at high cost—to accommodate these higher capacities. However, this kind of approach would be costly and too slow. On the other hand, distributed energy resources (DER)—located in proximity to end-user loads—provide a promising alternative to grid reinforcements, building new centralized bulk generation capacity, or building new or upgraded transmission lines.

DER are relatively small energy sources, with rated capacity ranging from a few kW in residential buildings to several MWs on the distribution grid. DER can also be either conventional (e.g., micro-turbines and diesel generators) or renewable energy sources (RES) (e.g., solar photovoltaic (PV), wind turbines and biomass converters). Due to growing concerns of climate change, RES are increasingly preferred to conventional sources.

One of the issues related to RES integration is their intermittent generation characteristic [49]. The stochasticity of RES output, combined with the uncertain behavior of the consumer, implies greater difficulties in ensuring a real-time balance between generation and demand for system operators. The uncertainty in availability of generation and demand can be mitigated using energy storage, but this solution is currently either prohibitively costly or inefficient at bulk levels, or fraught with environmental constraints (such as for pumped hydro storage systems). A recent change is that connecting additional RES is becoming less expensive than traditional grid reinforcements. However, this requires advanced control methods adequately integrate these sources in current electricity infrastructures.

Another approach is to increase the flexibility of demand-side resources, i.e., the electric loads. Such approaches require extensive, reliable information on the whole system. This data can be accessible through ICT, typically using sensors and supervisory control and data acquisition (SCADA) on the T&D system. This in turn enables monitoring and control of resources such as DER and storage, which may then result in reverse energy flows, from consumers to the utility. Through such local resources, end-users are thus able to actively participate in electric network operations. This is a major shift from traditional bulk power generation, as many more small-scale producers are expected to connect to the grid. Moreover, consumers can also be small-scale producers (prosumers) by investing in DER, and benefit from market opportunities by deploying SG technologies [41]. This in

turn facilitates improving energy efficiency for a better utilization of resources, at all levels of the networks, with bidirectional exchange of information and power. The concept of SG is illustrated in Fig. 1.1.

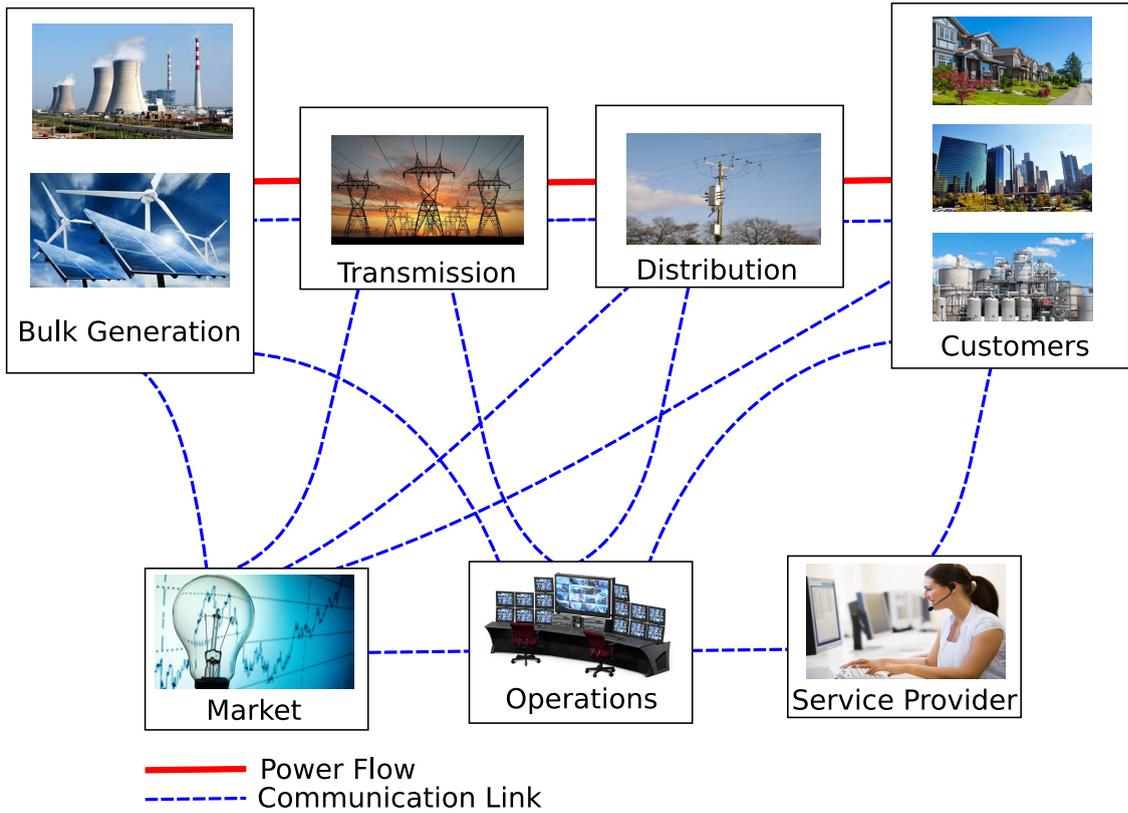


Figure 1.1: Conceptual model of the SG.

1.2/ ELECTRIC ENERGY MANAGEMENT

With the implementation of the advanced metering infrastructure (AMI) [42], customers become active participants by generating or storing energy, and/or changing their consumption patterns. Therefore, customer interaction plays a key role in network operations for the successful implementation of electric management strategies.

1.2.1/ DEMAND SIDE MANAGEMENT

Demand side management (DSM) approaches focus on improving the efficiency of utilization of energy resources in the customer domain. However, DSM can be applied to all types of energy resources, not just electricity. DSM is commonly defined as “the planning, implementation, and monitoring of those utility activities designed to influence customer use of electricity in ways that will produce desired changes in the utility’s load shape, i.e., changes in the time pattern and magnitude of a utility’s load. Utility programs falling under the umbrella of demand-side management include: load management, new uses, strategic conservation, electrification, customer generation, and adjustments in market share” [129, 45].

CHAPTER 1. DEMAND-SIDE MANAGEMENT IN THE SMART GRID

The following DSM approaches are listed in the literature according to their objectives [123]:

- **Peak shaving**, or reduction of the system peak load, aims to decrease peak power consumption during on-peak hours. Peak shaving can help reduce the necessary peaking capacity and hence lower operating costs and dependence on fossil fuels.
- **Valley filling** aims to increase demand during low consumption hours, in order to profit from lower prices, while decreasing the overall cost and improving the system efficiency.
- **Load shifting** reduces demand during on-peak hours by deferring loads to off-peak hours. It is commonly achieved by scheduling load operation times to flatten the consumption curve, and improve efficient generator use.
- **Strategic conservation** aims to reduce in the general load profile, for example via increased energy efficiency measures.
- **Strategic load growth** aims to “intelligently” increase the total load over the time horizon, beyond valley filling. This growth can result from transfers between types of energy, for example, related to the integration of heat pumps or electric vehicles.
- **Flexible load shaping** is a form of advanced consumption shaping, that sets load-limits at specific hours on the requirements of the grid, such as system reliability and planning constraints.

Peak shaving, strategic conservation and load shifting aim to reduce the load and are the most frequently listed techniques in the literature, as they enable deferring or canceling heavy investments in equipment with higher capacity (such as power lines and transformers). An illustration of the impact of the different approaches is shown in Fig. 1.2.

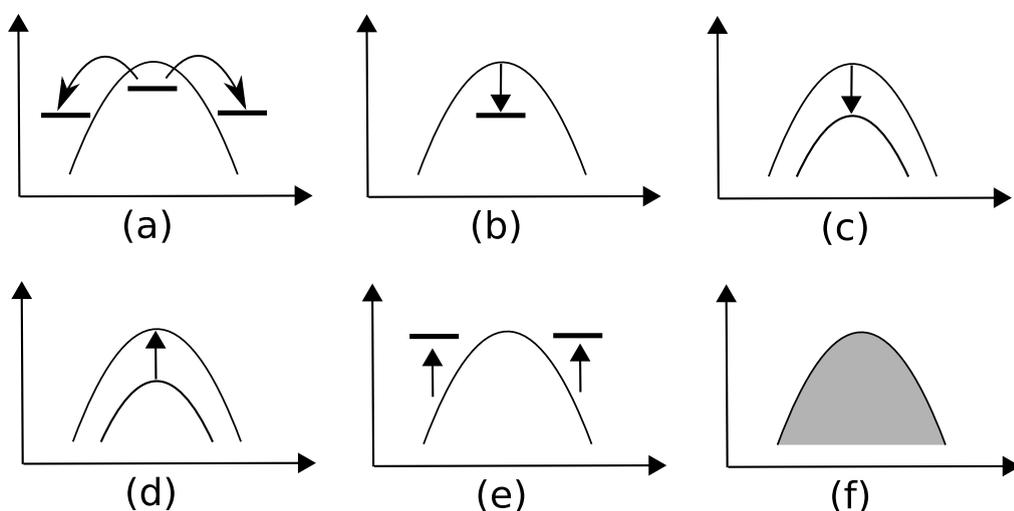


Figure 1.2: DSM approaches, adapted from [123]: (a) load shifting, (b) peak shaving, (c) strategic conservation, (d) strategic load growth, (e) valley filling, (f) flexible load.

1.2.2/ DEMAND RESPONSE

The demand response (DR) concept was introduced several decades ago, but has only gained widespread popularity over last few years due to progress in ICT and AML applications. The terms DR and DSM have relatively close meanings, but are used to address different philosophies. The goal of DR is to change end-users' consumption (i.e., the load curve), typically in the range of 1-4 h, as a result of interactions with a service provider, while the objective of DSM is to improve the efficiency of consumption from the customer side. A common definition of DR is: "changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity, or incentive payments designed to induce lower electricity use at time of high wholesale market prices or when system reliability is jeopardized" [13, 11].

In the literature, DR programs are mainly divided into two main groups [122]: incentive-based programs (IBP) and price-based programs (PBP). IBP and PBP programs are further subdivided by the Federal Energy Regulatory Commission (FERC) [44] as shown in Fig. 1.3.

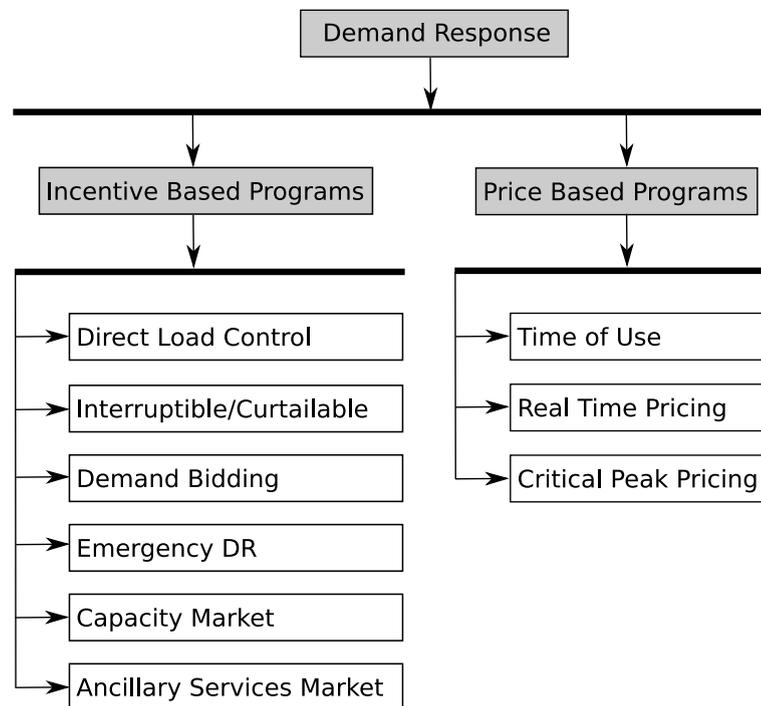


Figure 1.3: Types of DR programs.

IBP can be classified into six categories depending on their control modes: direct load control (DLC) [97, 126], interruptible/curtailable (I/C) [110], demand bidding (DB) [29], emergency DR (EDR) [103, 18], capacity market (CM) [26], and ancillary services market (AS) [111, 124]. In IBP, the participants receive a financial incentive if they change their consumption according to terms defined in a contract.

- In **DLC**, the service provider has a remote access to the loads of the customers and can directly control them.
- In **I/C**, the service provider only offers discounts to customers for a specific amount

CHAPTER 1. DEMAND-SIDE MANAGEMENT IN THE SMART GRID

of consumption reduction.

- **DB**, customers bid for load reduction at a given price, and if the bid is cleared, customers decrease their consumption, otherwise they are penalized by the service provider.
- In **EDR**, financial incentives are only offered for load reductions when the system reliability is in danger.
- In **CM**, load reductions are committed before the occurrence of the critical conditions.
- In **AS**, customers bid load reductions on the ancillary services market. If their bid is accepted, they perform the curtailment and receive the market price as a compensation.

In PBP, the utility indirectly affects the electricity consumption of the customers using time-varying pricing schemes, usually in order to reduce the peak consumption of demand. In other words, the time-varying pricing mechanisms (shown in Fig. 1.4) are designed to modify the behavior of the customer, thus the customer is able to change the amount and time of electricity energy usage depending on its preferences. Various pricing algorithms are used to encourage customers to actively participate [80, 121]:

- **Time-of-use (TOU)** is a pricing mechanism in which different rates are used depending on the time of the day. Several blocks of hours are defined as off-peak, average load and on-peak periods. The rate is designed to be higher during the on-peak periods, and lower during the off-peak periods [138].
- **Real-time pricing (RTP)** has dynamic rates that change for every hour of the day. The forecasts of these rates are given a day or an hour in advance by the service provider to the customers. RTP is more fluctuating than TOU and better reflects the real-time balance between generation and demand [119].
- **Critical peak pricing (CPP)** is a pricing mechanism that is sometimes used in addition to TOU in order to present higher charges to the customers during times when operating conditions are critical, such as during contingencies, and is therefore only used a few times a year [143].

DR programs are a key concept not only to reduce the electricity cost, but also to decrease carbon-dioxide (CO₂) emissions by reducing the need for polluting peaking power plants. As a consequence, DR is able to provide benefits for both the customers and the service provider. On the one hand, customers can change their consumption habits so that their electricity expenses are reduced, and on the other hand, DR helps the service provider by reducing the stress of operation on grid assets, decreasing outage risk, providing efficient utilization of RES, and securing grid reliability and stability.

1.3/ FLEXIBILITY OF DEMAND-SIDE RESOURCES

Understanding the operation of the different load types and user consumption habits on the customer side—residential, commercial, industrial and transportation—plays a key

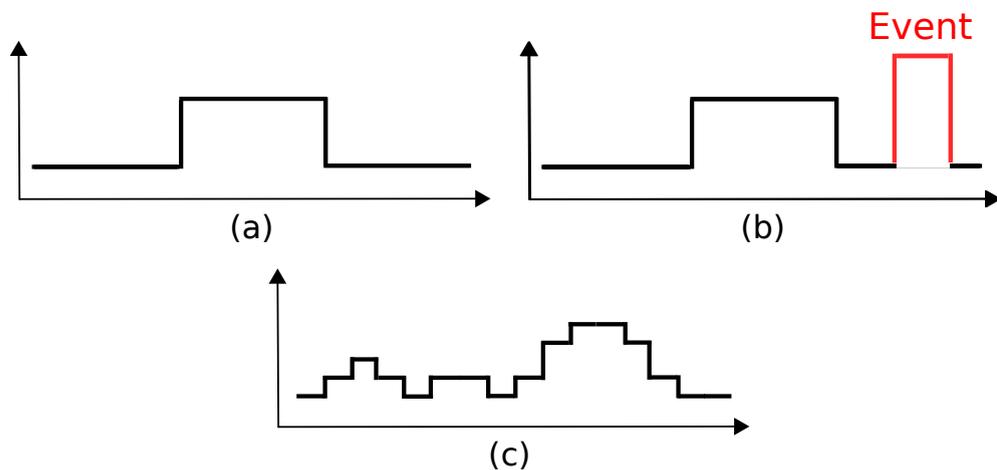


Figure 1.4: DR pricing shemas: (a) TOU, (b) CPP, (c) RTP.

role to determine flexibility options for DSM programs. Typically, flexibility is needed for applying load control algorithms in which customers respond to price signals, and/or enable remote control of their devices through DR programs. However, the provided flexibility capacity will be different for each sector, due to the diversity of equipment types and consumption purposes. Therefore, load curves and the participation opportunities of each electricity sector should be explored and classified for engagement of load-management models.

In Fig. 1.5, the electricity consumption percentage of each sector provided by the European Environment Agency for EU-27 countries in 2010 is shown [75]. The consumed electric energy is relatively close in residential, commercial and industrial sectors, which account for approximately 95% of all consumed electric energy. On the other hand, the transportation sector still has a small share with 2.4%. However, the highest energy consumption (i.e., not only electricity) is for the transportation sector with 31.7% (in Fig. 1.5) which means that other sources like petroleum and natural gas are the most commonly preferred resources for energy supply in the transportation sector.

1.3.1/ RESIDENTIAL SECTOR

Households are the main consumption sources in this sector, which represents 30% of the total energy consumption. Understanding the flexibility opportunities in this sector is non-trivial due to the distributed architecture and self-interested character of the users. Privacy concerns, levels of comfort, and diversity in household structures and equipment types are the primary obstacles.

However, over the last few years, classical residential building technologies have evolved to include more advanced features so as to enable the transformation of traditional structures into so-called “smart homes” [92]. These homes typically include schedulable appliances, DG, energy storage, electrical vehicle (EV), and a home energy management system (HEMS) controller providing access to near real-time information on electricity consumption, weather, changing electricity rates, and enabling technologies such as the Internet-of-things. Fig. 1.6 depicts the smart home concept with its components.

HEMS are responsible for managing the energy consumption, generation, and storage

CHAPTER 1. DEMAND-SIDE MANAGEMENT IN THE SMART GRID

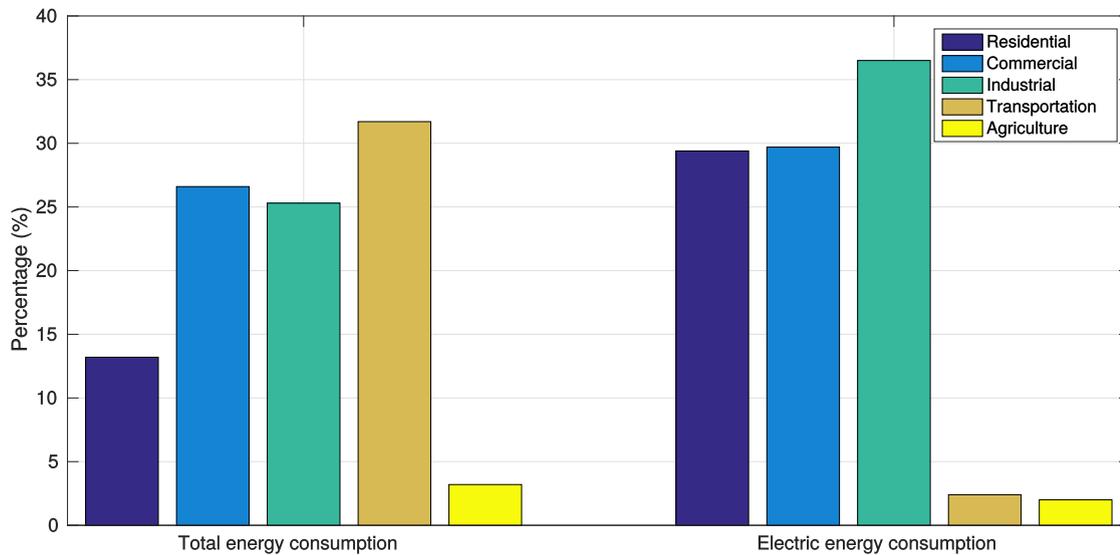


Figure 1.5: Total energy and electric energy breakdown for each sector.

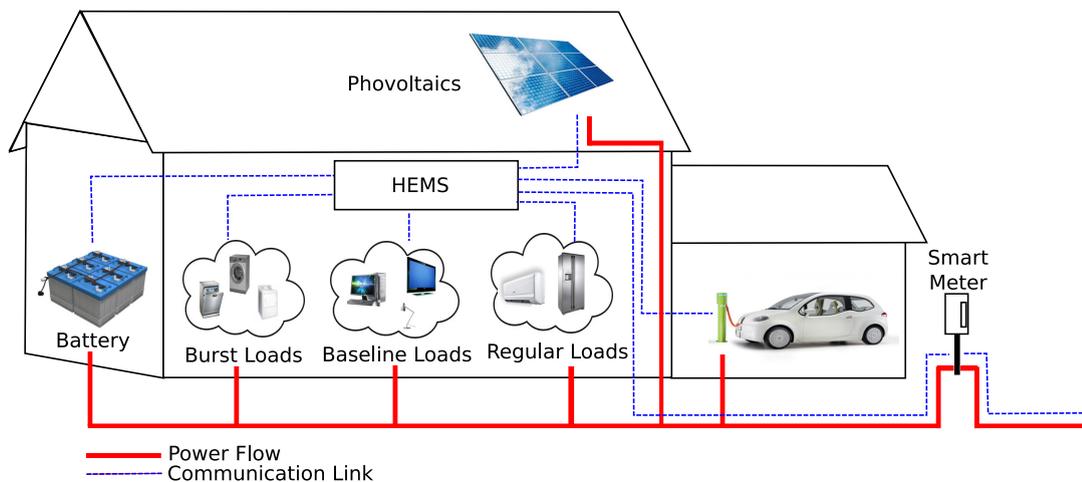


Figure 1.6: Smart home architecture.

needs of customers while meeting their comfort and economic requirements. Communication between the service provider and the customer is achieved through AMI and smart meters. Using the information provided by the service provider (e.g., forecast and real-time prices, DR requests) and local information on generation and loads, HEMS attempt to change the electricity profile of smart homes by adequately scheduling the use of local and grid resources.

In smart homes, the power consumption of the various loads can be measured by “smart plugs” [10], and additional information may be collected by sensors for environmental factors such as temperature and irradiance [81]. The gathered information is typically centralized by the HEMS, through wireline or wireless communication, together with the price signal. A graphical user interface (GUI), commonly delivered to the user via a computer interface or a smartphone app provides the user with information on current conditions (e.g., consumption, price). Such information is vital for making informed decisions, setting preferences for using smart appliances, or for overriding automatic schedules.

Household appliances are often divided into three categories, according to their operational characteristics and controllability, although terms may vary: baseline loads (not controllable), burst loads (fully controllable), and regular loads (partially controllable) [52]:

- **Baseline loads**, also called non-deferrable loads or must-run appliances, include appliances which are run directly by the customers, and are not controlled by an automated HEMS algorithm. As the usage of such loads is entirely dependent on end-user behavior, there are no exact operation time intervals for them. As a consequence, models of these loads typically rely on historical load profiles. Lighting, computers, televisions, ovens, music players and other electronic devices are examples of baseline loads.
- **Burst loads**, also called deferrable-shiftable or scheduable loads, have specific operation time intervals with a given energy consumption defined by the technical characteristics of the appliance. These loads can be shifted in time, and may also be paused at specific predefined cycle times. This ability enables significant energy consumption flexibility. For example, a washing machine cycle includes several phases. At the end of each phase, the machine can stop and resume its cycle a few minutes or hours later [107]. Similarly, a clothes dryer usually operates after a washing machines cycle is over. Therefore, the clothes dryer cycle may also be shifted several hours later [71].
- **Regular loads**, also called deferrable-thermal loads, are periodically working appliances with varied operation cycles, and that are affected by environmental conditions. These loads can be interruptible and manageable for short periods of time, depending on end-user preferences. Thermal loads such as electric water heaters, space heating, air conditioning and refrigerators are included in this category [68, 66].

In the residential sector, each end-user has different energy consumption habits depending on behavioral patterns, house occupancy, geographic location, climate conditions, and economics. Therefore, in addition to the technical characteristics of appliances, historical information about the end-user must also be taken into account while modeling the energy consumption of a house [50].

1.3.2/ COMMERCIAL SECTOR

The commercial sector consists of a wide variety of buildings, such as retail, banks, hotels, real estate, education centers (e.g., universities, institutes), and electricity, gas and water supply services. Compared to the residential section, the commercial sector has a more centralized structure as each building has a higher energy consumption, such as for hotels (hundreds of rooms with big halls and various facilities). Most of the consumption sources are the same as in the residential sector, however a larger amount of such sources is to be considered compared to households.

Commercial buildings are high consumption sources, and thereby can provide ancillary services to the utility (by load curtailment) in the distribution grid. Demand-side solutions (load-management and DG integration) can provide significant operational cost reduction while reducing the peak load consumption of buildings in critical conditions by deferring unit operation, such as with Heating-Ventilation-Air-Conditioners (HVAC) devices [142].

CHAPTER 1. DEMAND-SIDE MANAGEMENT IN THE SMART GRID

However, such methods require detailed and accurate modeling of the building structure to estimate and control indoor temperature without violating user preferences in the facilities.

On the other hand, when outages occur on the main grid, commercial buildings can disconnect from the main grid to keep critical services alive. To enable this feature, backup power sources must be installed to provide electric energy during blackouts [133]. Most commonly, outages are often backed up with diesel generators, which are generally more expensive (in terms of operational expenditures) compared to grid prices [142]. Hence, RES and storage units can be used as an alternative to diesel generators. However, such a change requires more detailed analysis by taking into account the intermittent nature of RES.

1.3.3/ INDUSTRIAL SECTOR

Industrial loads consume the highest amount of energy compared to other sectors. Hundreds of different types of industries (e.g., automotive, textile, furniture, electronics) exist with various types of electric machinery (e.g., engines, turbines, valves, pumps, compressors). Therefore, the industrial sector can provide various opportunities for demand-side management in the electricity network.

As in the commercial sector, industry has a centralized structure with high power electric machines that are used for different tasks, such as carrying, lifting, crushing and melting. Load profiles exhibit differences as different products and materials are used. Therefore, understanding and using the flexibility opportunities with industrial loads is more difficult than for other sectors [3]. However, the impact of DSM tools is more effective compared to other sectors, hence the flexibility of the loads in this area plays a crucial role for ancillary services.

However, the delay of operation of a single unit can cause losses amounting to thousands of dollars or more. Thus, load-management sometimes may not be possible for specific loads and/or during specific times. For example, a particular process may be inter-locked with other processes, or sometimes certain processes are continuous hence it is not possible to stop them [6]. In such cases, the loads are must be controlled in a coordinated manner and, if necessary, some storage space can be placed between two processes. Efficiency and effectiveness of the load-management algorithms can then be secured. Consequently, DR has to be adapted to each customer, so it is difficult to have a generic solution for all types of customers.

1.3.4/ TRANSPORTATION SECTOR

Although the transportation sector consumes the lowest amount of electric energy, it is responsible for the highest energy consumption among all other sectors. The reason is that most of the energy is from carbon-based energy resources (i.e., petroleum). The transportation sector consists of many forms of vehicles such as personal cars, buses, trains, boats and ships. Many of these vehicles currently do not use electric motors. Therefore, combustion engines are still common in transportation, which impacts CO₂ emissions.

In this respect, due to environmental concerns, and over the last few decades, the in-

Interest in electric vehicles (EV) has increased for cars, buses and trains. However, these changes threaten the reliability and the stability of the electricity network. Charging of an EV (i.e., a personal car) can require two or three times more power compared to a typical single home power consumption. Therefore, as mentioned earlier, the grid should be reinforced with increasing capacity in transmission and distribution, which is costly and slow. Otherwise, intelligent charging strategies should be deployed to protect grid reliability and customer comfort.

1.4/ PROBLEM STATEMENT

SG technology is based on the collection of relevant data, and the implementation of control strategies to increase the efficiency of resource utilization in addition to ensuring grid reliability. However it is certainly not possible to process data from every level of the electrical network, which may contain billions of resources. Therefore, decentralized control strategies are required.

Especially, as DG gains in popularity throughout the world, neighborhoods are expected to turn into small microgrids (MG) (also known as nanogrids) that can operate independently from the rest of the main grid. This feature is only possible if such neighborhoods are constructed with AMI, and homes are equipped with smart meters and HEMS to make local resources (appliances, DG, storage, and electric vehicles) accessible and controllable. This, in turn, enables self-consumption mechanisms, where smart homes consume their own generated energy, or through cost-efficient electric energy management. Thus, with SG technologies, customers gain the opportunity to become active participants through smart homes, e.g. by controlling their appliances in response to system conditions [130, 108].

At the scale of a smart home, several resources can be used: DG, typically in the form of PV panels, energy storage (batteries), and DSM in the form of DR. By enabling some loads to be stopped or shifted in order to reduce the energy consumption at a given time, DR programs bring flexibility to the customer side in neighborhoods. However, comfort and cost reduction levels are crucial issues for active participation: end-users need to find a trade-off between the loss of comfort and the expected savings. If an end-user thinks that the signed DR program may not be worth using, he/she may decide to turn the controller off, and become a passive customer again [14]. Moreover, DR programs should take into account end-user preferences, which are typically determined by their living habits. Depending on usage and characteristics, appliances need to be categorized (non-deferrable, deferrable–shiftable, and deferrable–interruptible) to ease the control process without impacting user comfort.

Although individual customers are encouraged to take advantage of participation in DR programs, uncoordinated decision-making (single home load-management) may limit the overall performance of the proposed algorithms. This may lead, for example, to unexpected issues in the distribution grid, such as rebound peaks, overloading, or contingencies [39]. An example is shown in Fig. 1.7, where the peak load is higher after DR than before, as most loads were shifted to the same period. As a consequence, the system stability can be put at risk. Hence, the design of coordination mechanisms for smart homes is necessary in neighborhoods, so that smart homes can adjust their strategies without negative side-effects for the utility or the community as whole.

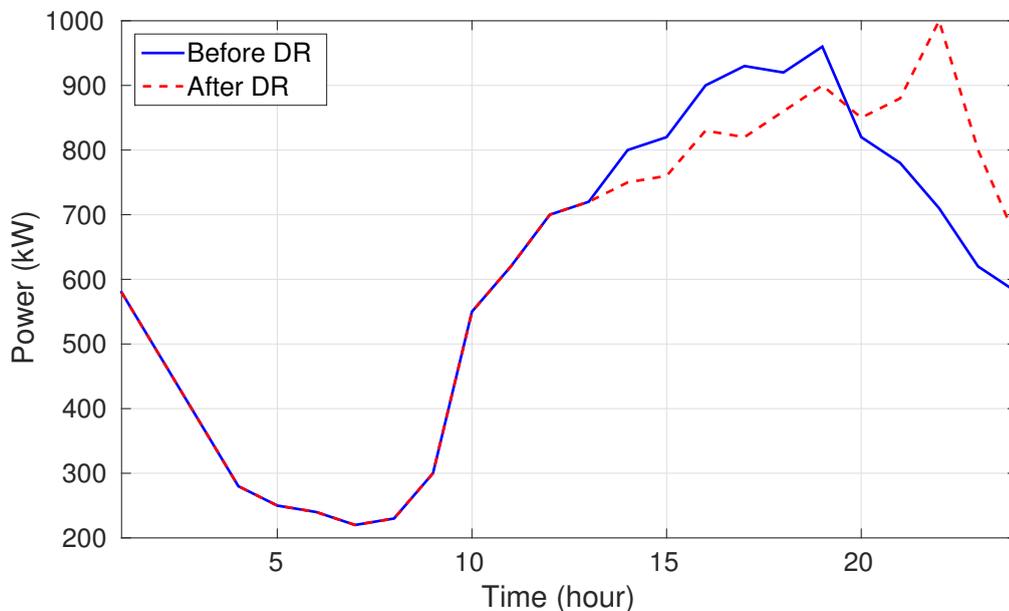


Figure 1.7: Rebound peak effect with uncoordinated DR.

Under this purpose, this dissertation focuses on the development of coordination mechanisms established among smart homes in a neighborhood area. Various coordination mechanisms are presented and compared, using different control approaches (centralized and decentralized), and various pricing schema, with two complementary objectives: economic well-being (cost reductions) for end-users and grid reliability (peak reduction) for the utility.

1.5/ ORGANIZATION OF THE DISSERTATION

The remainder of this dissertation is organized in five chapters as follows. In chapter 2, a detailed state-of-art review is presented for electric energy management strategies through the coordination of multiple smart homes. The chapter starts by giving an overview of load-modeling techniques and single home energy management using DR programs. After that, this chapter explains why coordination mechanisms are required and how smart homes can be controlled in a coordinated manner in neighborhoods. Accordingly, coordination mechanisms are classified based on the used control and communication architecture, and popular coordination techniques are listed by reviewing selected studies. Lastly, the chapter is concluded with a summary of the reviewed coordination studies from the literature. Parts of this chapter are adapted from a published journal article [145].

In chapters 3, 4 and 5, several centralized and decentralized coordination mechanisms are proposed. These methods are compared with a baseline scenario (without control and coordination)—in all chapters—and with selfish control (without coordination)—in chapters 3 and 4—to evaluate the effectiveness of the presented algorithms. In chapter 3, an energy trading algorithm is presented where smart homes are sellers and buyers in the neighborhood. To increase the interest in energy trading inside the area, a neigh-

CHAPTER 1. DEMAND-SIDE MANAGEMENT IN THE SMART GRID

neighborhood pricing scheme is proposed with an enhanced grid TOU, a feed-in tariff (FIT) and incentives. In the neighborhood, customers only trade with each other using self-generated renewable energy. End-users are the owners of DG and the energy storage in the neighborhood area. Centralized and decentralized control algorithms (scheduling electricity appliances and battery charging/discharging) are developed and compared with each other in terms of cost reduction and computation times. In the centralized one, the aggregator is the controller that determines the control decisions using the received household information. In the decentralized one, HEMSs are the controllers in the smart homes. They optimize themselves, and the aggregator is the advisor which informs HEMSs about the electricity price and the neighborhood electricity (consumption, generation and storage) situation. Parts of this chapter are adapted from a published book chapter [132].

In chapter 4, two decentralized coordination algorithms are proposed as an extension of the work in chapter 3. Compared to it, the control and communication architecture is improved, although there are similarities with the proposed coordination mechanisms. In this work, a dynamic pricing structure is based on the neighborhood consumption and the grid TOU price is used to bill customers for their electricity consumption. Moreover, the effects of forecasting errors on the consumption and generation profiles are also considered. The performance of the control algorithms are evaluated with annual simulations through three novel metrics. Parts of this chapter are adapted from a journal publication [144].

In chapter 5, the impact of residential PVs on aggregator and customer profits is analyzed. The aggregator interacts with the spot market and the utility as well as smart homes to control electricity appliances, by proposing an alternative price called customer incentive pricing (CIP). The aggregator achieves to make profit as long as it proposes a convincing price (i.e., lower than spot and/or utility price) for controlling home electricity appliances. The existing control algorithm is modified to integrate residential PVs, and simulation results are compared with a no-PV case. Parts of the explanations related to this work, which was developed in collaboration with Colorado State University, are based on an accepted conference publication [146].

Lastly, the contributions of this work are overviewed, and the possible future works are listed in chapter 6. After that, this dissertation is concluded.

STATE-OF-THE-ART REVIEW

HEMS create opportunities to develop flexibility strategies for the residential sector through smart meters and AMI. The proposed control algorithms motivate users via economic profits, but also benefit service providers by reducing operation expenses as well as maintaining the reliability of the system. Moreover, these approaches can also be combined with RES and energy storage to try to balance generation and consumption under the concepts of self-consumption and self-sufficiency.

However, most of the time, uncoordinated HEMS are not able to reach their target objectives in terms of economic and environmental efficiency. Moreover, based on the area electricity profile, these methods may lead to the occurrence of unexpected consequences (e.g. contingencies). Hence, proper control methodologies should be explored to overcome efficiency and reliability issues through coordination between entities in the residential sector.

This chapter discusses several aspects related to coordination, from load modeling to multiple-home energy management. With respect to this defined objective, literature papers between 2010 and 2016 are reviewed and classified according to their similarities and differences.

2.1/ LOAD MODELING TECHNIQUES

Designing efficient and reliable HEMS usually requires load models to estimate the impact of control strategies on home energy consumption. In the literature, two main approaches are followed for modeling residential loads: top-down and bottom-up approaches. While top-down approaches model each home or the whole residential area as a single unit, bottom-up approaches investigate the energy consumption of each individual load (or group of loads), and aggregate these to obtain the consumption of the whole area or house. A comparison between two approaches is given in Table 2.1. A comparative review of such models for the residential sector may also be found in [23].

2.1.1/ TOP-DOWN APPROACHES

The principle of the top-down approach is to aggregate all energy consumption units in one spot (e.g., a home or several ones); thus only the total energy consumption of a house or a residential area is known [55]. Top-down models often rely on historical data to

CHAPTER 2. STATE-OF-THE-ART REVIEW

model the energy consumption of an area, and are typically used to investigate the effect of long term changes (five years or more) on load profiles. The main advantage of this approach is simplicity, as load profiles. Such data is commonly available, for example from distribution transformers. On the other hand, the main drawback of this method is that information about individual peaks, types of loads, load factors and customer behavior are overlooked. As a consequence, precise control strategies cannot be studied, used, or developed with such models.

2.1.2/ BOTTOM-UP APPROACHES

Contrary to the top-down approach, the bottom-up approach investigates the energy consumption of each household appliance (or group of appliances) separately. By aggregating the consumption of each appliance, the load curve for a single home or several ones may be easily obtained [85]. Bottom-up models give control system designers the ability to identify areas of potential improvement. However, a drawback of bottom-up models is the difficulty to obtain such detailed data on the consumption of each appliance, as this is typically not readily available in standard homes due to limited instrumentation. Moreover, a validation of the model is required, e.g., by comparing the aggregated load curves with actual measurements from top-down approaches.

On the other hand, grouping household appliances helps in identifying which appliances can be controlled and how long they can be managed over a certain time horizon. The flexibility of the house demand can then be investigated. Therefore, bottom-up approaches enable understanding the behavior of each appliance as well as each home using statistical analysis. It is thus a requirement to enable the precise control of smart home resources using DR and related techniques.

2.2/ HOME ENERGY MANAGEMENT IN THE RESIDENTIAL SECTOR

With the concept of smart home, HEMS with DR programs in the residential sector have been a topic of interest, but only gained significant momentum recently, with the advent of what is now known as the SG. This led to publications in both scientific [67] and popular [101, 22] literature, indicating an interest from researchers as well as from the general public. In the following, single home energy management studies with DR programs are briefly reviewed.

Table 2.1: Residential energy consumption modeling approaches [23].

	Advantages	Disadvantages	Typical scale
Top-down	Simplicity, easy access to data.	Limited information on individual behaviors.	Neighborhood, city, region, or nation.
Bottom-up	Detailed information on individual behaviors.	High model complexity, difficulty of data acquisition.	Individual or groups of residences.

2.2.1/ INCENTIVE-BASED SINGLE HOME ENERGY MANAGEMENT

The following paragraphs review selected IBP methods, with a focus on single home energy management. In [61], a load commitment formulation is extended with a DLC program to control responsive loads in emergency conditions (e.g., the loss of a large generator or transmission line), and to provide lower electricity costs and peak-to-average (PAR) values through appliance scheduling. The gained profit is related to consumer comfort, and is determined by the electricity cost reduction. When the household consumption is decreased in the emergency condition, the electricity tariff decreases. Compared to the base case, when the consumer tariff decreases in the emergency condition, the consumer neglects its comfort, and a cost reduction is obtained for the simulation duration. However if the consumer gives priority to its comfort, the total cost slightly increases.

In [113], the HEMS problem is formulated as a mixed-integer nonlinear program (MINLP) with an inconvenience factor that corresponds to the difference between the baseline and optimal results. An incentive reward for power reduction during peak hours is considered. The MINLP program schedules 10 controllable appliances with operation time limits and power rates, as defined by the customer. Incentives are defined for early morning and after working hours. Compared to the reference scenario, customers can save up to 25% in electricity costs.

In [117], incentive rewards are used with battery and PV management for controlling household area consumption. The used method takes into account the stochastic behavior of price, water usage, PV generation and loads. Incentive rewards are offered based on the participation of the customer to the DR event. Results show that DR can decrease the customer electricity bill by 18%.

The above studies show that using IBP, in critical conditions, the utility can satisfy grid security requirements and consumers can reduce their electricity bills. However, consumers cannot benefit from frequent cost reductions, as they depend on utilities for receiving incentives. Moreover, if a consumer accepts the IBP contract and does not participate in the program when the request from the utility is received, he/she will be penalized. Also, if DR requests are too frequent and its comfort is impacted more often than expected, the customer may choose to opt-out of the program. Another difficulty lies in determining the baseline load profile for the end-user, so the financial compensation can be determined. While there is little difficulty in achieving this for selected types of industrial and commercial users, it may be more complex for residential ones due to the high number of small loads running.

2.2.2/ PRICE-BASED SINGLE HOME ENERGY MANAGEMENT

As for IBP, a short review of selected PBP methods is proposed below. In [54], TOU is used to minimize the electricity bill of consumers while taking into account end-user preferences and managing overload conditions. User preferences include the acceptable time intervals for appliances to run. TOU is used in three simulation scenarios, each with a different objective: (a) avoiding overload, (b) optimizing savings, and c) participating in a DR program. Simulation results show that all strategies achieve their expected goal; however, although b) can include a), c) considers different constraints and cannot be directly compared with others.

In [87], a decision-support tool with forecasting and scheduling capabilities is developed.

CHAPTER 2. STATE-OF-THE-ART REVIEW

An adaptive neural fuzzy inference system (ANFIS) is used for forecasting the expected electricity demand, then a branch-and-bound method is used for appliance scheduling. This study takes into account TOU tariffs with power availability at specific time intervals and consumer comfort. Results show a reduction in the total cost of deferrable appliances electricity cost from \$0.19 to \$0.14, for the simulation duration.

In [40], a performance comparison is presented for different HEM applications for consumer benefit. The impact of TOU, RTP, and priority-based scheduling are compared. Simulations are performed for 210 days. Cost reductions are determined for several scenarios: 30% with TOU, 45 % with TOU and PV with FIT, 27% without the FIT, 9% with priority-based scheduling, and 18 % with an RTP program.

In [51], scenario-based stochastic and robust optimization algorithms are presented to schedule household appliances using 5-min intervals with RTP pricing. The presented methods also take into account RTP uncertainties while minimizing operation costs. Both optimization methods are compared in terms of performance and computation time. Results show that while stochastic optimization achieves 26.6% cost reduction, robust optimization exhibits lower performance with 24.3% reduction. However, the computation time for robust optimization is shorter than for stochastic optimization.

In [77], an HEMS is presented to reduce the cost of consumed energy under RTP by scheduling resources and PV and battery operations. It uses a framework called Action Dependent Heuristic Dynamic Programming (ADHDP) that relies on neural networks. An online and an offline particle swarm optimization (PSO) algorithm are used to determine the optimal schedule, as well as for pre-training the networks and improve algorithm performance. While the online PSO algorithm works only in the current time period, the offline PSO algorithm also uses data on forecast RES generation, load and prices near the current state. Results are compared in four different cities. Depending on the considered city, savings can reach 9.3%, and ADHDP with offline PSO pre-training returns the best results.

In [72] and [100], authors combined the RTP price with incremental block rates (IBR). IBR is a pricing scheme where the unit price increases with the amount of electricity consumption, i.e., the higher the consumption, the higher the unit price. In [72], two approaches are considered for HEM design: deterministic and stochastic. The stochastic approach considers uncertainties in appliance operation time and consumed energy through an energy adaptation variable β , while the deterministic approach, based on linear programming, does not. A total load consumption limit is defined for the smart home, so that excess loads are tripped. Compared to the baseline case, results show that to the total cost can be reduced by up to 41%.

In [100], the authors combine RTP with IBR and compare full and partial flexibility in load scheduling. In the full flexibility approach, individuals only focus on profit (or savings) and preferences are not considered, while for the partial flexibility approach, customer preferences are also taken into account in the scheduling process. Both are formulated as mixed integer linear optimization problems. Results show that end-user costs decrease on average by about 20% when the schedule is partially flexible.

In [95], an HEMS is developed with a two-horizon algorithm (THA) and a rolling-horizon technique. Goals are to increase computational efficiency compared to traditional moving-window algorithms, and to achieve load management with TOU, RTP and a pre-defined peak demand charge (PDC) paid for electricity bought during peak periods. The algorithm uses two time horizons: one is for short-term scheduling with a high time reso-

lution (THA-s) and the other is for longer term scheduling with a lower resolution (THA-l). THA-s is combined with THA-l in the rolling horizon technique to reduce the computational burden of the energy management algorithm. The study shows that the proposed THA algorithm returns 18% better results with RTP than with TOU for a one-week simulation. Results show that when the PDC price increases, the THA algorithm achieves more cost reduction.

Through time-varying price signals, the utility or the aggregator provides opportunities for consumers to reduce their bills. Consumers, on the other hand, try to find the right balance between the induced loss of comfort and the financial gains from the DR program. Overall, PBP can be expected to provide more frequent cost reduction opportunities compared to IBP, as they are not necessarily linked with grid conditions. However, PBP approaches introduce some uncertainty for the utility, as the achieved load reduction amount depends on end-user response to prices. Moreover, due to their frequent and hard to predict variations, schemes such as RTP are difficult for end-users to adapt to, and may be rejected.

2.3/ NEIGHBORHOOD ENERGY MANAGEMENT

In the previous sections, the proposed methodologies ignored the energy consumption of other households while controlling their own loads. Such myopic HEM strategies may potentially lose the benefits of a global optimum in energy management goals. In typical DR programs, all customers receive the same signal from the utility, thus posing a potentially significant risk that they may all shift their appliances to run during the same hours [57, 125]. In this case, although the objective of the DR program was to reduce demand during high price periods, an unexpected peak demand called “rebound peak” may occur immediately after the DR event has ended. This effect may lead to an even higher demand peak that the DR program tried to avoid in the first place and that may in turn threaten grid stability [63, 70]. For this reason, from the perspective of the utility, such narrowly focused individual customer-side optimization can reduce the effectiveness of DR programs [28]. Coordination mechanisms are therefore required for neighborhood energy management.

In this section, the concept of neighborhood-level coordination is introduced. The communication and control structures, the roles of entities (utility, aggregator, and end-users), and the coordination mechanisms used in the literature are described with their respective underlying theories.

2.3.1/ CONCEPT OF NEIGHBORHOOD AREA

Smart neighborhoods rely on individual smart homes, that are interconnected through an electricity and a communication network. These networks enable a variety of mechanisms for managing energy at the neighborhood level.

CHAPTER 2. STATE-OF-THE-ART REVIEW

2.3.1.1/ NEIGHBORHOOD AREA STRUCTURE

A neighborhood area may be defined as a group of houses located in the same geographical area. Its size may range from a few houses to possibly a few hundreds. A neighborhood area network (NAN) enables smart homes to communicate and coordinate their actions. The NAN is formed by a collection of smart homes equipped with smart meters to collect consumption and generation data from resources (DG, storage devices, loads). Each meter has two-way communication ability in the NAN. Information is usually aggregated at the feeder or substation level by a concentrator or gateway [76]. This concentrator can then communicate with the utility information system or the aggregators.

Aggregators are new entities that, as the name implies, aggregate energy or power from small scale consumers and try to sell this aggregated capacity on markets. Aggregators typically aggregate load reduction capacity from many customers and sell it on markets, hence generating revenue for the participating customers [56, 78].

Depending on the size of the area and local legislation, none, one or multiple aggregators may be available [84, 27]. An aggregator may not be required if the local utility communicates directly with each home. However, for large regions serving hundreds of thousands of customers, the number of controllable assets increases dramatically and aggregators can facilitate the coordination of these resources. Aggregators can thus act as intermediaries between the utility and customers for specific needs. In a restructured market, multiple aggregators may be competing with each other, and also potentially with suppliers as in Fig. 2.1.

2.3.1.2/ ROLE OF ENTITIES

In this subsection, the roles of the various entities depicted in Fig. 2.1 are reviewed.

- **Utility operator:** At the top level, the utility has to ensure reliable electricity delivery to end-users. As issues such as T&D congestion may occur, DG and DR programs may be useful for the utility to increase local generation or decrease load. The utility can communicate with aggregators and possibly customers to coordinate their actions, e.g., for DR.
- **Aggregator:** At the middle level, aggregators have three roles depending on operation conditions: a) The aggregator negotiates with end-users (customers) in the neighborhood to provide DR services to the utility. In this condition, from the end-user perspective, the aggregator temporarily undertakes part of the role of the utility operator, and influences electricity consumption patterns through price/energy-volume signals in the retail market; b) The aggregator receives ancillary service requests from the utility operator to secure the system; c) The aggregator acts as an independent entity and tries to profit from electricity trade, by selling negative load on markets [120].
- **End-users:** With the increase in penetration of DG and storage devices, end-users can play several roles [32]. Depending on the electricity balance between household electricity components (e.g., loads, DG, storage units, and EV), end-users are alternatively taking the role of consumer or producer from the perspective of the aggregator.

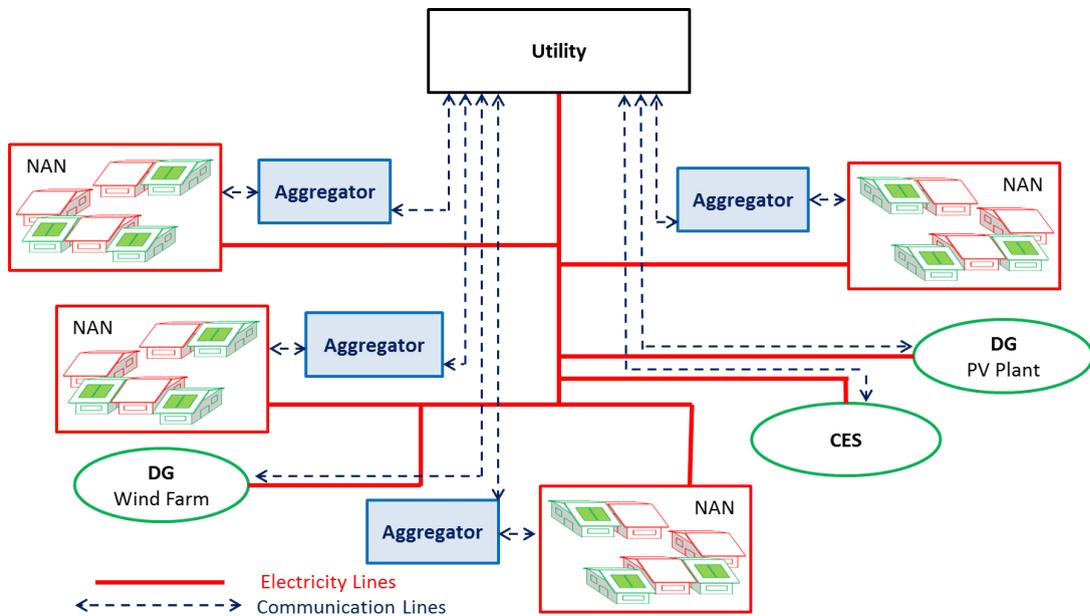


Figure 2.1: System architecture with neighborhood area networks (CES: Community energy storage).

This structure provides a basic infrastructure for electricity and information flow, that coordination algorithms use to achieve their objectives.

2.3.2/ COORDINATION STRUCTURE AND OBJECTIVES

In this section, two coordination structures, namely centralized and decentralized, are distinguished, depending on the used communication and control architectures.

2.3.2.1/ CENTRALIZED COORDINATION

In this framework, as shown in Fig. 2.2, there is one central operator, which can be the utility or an aggregator. This central operator manages (a part of) the electricity usage of all smart homes. It has direct access to all information on end-users' household electricity appliances through secure AMI networks. Smart meters and HEMS send information about their electricity usage and preferences to the central operator. The operator then optimizes electricity consumption by scheduling appliances operation for each household. The decisions taken by the central operator are then sent to smart homes and the strategy is applied.

In the following, selected papers that use centralized coordination schemes are reviewed. In [58], a day-ahead DSM strategy coordinated by a central operator is proposed for a large residential area including 2600 smart appliances. The goal is to minimize electricity consumption while reducing the PAR of the demand profile. To obtain the desired load consumption, the proposed DSM algorithm uses load shifting to bring the actual load curve as close as possible to an objective (target) load curve derived from the objective of the DSM strategy, i.e., to minimize costs. The proposed DSM method achieves a 5.0% cost reduction, and a 18.3% peak load reduction for the area.

CHAPTER 2. STATE-OF-THE-ART REVIEW

In [86], three centralized control algorithms are proposed for demand management in a neighborhood area. The main purpose of the presented algorithms is to decrease electricity consumption during on-peak hours by controlling refrigerators. The first proposed algorithm is a synchronous model in which a central controller sends on/off signals to all refrigerators in the area at the same time. Secondly, an asynchronous algorithm is proposed to trigger on/off signals at different times. Thirdly, a dynamic temperature interval management algorithm is proposed. In the latter method, the lowest and highest temperature points are sent rather than the on/off signals. Results show that while the synchronous model is effective to decrease peak load (close to zero), it also leads to a significant rebound peak. The asynchronous model results in a lower rebound peak but only achieves a 21.4% peak load reduction. The last strategy seems to provide the best results, with a peak load reduction of up to 41.5% and a negligible rebound peak.

In [109], a joint optimization algorithm for EV charging and HVAC control is proposed. The goal is to minimize the total electricity cost for the residential community while considering user preferences. In the neighborhood, parked EVs may also charge other EVs and provide electricity to HVAC units, in order to minimize electricity imports from the utility. Here, the aggregator collects information about the EVs and HVAC units, such as thermal dynamics, user climate comfort preferences, battery state, user travel patterns, and household occupancy. The community scale optimization result is compared with individual optimization for 100 households. According to results, the proposed algorithm manages to reduce the aggregated electricity cost by 22.8% for a hot summer day.

In [115], a centralized scheduling algorithm is proposed to minimize electricity imports from the main grid by allocating the loads and EV charging to periods when RES generation is high. A feed-in tariff program is presented that favors the discharge of EV to supply other household appliances in the grid. Three simulation results for centralized optimization are compared: naive (base case), optimal without EV discharge, and optimal with EV discharge. Compared to the base case, the optimal case without EV discharge returns a 4.3% cost reduction for 10 EV and around 75% for 400 EV, and the case with EV discharge returns a 8.5% cost reduction for 10 EV and 175% for 400 EV.

In [74], a real-time load management and optimal power generation algorithm is pre-

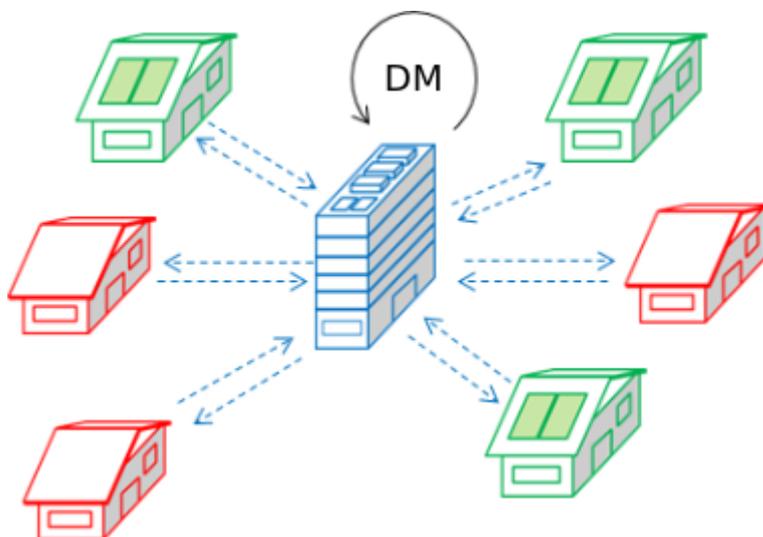


Figure 2.2: Principle of centralized coordination (DM: decision making).

sented for an islanded grid. A central coordinator is responsible for the cost and capacity limit of a backup generator, RES, and storage devices. Each household informs the central operator about the electricity consumption of its appliances, then the operator responds with an optimal scheduling strategy that considers the capacity limits of generation and storage units. Two algorithms are proposed: an offline algorithm that relies on forecasts, and an online algorithm that handles disturbances in real-time. Based on simulation results, the offline control method reduces the total electricity cost from \$11.12 to \$8.03 for the simulation duration, when disturbances are neglected. On the other hand, the online scheduler, when uncertainty on solar generation and appliance operation is considered, reduces the total electricity cost from \$10.8 to \$7.80.

In [120], an aggregator-based control approach for DR is proposed. The aggregator tries to maximize its profit by selling on markets the capacity aggregated from customer smart appliances. Each customer can choose in real-time between buying electricity from the aggregator (at a price called customer incentive price) or from the utility (at the real-time price). The aggregator gathers settings from end-users and computes optimal set points using a genetic algorithm for 5,555 households and 56,642 appliances. Results show that customers can save from \$0.02 to \$0.33, while the aggregator generates a profit of \$947.9.

Several other studies using centralized coordination focus on specific aspects. For example, in [140], authors propose an algorithm capable of allocating a fair share of distribution transformer capacity among users. In [139], model predictive control is used for the centralized coordination of smart buildings and considers the stochasticity of renewable energy sources and loads.

Overall, studies show that centralized approaches enable finding the optimal strategy for efficient electric energy use, as well as for maximizing the utilization of DG. A drawback is however the computation burden required by the optimization, especially for a large number of assets to control [120]. Centralized control is thus not suitable for large-scale applications where computation time would become prohibitive. Nevertheless, results from centralized coordination can be used as a reference for comparison with other coordination methods [112].

2.3.2.2/ DECENTRALIZED COORDINATION

While in centralized coordination, the central operator has access to information about all consumers, in decentralized coordination, the end-users schedule their assets directly, without any omniscient central entity. To achieve this, smart homes have to communicate with each other or with a central entity to gather sufficient information about the neighborhood electricity profile. Depending on the communication structure in the neighborhood and the level of decentralization, three approaches are distinguished: fully-independent, partially-independent and fully-dependent:

- In the *fully-dependent* structure (Fig. 2.3), smart homes receive information on the neighborhood electricity profile through a central entity without sharing any data with each other. Neighborhood communication is dependent on the central entity. The difference with centralized coordination is that the decisions are taken by the smart homes, and not by the central entity.
- In the *fully-independent* structure (Fig. 2.4), smart homes communicate with each

other in the neighborhood, without any central entity. They are able to communicate with each other directly, and share data on the neighborhood load profile.

- In the *partially-independent* structure (Fig. 2.5), smart homes communicate with each other, and also interact with a central entity.

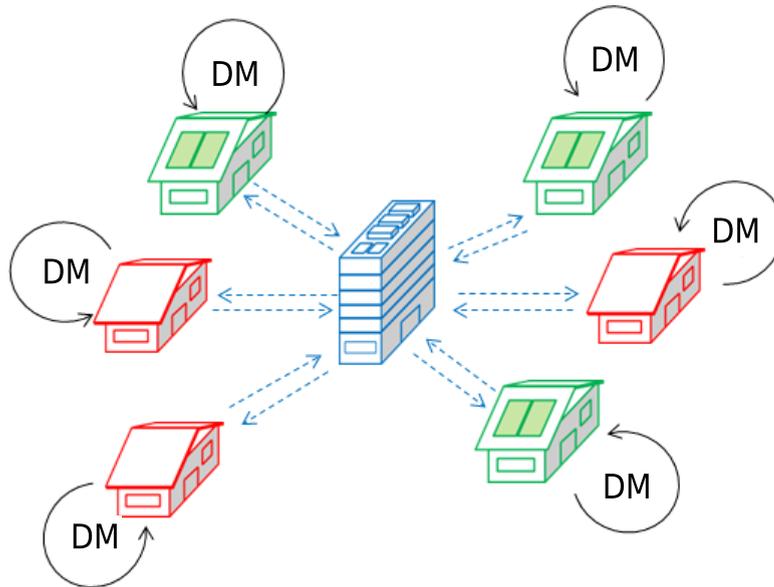


Figure 2.3: Fully-dependent decentralized coordination (DM: decision making).

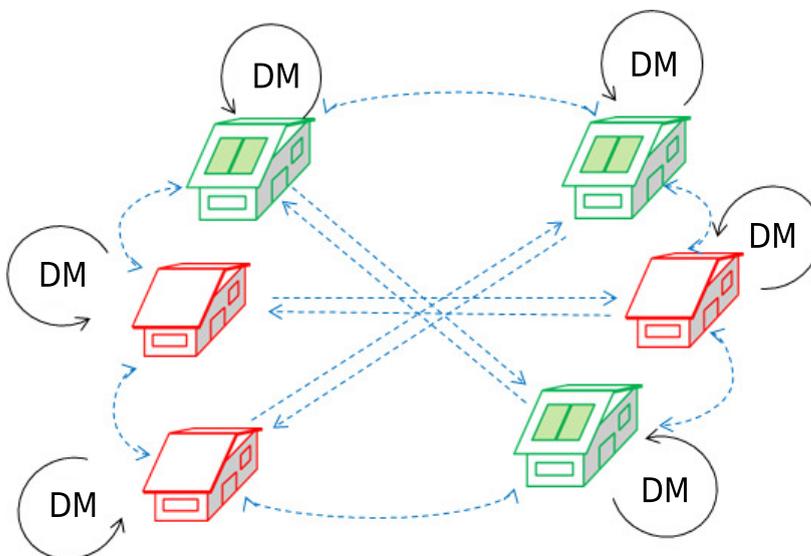


Figure 2.4: Fully-independent decentralized coordination (DM: decision making).

In the following, selected papers that use a decentralized coordination structure are reviewed. In [57], the rebound peak issue due to uncoordinated load shifting of appliances to off-peak hours is addressed. To solve it, a fully-dependent optimization algorithm is used to coordinate electricity consumption in the neighborhood. As the same DR program—triggered by the same price signal—is used in all smart homes, all controllable appliances in the area are shifted to the same off-peak hours, which may cause

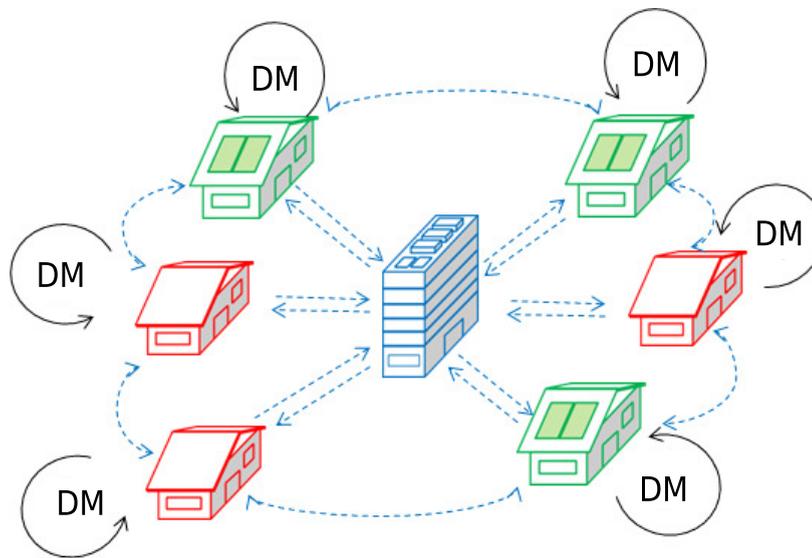


Figure 2.5: Partially-independent decentralized coordination (DM: decision making).

another peak. To avoid the resulting rebound peak effect, four techniques are compared, each with different DR and price signals: random DR scheduling without and with flattening, different prices for different homes (although the legal feasibility of this approach is questionable), and maximum power constraint. Compared to a base case, the various techniques return peak and cost reductions ranging from 19.4% to 33.9%, with the last technique providing the best results.

In [96], a fully-dependent decentralized energy management algorithm is proposed. The proposed greedy algorithm tries to minimize electricity bills by optimizing the start time and operation mode of appliances in smart homes. The cost of electricity is modeled by a time-dependent unit retail price, which means that the electricity price changes with the aggregated consumption in the neighborhood. To determine the price, the utility receives information on the consumption of each individual house, and sends a price signal to each consumer. Depending on the price, consumers schedule their controllable appliances to decrease their expenses. Then, depending on the scheduled consumption, the utility aggregates the total load again and determines the new electricity price. After that, consumers, depending on the new price, schedule their appliances again. This process continues until the difference between consecutive decisions becomes negligible. Results show that individual users are able to reach cost reductions of about 20%, and that results for the proposed distributed method are close to the ones obtained using classical sequential optimization.

In [79], a fully-dependent energy management algorithm is presented to decrease the total electricity cost of a neighborhood. The neighborhood area includes a central operator called load serving entity (LSE) and multiple households with RES, storage devices, and controllable and non-controllable loads. Each household, depending on information received from the LSE, solves an optimization problem to minimize its electricity bill using an approach called Lyapunov-based cost minimization. After the LSE has received the consumption information from each household, it determines the electricity price for the defined period, and each household solves the optimization problem again with the new price. This process continues until convergence is obtained. In the results, the proposed algorithm is compared with two other cases: no storage and no DR (case 1), and with

CHAPTER 2. STATE-OF-THE-ART REVIEW

storage and no DR (case 2). Over a six month period, the presented control method reduces electricity costs by 20% and 13% compared to cases 1 and 2, respectively.

In [141], a fully-dependent two-level load control strategy is proposed to address the rebound peak issue. The proposed method does not rely on a specific electricity pricing scheme, hence customers are free to select the scheme (flat, TOU or RTP) of their choice. To eliminate the rebound peak and minimize costs at the same time, two different optimization algorithms are defined. First, homes receive the electricity price, optimize their assets schedule, and send the results to the service provider. This service provider then calculates the aggregated profile and sends it with a desired (flatter) aggregated profile back to the customers. As a second step, customers optimize their profile again to flatten the area profile and try not to jeopardize their previous cost results. Compared to non-coordinated control (i.e., with only the first step), the proposed method achieves a 16.8% additional peak load reduction.

In [98], two fully-independent selfish DSM algorithms are presented. The neighborhood is modeled as a graph, and close neighbors exchange messages with each other. These messages enable two coordination mechanisms: synchronous agreement-based, and asynchronous gossip-based mechanisms. In the synchronous agreement-based algorithm, consumers estimate and share the predicted aggregated consumption at the same time using information on their own consumption. The coordination process ends when consumers agree on the aggregated consumption of the neighborhood. In the asynchronous gossip-based algorithm, consumers update their knowledge of the aggregated consumption at different times. The electricity cost and the PAR value are reduced by 33.34% and 30.31%, respectively, with the proposed DSM programs. Although both algorithms return similar results, the gossip-based algorithm requires more iterations due to the asynchronous nature of the communication.

In [99], a partially-independent, selfish scheduling algorithm based on game theory is presented for the purpose of minimizing the PAR of the load profile. A central operator sends price information to the end-users, who have the ability to exchange data about their demand power. For each iteration, if the consumer changes his/her last decision, he/she needs to inform others. Scheduling is then performed while considering temporally-coupled constraints. For example, an EV should be fully charged by the time the driver expects to leave home, hence the scheduler can only shift the corresponding asset schedule to a certain limit to enable a full charge. In results, the PAR of three customers are reduced from 2.6, 2.7, and 2.4, to 2.1, 2.2 and 2.0, respectively. The scalability of the algorithm is also investigated, and results show that the approach could be scaled to real-world problems.

In [30], a partially-independent coordination structure aims to minimize the electricity bills of the end-users while taking into account the aggregated neighborhood consumption. End-users participate in a scheduling game to reduce their electricity bill, as well as the PAR of the neighborhood demand. The electricity provider determines the electricity price according to the aggregated consumption profile. End-users are charged based on the ratio of their individual consumption over the aggregated consumption. As a result, the aggregated electricity cost of the residential area is reduced from \$44.77 to \$37.90 for the simulation duration, and the PAR is decreased from 2.1 to 1.8.

In [70], a partially-independent collaborative energy management algorithm is presented to reduce the real-time power balancing electricity cost of a neighborhood. While consumers are connected to an aggregator or retailer, they coordinate their actions by ex-

changing messages with each other. In the presented study, the retailer pays a price higher than the real-time electricity market price, which is different from the wholesale day-ahead electricity market due to uncertainties in demand. The proposed algorithm focuses on the minimization of the total cost in the real-time electricity market. It is compared with selfish scheduling, which causes a rebound peak in the aggregated consumption profile, while the proposed approach does not. Cooperative scheduling also returns the lowest aggregated deviation compared to cases without scheduling and with selfish scheduling.

Additional papers introduce interesting methods based on a decentralized approach. In [137], decentralized coordination is achieved with a two-level optimization in which customers optimize their utility function and the aggregator determines the lower and upper bounds of the consumption of each customer. In [136], a detailed mathematical model is presented for decomposing the centralized optimization problem into a set of independent decentralized problems. Finally, in [135], energy trading between smart homes with PV and centralized energy storage and the grid is studied using a decentralized game theoretic approach.

Overall, the reviewed papers show that decentralized coordination leaves more freedom of choice to the end-users; however the aggregated cost is usually higher than for centralized coordination. On the other hand, some individual homes may be gaining more than others, e.g., when they have more flexibility. As this approach requires frequent communication and sometimes a large number of iterations to converge, a drawback is that the necessary bandwidth and the convergence time may be significant.

2.3.3/ COORDINATION TECHNIQUES

This section focuses on how houses cooperate, compete, or coordinate their actions to achieve certain pre-determined goals. Three main approaches are discussed: a) multi-agent systems (MAS); b) game theory (GT); and c) optimization techniques.

2.3.3.1/ MULTI-AGENT SYSTEMS

MAS are widely studied and used in various fields, ranging from economics to computer science, mainly due to their suitability for distributed problem solving [73]. Over the last few years, especially as a consequence of the rapid penetration of DG installations in the distribution grid and the associated need for decentralized control, MAS have become a technique of interest to power control engineers [12, 89]. Applications range from building energy management [91] to microgrids [33], distribution systems [125] and power plants [88].

According to [24], an “agent is a software or hardware entity that is situated in some environment and is able to autonomously react to changes in that environment.” In this definition, autonomy means that each agent can make its own decisions in order to attain its objectives. The environment corresponds to everything surrounding the agent, except itself. According to [12], agents have three main properties: i) *reactivity*: the ability of an agent to react to changes in its environment; ii) *proactivity*: the ability of an agent to proactively behave according to its defined objectives; and iii) *social ability*: the ability of an agent to negotiate (compete or cooperate) with other agents.

CHAPTER 2. STATE-OF-THE-ART REVIEW

A MAS is a group of agents with the ability to communicate with each other to cooperate or compete for achieving their objectives in a changing environment. Under the scope of this dissertation (coordination of multiple houses), agents are usually the controllers of the HAN in the smart homes. They meter and control the household appliances; additionally, they also communicate with other HAN and NAN agents in the neighborhood. Through such communication, they can observe the grid condition and act on it if required (*reactivity*), cooperate (*social ability*) to ensure the reliability of the system (*proactivity*) or compete (*social ability*) with each other to minimize their electricity bills (*proactivity*). As a consequence, while MAS may not be considered as an algorithm, they are an enabler for decentralized coordination techniques.

The organizational structure is an important characteristic of a MAS and includes the following types: hierarchies (the most commonly used for power system applications), holarchies, coalitions, teams, congregations, societies, federations and marketplaces [89].

In a hierarchical MAS, the electricity network is divided into several levels, typically three. Agents are categorized into these levels depending on their duties or objectives [106]. The upper level is the system control level that decides about operation strategies and operation modes. The middle level is the central control level with tasks such as energy generation and consumption forecasting, voltage and frequency control, supply-demand matching, and day-ahead optimal DG scheduling operations. The bottom level is the local control level for coordinating local resources. Three types of agents are typically defined at the bottom level, such as a) *DG agent*: responsible for controlling (whenever possible) the output of a DG; b) *storage agent*: responsible for the charge and discharge operation of a storage device; c) *household agent*: responsible for organizing the schedules and shedding operations of appliances (including PV units) with the objective of minimizing electricity bills while ensuring a minimum impact on consumer comfort. With the development of transportation electrification, EV may also be modeled as agents for charging (home-to-vehicle: H2V) and discharging (vehicle-to-home: V2H) [59].

In [83], a MAS-based DSM algorithm is proposed for an islanded grid with multiple sources. A four-layer structure is used for modeling the network, with: a) a prediction layer, b) an activation layer, c) an intelligent supervisory layer, and d) a control layer. Prediction layer agents estimate the future electricity generation from PV panels and wind turbines. Activation layer agents use frequency control to decide whether or not to activate load shedding depending on the frequency fluctuations. The activation layer agents use the prediction information received from the prediction layer agents and storage information received from the control layer agents (e.g., fuel cell agent, desalination unit agent, and electrolyzer agent). In the intelligent supervisory layer, the supervisor agents of the households negotiate with each other to decide whether to turn-on or off household appliances, after receiving the control signal from the activation layer. In the control layer, control agents are responsible for controlling home appliances. Simulation results show that shedding is activated for a total of 62 hours in summer.

In [105], electricity trading inside and outside of a neighborhood is studied. Consumers are modeled as agents and decide about selling, buying, or storing electricity. To take decisions, consumer agents communicate with each other and take decisions on their actions using a rule-based algorithm. For example, the agents can decide whether to store excess energy or sell it inside the neighborhood (first priority), or to sell it to the utility (second priority). After scheduling their appliances, agents can then choose to buy either from the utility or from inside the neighborhood. To minimize electricity bills, consumers

thus have four options: load shifting, purchasing electricity from the neighborhood, battery charge or discharge, and selling excess energy to the grid or the neighborhood. Results show that customers could benefit from diversity in end-user types, in the form of increased savings (up to 10%). Depending on the assumed penetration rate of PV and battery units, end-users could also expect to save up to 40% on their electricity bill.

In [53], DR and DG management are combined to study the overloading issue in islanded grids while taking into account plug-in hybrid vehicles (PHEV). In the proposed study, a three-level hierarchical MAS structure is used. From top to bottom: grid agents control grid resources (battery, wind turbine and DG), control agents communicate with the grid and resident agents for satisfying the balance between generation and consumption, and resident agents collect information on demand and PHEV battery state-of-charge. Control actions are determined by defining a critical peak price in the microgrid to shed low priority loads, reduce electricity consumption, and decide about the charging modes of the PHEV. Three cases are presented and compared. Results show that the peak load in the studied system can be reduced from 900 to 800 kW, i.e., by 11%.

The above reviewed studies show that a MAS advantage is the possibility to have a decentralized intelligence, with numerous homes modeled after a single template agent while all can have different characteristics (e.g., appliance count and preferred operation times). Agents can also automatically adapt to environmental changes such as changes in the structure of the neighborhood (e.g., a new home), without requiring any major interruption and changes in the algorithm. Drawbacks include the cost of such approaches, that result from a larger number of communicating entities. Additionally, few standards (e.g., IoT standards) currently exist, which makes development longer and costlier.

2.3.3.2/ GAME-THEORETIC APPROACHES

GT is a strategic decision-making process, originally developed by J. von Neumann and O. Morgenstern [17]. GT is the science of strategy that determines the relationship and interactions between players, and analyzes their behaviors under some given circumstances, called games. In these games, players choose the best strategy as an action to achieve the best outcome by anticipating the strategy of other players. Although GT is mostly used in economics [1, 5], it has also been widely applied to other fields such as computer science [4, 8] and electrical engineering [7].

According to the previous definition, GT may be applied to power systems with the following adaptations: a) participants (typically, end-users) are defined as rational and strategic decision-makers [20]; b) players select the best strategy they can by anticipating the actions of other players [116]; c) consumers make their own decisions through decentralized problem solving [30, 94].

Games consist of three components (player, strategy and payoff function), and are usually noted $\mathcal{G} = \{\mathcal{U}, \{\mathcal{L}\}, \{\mathcal{F}\}\}$. \mathcal{U} represents the households set. \mathcal{L} represents the strategy space of the game, hence $\mathcal{L}_u = \{l_u(1), l_u(2), l_u(3), \dots, l_u(t)\}$ is the set of strategies (generally, the consumption for the home) for home u . \mathcal{F} represents the set of payoff functions (electricity costs or savings). A Nash equilibrium is reached when the following condition is met:

$$\mathcal{F}_u(\mathcal{L}_u^*, \mathcal{L}_{-u}^*) \geq \mathcal{F}_u(\mathcal{L}_u, \mathcal{L}_{-u}^*) \quad (2.1)$$

\mathcal{L}_u^* is the strategy of house u at the Nash Equilibrium, and \mathcal{L}_{-u}^* is the strategy of other

CHAPTER 2. STATE-OF-THE-ART REVIEW

players, also at the Nash Equilibrium. \mathcal{L}_u represent the deviant strategy of player u , i.e., a strategy that does not lead to a Nash equilibrium. In other words, a Nash equilibrium represents a balanced state where players can no longer improve their payoff by changing their optimal strategy when considering others' strategies as fixed [93, 9]. The outline of a Nash equilibrium game algorithm for multiple smart homes with one aggregator is described in **Algorithm 1**.

Algorithm 1 Outline of a simple Nash equilibrium game algorithm.

- 1: The aggregator initializes the game by determining the aggregated area profiles and/or the area electricity price.
 - 2: **repeat**
 - 3: All users receive the necessary information (area profile and/or electricity price) from the aggregator.
 - 4: Users optimize their payoff functions by minimizing their electricity bills and/or maximizing the incentive gains.
 - 5: Users send to the aggregator the determined individual home consumption profiles.
 - 6: The aggregator receives the updated home profiles and updates the aggregated area profile and/or area electricity price.
 - 7: The aggregator sends the updated data to all users again.
 - 8: **until** convergence is achieved, when nobody changes its decision anymore.
-

In the following, selected studies from the literature employing GT are reviewed. In [60], a scheduling game is formulated to reduce the PAR of the neighborhood with a retail pricing model. Consumers try to minimize their own electricity costs by participating in a non-cooperative game for optimum energy consumption and storage management. In this algorithm, the price signal is received by the consumers from the utility through a dedicated communication link. When consumers receive the price signal, they optimize their local energy consumption individually and send it to the energy provider. Based on the new aggregated energy consumption, the utility calculates the new electricity price and sends it back to the consumers. This process continues until convergence is obtained. In the results, the PAR value of the system is reduced from 1.87 to 1.33 for the reference (centralized) case, to 1.39 for a case with DR and battery storage, and to 1.65 for a case with DR but without battery storage.

In [93], a non-cooperative game is developed to control the charge and discharge of household batteries. Consumers schedule their household appliances depending on the electricity price during the day and charge their batteries with residual electric power (i.e., power not used to supply other loads). Consumers can then use the electric energy from their battery during on-peak hours. Therefore, two pricing schemes are determined. The first is an RTP scheme for household appliances, and the second is the charging price for the battery charging game to encourage consumers to charge their batteries. The charging price is lower than the regular pricing tariffs, but as charging requests increase, this price comes close to the regular price and becomes less attractive. Consumers define their charging strategies based on their earliest starting time, deadlines, and the amount of requested power for charging. Depending on the surplus energy, load, and the state-of-charge of the batteries, the households optimize their payoffs. The proposed game is tested on three houses and is compared with a reference case.

In [48], a scheduling game is proposed for a neighborhood area. Consumers pay the

same average daily unit price, and their costs are proportional to their electricity consumption. Consumers receive the TOU rate in order to establish the initial schedule of their appliances. They then receive the scheduling plans of other consumers. Based on the aggregated consumption, a dynamic price is calculated according to the TOU price by each smart home. Using this price, consumers optimize the schedule of their appliances to decrease the overall electricity cost of the neighborhood. The game continues until consumers make no more change in their scheduling plan. Results for the distributed coordination model return a total cost of £36.69, against £38.20 for selfish scheduling over the simulation duration.

Overall, GT appears as a promising tool for residential load management, and especially for decentralized coordination. Smart homes (players) control their electricity profile to increase their payoff function, i.e., to minimize their own electricity costs. This type of game is defined as a non-cooperative game [130], where players only focus on their own benefits. Games may also be designed in a cooperative way, as in [128], where players can form coalitions to reach higher individual payoffs while increasing the total gain for the group. However, due to fairness concerns, coalitions are not permitted in most countries. GT has the advantage of providing flexible games, where the participation of new players does not require changes in the game. However, frequent message exchanges are required for decentralized coordination.

2.3.3.3/ OPTIMIZATION TECHNIQUES

In HEMS, optimization techniques are typically used to allocate the run time of household appliances over a given time horizon and with a specific objective. The goal generally is to decrease electricity bills or the PAR ratio to obtain flatter load curves. In the literature, problems can take into account grid conditions (e.g., congestion) in the optimization. Formulations can also consider stochastic problems (e.g., with uncertainty on consumption [79] and renewable generation [43]), multiple objectives [82, 102], or other objectives such as maintaining voltage stability [65] or decreasing active power losses [104].

Optimization problems are typically formulated as follows, for a simple decentralized case:

$$\text{minimize} \quad \sum_{t=1}^T P_u^c(t) \cdot \lambda(t) \quad (2.2)$$

$$\text{subject to} \quad P_u^c(t) \in \Psi_u(t) \quad (2.3)$$

where $P_u^c(t)$ is the power consumption of house u at time t , and $\lambda(t)$ is the price at time t . For the centralized case, the equation becomes:

$$\text{minimize} \quad \sum_{u=1}^U \sum_{t=1}^T P_u^c(t) \cdot \lambda(t) \quad (2.4)$$

$$\text{subject to} \quad \begin{cases} P_u^c(t) \in \Psi_u(t), \forall u \\ \sum_{u=1}^U P_u^c(t) \in \Phi(t) \end{cases} \quad (2.5)$$

Equation (2.3) represents the constraints set for smart homes, where $\Psi_u(t)$ represents the set of feasible power values (e.g., due to the operation time limits of appliances). Equation (2.5) represents the constraints set for smart homes and the grid, where $\Phi(t)$

CHAPTER 2. STATE-OF-THE-ART REVIEW

represents the set of feasible power values (e.g., due to the operation time limits of the electricity network [61, 51]). As mentioned earlier, other objectives and constraints may be considered [117, 90]. For decentralized optimization, typical objective formulations only sum on t and not on u , as each home optimizes its own consumption.

In [82], a multi-objective problem aims for cost minimization and load factor maximization. The forecast area load profile is used in a fitness function to optimize electricity usage with a multi-objective genetic algorithm. Penalty and rebate terms are generated by the utility based on a normal distribution curve over the load. As a uniform load distribution is desired, customers pay a penalty or receive a rebate depending on the difference between their load and the curve. Compared to the base case, cost reductions reach 74% and PAR reductions 42%.

In [104], the optimization problem aims to minimize the users' electricity bill, and considers the cost of active power losses, as well as the need to avoid line overload. Investigations focus on the optimal coordination of residential resources, in a distributed fashion, and consider private objectives as well as objectives common to all consumers (here, minimizing losses). Numerical examples show that the proposed decentralized algorithm achieves results similar to what is obtained with a reference centralized algorithm. However, with this algorithm, when losses are considered in the optimization, losses decrease by 4.2%.

Overall, optimization techniques are commonly used in energy management studies, and have the advantage of providing optimal or near optimal solutions, whether it is for individual customers in a selfish fashion, or for entire neighborhoods with coordination. Drawbacks of these techniques are similar to the ones of centralized coordination (both are commonly combined). They include high computational requirements that increase with problem size, and significant detailed information on end-user resources, which may raise some privacy issues. A more comprehensive study focused on optimization algorithms used for DR can be found in [127].

2.4/ OVERVIEW OF THE STATE-OF-THE-ART

HEMS are an important development in the smart grid concept, to control household loads, generation, and storage devices. With DR programs, end-users are no longer considered as passive participants; they can actively participate in electricity markets (directly or through aggregators) and schedule appliance run times to reduce their electricity consumption and bills with limited impact on their comfort. Appliance scheduling does not only provide benefits for end-users, but also for utilities. For example, utility companies are responsible for providing electric energy to consumer at all times, including during peaks when utilities need to generate more (or purchase additional) power. However, demand peaks occur only for short durations in a year, and the additional and usually expensive generation capacity [31] remains idle most of the time during the year. Other applications of DR lie in the provision of ancillary services by the neighborhood to the utility. Utility companies thus use "smart" pricing mechanisms or incentives to influence customers to change their consumption patterns, and hence change the load and, at the same time, enable end-users to reduce their electricity bills. However, when households selfishly schedule their electricity appliances, rebound peaks may appear at unexpected hours [125]. To avoid this situation, coordinating smart homes is an important requirement

for neighborhood energy management, especially when considering DG and storage devices.

Several aspects should be considered when comparing approaches to neighborhood energy management: pricing mechanisms, coordination structures, and coordination techniques. Financial mechanisms are basic tools for utilities to help shape load profiles, through specific pricing schemes or incentive mechanisms. The coordination structure of a neighborhood can be organized around a single entity—a utility or third-party like an aggregator—or by multiple households interacting with each other to take decisions. Coordination mechanisms can then enable strategic energy management, e.g., to prevent the emergence of a rebound peak.

To avoid demand peaks, utilities can resort to various mechanisms that provide an incentive for the end-user to modify electricity consumption. Mechanisms can be based on an incentive (IBP) the customers receive when they reduce their demand, or on specific pricing schemes (PBP, such as TOU or RTP) designed to favor electricity consumption during low-demand periods. While IBP comparatively provide a higher level of confidence for the utility in terms of load reduction, PBP have the advantage of requiring less enabling technologies. On the other hand, complex pricing schemes may not be accepted by all customers, who may suffer for increased bills if they are not able to properly understand how to suitably adapt their consumption.

These mechanisms by themselves are however insufficient to enable efficient neighborhood-level coordination. Communication and coordination are enabled through various structures. In centralized coordination, a central operator can directly optimize appliances schedules for each household or can influence customers by sending price signals, as in [120]. Such coordination typically has better performance than other structures. Having access to all required information, the central entity is able to find the optimal schedule for the entire neighborhood area, or for each individual end-user. However, the scalability of such approaches is limited, as they require significant computational resources for large neighborhood areas.

Algorithms with variable degrees of decentralization are also able to coordinate households scheduling processes, by enabling end-users to exchange information about their consumption profiles, as in [131]. Rather than sending all information to a central entity, end-users can only share selected information and decide on a management strategy themselves. Three types of decentralized coordination may then be distinguished, depending on the independence level from the central entity: fully-dependent, partially-independent and fully-independent (see Table 2.2):

- The fully-dependent one is the most commonly studied structure, where the central entity only influences the consumers with a price signal and transmits information on the aggregated electricity profile of the area.
- In partially-dependent structures, customers communicate with each other by sharing information about their decisions. The central entity influences customers by calculating the electricity price according to the aggregated consumption profile. This central entity enables the utility not to disclose information on its profits.
- The fully-independent structure is the least studied method so far. Customers have the ability to communicate with each other directly and no central entity is used in the decision-making process.

Table 2.2: Comparison of coordination structures.

Properties	Centralized		Decentralized					
			Fully-dep.		Partially-indep.		Fully-indep.	
Communication	Customer	via utility	Customer	via utility	Customer	via customer and/or utility	Customer	via customer
Decision-maker (optim.)	Utility		Customer with or without utility		Customer with or without utility		Customer	
Privacy issues	High (customer)		High (customer)		Low (customer)		High (customer and utility)	
Communication burden	Medium to high		Low		Medium		Medium to high	
Computation burden	High		Low		Low		Low	
Iterative process	No		Yes		Yes		Yes	
Scalability	Limited		Yes		Yes		Yes	
Number of studies reviewed	High		High		Medium		Low	

The main differences between these approaches are thus the degree of centralization of information, and the resulting performance (e.g., costs and PAR). While decentralized structures tend to return less efficient results than centralized ones, they better respect the need for privacy of the customers, which is a growing concern [21]. End-users prefer not to share too much information with their neighbors, as it can give details about their life habits.

In terms of coordination techniques, three main types of algorithms are used in the literature: MAS, GT, and optimization. While they are not an algorithm per se, MAS have the advantage of inherently enabling advanced, distributed coordination between homes. Moreover, MAS enable modeling each component or agent separately and define their interactions, as in a real system. Optimization is commonly used to determine optimal schedules, either for individual smart homes or for the entire neighborhood. Various objectives (e.g., costs, losses) may be used, together with multiple sets of user or system-level constraints. As optimization is commonly used with centralized coordination, both approaches suffer from a limited scalability to large system dimensions. Game theory is another approach that provides decision-making ability to independent players [130, 64], i.e., smart homes, whether the game is cooperative or not [93, 60]. Like MAS, GT is especially suitable for decentralized coordination, and can easily include new players to the game. However, the difficulty to reach an equilibrium state in a large system increases with its size.

Table 2.3 summarizes the studies analyzed in the previous sections. An analysis of this table shows that PBP are the most commonly used DR type for both centralized and decentralized coordination studies. Decentralized coordination is more frequently studied at the neighborhood level than centralized approaches. Among decentralized coordination papers, while the fully-dependent method is the most used, the fully-independent method is little researched so far, due to the difficulty in obtaining efficient results with limited computation and communication resources. Regarding coordination techniques,

Table 2.3: Summary of the reviewed studies.

References	DR type		Structures		Techniques		Resources		Appliance number		
	IBP	PBP	Centralized	Decentralized	MAS	GT Optim.	RES	Storage	1–100	101–1,000	>1,000
[61]	✓	✓	-	-	-	✓	-	✓	✓	-	-
[113]	✓	✓	-	-	-	✓	-	-	✓	-	-
[117]	✓	✓	-	-	-	✓	✓	✓	✓	-	-
[54]	✓	✓	-	-	-	✓	-	-	✓	-	-
[87]	-	✓	-	-	-	✓	-	-	✓	-	-
[40]	-	✓	-	-	-	✓	✓	-	✓	-	-
[51]	-	✓	-	-	-	✓	-	-	✓	-	-
[77]	-	✓	-	-	-	✓	✓	✓	✓	-	-
[72]	-	✓	-	-	-	✓	✓	✓	✓	-	-
[100]	-	✓	-	-	-	✓	-	-	✓	-	-
[95]	-	✓	-	-	-	✓	✓	-	✓	-	-
[58]	-	✓	-	-	-	✓	✓	-	-	✓	-
[86]	✓	-	✓	✓	-	-	-	-	✓	-	-
[109]	-	✓	✓	✓	-	✓	-	-	-	✓	-
[115]	-	✓	✓	✓	-	✓	✓	✓	-	-	✓
[74]	-	-	✓	-	-	✓	✓	✓	✓	-	✓
[120]	-	✓	✓	✓	-	✓	-	-	-	-	✓
[57]	-	✓	-	✓	-	✓	-	-	-	✓	-
[96]	-	✓	✓	✓	-	✓	-	-	-	✓	-
[79]	-	✓	✓	✓	-	✓	✓	✓	✓	✓	-
[98]	-	✓	✓	✓	-	-	-	-	✓	-	-
[99]	-	✓	✓	✓	-	✓	-	-	✓	-	-
[30]	-	✓	✓	✓	-	✓	-	-	✓	✓	-
[141]	-	✓	✓	✓	-	✓	✓	✓	✓	✓	-
[70]	-	✓	✓	✓	-	✓	-	-	-	✓	-
[83]	-	-	✓	✓	✓	-	✓	✓	✓	-	-
[105]	-	✓	✓	✓	✓	-	✓	✓	✓	✓	-
[53]	-	✓	✓	✓	✓	-	✓	✓	✓	-	✓
[60]	-	✓	✓	✓	-	✓	-	✓	✓	-	-
[93]	-	✓	✓	✓	-	✓	-	✓	✓	-	-
[48]	-	✓	✓	✓	-	✓	-	✓	✓	-	-
[82]	-	✓	✓	✓	-	✓	-	-	✓	-	-
[104]	-	✓	✓	✓	✓	✓	✓	✓	-	✓	✓

CHAPTER 2. STATE-OF-THE-ART REVIEW

optimization is clearly the most commonly used. However, studies mostly focus on deterministic problem solving, and few consider the uncertainty on load, generation and consumer behavior. While MAS and GT have recently been popular tools in power system research, they are still little used for the coordination of multiple smart homes. Studies also typically test techniques on small-scale system, with less than 100 appliances. Only a few validate their approach on large systems with over 1000 appliances.

Lastly, although some studies consider RES and storage systems, these resources are usually located at the community scale, and not in individual houses. Moreover, most papers do not focus on maximizing the local use of RES but rather on minimizing costs.



COORDINATION MECHANISMS

INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

The share of RES in electricity generation is steadily increasing in both developed and developing countries, especially in the residential sector. Although the capital costs are high, the FIT offered by utilities (often with government support) incentivize customers to sell their generation back to the main grid. Specifically, while customers are able to produce and consume their own generated energy, they can also earn some profit by selling their surplus generation with FIT. This enables increasing the penetration level of RES in the electric grid, while customers benefit from financial incentives through self-consumption and FIT.

However, RES are not dispatchable, and their output cannot be controlled over the time horizon. Hence, when there is high RES generation, reverse power flow can occur on the distribution grid, which leads to increased losses, and transformers might become overloaded. Curtailment methods are thus needed. Under these circumstances, the efficient utilization of RES generation in the local area becomes a vital subject to study.

This chapter presents an incentive-based day-ahead electric energy management to increase renewable generation usage inside the neighborhood area by coordinating smart homes and enabling energy trading among users. For electricity pricing, TOU and FIT are used, and an incentive is defined to increase the interest in coordination and energy trading inside the neighborhood. In this respect, two types of coordination methodologies are presented (centralized and decentralized), and their performance is compared. The contributions of this chapter are listed as follows:

- The performance of the coordination mechanisms is evaluated by comparing the cost results with those for baseline and selfish scenarios.
- RES trading enables energy transfer among smart homes, hence the local renewable energy utilization is increased in the neighborhood.
- Multiple time resolutions are used for modeling electricity profiles, communication and optimization of energy storage.
- The pros and cons of the presented centralized and decentralized algorithms are investigated.

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

The rest of this chapter is organized as follows. In Section 3.1, the smart home and the neighborhood models are described, with the electricity pricing scheme. In Section 3.2, the proposed control and coordination algorithms are introduced. In Section 3.4, simulation results are presented, and in Section 3.5 the chapter is concluded.

3.1/ SYSTEM MODEL

In this study, an agent-based two level hierarchical neighborhood structure is deployed for modeling the electricity network. In the neighborhood, we assume that an aggregator and set of \mathcal{U} users are located in \mathcal{U} smart homes. A MAS (described in Section 2.3.3.1) is used for modeling entities in the neighborhood as agents, here the smart homes and the aggregator.

3.1.1/ HOME ENERGY SYSTEM

Smart homes are equipped with a home controller and are referred in the following as home agents. An example smart home is shown in Fig. 3.1. Although each electricity appliance can be modeled as an agent that can control appliance operation, we considered and modeled the HEMS as an agent that determines each appliance operation.

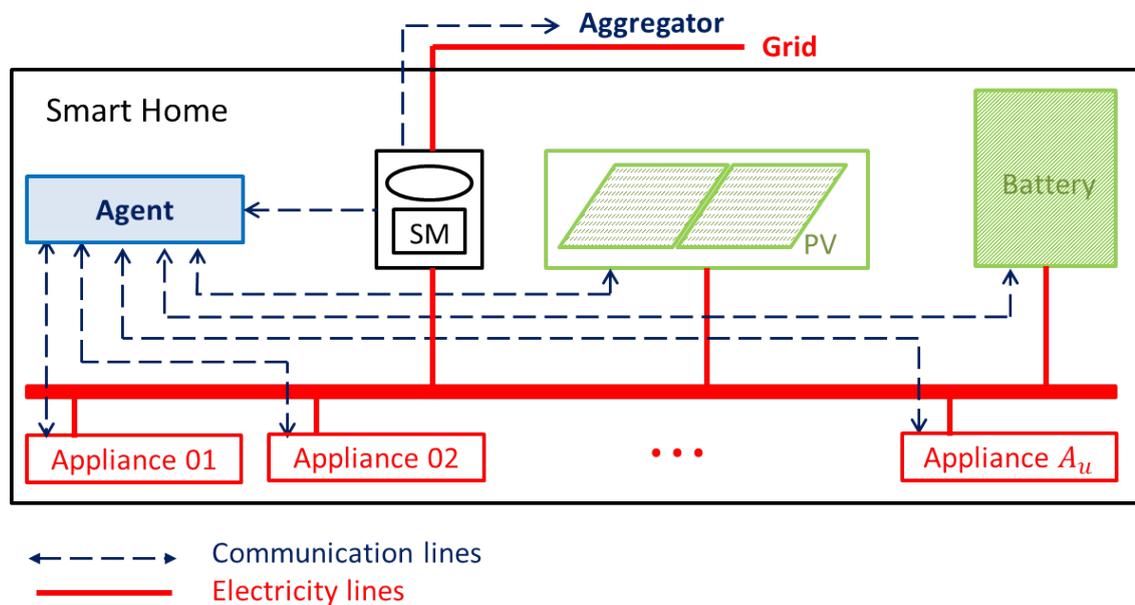


Figure 3.1: Smart home model (SM: smart meter).

Home agents measure environmental and electrical quantities, and communicate price and electrical data through AMI with other agents. We assume that each home has a user interface, e.g., in the form of a website or a smart phone application, where users can monitor their own consumption, generation and storage profile, and enter their preferences. Thus, a home agent controls its resources by coordinating with other entities in the neighborhood to accomplish their objectives, and while taking into account user

preferences (i.e., reducing daily bills using local generation). All electricity profiles in the smart home and the neighborhood are modeled with a 1-minute time resolution.

3.1.1.1/ CONSUMPTION MODEL

Based on their controllability, appliances are divided into two groups: non-controllable and controllable appliances. In total, 13 types of appliances are modeled. 10 of these (iron, toaster, etc.) are considered as non-controllable, and three of these (washing machine, clothes dryer and dish washer) are modeled as controllable-shiftable appliances (assets). The listed three controllable appliances are typically used in the literature [90]. In Table 3.1, home appliances and their respective power ratings are given.

Table 3.1: Amount, power rating and controllability of appliances (✓: controllable, –: non-controllable)

Appliances	Amount	Power rating (W)	Controllability
Lights	5	25 × 5	–
Kettle	1	450	–
Microwave	1	800	–
Vacuum cleaner	1	1,700	–
Television	1	150	–
Computer	1	250	–
Iron	1	650	–
Hair dryer	1	200	–
Toaster	1	500	–
Coffee marker	1	350	–
Washing machine	1	800	✓
Clothes dryer	1	1,000	✓
Dish washer	1	850	✓

Each smart home u has X_u non-controllable and Y_u controllable-shiftable appliances. Over the time horizon $t \in \mathbb{T}$, the operation interval of each appliance $x \in X_u$ and $y \in Y_u$ is denoted with binary values $\omega_u^x(t) \in \{0, 1\}$ and $\omega_u^y(t) \in \{0, 1\}$ (0 for off and 1 for on) as:

$$\omega_u^x(t) = \begin{cases} 1 & , \text{if } t \in [r_x^s, r_x^e] \\ 0 & , \text{elseif } t \in \mathbb{T} - [r_x^s, r_x^e] \end{cases} , \quad \forall x \in X_u \quad (3.1)$$

$$\omega_u^y(t) = \begin{cases} 1 & , \text{if } t \in [r_y^s, r_y^e] \\ 0 & , \text{elseif } t \in \mathbb{T} - [r_y^s, r_y^e] \end{cases} , \quad \forall y \in Y_u \quad (3.2)$$

where, r_x^s and r_x^e are the non-controllable appliances start and end times; and r_y^s and r_y^e are the controllable-appliances start and end times, respectively. Each appliance power rating is denoted P_u^{rx} and P_u^{ry} . Their consumption power is assumed to remain constant while the appliance is running, thereby the total electricity consumption of the smart home $P_u^c(t)$ is formulated with non-controllable $P_u^x(t)$ and controllable appliance $P_u^y(t)$ profiles as:

$$P_u^x(t) = P_u^{rx} \cdot \omega_u^x(t), \quad \forall t \in \mathbb{T} \quad (3.3)$$

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

$$P_u^y(t) = P_u^{r^y} \cdot \omega_u^y(t), \quad \forall t \in \mathbb{T} \quad (3.4)$$

$$P_u^c(t) = \sum_{x=1}^{X_u} P_u^x(t) + \sum_{y=1}^{Y_u} P_u^y(t), \quad \forall t \in \mathbb{T} \quad (3.5)$$

In this study, the operation start time and operation duration of appliances are modeled probabilistically using Gaussian distributions in the form of $\mathcal{N}(\mu, \sigma^2)$. Probability distribution parameters are defined arbitrarily. Start times and operation duration parameters are given in Table 3.2.

Table 3.2: Start time and operation duration parameters of appliances.

Appliances	Start time (h)		Duration (h)	
	Mean	Std. dev.	Mean	Std. dev.
Lights	5.5, 18.5	0.1, 0.1	1.5, 2.0	0.1, 0.1
Kettle	8.5, 13.5	0.1, 0.1	1.5, 1.5	0.1, 0.1
Microwave	5.5, 18.5	0.2, 0.2	1.5, 1.5	0.1, 0.1
Vacuum cleaner	13.5	0.1	1.5	0.1
Television	6.5, 19.5	0.1	1.5, 2	0.1, 0.1
Computer	11.0, 21.0	0.1, 0.1	1.5, 1.5	0.1, 0.1
Iron	21.5	0.1	1.5	0.1
Hair dryer	7.5	0.1	0.5	0.08
Toaster	6.5, 10.5	0.1, 0.1	0.5, 0.5	0.08, 0.08
Coffee marker	6.5, 20.5	0.1, 0.1	0.5, 0.5	0.08, 0.08
Washing machine	16.5	0.2	1.5	0.1
Clothes dryer	18.5	0.2	1.5	0.1
Dish washer	18.5	0.2	1.5	0.1

3.1.1.2/ PV GENERATION MODEL

PV systems are the most commonly used RES in the residential sector due their modular structure [118]. Moreover, PV systems can be easily integrated in building structures [69]. Therefore, we assume that building-integrated PV systems are used as RES in the neighborhood for local renewable generation. The power output of the installed PV array $P_u^g(t)$ is formulated as:

$$P_u^g(t) = N_u^s \cdot N_u^p \cdot P_u^{pv} \cdot \left(\frac{I(t)}{I_{STC}} \right) \quad (3.6)$$

where N_u^s and N_u^p are the number of series and parallel connected PV modules, respectively (see Fig. 3.2); P_u^{pv} is the recorded power output of a single PV module in standard test conditions (STC) where the irradiance is 1000 W/m^2 and the temperature is $25 \text{ }^\circ\text{C}$. $I(t)$ is the measured irradiance value on the PV module surface and I_{STC} is the irradiance value in STC.

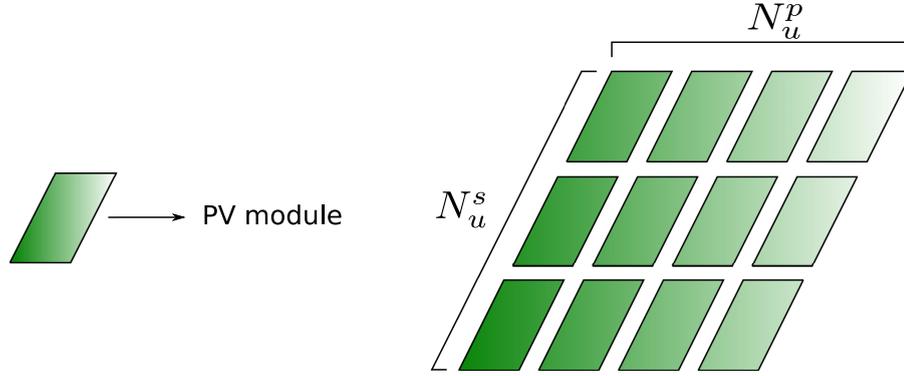


Figure 3.2: PV system structure.

3.1.1.3/ ENERGY STORAGE MODEL

As RES are not dispatchable energy resources, their output power cannot be controlled. Therefore, most of the time, the produced renewable power is fed back to the grid without being used in the smart home. To increase flexibility in the smart home as well as the local utilization of renewable energy, storage systems (such as lithium-ion batteries) are assumed to be installed. Surplus renewable generation can then be stored in the home storage system for later use when consumption is higher.

In this study, batteries are used to store renewable generation from residential PV systems. The injection and battery powers are denoted as $P_u^I(t)$ and $P_u^b(t)$, respectively, and the state-of-charge ($SO C_u(t)$) value is computed by:

$$P_u^b(t) = \begin{cases} P_u^I(t) \cdot \eta_u^c, & \text{if } P_u^I(t) > 0 \\ P_u^I(t) / \eta_u^d, & \text{else } P_u^I(t) \leq 0 \end{cases} \quad (3.7)$$

$$SO C_u(t) = SO C_u(t-1) + \frac{(P_u^b(t) \cdot \Delta t)}{E_u^{bat}} \quad (3.8)$$

where η_u^c and η_u^d are the battery charging and discharging efficiencies, respectively; E_u^{bat} is the battery energy capacity; and Δt is the simulation time step ($\Delta t = 1/60$ for 1-minute resolution). According to (3.7), $P_u^I(t)$ is positive while charging ($P_u^b(t) > 0$), and $P_u^I(t)$ is negative while discharging ($P_u^b(t) \leq 0$) the battery. Lastly, operation constraints of the battery for state-of-charge and battery power are given by:

$$\frac{\rho_u^d}{\eta_u^d} \leq P_u^b(t) \leq \rho_u^c \cdot \eta_u^c \quad (3.9)$$

$$SO C_u^{min} \leq SO C_u(t) \leq SO C_u^{max} \quad (3.10)$$

where ρ_u^c and ρ_u^d are the maximum battery charging and discharging power limits; and $SO C_u^{min}$ and $SO C_u^{max}$ are the minimum and maximum state-of-charge values of the home batteries.

3.1.2/ NEIGHBORHOOD AREA

A two-layered hierarchical neighborhood MAS architecture is used. The power and communication schemas are given in Fig. 3.3. All home agents are assumed to have two-

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

way communication ability through AMI, and to exchange messages with the aggregator agent. Smart homes are directly connected to the electricity grid for supplying their demand load, hence the aggregator agent does not have the ability to directly control the neighborhood electricity grid and/or smart appliances in the smart homes.

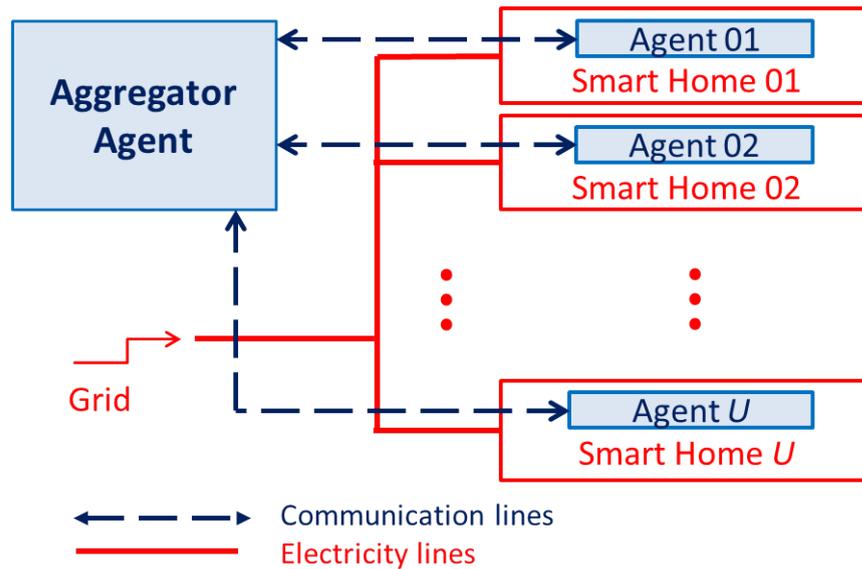


Figure 3.3: Neighborhood agent model with power and communication structures.

The aggregator agent is located at the upper level and only advises home agents through message exchanges (i.e., price and power data). At the bottom level, home agents receive and send data from/to the aggregator agent, and perform actions based on the coordination model (centralized or decentralized). In this study, it is assumed that home agents do not communicate with each other due to privacy concerns, hence they only communicate with the aggregator agent as in the centralized or fully-dependent decentralized models described in Section 2.3.2.

3.1.3/ ELECTRICITY PRICING: NEIGHBORHOOD INCENTIVE MODEL

To bill home users, TOU pricing $\lambda_{TOU}(t)$ and FIT schema λ_{FIT} are used and combined based on French policy [147, 134]. TOU and FIT are assumed fixed throughout the year, and do not change with seasons. TOU is utilized for consumption, and FIT is defined for selling surplus generation to the main grid. However, classic TOU and FIT are not able to increase interest in self-consumption in smart homes and/or the neighborhood. Therefore, an incentive λ_i is defined to enable and coordinate electricity trading among smart homes. The grid and enhanced neighborhood price with incentive are given in Table 3.3 and Fig. 3.4. As for FIT, the incentive could be supported by governmental entities (i.e., tax offices) under the aim of increasing local renewable energy usage in the neighborhood.

In this work, the benefits of self-consumption in the smart homes and of selling electricity to neighbors are considered to be more beneficial than selling energy back to main grid using the incentive price. While smart homes earn $(\lambda_{FIT} + \lambda_i/2)$ for selling electricity to their neighbors, they also earn $(\lambda_{FIT} + \lambda_i - \lambda_{TOU}(t))$ for self-consumption, without paying

anything to the main grid (as their net load is zero) Beside that, purchasing electricity from neighbors costs less than buying from the grid. Thus, electricity trading among smart homes is encouraged by the proposed incentive.

Table 3.3: Electricity grid and neighborhood trading tariffs.

Source	Tariffs	Period	Time (h)	€/kWh
Grid	TOU price	off-peak	(12:00–15:00) (22:00–06:00)	0.127
		on-peak	(06:00–12:00) (15:00–22:00)	0.156
	FIT	—	(00:00–24:00)	0.246
—	Incentive	—	(00:00–24:00)	0.020
Neighborhood	Import price	off-peak	(12:00–15:00) (22:00–06:00)	0.117
		on-peak	(06:00–12:00) (15:00–22:00)	0.146
	Export price	—	(00:00–24:00)	0.256

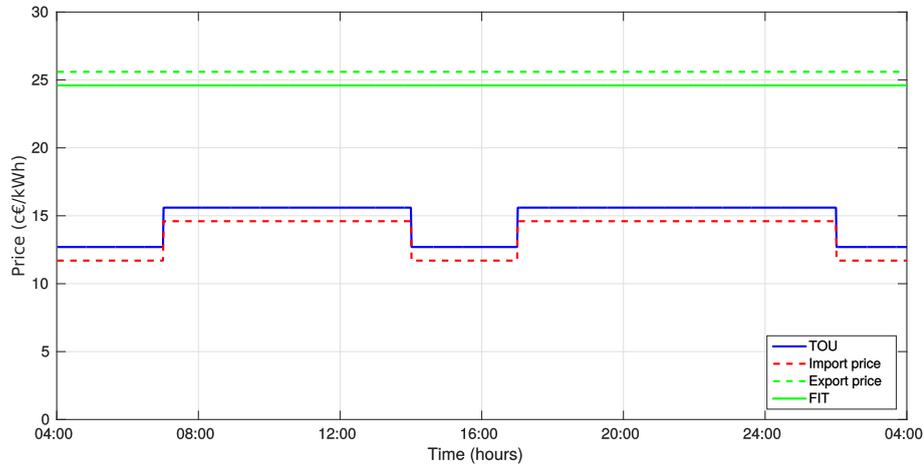


Figure 3.4: TOU, FIT and neighborhood pricing.

3.2/ PROBLEM FORMULATION

In this section, two base scenarios (baseline and selfish) and two proposed algorithms (decentralized and centralized) are formulated to show how home agents control their resources and/or coordinate their actions with each other. In Table 3.4, an overview and comparison of the presented algorithms are given.

3.2.1/ BASELINE SCENARIO

The first algorithm serves as a reference scenario to show the effectiveness of the proposed algorithm. In this scenario, home agents have no active role (no control and communication ability) in the household environment. Therefore, in battery-equipped smart homes, the battery charges when there is surplus PV generation and discharges

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

Table 3.4: Comparison of the algorithms (✓: used, -: not used).

	Baseline	Selfish	Decentralized	Centralized
Asset control	-	✓	✓	✓
Communication	-	✓	✓	✓
Trading	-	-	✓	✓
Objective	Basic asset management	Minimizing the electricity bill of the smart homes	Minimizing the electricity bill of the smart homes with trading	Minimizing the total electricity bill of the neighborhood with trading

whenever there is more consumption than PV generation. The battery cannot efficiently charge/discharge for the benefit of the customers. Moreover, in all smart homes, smart appliances are considered as baseline appliances, therefore they cannot be scheduled over the time horizon. Accordingly, the net consumption $P_u^{nc}(t)$ and surplus generation $P_u^{sp}(t)$ in a smart home are formulated as:

$$P_u^n(t) = P_u^c(t) - P_u^s(t) + P_u^b(t) \quad (3.11)$$

$$P_u^{nc}(t) = \begin{cases} P_u^n(t) & , \text{if } P_u^n(t) > 0 \\ 0 & , \text{else } P_u^n(t) \leq 0 \end{cases} \quad (3.12)$$

$$P_u^{sg}(t) = \begin{cases} 0 & , \text{if } P_u^n(t) > 0 \\ -P_u^n(t) & , \text{else } P_u^n(t) \leq 0 \end{cases} \quad (3.13)$$

where $P_u^n(t)$ is called the net (load) profile of a smart home. A negative $P_u^n(t)$ means that there is surplus generation the smart home. In this work, the same neighborhood pricing scheme (given in Table 3.3) is used for fair comparison in all simulation cases. Thereby, the surplus generation is sold to the main grid with λ_{FIT} and self-consumption is rewarded with λ_i as follows:

$$P_u^{sc}(t) = P_u^c(t) - P_u^{nc}(t) \quad (3.14)$$

$$C_u = \Delta t \cdot \sum_{t=1}^{\mathcal{T}} P_u^{nc}(t) \cdot \lambda_{TOU}(t) - P_u^{sg}(t) \cdot \lambda_{FIT} - P_u^{sc}(t) \cdot (\lambda_{FIT} + \lambda_i - \lambda_{TOU}(t)) \quad (3.15)$$

where $P_u^{sc}(t)$ is the self-consumption power and C_u is the daily electricity cost of smart homes in the baseline scenario.

3.2.2/ SELFISH SCENARIO

In the selfish scenario, home agents receive pricing information ($\lambda_{TOU}(t)$, λ_{FIT} , and λ_i) to selfishly control their assets without sharing any information with the aggregator and other houses. Hence, home agents cannot trade energy with each other, as they do not know the neighborhood electricity profile. In this case, an optimization algorithm is formulated by taking into account the following assumptions:

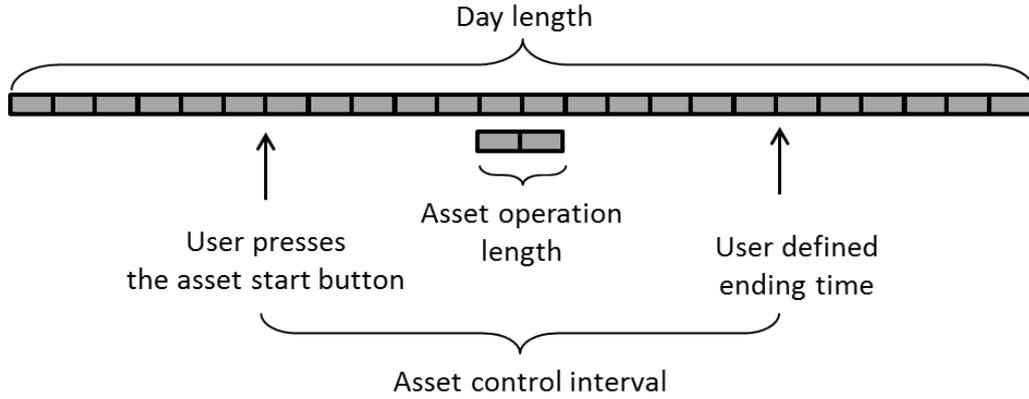


Figure 3.5: Representation of the appliance control interval over 24 hours. Each block represents a 60-minute time interval.

- Appliance assets cannot be shifted to operate on the next scheduling day, so the total energy consumption in a day is conserved,
- For battery optimization, a new time resolution (called battery control interval) is defined instead of the actual one (used for modeling electricity profiles) to control charging/discharging/idle operations, in order to reduce the computation burden.

Firstly, we assume that users define the control interval of each asset for load scheduling, as shown in Fig. 3.5. In the control interval, home agents pick the most beneficial time to run assets (mostly during low-price periods). This interval must be at least equal to the appliance operation duration, however it preferably needs to be wide enough for gaining more profit from the scheduling operation. In other words, the larger the flexibility, the higher the potential gains. The constraint for asset scheduling is given by:

$$[r_y^s, r_y^e] \subseteq [t_y^s, t_y^e] \quad (3.16)$$

where t_y^s and t_y^e are the user-defined acceptable start and end times, respectively. In the smart home, the operation of some assets, such as the washing machine and clothes dryer are not independent. For instance, the clothes dryer should always operate after the washing machine has finished its work. Therefore, during the modeling and the optimization, an additional constraint is formulated as:

$$r_{wm}^s < r_{cd}^s - (r_{wm}^e - r_{wm}^s) \quad (3.17)$$

$$t_{wm}^s < t_{cd}^s - (r_{wm}^e - r_{wm}^s) \quad (3.18)$$

Secondly, as a reminder from Section 3.1.1, all smart homes and the neighborhood electricity profiles are modeled with a 1-minute time resolution in this chapter. Related to that, in total, 1,440 inputs are required to determine the battery output for one day in the optimization problem. Using such a high number of inputs increases the computation time of the optimization problem. Therefore, a larger time step (15 minutes as in Fig. 3.6) is used to reduce the size of the optimization problem and return results in reasonable computation time.

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

The battery output power is determined with two time indexes: the actual one “ $t \in \mathbb{T}$ ”, and “ $z \in \mathbb{Z}$ ”, with the battery control time resolution. Accordingly, the output power of the battery is determined with binary variables $\gamma_u^b(z) \in \{0, 1\}$ (defined for logically controlling battery charging/discharging/idle status) as:

$$P_u^b(t) = \begin{cases} (P_u^g(t) - P_u^c(t)) \cdot \eta_u^c & , \text{if } \gamma_u^b(z) = 0, P_u^g(t) > P_u^c(t) \\ 0 & , \text{elseif } \gamma_u^b(z) = 0, P_u^g(t) \leq P_u^c(t) \\ (P_u^g(t) - P_u^c(t)) / \eta_u^d & , \text{else } \gamma_u^b(z) = 1 \end{cases} \quad (3.19)$$

where $\gamma_u^b(z)$ is the optimization input parameter used for determining battery output power. In total, $\mathcal{Z} = \mathcal{T}/15$ inputs are required for optimizing battery output. At last, home agents solve the following optimization problem individually for the selfish scenario:

$$\begin{aligned} & \text{minimize } \left\{ C_u = \Delta t \cdot \sum_{t=1}^{\mathcal{T}} P_u^{nc}(t) \cdot \lambda_{TOU}(t) - P_u^{sg}(t) \cdot \lambda_{FIT} - P_u^{sc}(t) \cdot (\lambda_{FIT} + \lambda_i - \lambda_{TOU}(t)) \right\} \quad (3.20) \\ & \text{s.t. } (3.1), (3.2), (3.9), (3.10), (3.16), (3.17), (3.18) \end{aligned}$$

3.2.3/ DECENTRALIZED COORDINATION

The first proposed method is referred to as “decentralized coordination”. In this algorithm, a two-way communication link is required between home agents and the aggregator for frequently exchanging messages. The message transfer and the algorithmic operation principles of the home agents and the aggregator are shown in Fig. 3.7, and can be explained in four steps as follows:

Step 1:

Firstly, home agents initialize their electricity profiles simultaneously, and the aggregator sends the price information ($\lambda_{TOU}(t)$, λ_{FIT} , and λ_i) to all home agents. Then, home agents optimize their daily electricity bill by scheduling and controlling battery output according to the optimization problem formulated in (3.20). Home agents optimize electricity costs as in the selfish scenario, due to not having any additional information about the neighborhood electricity profile. It should also be noted that home agents act simultaneously at each step, thereby they optimize and send messages at the same time, and wait until others have finished. At the end of the optimization, home agents generate two types of data: the net consumption (3.12) and the surplus generation (3.13) profiles.

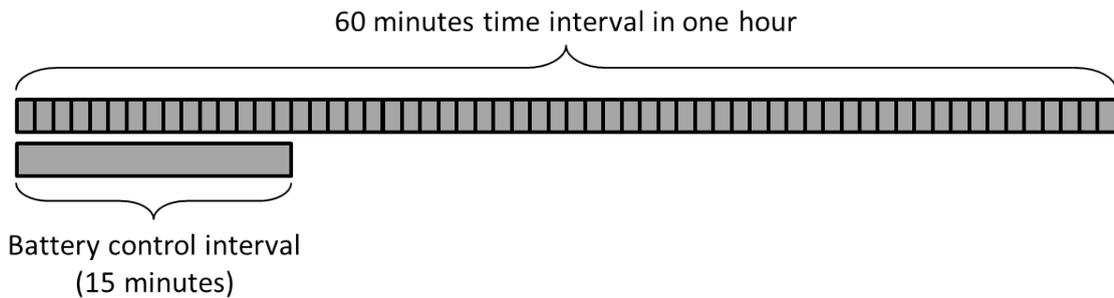


Figure 3.6: Representation of the battery control interval (15 minutes) in one hour.

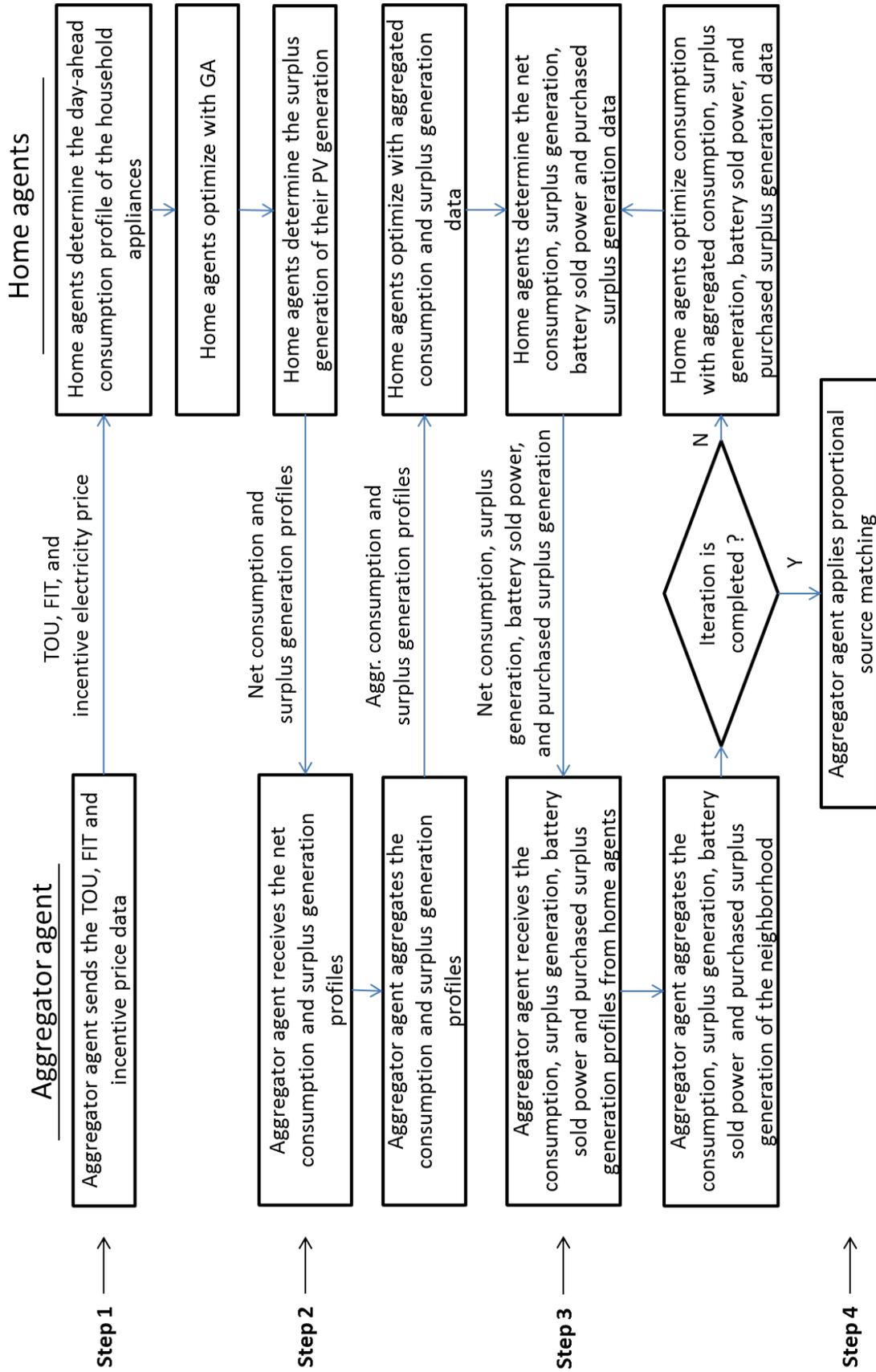


Figure 3.7: Flowchart of the decentralized coordination method.

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

To inform the aggregator agent, home agents send these electricity profiles through AMI. However, they first calculate the average of each electricity profile for certain time intervals “ \mathcal{L} ”, as in Fig. 3.8. A new time resolution “ $l \in \mathbb{L}$ ” is defined for communication, for the following reasons:

- Taking the average of the actual data for certain time intervals is a basic privacy protection method. In this case, customers do not want to share exact information with the aggregator, hence they only send average data.
- To reduce the communication burden of the aggregator, as message size is reduced from \mathcal{T} to \mathcal{T}/\mathcal{L} for an electricity profile.

$$P_u^{nc}(t) \rightarrow \hat{P}_u^{nc}(l) \quad (3.21)$$

$$P_u^{sg}(t) \rightarrow \hat{P}_u^{sg}(l) \quad (3.22)$$

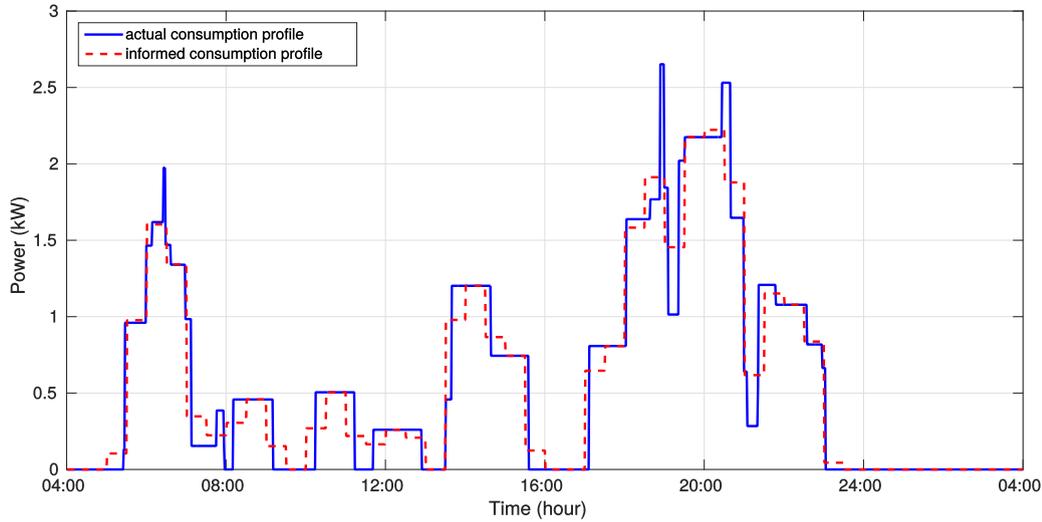


Figure 3.8: Actual and communication data of a consumption profile.

Step II:

At the beginning of the second step, the aggregator receives the individual profiles of the smart homes and aggregates them to determine the neighborhood electricity profiles.

$$\hat{\mathbf{P}}_{agg}^{nc}(l) = \sum_{u=1}^{\mathcal{U}} \hat{P}_u^{nc}(l) \quad (3.23)$$

$$\hat{\mathbf{P}}_{agg}^{sg}(l) = \sum_{u=1}^{\mathcal{U}} \hat{P}_u^{sg}(l) \quad (3.24)$$

After that, the aggregator agent sends the aggregated profiles with the price data to the home agents. When home agents receive the electricity profiles, they determine the neighborhood profile by subtracting their electricity profiles (called perspective aggregated profiles in the smart homes):

$$\hat{P}_{agg,u}^{nc}(l) = \hat{\mathbf{P}}_{agg}^{nc}(l) - \hat{P}_u^{nc}(l) \quad (3.25)$$

$$\hat{P}_{agg,u}^{sg}(l) = \hat{\mathbf{P}}_{agg}^{sg}(l) - \hat{P}_u^{sg}(l) \quad (3.26)$$

Then, they convert the perspective profiles from the communication data structure to the actual data structure (i.e., from the l -domain to the t -domain):

$$\hat{P}_{agg,u}^{nc}(l) \rightarrow P_{agg,u}^{nc}(t) \quad (3.27)$$

$$\hat{P}_{agg,u}^{sg}(l) \rightarrow P_{agg,u}^{sg}(t) \quad (3.28)$$

Now, home agents have additional information in addition to price data: neighborhood net consumption and surplus generation profiles. Using these two additional information, home agents in battery-equipped smart homes can discharge their batteries to sell battery energy to neighbors, and all smart homes can purchase energy from neighbors surplus generation. To do that, home agents determine the net area profile $P_{agg,u}^n(t)$ by:

$$P_{agg,u}^n(t) = P_{agg,u}^{nc}(t) - P_{agg,u}^{sg}(t) \quad (3.29)$$

Then, they calculate their battery output profile by making condition comparisons between electricity profiles ($P_u^c(t)$, $P_u^g(t)$, and $P_{agg,u}^n(t)$) as follows:

$$P_u^b(t) = \begin{cases} (P_u^g(t) - P_u^c(t)) \cdot \eta_u^c & , \text{ if } \gamma_u^b(z) = 0, P_u^g(t) > 0, P_u^g(t) > P_u^c(t), P_{agg,u}^n(t) \leq 0 \\ 0 & , \text{ elseif } \gamma_u^b(z) = 0, P_u^g(t) > 0, P_u^g(t) \leq P_u^c(t), P_{agg,u}^n(t) \leq 0 \\ (P_u^g(t) - P_u^c(t) - P_{agg,u}^n(t)) \cdot \eta_u^c & , \text{ elseif } \gamma_u^b(z) = 0, P_u^g(t) > 0, P_{agg,u}^n(t) > 0, P_u^g(t) > P_{agg,u}^n(t) \\ (P_u^g(t) - P_u^c(t) - P_{agg,u}^n(t)) / \eta_u^d & , \text{ elseif } \gamma_u^b(z) = 0, P_u^g(t) > 0, P_{agg,u}^n(t) > 0, P_u^g(t) \leq P_{agg,u}^n(t) \\ -P_u^c(t) / \eta_u^d & , \text{ elseif } \gamma_u^b(z) = 0, P_u^g(t) = 0, P_{agg,u}^n(t) \leq 0 \\ (-P_u^c(t) - P_{agg,u}^n(t)) / \eta_u^d & , \text{ elseif } \gamma_u^b(z) = 0, P_u^g(t) = 0, P_{agg,u}^n(t) > 0 \\ (P_u^g(t) - P_u^c(t)) \cdot \eta_u^c & , \text{ elseif } \gamma_u^b(z) = 1, P_u^g(t) > 0, P_u^g(t) > P_u^c(t) \\ 0 & , \text{ elseif } \gamma_u^b(z) = 1, P_u^g(t) > 0, P_u^g(t) \leq P_u^c(t) \\ 0 & , \text{ elseif } \gamma_u^b(z) = 1, P_u^g(t) = 0, P_{agg,u}^n(t) \leq 0 \\ -P_u^c(t) / \eta_u^d & , \text{ else } \gamma_u^b(z) = 1, P_u^g(t) = 0, P_{agg,u}^n(t) > 0 \end{cases} \quad (3.30)$$

Compared to (3.19), home agents apply a more advanced control method for *charging/discharging/idle* operations, in other words to determine the battery output power while taking into account the neighborhood profile. In (3.30), home agents are also able to discharge their battery for neighborhood consumption to increase their profit using the incentive price " λ_i ". Therefore, home agents need to determine how much energy to sell to the neighborhood from the calculated battery power with:

$$P_u^{bs}(t) = \begin{cases} 0 & , \text{ if } \gamma_u^b(z) = 0, P_u^c(t) \geq -P_u^b(t) \\ -P_u^b(t) - P_u^c(t) & , \text{ elseif } \gamma_u^b(z) = 0, P_u^c(t) < -P_u^b(t) \\ 0 & , \text{ else } \gamma_u^b(z) = 1 \end{cases} \quad (3.31)$$

According to (3.31), the discharged energy is firstly used for self-consumption and then sold for neighborhood electricity consumption. After that, home agents calculate their net profile with:

$$P_u^n(t) = P_u^c(t) - P_u^g(t) + P_u^b(t) + P_u^{bs}(t) \quad (3.32)$$

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

Next, home agents separate the net consumption $P_u^{nc}(t)$ from the surplus generation $P_u^{sg}(t)$ using (3.12) and (3.13). Thus, home agents calculate the purchased surplus generation $P_u^{sp}(t)$ from neighbors using:

$$P_u^{sp}(t) = \begin{cases} P_u^{nc}(t) & , \text{ if } P_{agg,u}^{sg}(t) > P_{agg,u}^{nc}(t) + P_u^{nc}(t) \\ P_{agg,u}^{sg}(t) \cdot \left(\frac{P_u^{nc}(t)}{P_{agg,u}^{nc}(t) + P_u^{nc}(t)} \right) & , \text{ else } P_{agg,u}^{sg}(t) \leq P_{agg,u}^{nc}(t) + P_u^{nc}(t) \end{cases} \quad (3.33)$$

After that, home agents update the net electricity by adding surplus generation, then apply (3.12) and (3.13), and calculate the self-consumption profile:

$$P_u^n(t) = P_u^c(t) - P_u^g(t) + P_u^b(t) + P_u^{bs}(t) - P_u^{sp}(t) \quad (3.34)$$

$$P_u^{sc}(t) = P_u^c(t) - P_u^{nc}(t) - P_u^{sp}(t) \quad (3.35)$$

Finally, home agents optimize their resources by solving the following problem:

$$\begin{aligned} & \text{minimize} \left\{ C_u = \Delta t \cdot \sum_{t=1}^T P_u^{nc}(t) \cdot \lambda_{TOU}(t) - P_u^{sg}(t) \cdot \lambda_{FIT} + P_u^{sp}(t) \cdot (\lambda_{TOU}(t) - \lambda_i/2) \right. \\ & \left. - P_u^{sc}(t) \cdot (\lambda_{FIT} + \lambda_i - \lambda_{TOU}(t)) - P_u^{bs}(t) \cdot (\lambda_{FIT} + \lambda_i/2) \right\} \quad (3.36) \\ & \text{s.t. } (3.1), (3.2), (3.9), (3.10), (3.16), (3.17), (3.18) \end{aligned}$$

At the end of the optimization problem, home agents inform the aggregator agent after determining the communication data in the l -domain (in addition to (3.21) and (3.22)):

$$P_u^{bs}(t) \rightarrow \hat{P}_u^{bs}(l) \quad (3.37)$$

$$P_u^{sp}(t) \rightarrow \hat{P}_u^{sp}(l) \quad (3.38)$$

where $\hat{P}_u^{bs}(l)$ and $\hat{P}_u^{sp}(l)$ are the communication data of sold power with battery discharge and the purchased surplus power in the smart home, respectively.

In this work, home agents do not have any knowledge about the buyers and sellers in the neighborhood. For instance, home agents only have information about the aggregated surplus generation and the net consumption profiles of the neighborhood. Hence, if they want to purchase energy, they purchase from the aggregated profile, thereby they do not need to find who is selling energy. Thus, buyers and sellers do not need to be matched during the optimization process. Secondly, incentive revenue is provided for both buyers and sellers. The revenue is shared equally (i.e., $\lambda_i/2$) between buyers and sellers, so that they can both gain some benefit from the coordination. It should be noted that the divided revenue is added to the FIT for sellers ($\lambda_{FIT} + \lambda_i/2$), and subtracted from the TOU price for buyers ($\lambda_{TOU}(t) - \lambda_i/2$). However, home agents can also gain the entire incentive revenue by themselves, only if the produced renewable energy consumed in the same smart home for self-consumption ($\lambda_{FIT} + \lambda_i - \lambda_{TOU}(t)$).

Step III:

At the beginning of the third step, home agents send the following information in order, and the aggregator agent sums individual profiles (in addition to (3.25) and (3.26)):

$$\hat{\mathbf{P}}_{agg}^{bs}(l) = \sum_{u=1}^{\mathcal{U}} \hat{P}_u^{bs}(l) \quad (3.39)$$

$$\hat{\mathbf{P}}_{agg}^{sp}(l) = \sum_{u=1}^U \hat{\mathbf{P}}_u^{sp}(l) \quad (3.40)$$

After that, the aggregator agent sends the aggregated profiles to the home agents. When home agents receive the aggregated profiles, they create the perspective profiles (in addition to (3.25) and (3.26)):

$$\hat{P}_{agg,u}^{bs}(l) = \hat{\mathbf{P}}_{agg}^{bs}(l) - \hat{P}_u^{bs}(l) \quad (3.41)$$

$$\hat{P}_{agg,u}^{sp}(l) = \hat{\mathbf{P}}_{agg}^{sp}(l) - \hat{P}_u^{sp}(l) \quad (3.42)$$

Then, they convert all of them from communication to actual data structure (in addition to (3.27) and (3.28)):

$$\hat{P}_{agg,u}^{bs}(l) \rightarrow P_{agg,u}^{bs}(t) \quad (3.43)$$

$$\hat{P}_{agg,u}^{sp}(l) \rightarrow P_{agg,u}^{sp}(t) \quad (3.44)$$

Home agents use (3.29), (3.30) and (3.31) to determine the battery output power and the sold power with battery discharge, respectively. However, home agents, after (3.31), need to correlate their sold power with battery discharge by taking into account the decisions of others (on sold power):

$$P_u^{bs}(t) = \begin{cases} P_u^{bs}(t) & , \text{ if } P_{agg,u}^{nc}(t) \geq P_{agg,u}^{bs}(t) + P_u^{bs}(t) \\ P_{agg,u}^{nc}(t) - P_{agg,u}^{bs}(t) & , \text{ else } P_{agg,u}^{nc}(t) < P_{agg,u}^{bs}(t) + P_u^{bs}(t) \end{cases} \quad (3.45)$$

Later, home agents use (3.32), (3.12), (3.13) and (3.33), in this order, to calculate the purchased surplus energy. At the end of this step, home agents optimize with (3.36), and convert electricity profiles from actual to communication resolution using (3.21), (3.22), (3.37), and (3.38). Then, the process is repeated until the number of iterations is reached.

Step IV:

When the iterations have ended, the aggregator agent gathers the latest decisions of the home agents and calculates the daily electricity bill of each smart home. However, the aggregator firstly needs to balance the sold and bough powers inside the neighborhood by matching the electricity profiles. To do that, a method called *proportional source matching* is applied for these mismatch conditions. Mismatches occur because:

- Home agents are all optimizing simultaneously, so they might take the same decision for selling and/or purchasing for the same consumption and/or generation units. Hence, the aggregated trading decisions during the optimization might be higher than the actual electricity profiles.
- Home agents communicate with average data rather than actual data. Therefore, there might be some ups and downs in the actual data during the communication time interval (i.e., 30 minutes). As a result, there can be differences between the actual and the decided profiles, that need to be corrected.

At the final steps, the aggregator checks the existence of mismatch conditions and makes decisions on behalf of home agents by using *proportional source matching*. Basically, the method distributes the amount of sold and bought power according to the ratio of the

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

smart home electricity profile (decision at latest iteration) with respect to the aggregated power profile.

Accordingly, the purchased surplus $P_u^{sp}(t)$ and the sold surplus generation $P_u^{ss}(t)$ powers are formulated as:

$$P_u^{sp}(t) = \begin{cases} P_u^{nc}(t) & , \text{ if } \mathbf{P}_{agg}^{sg}(t) \geq \mathbf{P}_{agg}^{sp,d}(t), P_u^{sp,d}(t) > P_u^{nc}(t) \\ P_u^{sp,d}(t) & , \text{ elseif } \mathbf{P}_{agg}^{sg}(t) \geq \mathbf{P}_{agg}^{sp,d}(t), P_u^{sp,d}(t) \leq P_u^{nc}(t) \\ P_u^{nc}(t) & , \text{ elseif } \mathbf{P}_{agg}^{sg}(t) < \mathbf{P}_{agg}^{sp,d}(t), \mathbf{P}_{agg}^{sg}(t) \cdot \left(\frac{P_u^{sp,d}(t)}{\mathbf{P}_{agg}^{sp,d}(t)} \right) > P_u^{nc}(t) \\ \mathbf{P}_{agg}^{sg}(t) \cdot \left(\frac{P_u^{sp,d}(t)}{\mathbf{P}_{agg}^{sp,d}(t)} \right) & , \text{ else } \mathbf{P}_{agg}^{sg}(t) < \mathbf{P}_{agg}^{sp,d}(t), \mathbf{P}_{agg}^{sg}(t) \cdot \left(\frac{P_u^{sp,d}(t)}{\mathbf{P}_{agg}^{sp,d}(t)} \right) \leq P_u^{nc}(t) \end{cases} \quad (3.46)$$

$$P_u^{ss}(t) = \begin{cases} P_u^{sg}(t) & , \text{ if } \mathbf{P}_{agg}^{sg}(t) > P_u^{sg}(t), \mathbf{P}_{agg}^{sp}(t) = \mathbf{P}_{agg}^{sg}(t) \\ \mathbf{P}_{agg}^{sp}(t) \cdot \left(\frac{P_u^{sg}(t)}{\mathbf{P}_{agg}^{sg}(t)} \right) & , \text{ elseif } \mathbf{P}_{agg}^{sg}(t) > P_u^{sg}(t), \mathbf{P}_{agg}^{sp}(t) < \mathbf{P}_{agg}^{sg}(t) \\ P_u^{sg}(t) & , \text{ elseif } P_{agg}^{sg}(t) = P_u^{sg}(t), \mathbf{P}_{agg}^{sp}(t) = P_u^{sg}(t) \\ \mathbf{P}_{agg}^{sp}(t) & , \text{ else } \mathbf{P}_{agg}^{sg}(t) = P_u^{sg}(t), \mathbf{P}_{agg}^{sp}(t) < P_u^{sg}(t) \end{cases} \quad (3.47)$$

where $P_u^{sp,d}(t)$ and $\mathbf{P}_{agg}^{sp,d}(t)$ are the home and aggregated neighborhood purchased surplus generation at the latest iteration, respectively. After that, $P_u^{nc}(t)$ and $\mathbf{P}_{agg}^{nc}(t)$ are updated to determine the purchased $P_u^{bp}(t)$ and sold $P_u^{bs}(t)$ power with battery discharge as follows:

$$P_u^{nc}(t) = P_u^{nc}(t) - P_u^{sp}(t) \quad (3.48)$$

$$\mathbf{P}_{agg}^{nc}(t) = \mathbf{P}_{agg}^{nc}(t) - \sum_{u=1}^{\mathcal{U}} P_u^{sp}(t) \quad (3.49)$$

$$P_u^{bp}(t) = \begin{cases} P_u^{nc}(t) & , \text{ if } \mathbf{P}_{agg}^{nc}(t) > P_u^{nc}(t), \mathbf{P}_{agg}^{bs,d}(t) \geq \mathbf{P}_{agg}^{nc}(t) \\ \mathbf{P}_{agg}^{bs,d}(t) \cdot \left(\frac{P_u^{nc}(t)}{\mathbf{P}_{agg}^{nc}(t)} \right) & , \text{ elseif } \mathbf{P}_{agg}^{nc}(t) > P_u^{nc}(t), \mathbf{P}_{agg}^{bs,d}(t) < \mathbf{P}_{agg}^{nc}(t) \\ P_u^{nc}(t) & , \text{ elseif } \mathbf{P}_{agg}^{nc}(t) = P_u^{nc}(t), \mathbf{P}_{agg}^{bs,d}(t) \geq \mathbf{P}_{agg}^{nc}(t) \\ \mathbf{P}_{agg}^{bs,d}(t) & , \text{ else } \mathbf{P}_{agg}^{nc}(t) = P_u^{nc}(t), \mathbf{P}_{agg}^{bs,d}(t) < \mathbf{P}_{agg}^{nc}(t) \end{cases} \quad (3.50)$$

$$P_u^{bs}(t) = \begin{cases} \mathbf{P}_{agg}^{bp}(t) & , \text{ if } \mathbf{P}_{agg}^{bs,d}(t) = P_u^{bs,d}(t), P_u^{bs,d}(t) > \mathbf{P}_{agg}^{bp}(t) \\ P_u^{bs,d}(t) & , \text{ elseif } \mathbf{P}_{agg}^{bs,d}(t) = P_u^{bs,d}(t), P_u^{bs,d}(t) = \mathbf{P}_{agg}^{bp}(t) \\ \mathbf{P}_{agg}^{bp}(t) \cdot \left(\frac{P_u^{bs,d}(t)}{\mathbf{P}_{agg}^{bs,d}(t)} \right) & , \text{ elseif } \mathbf{P}_{agg}^{bs,d}(t) > P_u^{bs,d}(t), \mathbf{P}_{agg}^{bs,d}(t) > \mathbf{P}_{agg}^{bp}(t) \\ P_u^{bs,d}(t) & , \text{ else } \mathbf{P}_{agg}^{bs,d}(t) > P_u^{bs,d}(t), \mathbf{P}_{agg}^{bs,d}(t) = \mathbf{P}_{agg}^{bp}(t) \end{cases} \quad (3.51)$$

where $P_u^{bs,d}(t)$ and $\mathbf{P}_{agg}^{bs,d}(t)$ are the home and aggregated neighborhood sold energy with battery discharge at the latest iteration, respectively. As seen in (3.46), (3.47), (3.50) and (3.51), *proportional source matching* is used when the electricity sources are insufficient and when mismatches occur due to the above listed reasons (e.g., when the generated real-time surplus generation is not enough to provide the decided purchased surplus power by the neighborhood home agents).

Finally, the aggregator agent calculates the daily electricity bills of the users in real-time. First, the total home sold $P_u^{sold}(t)$ and purchased $P_u^{purchased}(t)$ powers are calculated:

$$P_u^{sold}(t) = P_u^{ss}(t) + P_u^{bs}(t) \quad (3.52)$$

$$P_u^{purchased}(t) = P_u^{sp}(t) + P_u^{bp}(t) \quad (3.53)$$

Then, the net profile is updated:

$$P_u^n(t) = P_u^c(t) - P_u^s(t) + P_u^b(t) + P_u^{sold}(t) - P_u^{purchased}(t) \quad (3.54)$$

After that, the net consumption is separated from surplus generation using (3.12) and (3.13), and the self-consumption power is determined as follows:

$$P_u^{sc}(t) = P_u^c(t) - P_u^{nc}(t) - P_u^{purchased}(t) \quad (3.55)$$

At the end, the daily bills of the users are calculated using:

$$C_u = \Delta t \cdot \left\{ \begin{array}{l} \sum_{t=1}^{\mathcal{T}} P_u^{nc}(t) \cdot \lambda_{TOU}(t) - P_u^{sg}(t) \cdot \lambda_{FIT} + P_u^{purchased}(t) \cdot (\lambda_{TOU}(t) - \lambda_i/2) \\ - P_u^{sc}(t) \cdot (\lambda_{FIT} + \lambda_i - \lambda_{TOU}(t)) - P_u^{sold}(t) \cdot (\lambda_{FIT} + \lambda_i/2) \end{array} \right\} \quad (3.56)$$

With (3.56), the decentralized coordination model is ended for the day-head scheduling. We should emphasize that, to trade electricity among the smart homes, there should be some surplus generation in the smart homes as an output of the installed PV system. Thus, home agents can share energy by trading with each other rather than feeding back the surplus power to the main grid. To sum up, the pseudo-code for the decentralized coordination is given in **Algorithm 2**.

3.2.4/ CENTRALIZED COORDINATION

In this chapter, the second proposed method is referred as “centralized coordination”. In this algorithm, the optimization problem is solved by the central entity (the aggregator agent in this case) by gathering detailed consumption/generation/storage information from all home agents. As in the decentralized model, a two-way communication link is required to receive information from the home agents and send back the control decisions. However, differently, the optimization problem is only solved one time by the aggregator agent in the centralized model, hence an iterative approach is not required (see Fig. 3.9).

The following optimization problem is solved by the aggregator agent:

$$\begin{array}{l} \text{minimize} \left\{ \begin{array}{l} \mathbf{C} = \Delta t \cdot \sum_{u=1}^{\mathcal{U}} \sum_{t=1}^{\mathcal{T}} P_u^{nc}(t) \cdot \lambda_{TOU}(t) - P_u^{sg}(t) \cdot \lambda_{FIT} + P_u^{purchased}(t) \cdot (\lambda_{TOU}(t) - \lambda_i/2) \\ - P_u^{sc}(t) \cdot (\lambda_{FIT} + \lambda_i - \lambda_{TOU}(t)) - P_u^{sold}(t) \cdot (\lambda_{FIT} + \lambda_i/2) \end{array} \right\} \\ \text{s.t.} \quad (3.1), (3.2), (3.9), (3.10), (3.16), (3.17), (3.18) \end{array} \quad (3.57)$$

In the centralized model, the aggregator agent focuses on minimizing the total electricity cost of the neighborhood. To do that, the aggregator agent also minimizes the daily electricity bill of the smart homes in parallel to the neighborhood total cost. The proposed centralized model can be expected to obtain near optimal solutions, as all information is available. However, this model requires more computation time, as it requires solving a larger optimization problem compared to the decentralized model. The pseudo-code of the centralized coordination model is given in **Algorithm 3**.

3.3/ SIMULATION SETUP

In this section, the studied test case and the programming details for the simulation design are introduced.

Algorithm 2 *Decentralized coordination algorithm.*

PDS : Price data set,

HDS_t : home data set (t – domain), HDS_l : home data set (l – domain),

ADS_t : aggregated data set (t – domain), ADS_l : aggregated data set (l – domain),

APS_t : perspective data set (t domain), APS_l : perspective data set (l – domain),

1: **Step I**

2: The aggregator agent sends $PDS = \{\lambda_{TOU}(t), \lambda_{FIT}, \lambda_i\}$ to all home agents, $\forall u \in \mathcal{U}$.

3: $\forall u \in \mathcal{U}$ get PDS , and solve (3.20).

4: $\forall u \in \mathcal{U}$ determine $HDS_t = \{P_u^c(t), P_u^g(t), P_u^b(t), P_u^{nc}(t), P_u^{sg}(t), P_u^{sc}(t)\}$.

5: $\forall u \in \mathcal{U}$ convert $\{P_u^{nc}(t), P_u^{sg}(t)\}$ to $HDC_l = \{\hat{P}_u^{nc}(l), \hat{P}_u^{sg}(l)\}$ and send HDS_l to the aggregator agent.

6: The aggregator agent determines $ADS_l = \{\hat{P}_{agg}^{nc}(l), \hat{P}_{agg}^{sg}(l)\}$, and sends it to $\forall u \in \mathcal{U}$ with PDS .

7: _____

Step II

8: $\forall u \in \mathcal{U}$ get PDS and ADS_l , and determine $APS_l = \{\hat{P}_{agg,u}^{nc}(l), \hat{P}_{agg,u}^{sg}(l)\}$.

9: $\forall u \in \mathcal{U}$ convert APS_l to $APS_t = \{P_{agg,u}^{nc}(t), P_{agg,u}^{sg}(t)\}$, and solve (3.36).

10: $\forall u \in \mathcal{U}$ determine $HDS_t = \{P_u^c(t), P_u^g(t), P_u^b(t), P_u^{nc}(t), P_u^{sg}(t), P_u^{sc}(t), P_u^{bs}(t), P_u^{sp}(t)\}$

11: $\forall u \in \mathcal{U}$ convert $\{P_u^{nc}(t), P_u^{sg}(t), P_u^{bs}(t), P_u^{sp}(t)\}$ to $HDS_l = \{\hat{P}_u^{nc}(l), \hat{P}_u^{sg}(l), \hat{P}_u^{bs}(l), \hat{P}_u^{sp}(l)\}$, and send HDS_l to the aggregator agent.

12: The aggregator agent determines $ADS_l = \{\hat{P}_{agg}^{nc}(l), \hat{P}_{agg}^{sg}(l), \hat{P}_{agg}^{bs}(l), \hat{P}_{agg}^{sp}(l)\}$, and sends it to $\forall u \in \mathcal{U}$ with PDS .

13: _____

Step III

14: **while** $k \leq k_{max}$ **do**

15: $\forall u \in \mathcal{U}$ get PDS and ADS_l , and determine $APS_l = \{\hat{P}_{agg,u}^{nc}(l), \hat{P}_{agg,u}^{sg}(l), \hat{P}_{agg,u}^{bs}(l), \hat{P}_{agg,u}^{sp}(l)\}$.

16: $\forall u \in \mathcal{U}$ convert APS_l to $APS_t = \{P_{agg,u}^{nc}(t), P_{agg,u}^{sg}(t), P_{agg,u}^{bs}(t), P_{agg,u}^{sp}(t)\}$, and solve (3.36).

17: $\forall u \in \mathcal{U}$ determine HDS_t .

18: $\forall u \in \mathcal{U}$ convert HDS_t to HDS_l , and send HDS_l to the aggregator agent.

19: The aggregator agent determines ADS_l , and sends it to $\forall u \in \mathcal{U}$ with PDS .

20: **end while**

21: _____

Step IV

22: The aggregator agent applies *proportional source matching* using (3.46), (3.47), (3.50) and (3.51)

23: The aggregator agent calculates the daily electricity bill of $\forall u \in \mathcal{U}$ using (3.56) in real-time.

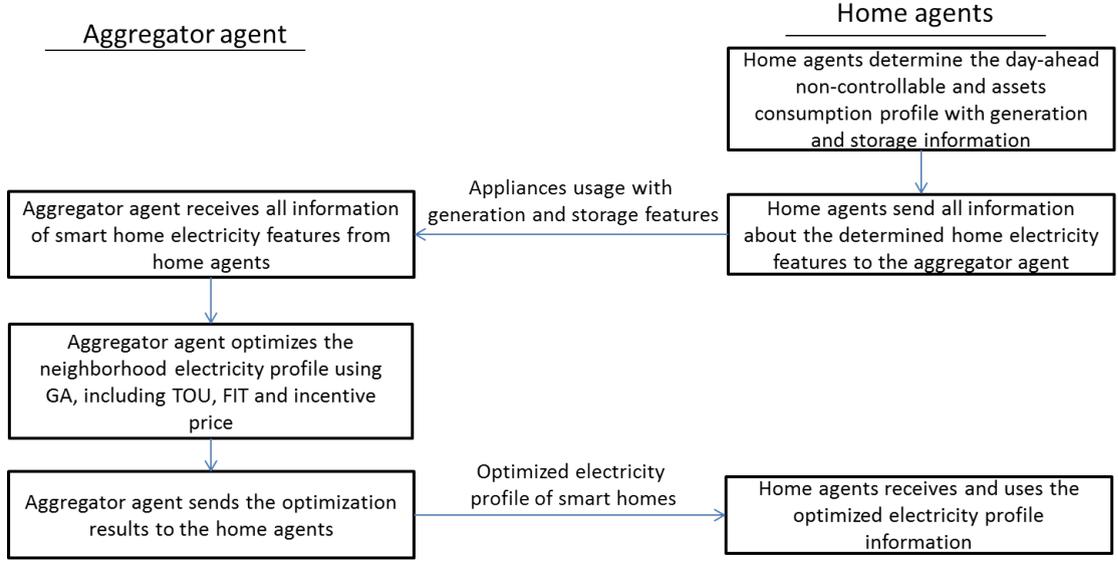


Figure 3.9: Flowchart of the centralized coordination method.

3.3.1/ SIMULATION PARAMETERS

We assume that the neighborhood is formed by $\mathcal{U} = 5$ smart homes, including 2 homes with PV and battery, 1 with just PV, and 2 with none (no PV and no battery). The installation capacity of the resources in smart homes is given in Fig. 3.10. All smart homes are equipped with an HEMS to control their appliances and communicate with the aggregator agent. The day is divided into 1-minute time intervals, and the day-ahead problem is solved for two days ($\mathcal{T} = 2, 880$) using the rolling horizon approach shown in Fig. 3.11.

The objective of the deployed rolling horizon algorithm is to solve the optimization problem for two days. By taking the output results of the first day at $t = 1, 440$ as an input for the second day, the process is repeated for the next two days. Thus home agents in smart homes with battery systems foresee the next day consumption and might decide to save some energy in their batteries for the next day rather than discharge for the current day electricity consumption. Another important assumption is that assets are not able to be scheduled to the next day, although the optimization problem is solved for the two days. Therefore, the total consumed energy in the smart home remains constant in all scenarios and coordination algorithms. Lastly, communication data is determined with the average of every $\mathcal{L} = 30$ minutes, and battery decisions are determined for every $\mathcal{Z} = 15$ minutes.

Algorithm 3 *Centralized coordination algorithm.*

- 1: $\forall u \in \mathcal{U}$ send all appliance, PV system and battery system information to the aggregator agent.
 - 2: The aggregator agent solves (3.57).
 - 3: The optimization results (control decisions) are sent back to $\forall u \in \mathcal{U}$.
 - 4: $\forall u \in \mathcal{U}$ applies the control decisions.
 - 5: The aggregator agent calculates the daily electricity bill of $\forall u \in \mathcal{U}$ using (3.56) in real time.
-

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

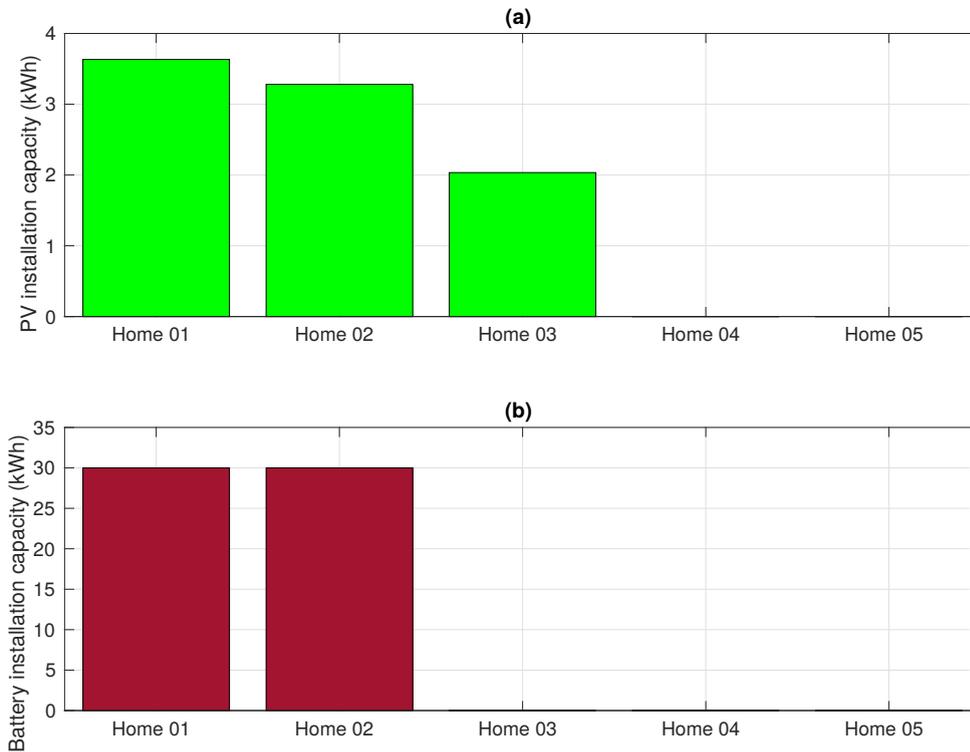


Figure 3.10: Installation capacity of the resources in the neighborhood. (a) PV capacities, (b) battery capacities in smart homes.

3.3.2/ CO-SIMULATION PLATFORM

To model the system and perform optimization, a co-simulation platform is designed and adapted from [34] using Java Agent Development (JADE) and MATLAB, as shown in Fig. 3.12. Homes and aggregator agents are modeled using the JADE framework, which enables communication between agents. In MATLAB, the genetic algorithm (GA) from the optimization toolbox is used for solving the formulated optimization problems. The two software are interconnected by using Transmission Control Protocol / Internet Protocol (TCP/IP). Each home agent is assigned to a TCP/IP port to send the electricity profiles and receive the results to/from MATLAB. Lastly, the simulations are performed on a desk-

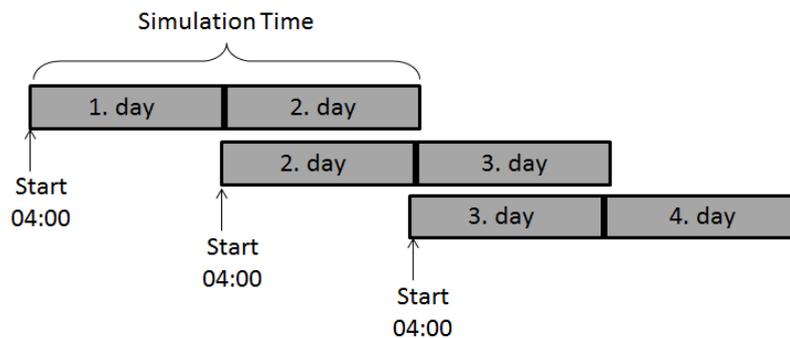


Figure 3.11: Rolling horizon approach principle.

top computer with an Intel Core i7 3.40 GHz processor and 8 GB RAM with a 64-bit Ubuntu 16.04.2 LTS operating system.

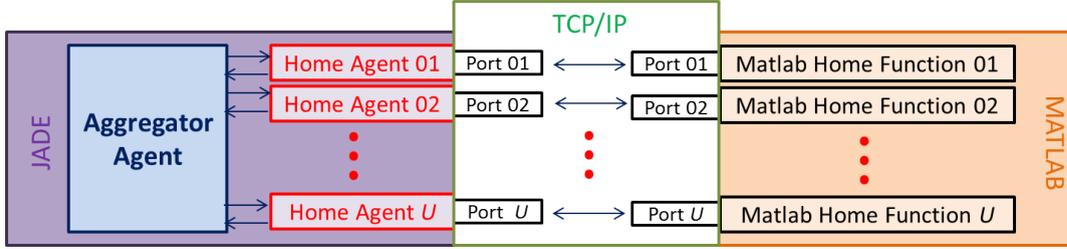


Figure 3.12: Co-simulation platform.

3.4/ PERFORMANCE EVALUATION

Simulation results are given for one day by simulating for the 1st and 2nd days using the *rolling horizon* method. After that, the scalability of the algorithm is tested for four different neighborhood areas with a different number of smart homes (5, 10, 15, and 20 smart homes).

3.4.1/ COST AND COMPUTATION TIME ANALYSIS

The cost results of the smart homes and the neighborhood for one-day simulation are given in Table 3.5. According to these results, the decentralized coordination method shows a better performance compared to the baseline and selfish scenarios. Moreover, each smart home reduced its electricity bill, which means that all users benefit from coordination and trading in the neighborhood.

Table 3.5: Smart homes and total neighborhood electricity costs (**: smart home with PV and battery, * smart home with PV).

Smart homes	Baseline (€)	Selfish (€)	Decentralized (€)	Centralized (€)
Home 01**	-1.83	-1.91	-2.48	-3.27
Home 02**	-1.40	-1.49	-1.96	-2.97
Home 03*	0.89	-0.97	-1.02	-1.04
Home 04	1.90	1.88	1.85	1.82
Home 05	2.07	1.99	1.95	1.93
Total	1.63	-0.5	-1.66	-3.53

Compared to the decentralized coordination method, the centralized control algorithm yields the best results for the neighborhood and each home user. However, the centralized coordination method requires more time than the decentralized one to solve the optimization problem. While the centralized method needs 27 minutes to optimize the electricity profiles of the smart homes, decentralized coordination requires approximately 20 seconds (in smart homes with battery) to solve the optimization problem for each iteration. In total, the decentralized method requires about 1 minute to finalize the coordination

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

process. Therefore, although the centralized method provides better results in terms of cost, the decentralized algorithm offers significant advantage in terms of computation time.

3.4.2/ POWER AND ENERGY ANALYSIS

In this section, the algorithms are analyzed by comparing the power and energy results of each smart home and the neighborhood. From Fig. 3.13 to Fig. 3.15, the load and net consumption profiles of each smart home for each case are given.

In smart home 01 (with PV and battery), the electricity is only consumed during early morning hours due to the lack of stored energy in the battery (in baseline, selfish and decentralized cases). Significant consumption is observed in centralized case. The reason is that the aggregator agent focuses on decreasing the total electricity cost of the neighborhood, hence it is not optimizing for increasing the individual benefits of this user. However, the smart home has more economic income (as seen in Table 3.5) due to selling more energy than in other cases, although it consumes more. Therefore, less energy is left at the end of the day (see Fig. 3.16), which means that the stored energy is used for selling to the neighbors.

In smart home 03 (with PV and without battery), the generated PV energy is only used during sunny hours, and the rest of the generation is fed back to the main grid due to the absence of a battery system (in baseline and selfish cases). However, the smart home can sell the surplus generation to the other smart homes in the decentralized and centralized cases. Furthermore, it can purchase energy through the trading ability from other battery-equipped smart homes in decentralized and centralized control cases, in order to receive the proposed incentive.

In the selfish case, the home agent can only schedule the assets in smart home 04 to decrease the daily electricity bill. With the decentralized and centralized cases, smart home 04 (without PV and battery) has the ability to purchase energy from neighbors with only PV and neighbors with PV and battery-equipped smart homes. It can also be seen that the smart home purchases more energy in the centralized case compared to the decentralized case, hence it achieves more cost reduction.

For a more detailed analysis, the energy profiles of all smart homes are shown for both decentralized and centralized cases in Fig. 3.17 and 3.18. When the two coordination methods are compared, it can be seen there is a significant difference in terms of cost, power profiles and energy profiles. The reason is that while smart homes with battery systems are using their stored energy mostly for their own consumption in the decentralized case, they sell the stored energy to other smart homes in the centralized case.

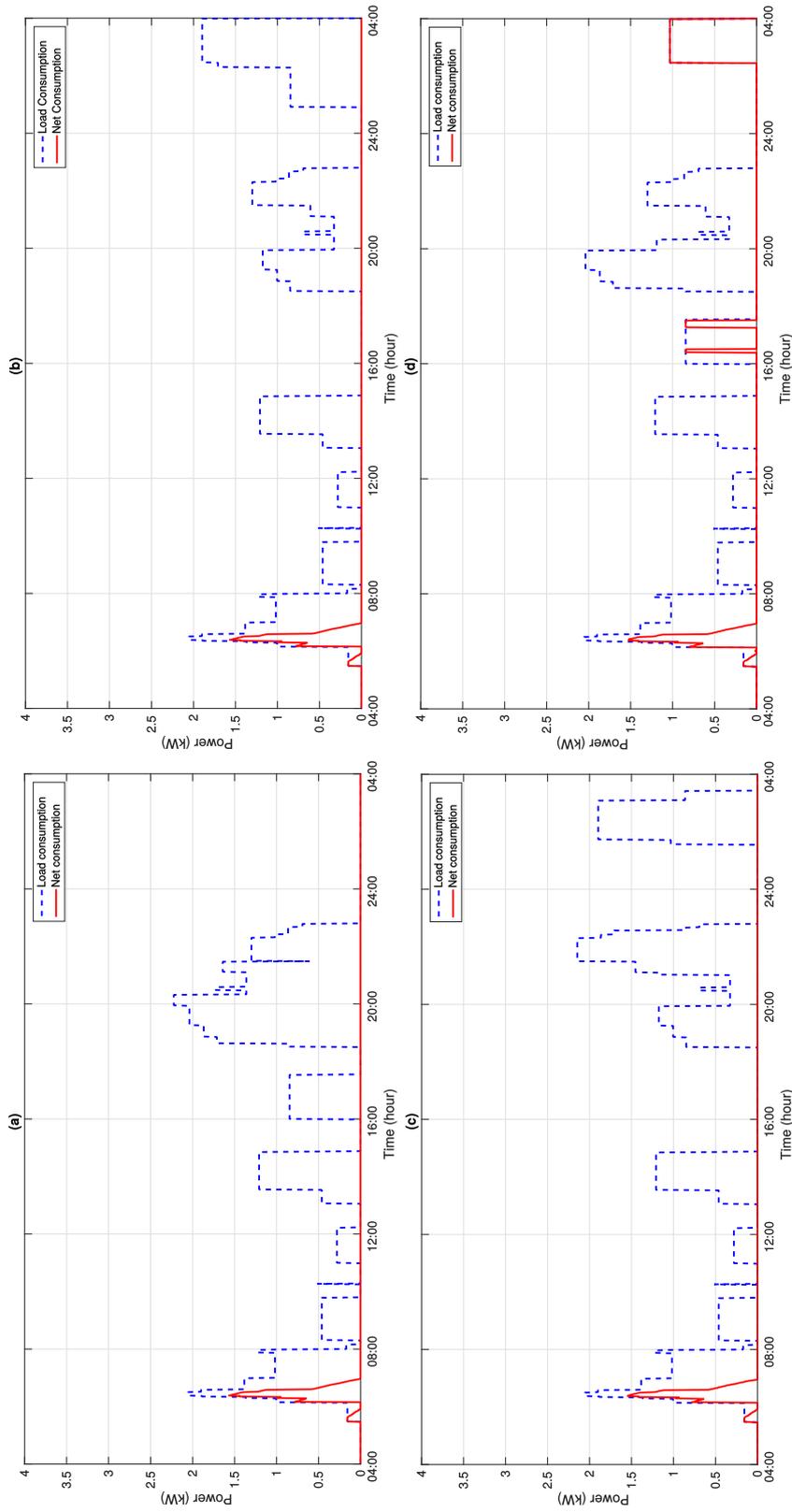


Figure 3.13: Smart home 01 (with PV and battery) electricity consumption profiles: (a) baseline, (b) selfish, (c) decentralized (d) centralized.

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

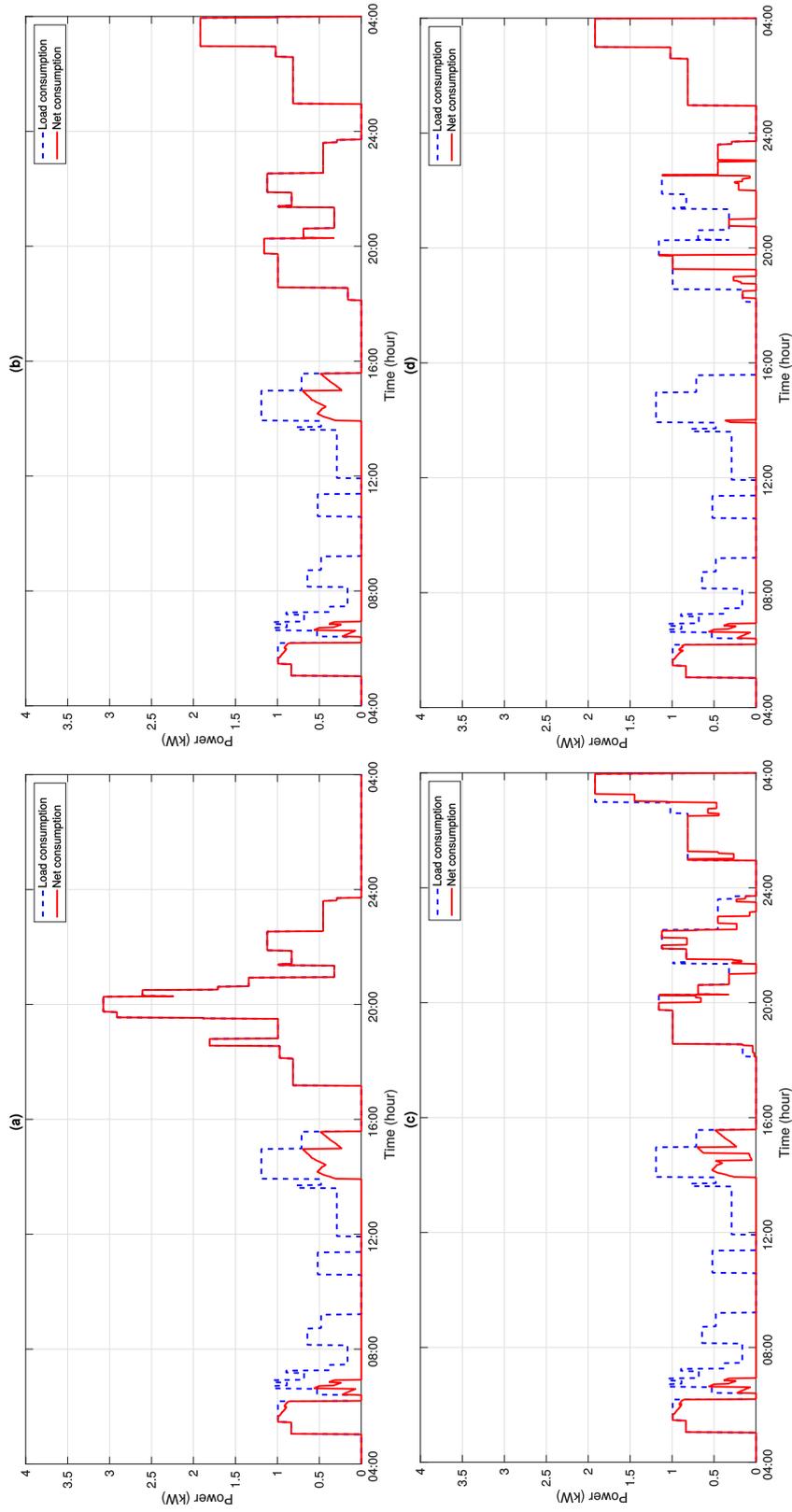


Figure 3.14: Smart home 03 (with PV and without battery) electricity consumption profiles: (a) baseline, (b) selfish, (c) decentralized (d) centralized.

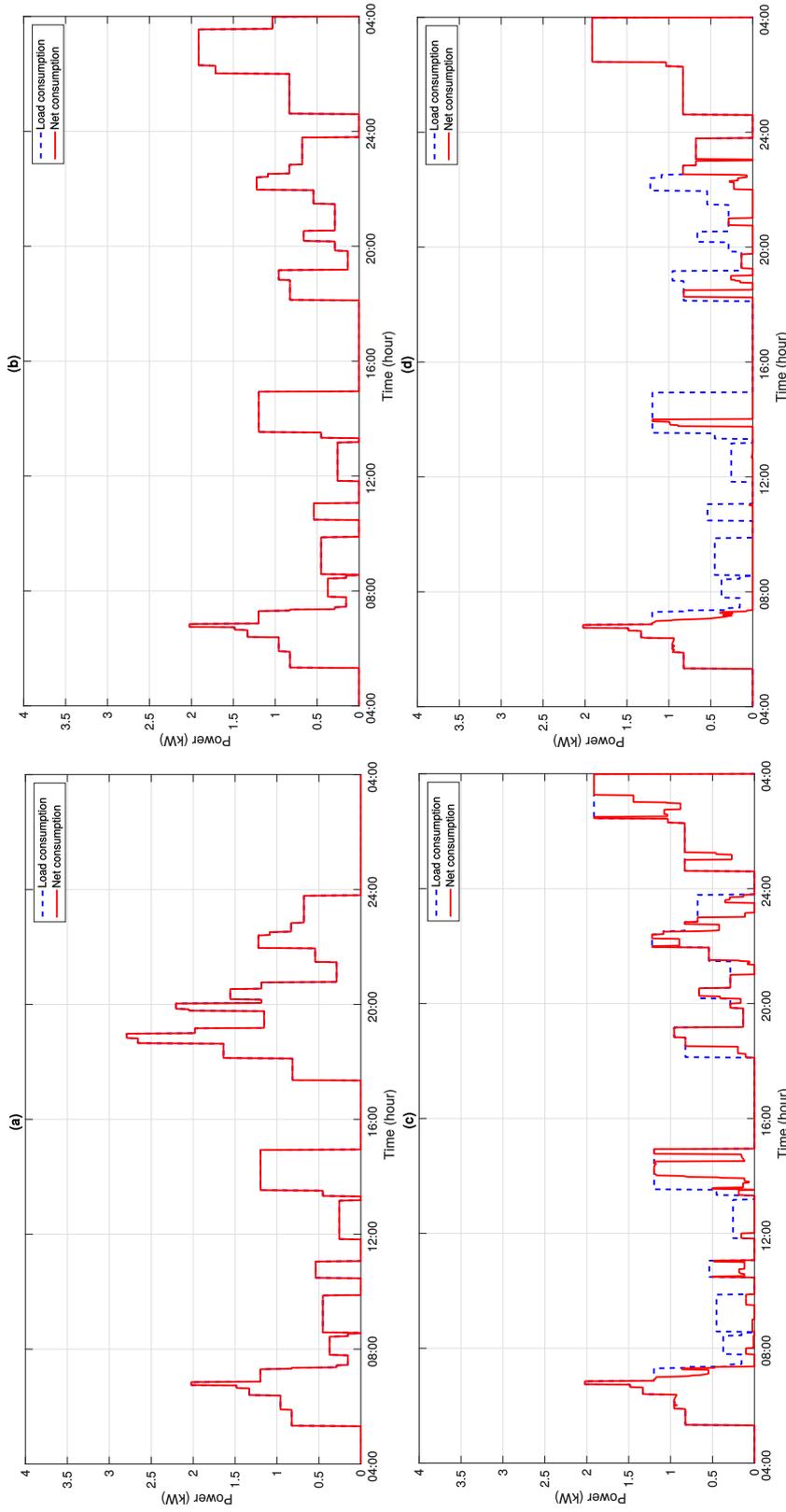


Figure 3.15: Smart home 04 (without PV and battery) electricity consumption profiles: (a) baseline, (b) selfish, (c) decentralized (d) centralized.

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

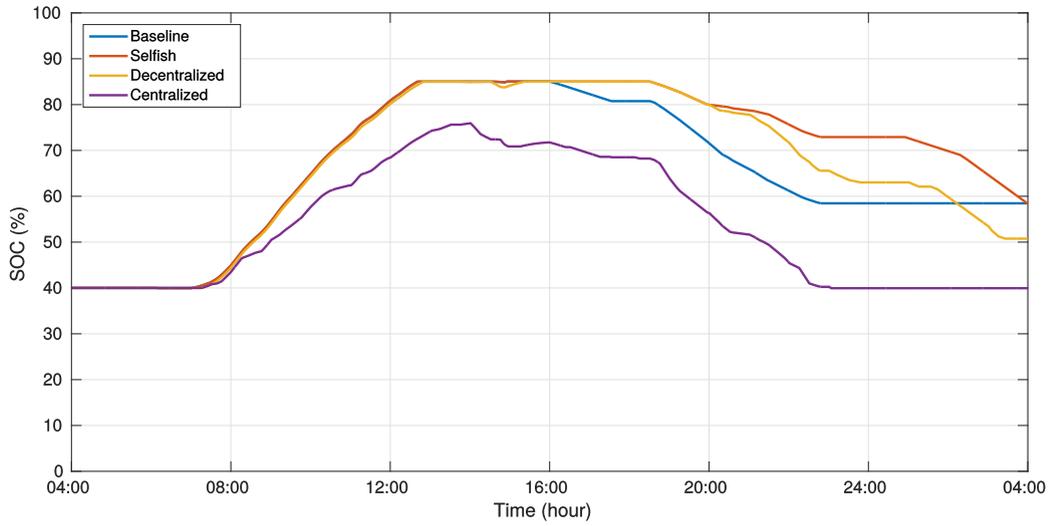


Figure 3.16: State-of-charge of the battery system for each case.

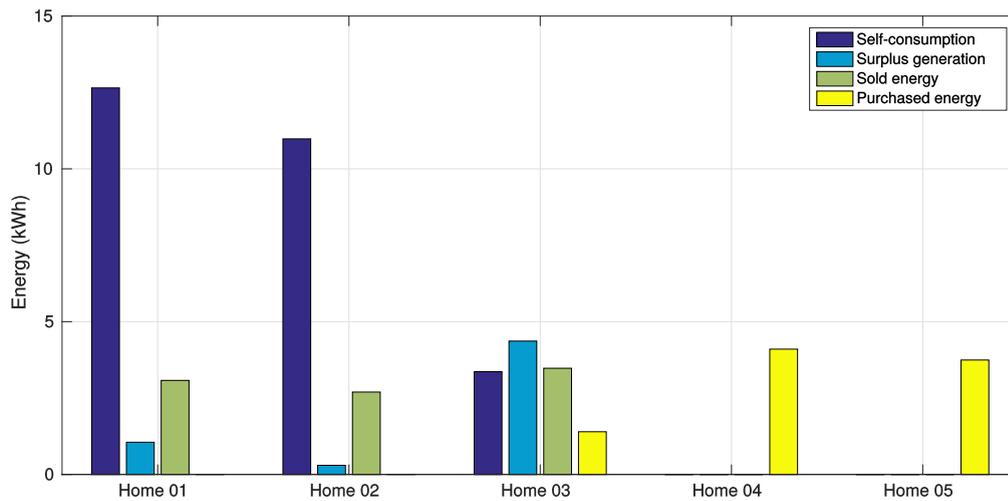


Figure 3.17: Energy analysis of the smart homes in the decentralized coordination.

As a result of this, smart homes with no battery system purchase more energy in the centralized case. As a reminder, we emphasize that the aggregator agent aims to minimize total neighborhood electricity cost, hence using energy for trading among smart homes or utilizing it for self-consumption does not make any difference in the optimization function. However, as a result of optimizing all smart homes profiles in one spot, the locally generated PV energy is traded more and batteries are discharged more than in the decentralized case.

Overall, simulation results show that the proposed coordination algorithms achieve more cost reduction than the baseline and selfish scenarios. Moreover, all smart homes, no matter the type of equipment they have (PV and/or battery), achieve to reduce their daily electricity bill by utilizing more PV energy inside the neighborhood.

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

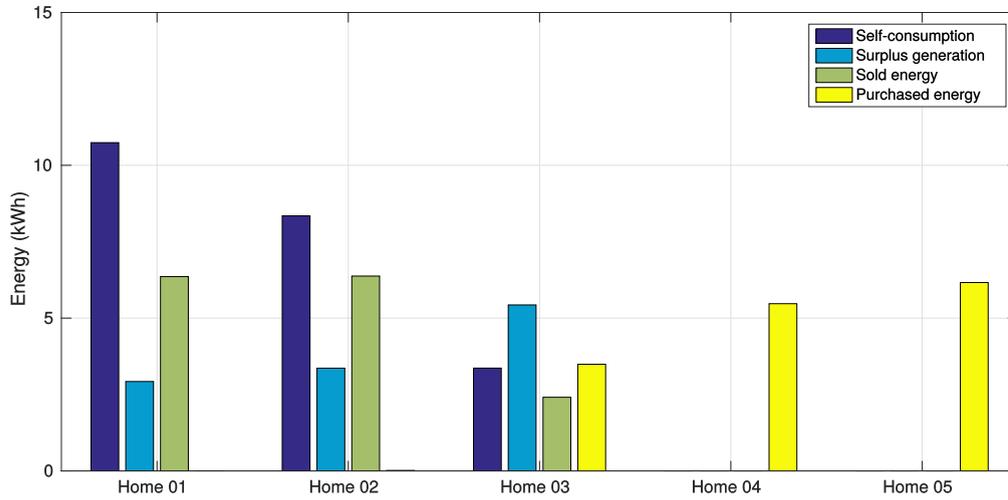


Figure 3.18: Energy analysis of the smart homes in the centralized coordination.

3.4.3/ SCALABILITY ANALYSIS

In this section, a scalability analysis is performed by varying the number of smart homes in the neighborhood area. The simulations are performed for four different neighborhood area sizes (5, 10, 15, and 20). The numbers of PV and battery owners are given in Table 3.6. The simulation results are given and enable comparing the achieved profit

Table 3.6: Neighborhood area number of resource owners.

Neighborhood	Number of PV and battery owners	Number of PV owners	Number of no PV and battery owners
5 smart homes	2	1	2
10 smart homes	4	2	4
15 smart homes	6	3	6
20 smart homes	8	4	8

against the baseline case. In Fig. 3.19, the determined profits for each control and each neighborhood area size are given. The results show that total profit is increased for each control method when the number of the smart homes increases. Furthermore, simulation results also show that the profit gained by the decentralized control method gets close to the profit gained by the centralized control method. Lastly, this scalability analysis proves that the presented control algorithms provide cost-beneficial coordination strategies for different sizes of neighborhoods.

3.5/ CONCLUSION

This chapter has presented two coordination algorithms (centralized and decentralized) for electric energy management in a neighborhood area using MAS. The neighborhood area is formed by the aggregator and smart homes equipped with distributed energy

CHAPTER 3. INCENTIVE-BASED RENEWABLE ENERGY TRADING AMONG SMART HOMES

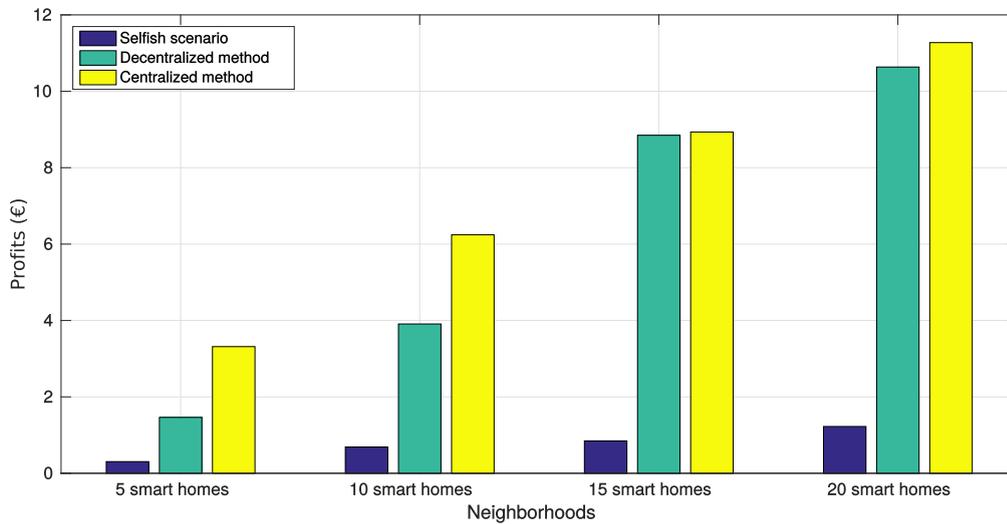


Figure 3.19: Determined neighborhood profits for each control method and neighborhood size.

resources (appliances, PV and battery). The presented coordination algorithms rely on TOU, FIT and an incentive price, combined to a form of DR program. In the centralized method, the aggregator agent gathers all available information from the smart homes and controls the assets and batteries to minimize the total neighborhood cost. In the decentralized method, on the other hand, home agents focus on their own benefit by using price and aggregated data information from the aggregator agent. Both control methods aim to increase the utilization of locally produced renewable energy in the neighborhood by adapting energy trading ability among smart homes. To do that, home agents enable scheduling their assets to surplus generation hours, as well as discharging their batteries during high consumption hours. In this regard, the presented coordination algorithms are compared with two base scenarios (baseline: no control, no trading; selfish: with control, no trading), and gave better results in terms of daily cost reduction. Between the two coordination algorithms, while the centralized method outperforms the decentralized one in terms of cost reduction, the decentralized method solves the optimization and converges faster than the centralized one.

DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

With the increasing integration of DER and HEMS into distribution systems, decentralized energy management is becoming relevant for smart neighborhoods. Hence, designing a coordination mechanism for efficient load management in neighborhoods using suitable pricing schemes is now necessary. In this regard, service providers (i.e., utilities) can use time-varying price models (TOU, as described in Section 1.2.2) to influence user electricity consumption habits in return for some profit or savings. However, these pricing structures remain fixed, and prices do not change dynamically based on the electricity load in the neighborhood area. Therefore, the performance of the proposed control methods may not be as efficient as predicted in terms of peak reduction even if users change their consumption patterns.

In this chapter, we introduce two decentralized coordination strategies (group-based and turn-based) based on a dynamic pricing structure. The neighborhood electricity price is determined by merging a TOU tariff from the main grid which remains constant during the optimization, together with a quadratic function that changes the price during the optimization according to the area electricity profile. Thereby, the main grid price and the neighborhood electricity profile are affected by the decision-making process in the smart homes using a single pricing schema. This chapter, which is an extension of Chapter 3, also focuses on decentralized energy management with energy sharing in neighborhood areas. However, although the control algorithms and coordination models of both works have some similarities, there also have distinct differences, as listed in Table 4.1.

Table 4.1: Comparison of proposed methods in Chapters 3 and 4.

	Chapter 3	Chapter 4
Objective	Cost reduction	Cost and peak reduction
Pricing schema	Static (TOU, FIT, and an incentive)	Dynamic (TOU and quadratic)
Communication	Exchanges four data types	Exchange two data types
Trading/sharing	Incentive required	No incentive required
RES utilization (priority)	Home self-consumption	Neighborhood consumption

Basically, we present an advanced model of the previous work by modifying the formula-

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

tion of the optimization problem and proposing a new coordination model. Furthermore, in this chapter, forecasting errors are taken into account while evaluating the performance of the algorithms, and simulations are performed over a horizon of one year to take into account seasonal differences on the generation profile. The key contributions of this chapter are summarized as follows:

- Two decentralized (fully-dependent) coordination mechanisms are presented by formulating and solving one optimization problem. The impact of the sequence of operation of agent actions (group-based vs. turn-based) is analyzed in terms of cost, peak reduction, and computation time with annual simulations.
- Three different success metrics (SM-01, SM-02, and SM-03) are introduced to determine the performance of the annual simulations compared to base scenarios (baseline and selfish).
- Uncertainty in consumption and renewable generation profiles is considered by taking into account forecasting errors in day-ahead electricity profiles.

The rest of the chapter is organized as follows: the system model is presented in Section 4.1. The optimization problem for the control algorithm is formulated in Section 4.2, and coordination mechanisms are introduced in Section 4.3. In Section 4.4, the simulation results are given, and in Section 4.5, the chapter is concluded.

4.1/ SYSTEM MODEL

The agent-based two-level hierarchical model introduced in Section 3.1 is used and improved in this work. The same notations are used in the modeling and the formulation of the optimization problem. For instance, \mathcal{U} smart homes are located in the neighborhood area with X_u non-controllable and Y_u controllable appliances (assets) in each smart home $u \in \mathcal{U}$. Compared to the model of Chapter 3, a more detailed probabilistic model is used to increase diversity among the smart homes in the neighborhood area. To do that, a new parameter called “consumption rate” is introduced, and five rates are defined to characterize smart homes consumption. The probability values of these consumption rates are given in Fig. 4.1.

This level of assigned consumption rate is used for determining the number of appliances, as well as PV modules and battery installation capacities in the smart homes. For example, if the consumption rate is “very high”, the ownership probability of the appliances, PV and battery systems with their installation capacity are high compared to other rates. As a consequence, a higher consumption rate will imply a high energy consumption, and thus the user will be more willing to invest in additional resources, such as PV and battery systems.

4.1.1/ HOME ENERGY SYSTEM

In smart homes, 13 types of electricity appliances are modeled by using the same power ratings given in Table 3.1. Based on the assigned consumption rate of a smart home, the number of appliances and their ownership probabilities are given in Table 4.2. As shown

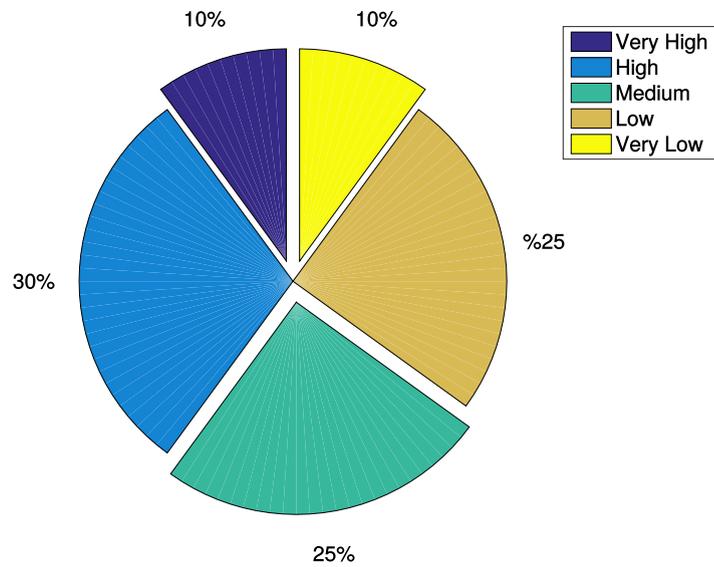


Figure 4.1: Breakdown of the probability values of the different consumption rates among smart homes.

in this table, for realistic modeling, the number of some appliances can reach eight in a household, such as for lights. The number of some other appliances cannot be more than one, such as for assets. We emphasize that the parameters are chosen arbitrarily, however they can be easily adapted to model different usage habit (i.e., with a survey analysis) in different regions or countries.

At a second step of the modeling, appliance operation times are determined probabilistically. In Table 4.3, each appliance duration and operation mode is given. The operation mode describes how many times the appliances are used by the user during the day. If the operation mode is “single”, the appliance is used only one time, otherwise it can be used multiple times. For example, a vacuum cleaner can only be used one time, for 30 minutes, during the day. On the other hand, lights can be used multiple times with a minimum of 15 minutes. For instance, when a light is used for 15 minutes, it can be used again for another 15 minutes without waiting, or it can be used at any other time. According to this principle, the operation start times of the appliances are determined probabilistically during the day. From Fig. 4.2 to Fig. 4.14, the probability values of each appliance start times during the day are given, based on the consumption rate of the smart homes.

Using the given probability profiles, the electricity consumption profiles of the non-controllable appliances are determined. Controllable appliances are assumed to have changing probabilistic profiles according to appliance usage history over the previous days. For example, the run probability value of the washing machine is assumed to be 70% from 17:00 to 23:00. This value is a maximum, hence when the washing machine is used during a day, this 70% value decreases to 10% for the next day utilization. After that, if this appliance is not used during the next day, the 10% value increases to 20% for the following day, and this process continues until 70% is reached again, or until the appliance is used.

This strategy aims to create realistic consumption scenarios for asset usage, hence the assets are not used for all days during the year. Lastly, in this work, we assume that users choose scheduling intervals of the assets between times with probability values. Thereby,

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

Table 4.2: Number of smart home appliances and corresponding probabilities.

	Amount	Very Low	Low	Medium	High	Very High
Lights	2	40%	-	-	-	-
	3	40%	-	-	-	-
	4	20%	40%	-	-	-
	5	-	40%	40%	-	-
	6	-	20%	40%	40%	40%
	7	-	-	20%	40%	40%
	8	-	-	-	-	20%
Kettle	0	50%	50%	-	-	-
	1	50%	50%	100%	100%	100%
Microwave	0	50%	50%	-	-	-
	1	50%	50%	100%	100%	100%
Vacuum cleaner	0	50%	25%	-	-	-
	1	50%	75%	100%	100%	100%
Television	0	25%	15%	-	-	-
	1	75%	85%	15%	15%	-
	2	-	-	85%	85%	15%
	3	-	-	-	-	85%
Computer	1	100%	-	-	-	-
	2	-	100%	75%	50%	-
	3	-	-	25%	25%	50%
	4	-	-	-	25%	25%
	5	-	-	-	-	25%
Iron	0	25%	15%	-	-	-
	1	75%	85%	100%	100%	100%
Hair dryer	0	25%	15%	-	-	-
	1	75%	85%	100%	100%	100%
Coffee Maker	0	25%	15%	-	-	-
	1	75%	85%	100%	100%	100%
Toaster	0	25%	15%	-	-	-
	1	75%	85%	100%	100%	100%
Washing machine	0	25%	15%	-	-	-
	1	75%	85%	100%	100%	100%
Clothes dryer	0	75%	50%	25%	15%	-
	1	25%	50%	75%	85%	100%
Dish washer	0	75%	50%	25%	-	-
	1	25%	50%	75%	100%	100%

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

Table 4.3: Appliance operation duration and mode.

Appliance	Duration (minutes)	Mode	Appliance	Duration (minutes)	Mode
Lights	15	Multiple	Hair dryer	10	Multiple
Kettle	15	Multiple	Coffee maker	10	Multiple
Microwave	10	Multiple	Toaster	10	Multiple
Vacuum cleaner	30	Single	Washing machine	90	Single
Television	30	Multiple	Clothes dryer	90	Single
Computer	30	Multiple	Dish washer	60	Single
Iron	30	Single			

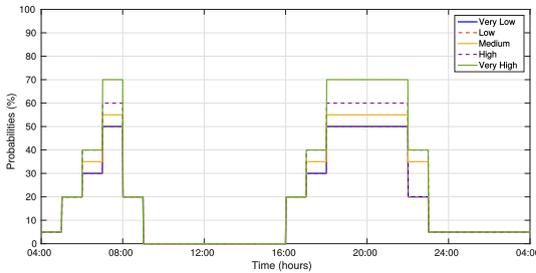


Figure 4.2: Start time probability of lights.

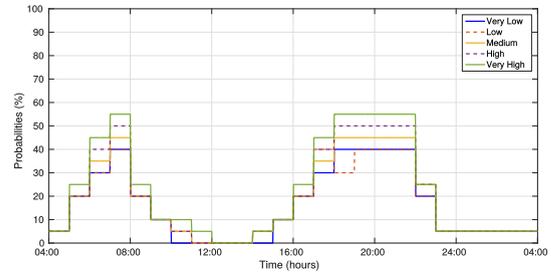


Figure 4.3: Start time probability of the kettle.

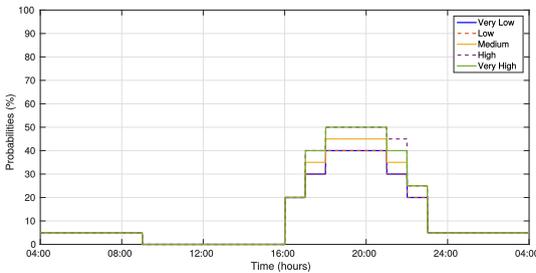


Figure 4.4: Start time probability of the microwave.

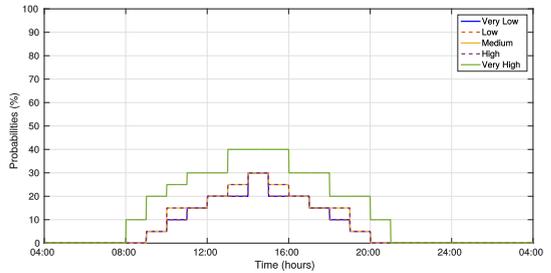


Figure 4.5: Start time probability of the vacuum cleaner.

a washing machine cannot be shifted to hours later than 23:00, and a clothes dryer and a dish washer can only be operated until 01:00, because of the users' noise preferences. In other words, they are not willing to be disturbed by appliance operation during late night hours (after 01:00).

For modeling RES generation and energy storage, PV and battery systems are considered in the smart home environment. The installation capacities of both systems are determined based on the assigned consumption rate in the smart home, as shown in Table 4.4. Accordingly, smart homes with a higher consumption rate are more willing to install PV and battery systems because they can afford it.

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

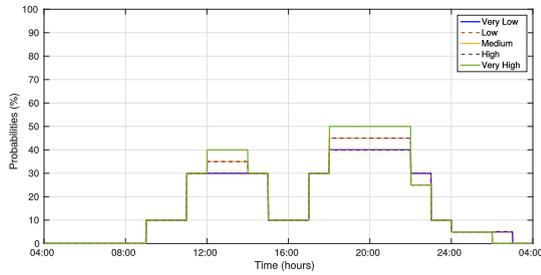


Figure 4.6: Start time probability of the television.

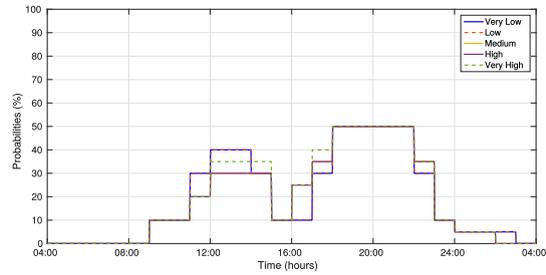


Figure 4.7: Start time probability of the computer.

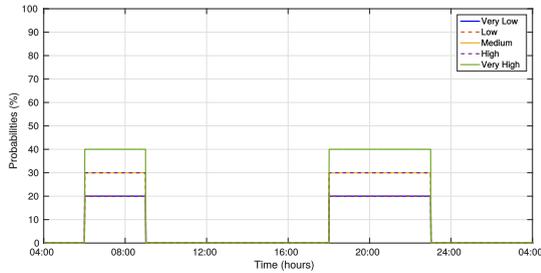


Figure 4.8: Start time probability of the iron.

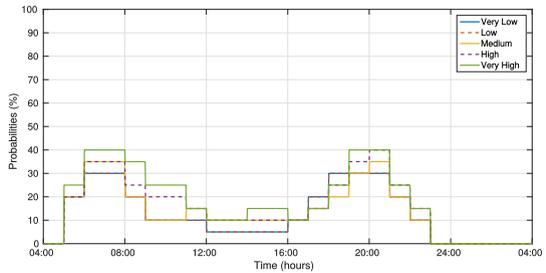


Figure 4.9: Start time probability of the hair dryer.

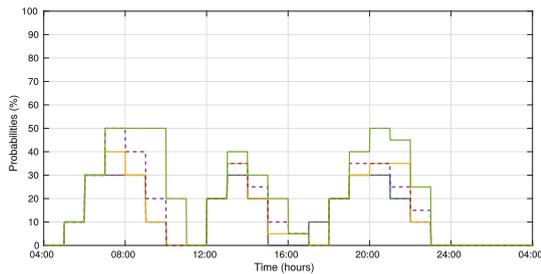


Figure 4.10: Start time probability of the coffee maker.

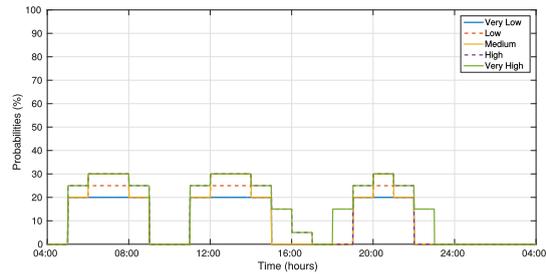


Figure 4.11: Start time probability of the toaster.

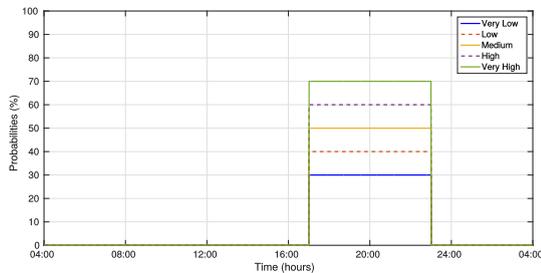


Figure 4.12: Start time probability of the washing machine.

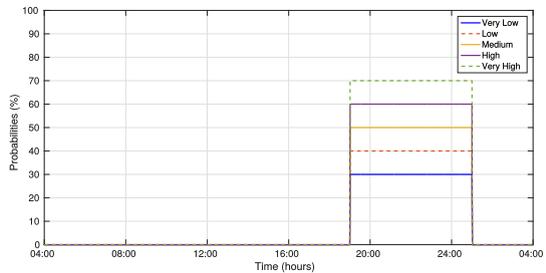


Figure 4.13: Start time probability of the clothes dryer.

4.1.2/ FORECASTING ERROR MODEL

Forecasting errors are considered for non-controllable appliances consumption and the output of PV generation. We assume that operation details of the assets are already defined and entered into the HEMS by users in the previous days. For non-controllable appliances, Gaussian distributions are used to model the start time and the operation

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

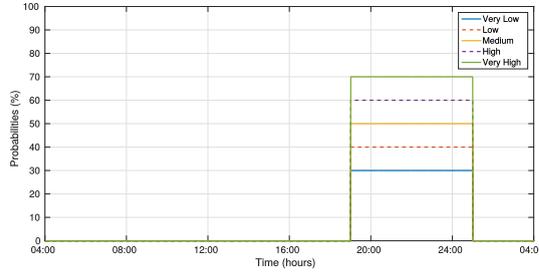


Figure 4.14: Start time probability of the dish washer.

Table 4.4: PV and battery systems ownership and ratings.

Consumption Rate	PV ownership probability	Series modules N_u^s	Parallel modules N_u^p	Module power rating P_u^{PV}	Battery ownership
Very low	30%	1 — 4	1 — 4	160 — 200	20%
Low	40%	2 — 5	1 — 4	160 — 200	30%
Medium	50%	2 — 5	2 — 5	180 — 200	40%
High	60%	3 — 6	2 — 5	220 — 240	50%
Very high	70%	3 — 6	3 — 6	220 — 240	60%

duration of the appliances as follows:

$$r_x^{s,e} = r_x^s + \epsilon_x^s \quad (4.1)$$

$$d_x^e = d_x + \epsilon_x^d \quad (4.2)$$

where ϵ_x^s and $r_x^{s,e}$ are the error value for the start time, and the start time with forecasting error, respectively; and ϵ_x^d and d_x^e are the error value for the operation duration and the duration with forecasting error, respectively. The error values (ϵ_x^s and ϵ_x^d) are determined by a Gaussian Distribution $\mathcal{N}(\mu, \sigma^2)$ [114]. The mean value μ is chosen equal to zero, and the standard deviation σ is assumed to be variable in terms of minutes according to the quantity and the appliance type. Note that we assume that home agents know the exact power rating of each appliance (e.g., using smart plugs).

Each home agent forecasts its own generation profile individually, hence the errors are calculated differently in each smart home. To consider the forecasting error in the generation profile, the received solar irradiance is modeled by including forecasting errors using the Gamma distribution [2]:

$$G_u^e(t) = G(t) \times \epsilon_g \quad (4.3)$$

where $G_u^e(t)$ and ϵ_g are the solar irradiance with forecasting error and the prediction error parameter for solar irradiance, respectively. The error value (ϵ_g) is determined using gamma noise with distribution $\mathcal{G}(\kappa, \theta)$, where $\kappa = 210$ is the shape parameter, and $\theta = 0.005$ is the scale parameter.

4.1.3/ ELECTRICITY PRICING: DYNAMIC MODEL

In the neighborhood area, users are charged for their electricity consumption based on a dynamic pricing model. The utilized pricing structure is formed by merging a TOU

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

price with a quadratic function. We assume that the service provider, at the upper level, determines the base price (TOU pricing “ $\lambda_{TOU}(t)$ ” in this case) for each time slot (typically hourly). Thus, the service provider, based on the upper level condition, also influences the neighborhood schedules through the base price. Then, the aggregator agent determines the electricity price in the neighborhood associated to the base price $\lambda_{TOU}(t)$ and the aggregated neighborhood profile at the point of common coupling (PCC). The PCC of the neighborhood and the variable $\mathbf{P}_{agg}^a(t)$ are shown in Fig. 4.15.

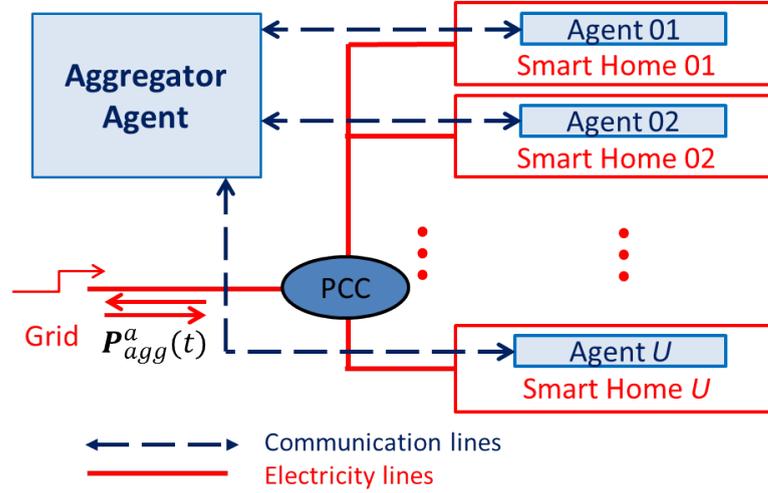


Figure 4.15: Neighborhood agent model with PCC.

To model the dynamic fluctuations in the neighborhood price which occur based on $\mathbf{P}_{agg}^a(t)$, a dynamic part $q(t, \mathbf{P}_{agg}^a(t))$ is formulated using a quadratic function as follows:

$$q(t, \mathbf{P}_{agg}^a(t)) = a(t) \cdot |\mathbf{P}_{agg}^a(t)|^2 + b(t) \cdot |\mathbf{P}_{agg}^a(t)| + c(t) \quad (4.4)$$

where $a(t) > 0$, $b(t) \geq 0$ and $c(t) \geq 0$ are positive time-dependent parameters. Note that these parameters are assumed constant during the day in this work, however they can be considered variable in some cases [130]. Then, the dynamic part is merged with a base price to determine the full dynamic price $\lambda_d(t, \mathbf{P}_{agg}^a(t))$ in the neighborhood using:

$$\lambda_d(t, \mathbf{P}_{agg}^a(t)) = \begin{cases} \lambda_{TOU}(t) - q(t, \mathbf{P}_{agg}^a(t)) & , \text{if } \mathbf{P}_{agg}^a(t) \leq 0 \\ \lambda_{TOU}(t) + q(t, \mathbf{P}_{agg}^a(t)) & , \text{else } \mathbf{P}_{agg}^a(t) > 0 \end{cases} \quad (4.5)$$

Overall, the aggregator enables users to control their assets not only according to the aggregated profile, but also according to the base structure, due to the main grid connection. Furthermore, the presented dynamic model is used for both consuming and selling energy in the smart homes, hence reverse power flow is enabled when generation is higher than consumption. The important feature of this price model is the consumption will be more desirable with decreased $\lambda_d(t, \mathbf{P}_{agg}^a(t))$ when there is high surplus generation, and oppositely, the sharing energy will be more beneficial when there is high consumption with increased $\lambda_d(t, \mathbf{P}_{agg}^a(t))$. Moreover, the surplus generation hours will be undesirable for the producers to share energy, because they are less profitable (as shown in Fig. 4.16). As an example, dynamic pricing is shown with the aggregated electricity profile in Figs. 4.17 and 4.18.

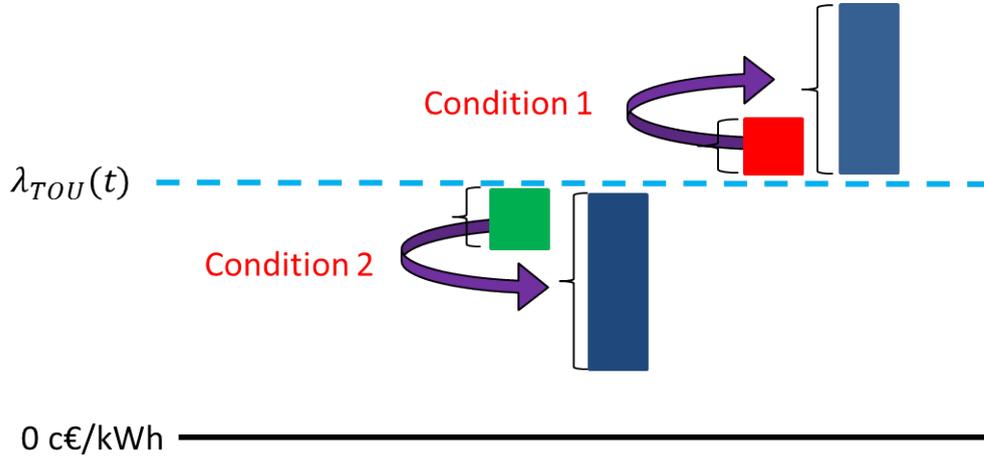


Figure 4.16: Full dynamic price in the neighborhood (condition 1: when surplus generation is increased, condition 2: when electricity consumption is increased).

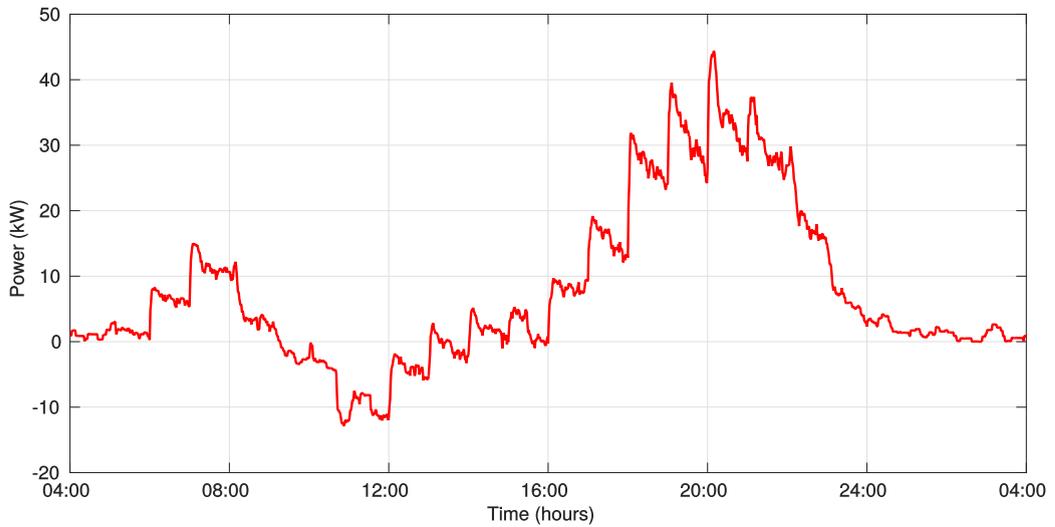


Figure 4.17: Neighborhood net load profile.

4.2/ PROBLEM FORMULATION

In this work, two base scenarios and two decentralized coordination models are simulated, and their performance is compared with each other. The baseline and selfish scenarios were described in Sections 3.2.1 and 3.2.2. However, in this chapter, these base scenarios are reformulated (due to the use of different pricing algorithms) as follows:

- Baseline scenario: daily electricity bill of the smart homes using the battery output power function (3.7) without optimization.

$$C_u = \Delta t \cdot \sum_{t=1}^{\mathcal{T}} (P_u^c(t) - P_u^g(t) + P_u^b(t)) \cdot \lambda_d(t, \mathbf{P}_{agg}^a(t)) \quad (4.6)$$

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

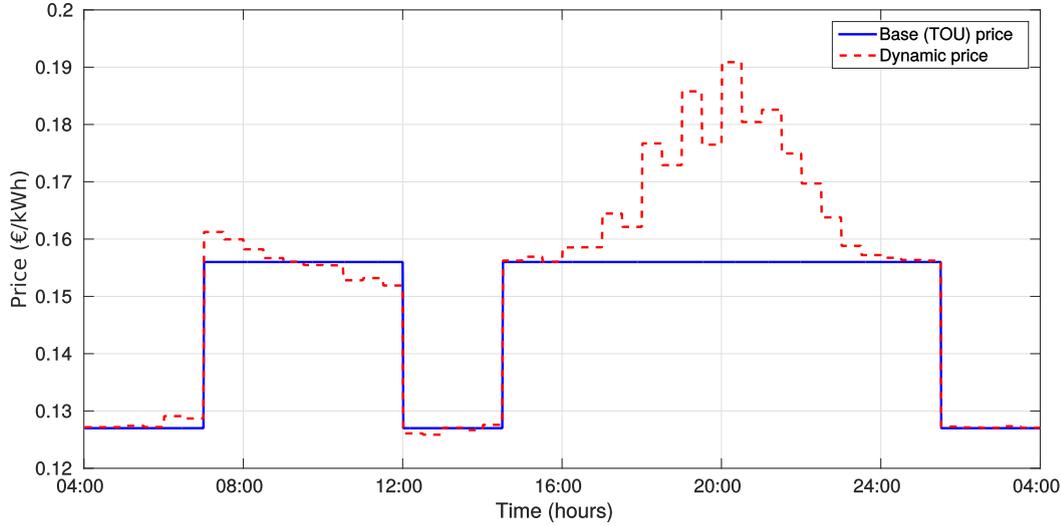


Figure 4.18: Base and full dynamic electricity pricing.

- Selfish scenario: optimization problem using the battery output power function (3.19).

$$\begin{aligned} & \text{minimize} \left\{ C_u = \Delta t \cdot \sum_{t=1}^{\mathcal{T}} \left(P_u^c(t) - P_u^s(t) + P_u^b(t) \right) \cdot \lambda_d(t, \mathbf{P}_{agg}^a(t)) \right\} \quad (4.7) \\ & \text{s.t.} \quad (3.1), (3.2), (3.9), (3.10), (3.16), (3.17), (3.18) \end{aligned}$$

To sum up base scenarios, in Baseline, smart homes do not communicate with the aggregator, share energy, nor control their assets. They are modeled as passive users. In Selfish, homes can control their electricity appliances and batteries according to the TOU price without coordination and energy sharing.

Also, as a reminder, asset scheduling is formulated as in Fig. 3.5, with control intervals defined by users for the Selfish scenario, and decentralized control algorithm. Again, we consider that the clothes dryer should operate after the washing machine.

In the decentralized control problem, the battery power output $P_u^b(t)$ is determined using the aggregated electricity profiles (aggregated net profile $\mathbf{P}_{agg}^n(t)$ and aggregated sold power profile with battery discharge $\mathbf{P}_{agg}^{bs}(t)$) and dynamic price $\lambda_d(t, \mathbf{P}_{agg}^a(t))$ received from the aggregator agent. Note that while home agents are sending four data types ($P_u^{nc}(t)$, $P_u^{sg}(t)$, $P_u^{bs}(t)$ and $P_u^{bp}(t)$) in Chapter 3, they only exchange two types of data ($P_u^n(t)$ and $P_u^{bs}(t)$) with the aggregator agent in this chapter. For the battery control, the same assumptions are also valid here, and are listed below:

- A home agent can use its battery for its own consumption and/or for sharing energy with its neighbors, but cannot discharge the battery to sell energy back to the main grid. This feature is left as future work, in which the utility (the upper level of the neighborhood) requires energy from the neighborhood.
- To decrease the computation burden, an additional time resolution “ $z \in \mathbb{Z}$ ” is defined, rather than using the actual time resolution “ $t \in \mathbb{T}$ ” as represented in Fig. 3.6.

To determine battery power, home agents firstly determine perspective electricity profiles

$\mathbf{R}_{agg,u}^n(t)$ (net profile) and $\mathbf{R}_{agg,u}^{bs}(t)$ (power sold with battery discharge) as in Section 3.2.3 with:

$$R_{agg,u}^n(t) = \mathbf{P}_{agg}^n(t) - P_u^n(t) \quad (4.8)$$

$$R_{agg,u}^{bs}(t) = \mathbf{P}_{agg}^{bs}(t) - P_u^{bs}(t) \quad (4.9)$$

Home agents then calculate the battery output power using binary variables $\gamma_u^b(z) \in \{0, 1\}$ for controlling the battery as follows:

$$P_u^b(t) = \begin{cases} \mathbf{fullcharge} \cdot \eta_u^c & , \text{ if } \gamma_u^b(z) = 0, P_u^g(t) > 0 \\ \mathbf{idle} & , \text{ elseif } \gamma_u^b(z) = 0, P_u^g(t) \leq 0 \\ \mathbf{charge} \cdot \eta_u^c & , \text{ elseif } \gamma_u^b(z) = 1, P_u^g(t) > P_u^c(t) + R_{agg,u}^n(t) - R_{agg,u}^{bs}(t) \\ \mathbf{discharge}/\eta_u^d & , \text{ elseif } \gamma_u^b(z) = 1, P_u^g(t) \leq P_u^c(t) + R_{agg,u}^n(t) - R_{agg,u}^{bs}(t) \end{cases} \quad (4.10)$$

The numerical outputs for battery operation are defined as:

$$\begin{aligned} \mathbf{fullcharge} & \rightarrow P_u^g(t) \\ \mathbf{idle} & \rightarrow 0 \\ \mathbf{charge} & \rightarrow P_u^g(t) - (P_u^c(t) + R_{agg,u}^n(t) - R_{agg,u}^{bs}(t)) \\ \mathbf{discharge} & \rightarrow -(P_u^c(t) - P_u^g(t) + R_{agg,u}^n(t) - R_{agg,u}^{bs}(t)) \end{aligned} \quad (4.11)$$

According to (4.11), **fullcharge** means charging the battery using PV generation and **charge** means charging with surplus generation after using it firstly for consumption. For battery **discharge**, the home agent discharges the battery only when the logical input is $\gamma_u^b(z) = 1$. After that, battery power sold with battery discharge is calculated by:

$$P_u^{bs}(t) = P_u^b(t) - P_u^c(t) \quad (4.12)$$

Thus, the battery power sold is $P_u^{bs}(t) \geq 0$ when the battery output power is $P_u^b(t) \leq 0$. According to (4.11) and (4.10), if there are home and neighborhood consumption at the same time when battery discharging is decided, the discharged power is firstly used for home consumption, and then sold to the neighbors.

Lastly, home agents determine the net electricity profile of the smart homes and optimize the following objective function, with the set of constraints to minimize the daily electricity bill of the users.

$$P_u^n(t) = P_u^c(t) - P_u^g(t) + P_u^b(t) + P_u^{bs}(t) \quad (4.13)$$

$$\begin{aligned} & \text{minimize } \left\{ C_u = \Delta t \cdot \sum_{t=1}^T (P_u^n(t) - P_u^{bs}(t)) \cdot \lambda_d(t, \mathbf{P}_{agg,u}^a(t)) \right\} \\ & \text{s.t. } (3.1), (3.2), (3.9), (3.10), (3.16), (3.17), (3.18) \end{aligned} \quad (4.14)$$

Note that $P_u^{bs}(t)$ is removed in (4.13) and added in (4.14). These variables are needed separately during the data exchange with the aggregator agent for implementing the coordination mechanisms described in Section 4.3.

4.3/ COORDINATION MECHANISMS

Two coordination models are proposed (group-based and turn-based), and differ in the decision-making principle of the home agents. In both models, the same optimization problem is solved and the same data structure is used for communication by the home agents, as shown in Fig. 4.19. Note that home agents do not communicate with each other, and take the average of the actual data over a given time interval “ \mathcal{L} ” for communicating with the aggregator, as in Chapter 3. In this respect, as a reminder, when a message is sent, the data size is modified from $[1 \times \mathcal{T}]$ to $[1 \times \mathcal{T}/\mathcal{L}]$, and reconverted from $[1 \times \mathcal{T}/\mathcal{L}]$ to $[1 \times \mathcal{T}]$ when a message is received.

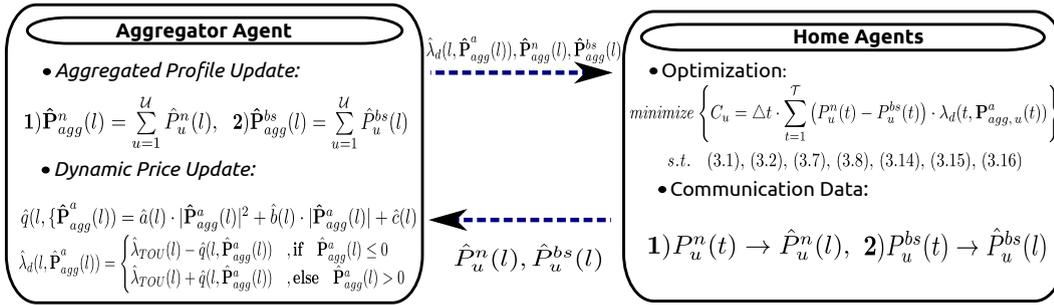


Figure 4.19: Communication diagram of the neighborhood agents.

4.3.1/ GROUP-BASED COORDINATION

The pseudo-code of the group-based coordination mechanism is given in **Algorithm 4**.

Algorithm 4 *Group-based coordination model.*

- 1: All users $\forall u \in \mathbb{U}$ receive $\hat{\lambda}_d(l, \hat{\mathbf{P}}_{agg}^a(l)) = \hat{d}(l)$, $\hat{\mathbf{P}}_{agg}^n(l) = 0$ and $\hat{\mathbf{P}}_{agg}^{bs}(l) = 0$ from the aggregator agent.
 - 2: **repeat**
 - 3: $\forall u \in \mathbb{U}$ generate $\hat{R}_{agg,u}^n(l)$ and $\hat{R}_{agg,u}^{bs}(l)$ with (4.8) and (4.9).
 - 4: $\forall u \in \mathbb{U}$ convert: $R_{agg,u}^n(t) \leftarrow \hat{R}_{agg,u}^n(l)$, $R_{agg,u}^{bs}(t) \leftarrow \hat{R}_{agg,u}^{bs}(l)$
 - 5: $\forall u \in \mathbb{U}$ solve (4.14) with (4.10)-(4.13).
 - 6: $\forall u \in \mathbb{U}$ create and send $\hat{P}_u^n(l)$ and $\hat{P}_u^{bs}(l)$.
 - 7: The aggregator generates $\hat{\lambda}_d(l, \hat{\mathbf{P}}_{agg}^a(l))$, $\hat{\mathbf{P}}_{agg}^n(l)$, $\hat{\mathbf{P}}_{agg}^{bs}(l)$ and sends them to $\forall u \in \mathbb{U}$.
 - 8: The aggregator calculates: $\sum_{l=1}^{\mathcal{T}/\mathcal{L}} \hat{\mathbf{P}}_{agg}^a(l) \cdot \hat{\lambda}_d(l, \hat{\mathbf{P}}_{agg}^a(l)) \cdot \Delta l$
 - 9: **until** convergence is achieved (Section 4.3.3).
-

At the beginning of the coordination (at the first iteration, $k = 1$), the aggregator sends $\hat{\lambda}_d(l, \hat{\mathbf{P}}_{agg}^a(l)) = \hat{\lambda}_{TOU}(l)$, $\hat{\mathbf{P}}_{agg}^n(l) = 0$, and $\hat{\mathbf{P}}_{agg}^{bs}(l) = 0$ to home agents. Home agents receive the data and solve the optimization problem with (4.14), simultaneously. After that, the home net profile $\hat{P}_u^n(l)$ and the home sold battery power profile $\hat{P}_u^{bs}(l)$ are sent to the aggregator agent. Then, the aggregator agent determines the aggregated profiles and the dynamic price in the neighborhood, and sends them back to the home agents. This process continues until convergence is reached (see Section 4.3.3).

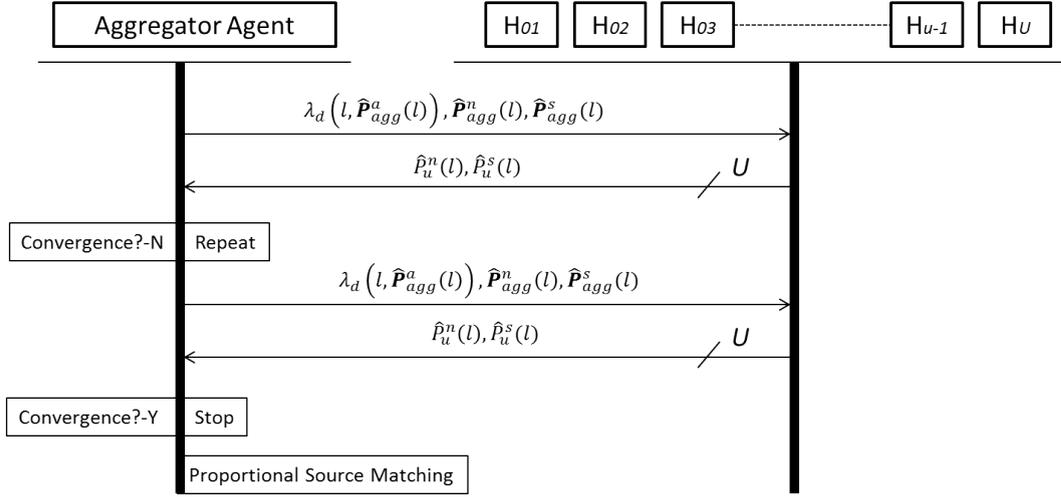


Figure 4.20: Coordination diagram of the group-based mechanism.

As all agents run the optimization simultaneously with **Algorithm 4**, $\mathbf{P}_{agg}^{bs}(t)$ may become higher than the aggregated consumption $\mathbf{P}_{agg}^n(t)$ (which can lead to mismatches) during the procedure on two occasions: i) at the end of each iteration, or ii) when final decisions are converted from the l -domain to the t -domain (as in Section 3.2.3). Therefore, for the first case, the aggregator agent determines the price by comparing $\hat{\mathbf{P}}_{agg}^{bs}(l)$ and $\hat{\mathbf{P}}_{agg}^n(l)$ in (4.15). There is a possibility that home agents can discharge their battery for neighborhood consumption at the same time due to simultaneous optimization, which may lead to $\hat{\mathbf{P}}_{agg}^n(l) \leq \hat{\mathbf{P}}_{agg}^{bs}(l)$ when $\hat{\mathbf{P}}_{agg}^n(l) > 0$.

$$\hat{\mathbf{P}}_{agg}^a(l) = \begin{cases} 0 & : \hat{\mathbf{P}}_{agg}^n(l) > 0, \hat{\mathbf{P}}_{agg}^n(l) \leq \hat{\mathbf{P}}_{agg}^{bs}(l) \\ \hat{\mathbf{P}}_{agg}^n(l) - \hat{\mathbf{P}}_{agg}^{bs}(l) & : \hat{\mathbf{P}}_{agg}^n(l) > 0, \hat{\mathbf{P}}_{agg}^n(l) > \hat{\mathbf{P}}_{agg}^{bs}(l) \\ \hat{\mathbf{P}}_{agg}^n(l) & : \hat{\mathbf{P}}_{agg}^n(l) \leq 0 \end{cases} \quad (4.15)$$

For the second case, a new defined *proportional source matching* method is applied, where the sold power of home agents is proportionally determined according to the total decided sold power after convergence is reached (see Section 3.2.3). If there is one seller ($\mathbf{P}_{agg}^{bs}(t) = P_u^{bs}(t)$) and the sold battery discharge power is less than or equal to the aggregated consumption ($\mathbf{P}_{agg}^n(t) \geq P_u^{bs}(t)$), no extra calculation is required ($P_u^{bs}(t) = P_u^{bs,d}(t)$). Otherwise, when the number of sellers is higher than one, $\mathbf{P}_{agg}^{bs}(t) > P_u^{bs}(t)$ and $\mathbf{P}_{agg}^{bs}(t) > \mathbf{P}_{agg}^n(t)$, then:

$$P_u^{bs}(t) = \mathbf{P}_{agg}^n(t) \cdot \frac{P_u^{bs,d}(t)}{\mathbf{P}_{agg}^{bs,d}(t)} \quad (4.16)$$

If a mismatch occurs between the l -domain and the t -domain, the aggregator stabilizes the system by determining $P_u^{bs}(t)$ for each user based on the ratio between $P_u^{bs,d}(t)$ and $\mathbf{P}_{agg}^{bs,d}(t)$ in real time. The coordination diagram for the group-based mechanism is shown in Fig. 4.21.

4.3.2/ TURN-BASED ALGORITHM

The pseudo-code of the turn-based coordination mechanism is given in **Algorithm 5**.

Algorithm 5 Turn-based coordination model.

- 1: All users $\forall u \in \mathcal{U}$ receive $\hat{\lambda}_d(l, \hat{\mathbf{P}}_{agg}^a(l)) = \lambda_{TOU}(l)$, $\hat{\mathbf{P}}_{agg}^n(l) = 0$ and $\hat{\mathbf{P}}_{agg}^s(l) = 0$ from the aggregator agent.
- 2: **repeat**
- 3: $u = 1$
- 4: **while** $u \leq \mathcal{U}$ **do**
- 5: User u generates the perspective data with (4.8) and (4.9).
- 6: User u converts: $R_{agg,u}^n(t) \leftarrow \hat{R}_{agg,u}^n(l)$, $R_{agg,u}^{bs}(t) \leftarrow \hat{R}_{agg,u}^{bs}(l)$.
- 7: User u solves (4.14) using (4.10)-(4.13).
- 8: User u creates and sends them $\hat{P}_u^n(l)$ and $\hat{P}_u^{bs}(l)$.
- 9: The aggregator generates $\hat{\lambda}_d(l, \hat{\mathbf{P}}_{agg}^a(l))$, $\hat{\mathbf{P}}_{agg}^n(l)$, $\hat{\mathbf{P}}_{agg}^{bs}(l)$ and sends to $u = u + 1$.
- 10: **end while**
- 11: The aggregator calculates: $\sum_{l=1}^{\mathcal{T}/\mathcal{L}} \hat{\mathbf{P}}_{agg}^a(l) \cdot \hat{\lambda}_d(l, \hat{\mathbf{P}}_{agg}^a(l)) \cdot \Delta l$
- 12: **until** convergence is achieved (in Section 4.3.3)

The main difference between the group-based and turn-based models is that home agents are communicating with the aggregator agent and solve the optimization problem one after another in the turn-based model, while it is done simultaneously in the group-based one. Hence, they do not need to apply (4.13), because they are informed of the changes after each home optimization ($\hat{\mathbf{P}}_{agg}^a(l) = \hat{\mathbf{P}}_{agg}^n(l) - \hat{\mathbf{P}}_{agg}^{bs}(l)$). In this model, k is increased after the \mathcal{U} -th home agent optimization. Then, if convergence is not achieved, each user $u \in \mathcal{U}$ runs the optimization again. The coordination diagram for the turn-based mechanism is shown in Fig. 4.21.

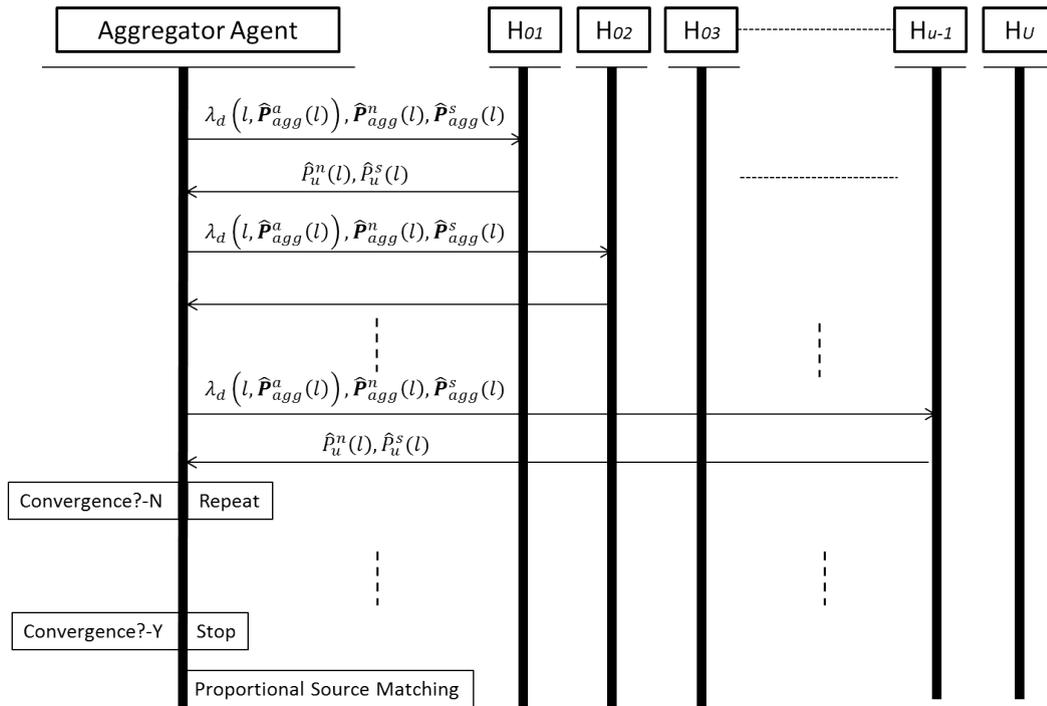


Figure 4.21: Coordination diagram of the turn-based mechanism.

4.3.3/ CONVERGENCE

For both proposed coordination models, **Algorithm 6** is defined with the pseudo-code for the convergence criteria.

Algorithm 6 Convergence criteria of **Algorithms 4** and **5**.

```

1:  $k \leftarrow 1, \epsilon \leftarrow 0$ 
2: while  $k \leq k_{max}$  do
3:   Apply Algorithm 1 or 2
4:    $\epsilon = \sum_{u=1}^U |(C_u^k - C_u^*)|$ 
5:   if  $k > k_{min}$  then
6:     if  $\epsilon < \epsilon_e$  then
7:       break while;
8:     end if
9:   end if
10:   $k \leftarrow k + 1$ 
11: end while

```

where ϵ is the cost deviation at the last iteration, ϵ_e is the acceptable cost deviation for convergence, C_u^k is the cost of the smart home at the last iteration, and C_u^* is the best achieved cost (minimum) of the smart home among all iterations. Lastly, k_{min} is the minimum iteration limit and k_{max} is the maximum iteration limit of the coordination process. According to **Algorithm 5**, the system reaches convergence when the total cost does not fluctuate more than ϵ_e . Otherwise, iterations continue until the maximum allowed number iterations is reached. Then, the aggregator agent ends the process and considers the latest decision of smart homes at k_{max} as the final one.

4.4/ PERFORMANCE EVALUATION

The same co-simulation platform as the one described in Section 3.3.2 is used to perform the simulations for a neighborhood formed by $\mathcal{U} = 25$ smart homes. The number of appliances in each smart home (Fig. 4.22) and PV (Fig. 4.23) and battery installation capacities (Fig. 4.24) are determined probabilistically. In total, 400 appliances are placed (352 non-controllable and 48 controllable) in the neighborhood. 11 smart homes are equipped with PV and 3 smart homes are deployed with PV and battery systems. An example electricity consumption and generation profile is given in Fig. 4.25.

The asset consumption and the PV generation ratio with respect to the total neighborhood consumption vary between 3–8% and 5–70%, respectively. The cause of these small ratios in the asset consumption share is that these appliances are not working every day in a year. A total of 229 assets are available in the neighborhood, and are used 8,044 times in a year (much less than $48 \times 365 = 17,520$ times).

Home agents solve the optimization problem for two days ($\mathcal{T} = 2,880$) using the rolling horizon technique, as in Section 3.3.1. For communication, home agents send average data for each $\mathcal{L} = 30$ minutes and the battery control interval is defined equal to $\mathcal{Z} = 15$ minutes. Simulations are performed on the same desktop computer described in Chapter 3. Lastly, the scalability of the algorithm is tested for four different neighborhood area

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

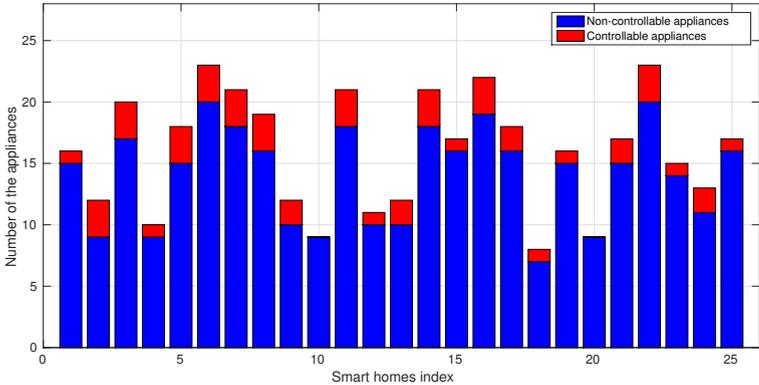


Figure 4.22: Assets and non-controllable appliance numbers in smart homes.

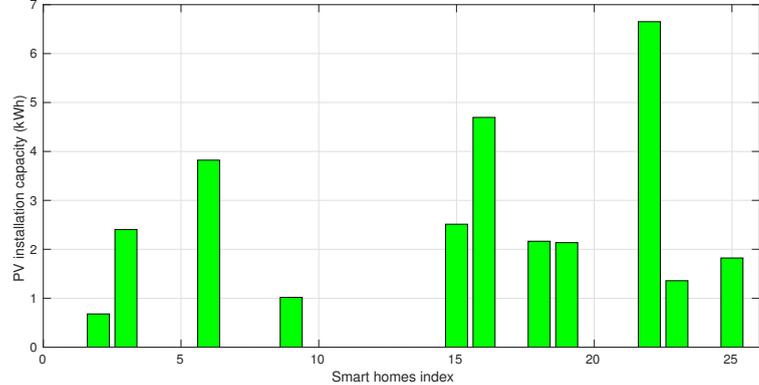


Figure 4.23: PV installation capacities in smart homes.

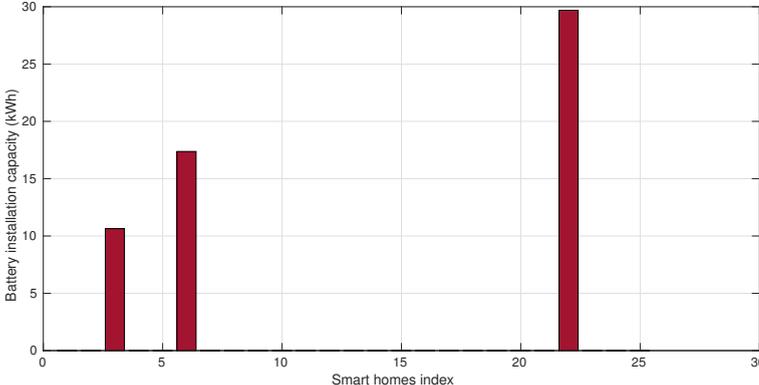


Figure 4.24: Battery installation capacities in smart homes.

sizes by varying the number of smart homes (25, 50, 75, and 100 smart homes).

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

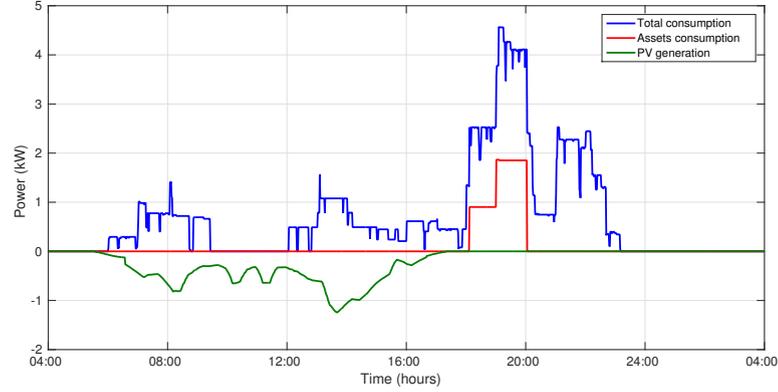


Figure 4.25: Smart home electricity profile example.

4.4.1/ DAILY SIMULATION RESULTS

Firstly, we run the simulations with and without considering forecasting errors for an arbitrarily chosen day (the 250th day) of the year. The prediction errors are calculated by the symmetrical mean absolute percentage errors (SMAPE) for the aggregated consumption (22.65 %) and generation profiles (5.08 %) of the neighborhood. The SMAPE formulation is defined as follows:

$$SMAPE = \frac{100}{\mathcal{T}} \sum_{t=1}^{\mathcal{T}} \frac{|F_v(t) - A_v(t)|}{(|A_v(t)| + |F_v(t)|) / 2} \quad (4.17)$$

where $F_v(t)$ is the forecast value and $A_v(t)$ is the actual value of the parameter. The cost and peak consumption results are given in Table 4.5, with absolute and percentage values. Percentages are calculated with respect to baseline results.

Table 4.5: Daily electric energy management results with (WE) and without (WoE) forecasting errors.

		Baseline	Selfish	Group-based	Turn-based
Cost (€)	WoE	34.51	33.33	32.46	32.14
	WE	—	33.90	32.47	32.23
Cost (%)	WoE	—	3.41	5.94	6.83
	WE	—	1.77	5.91	6.63
Peak (kW)	WoE	52.42	44.42	43.97	41.09
	WE	—	50.56	47.15	45.16
Peak (%)	WoE	—	15.26	16.11	21.61
	WE	—	3.54	10.05	13.85

The coordination methods show better performance compared to the baseline scenario, in terms of cost and peak demand reduction. The turn-based method shows a slightly better performance, and enables saving 0.32€ more compared to the group-based method. The selfish algorithm seems effective compared to the baseline scenario, but it is less ef-

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

fective than the proposed coordination mechanisms. Especially, when forecasting errors are taken into account, cost and peak reductions are decreased significantly, while the presented approaches show better performance.

Secondly, energy comparisons are shown in Fig. 4.26. Even though there is no coordination for baseline and selfish control, some energy is shared during high PV generation hours, which occurs naturally (physically, if there is enough load, surplus energy during daylight is used locally inside the neighborhood instead of being fed back to the main grid). Also, self-consumption is higher in these two algorithms as sharing energy by battery discharge is not allowed. Therefore, batteries are just discharged for the own consumption of the smart homes. On the other hand, home agents increase energy sharing and decrease self-consumption by discharging batteries for the neighborhood with both group-based and turn-based methods. These algorithms achieve decreasing the energy purchased from the utility. As there is no coordination, home agents discharge their batteries only for their own consumption in Fig. 4.27. On the other hand, with this coordination algorithm, home agents are able to discharge their batteries for neighborhood consumption, and decrease the purchased energy amount from the utility.

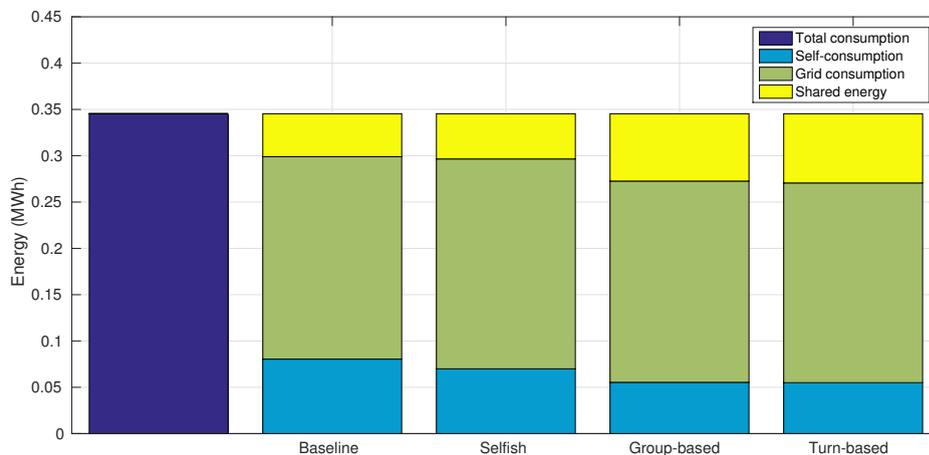


Figure 4.26: Comparison of the energy consumption breakdown for the different strategies.

Lastly, as expected, forecasting errors negatively impact all algorithms for both cost and peak reduction efficiencies. However, numerical results show that the proposed algorithms still provide better performance compared to the baseline due to their coordination and energy sharing ability.

4.4.2/ ANNUAL SIMULATION RESULTS

In this section, annual results are determined for both with and without considering forecasting errors. In Figs. 4.28 and 4.29, the neighborhood cost and peak consumption without considering forecasting errors are shown for a year. For all algorithms, total peak and cost results exhibit differences due to changes in PV generation during the seasons. Although there is a slight difference in the results, the presented group-based and turn-based coordination methods provide more benefits in lowering the peak consumption and the neighborhood cost during the year.

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

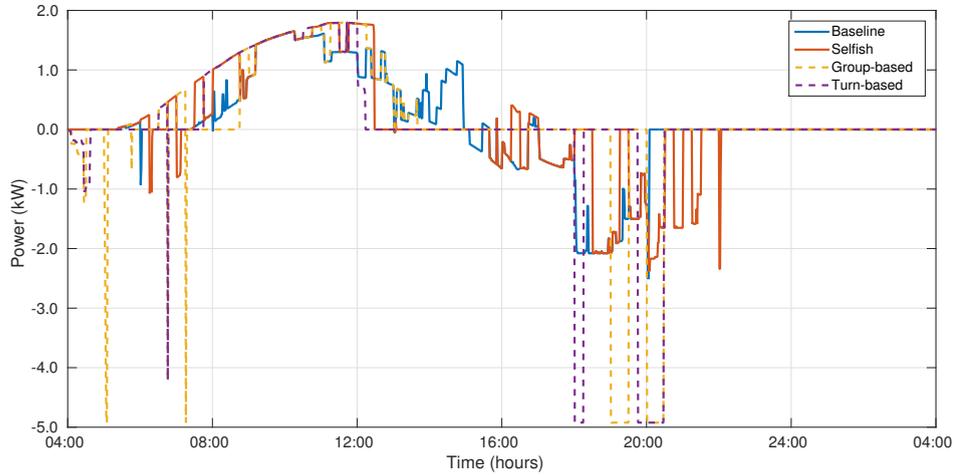


Figure 4.27: Smart home electricity profile example, using the different strategies.

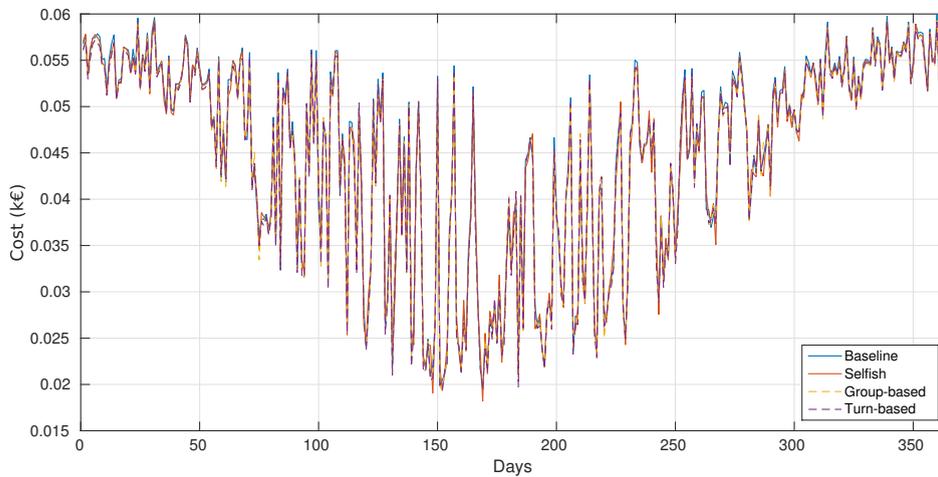


Figure 4.28: Annual neighborhood cost profiles.

To further analyze the presented methods in details, numerical results are given in Table 4.6.

Finally, we define three performance metrics to investigate the success rates (SR) of the presented coordination methods as follows:

- $SR-01$ is the percentage of the smart homes which have reduced their electricity bills.
- $SR-02$ is the percentage of the successful days for which the neighborhood cost has been reduced.
- $SR-03$ is the percentage of the successful days for which the neighborhood consumption has been reduced.

For $SR-01$, it can be seen that all smart homes succeed to decrease their electricity bill with both coordination methods, while with the selfish method, 8 of the smart homes lost

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

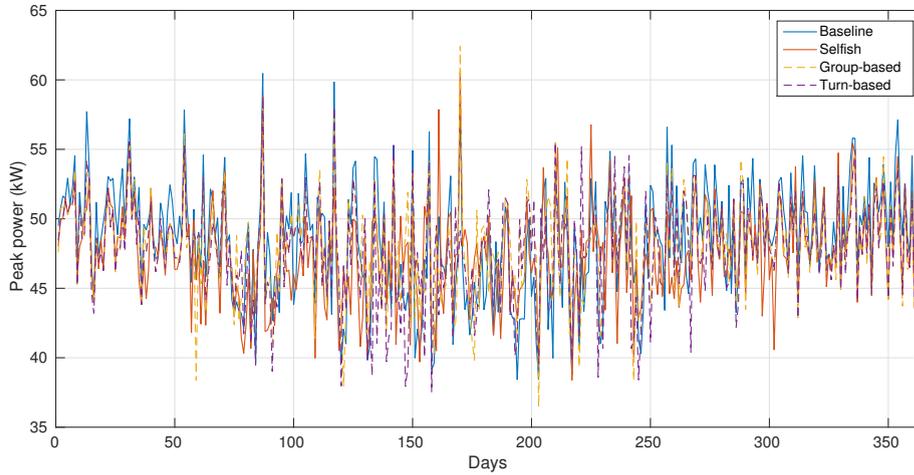


Figure 4.29: Annual neighborhood peak consumption profiles.

money. For the home energy management, all smart homes should earn some benefit in return for their efforts. Users may otherwise not be interested in active participation. In this respect, the proposed algorithms show 100% performance with coordination and energy sharing by the battery discharge in the neighborhood. For *SR-02*, both coordination mechanisms reduce the electricity cost for a minimum of 328 days, while the selfish algorithm reaches a maximum of 267 days. Lastly, for *SR-03*, both presented methods achieve to reduce the peak consumption for around 330 days, while the selfish algorithm reduces them only for 245 days.

Table 4.6: Annual electric energy management with (WE) and without (WoE) forecasting errors.

		Baseline	Selfish	Group-based	Turn-based
Cost (k€)	WoE	16.377	16.092	16.028	15.965
	WE	—	16.136	16.068	15.979
Cost (%)	WoE	—	1.74	2.13	2.52
	WE	—	1.47	1.89	2.43
Avg. peak (kW)	WoE	48.50	47.64	47.05	46.62
	WE	—	48.03	47.23	46.67
Avg. peak (%)	WoE	—	1.77	2.98	3.97
	WE	—	0.97	2.62	3.77
<i>SR - 01</i> (%)	WoE	—	92	100	100
	WE	—	92	100	100
<i>SR - 02</i> (%)	WoE	—	73.15	90.68	94.52
	WE	—	69.58	89.86	90.68
<i>SR - 03</i> (%)	WoE	—	67.12	92.05	93.69
	WE	—	66.30	90.68	91.50

Overall, the turn-based method returns the best performance in terms of cost and peak reduction, while the group-based method shows a slightly lower performance. However, the turn-based algorithm requires more computation time (maximum 1255 sec.) to coordinate the home agent strategies compared to the group-based model (maximum 75 sec.) In small neighborhoods, the turn-based approach can solve the coordination problem in acceptable time limits. However, for larger neighborhoods (such as with 1000 smart homes), the group-based method seems preferable. Lastly, results show that the selfish algorithm is not effective for scheduling and battery management in the neighborhoods.

4.4.3/ SCALABILITY ANALYSIS

In this section, a scalability analysis is performed by varying the number of smart homes in the neighborhood area. The simulations are performed for four different neighborhood area sizes (25, 50, 75, and 100). The numbers of PV and battery owners are given in Table 4.7.

Table 4.7: Neighborhood area number of resource owners.

Neighborhood	Number of PV and battery owners	Number of PV owners	Number of no PV and battery owners
25 smart homes	3	8	14
50 smart homes	8	24	18
75 smart homes	15	22	38
100 smart homes	20	35	45

The simulation results are given below, and enable comparing the achieved profit and peak consumption reductions against the baseline scenario. In Table 4.8, the determined profits and peak reductions are given for each control method with and without considering forecasting errors. This scalability analysis proves that the presented control algorithms provide cost-beneficial coordination strategies for different sizes of neighborhoods. It should be noted that simulations are performed for the same day (the 250th day), and that the number of the PV and battery owners clearly impact the performance of the algorithm. Although, there is no regular pattern on the results of Table 4.7, the proposed coordination algorithms show a better performance compared to the baseline and selfish scenarios in every neighborhood area size.

4.5/ CONCLUSION

This chapter has presented two decentralized coordination mechanisms (group-based and turn-based) for energy management and sharing in a neighborhood area considering forecasting errors. This chapter, as an extension of the previous chapter, has focused on increasing renewable energy usage in the neighborhood area by deploying more advanced decentralized coordination methods with a dynamic price structure. This price structure is modeled by merging grid a TOU price and a quadratic price function associated to the neighborhood electricity profile at the PCC. In both coordination mechanisms, the same optimization problem is solved by the home agents in a different order. Home

CHAPTER 4. DYNAMIC PRICING-BASED DECENTRALIZED HOME ENERGY SHARING COORDINATION

Table 4.8: Determined neighborhood profits and peak reductions for each control method and neighborhood size.

Neighborhood	Methods	Profits (€)		Peak reductions (kW)	
		WoE	WE	WoE	WE
25 smart homes	Selfish	1.18	0.61	8.00	1.86
	Group-based	2.05	2.04	8.45	5.27
	Turn-based	2.37	2.28	11.33	7.26
50 smart homes	Selfish	1.10	0.63	1.89	0.14
	Group-based	4.79	1.11	2.22	0.39
	Turn-based	8.04	6.98	5.36	4.79
75 smart homes	Selfish	3.58	0.32	1.86	0.54
	Group-based	5.50	1.55	2.24	1.18
	Turn-based	33.45	31.16	16.91	12.83
100 smart homes	Selfish	1.14	0.58	1.01	0.94
	Group-based	13.18	11.86	4.32	3.23
	Turn-based	47.42	35.14	21.13	16.64

agents optimize their power profiles to reduce their daily electricity bill by scheduling their assets and controlling their battery system. In the group-based method, home agents optimize simultaneously, while they do it one-by-one in the turn-based method. The results of the coordination methods are compared with two base scenarios (baseline and selfish), by performing annual simulations. The performance of the presented algorithms is evaluated according to cost and peak reductions, and with the three proposed metrics. The new metrics are evaluating the performance of the algorithms based on the determined cost and peak reductions in a year. Both methods show good performance compared to the base scenarios in terms of cost and peak reductions, and on the proposed metrics. Between the algorithms, the turn-based method gives the best results, while the group-based method is ranked second. However, the group-based method solves the optimization problem and converges significantly faster than the turn-based one.

AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

An aggregator is a market participant that bridges the gap between bulk generation and the emerging active users (mostly smart homes in the residential sector) by efficiently scheduling and/or allocating resources to meet certain objectives on behalf of users or the utility. In this respect, the aggregator is a third-party entity that aggregates the electricity utilization of the users and provides a value proposition to the bulk electricity market. The aggregator seeks to increase its revenue by obtaining economic benefits for the users, by controlling their assets, as well as by providing ancillary services to the grid operator. Therefore, in order to achieve market integration between users and the grid operator, aggregators are required to coordinate control operations, for instance with DR programs. By applying the control operations of assets, the aggregator aims to earn and increase its profit in return for its services. The location of the aggregator in the system and its purposes were defined in Section 2.3.1.

In the previous chapters, the interactions between the aggregator and the rest of the grid were assumed to be already arranged, and the profit of the aggregator was not determined. This chapter focuses on the determination of the aggregator profit with DR programs (denoted as smart grid resource allocation (SGRA) problem), and investigates the impact of residential PV systems integration on the economic performance of an aggregator. In this work, the aggregator is the central controller of the neighborhood area, and interacts with the local distribution utility and the bulk electricity market. Based on these interactions, the aggregator provides users an alternative pricing called CIP, introduced in [120], for incentivizing participation in the DR program. Through this, customers reduce their daily electricity bills while the aggregator also decreases the aggregated peak consumption of the area and generates a profit.

In this respect, the main aim of the aggregator is to improve its profitability by incentivizing the users in return for scheduling their assets. The aggregator achieves this by offering an alternative, yet competitive, pricing mechanism to the utility RTP. However, the aggregator must also take into account the PV generation in smart homes while determining the offered pricing and scheduling the assets. Therefore, in this chapter, we investigate the effect of RES penetration on the aggregator profit as an extension of previously published work in [120]. Moreover, we perform simulations over multiple days to evaluate the performance of the control algorithm compared to a baseline scenario. Furthermore,

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

using parallel processing techniques, the computation time of the optimization process is decreased.

The rest of the chapter is organized as follows: the system model is presented in Section 5.1. In Section 5.2, the optimization problem is formulated, and parallel processing methods are studied in Section 5.3. Simulation results are given in Section 5.4. In Section 5.5, the chapter is concluded.

5.1/ SYSTEM MODEL

We consider an electricity network and a market structure, where one utility, one aggregator and \mathcal{U} smart homes are operating. As this chapter is an extension of previously published research, we used the same modeling approach as the one described in [120]. Therefore, in this chapter, MAS are not used for modeling entities of the electricity network as agents.

5.1.1/ SMART HOME

In smart homes, electricity appliances are divided into two groups, as in Chapters 3 and 4: non-controllable and controllable. In total, 31 types of non-controllable and 18 types of controllable appliances (assets) are used to model the daily consumption profile of the smart homes. The non-controllable loads are probabilistically generated for each user based on data in [62], and assets are modeled probabilistically using the data in Table 5.1. The penetration rate is used to refer to the probability that the appliance exists in the smart home. All electricity profiles in smart homes and the neighborhood are modeled with a 15-minute time resolution.

Residential PV systems are considered as RES. The existence probability of PV in smart homes is defined arbitrarily. In Section 5.4, various cases studies are described based on the defined probability values of the PV system, in order to compare the effect of various PV penetration levels in the neighborhood area. The PV generation output is formulated using (3.6).

5.1.2/ ELECTRICITY NETWORK

The considered electricity network is shown in Fig. 5.1. The aggregator interacts with the residential customers (through their HEMS) in the neighborhood to provide them with cost-beneficial consumption options by scheduling their appliances. It offers an alternative pricing, so users can earn some profit in return for their efforts. To do that, the aggregator interacts with the bulk spot market and the utility to receive electricity pricing data (forecast and real-time data) from both sources. The data for the spot market price and utility price are obtained from PJM and ComEd, respectively. PJM is an American independent regional organization that operates competitive wholesale electricity markets and manages the high-voltage electricity grid to ensure its reliability [38]. ComEd (Commonwealth Edison Company) is a utility company that provides electricity services across Northern Illinois [36]. Examples of PJM and ComEd pricing data are given in Figs. 5.2 and 5.3.

Table 5.1: Modeling parameters of assets [120].

Penetration (%)	Power rating mean (kW)	Power rating std. dev. (kW)	Duration (15-minutes)	Start time mean (h)	Start time std. dev. (h)
70	0.5	0.05	4	7	1
70	0.5	0.05	4	14	3
70	0.5	0.05	4	17	1
50	0.75	0.10	3	7	1
50	0.75	0.10	3	14	3
50	0.75	0.10	3	17	1
30	1.0	0.20	2	7	1
30	1.0	0.20	2	14	3
30	1.0	0.20	2	17	1
100	0.25	0.01	8	1	1
100	0.25	0.01	8	14	3
100	0.25	0.01	8	17	1
10	1.5	0.30	2	7	1
10	1.5	0.30	2	14	3
10	1.5	0.30	2	17	1
80	0.4	0.05	6	7	1
80	0.4	0.05	6	14	3
80	0.4	0.05	6	17	1

5.2/ PROBLEM FORMULATION

In this section, the SGRA problem is formulated with and without considering the integration of residential PV systems into smart homes, and is solved by the aggregator. A day-ahead centralized control methodology (see Section 2.3.2.1) is applied in both cases,

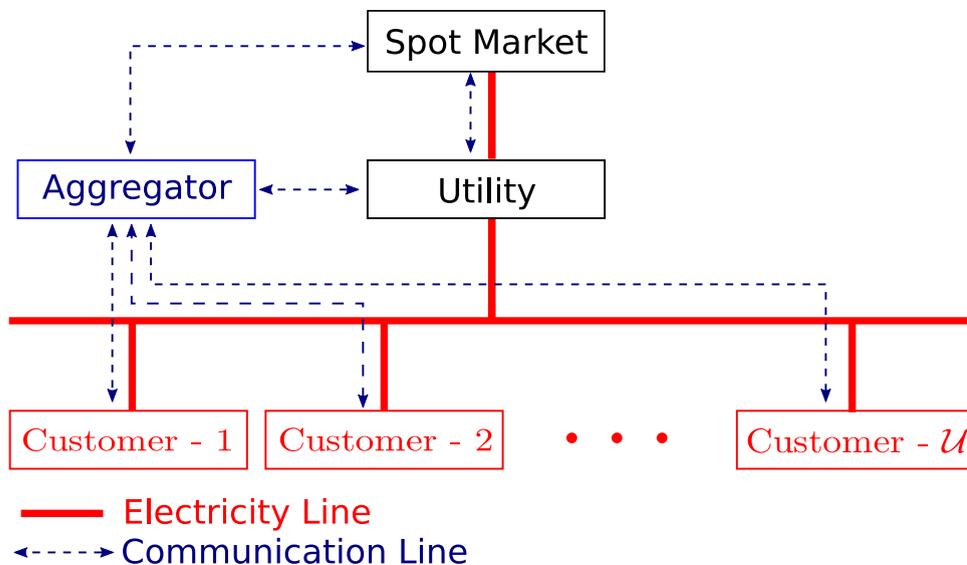


Figure 5.1: Electric and communication systems architecture.

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

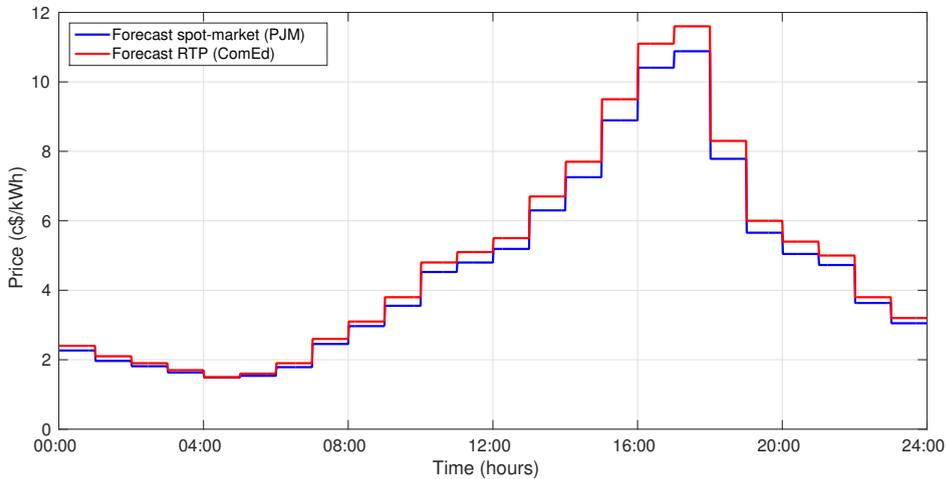


Figure 5.2: Forecast spot-market (PJM) and utility prices (ComEd) for July, 20 2017.

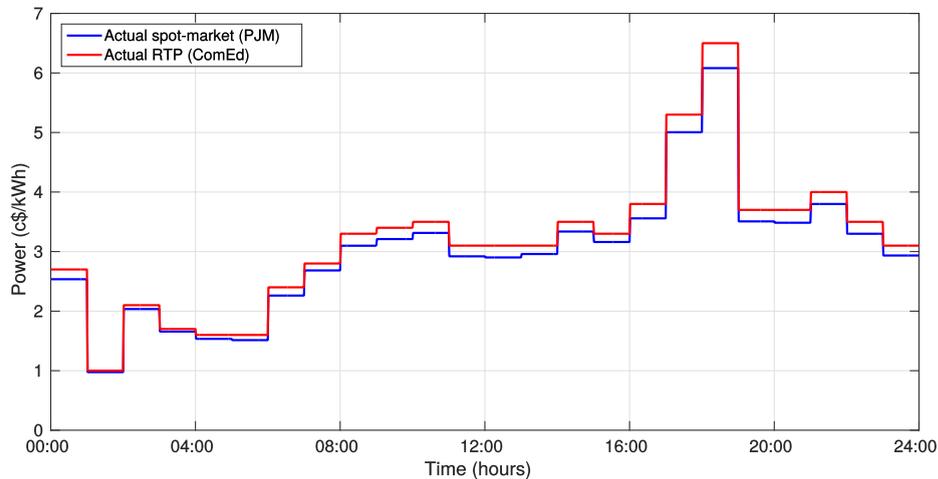


Figure 5.3: Actual spot market (PJM) and utility prices (ComEd) for July, 20 2017.

wherein the aggregator controls the controllable appliances (assets) in the smart homes. However, to convince the customers to participate in the transactions with the aggregator, a customer incentive pricing (CIP), which is a competitive price compared to the utility price for the residential customers, is offered by the aggregator.

In this respect, prior to each day, the aggregator receives price data from the spot market and the utility, and scheduling intervals of the assets. After that, the aggregator determines the operation start time of each asset with the CIP. As in Section 3.2, the assets are scheduled according to user-defined scheduling intervals, hence the same constraint (3.16) is formulated in the optimization problem. As the algorithm has no knowledge about appliance types, the interdependence among assets is not considered in this work. We assume that all assets operate independently from each other, thereby constraints (3.17) and (3.18) are not considered in the optimization problem.

However, users may not be willing to allow scheduling their assets in return for modest savings; rather, they might expect significant savings for their efforts in participating in the DR program. Therefore, customer willingness $\delta_{u,y}$ is formulated as a constraint for

allowing each asset $y \in \mathbb{Y}_u$ to be controlled by the aggregator. To consider that, the same model as in [120] is used to determine a threshold profit for each asset scheduling using α modeling. The customer willingness for each asset is formulated by:

$$\delta_{u,y} = \begin{cases} 1 & , \text{if } c_{u,y}^{sch} \leq \alpha_{u,y} \cdot c_{u,y}^0 \\ 0 & , \text{else } c_{u,y}^{sch} > \alpha_{u,y} \cdot c_{u,y}^0 \end{cases} \quad (5.1)$$

where $\delta_{u,y}$ is the customer willingness to allow scheduling of an asset ($\delta_{u,y} = 0$ disallows and $\delta_{u,y}$ allows scheduling); $\alpha_{u,y}$ is a threshold metric in percent; $c_{u,y}^{sch}$ and $c_{u,y}^0$ are the costs of consumption with and without scheduling, respectively. The costs for scheduled and non-scheduled conditions are calculated with:

$$c_{u,y}^{sch} = \sum_{t=t_{u,y}^{sch}}^{t=t_{u,y}^{sch}+(t_{u,y}^e-t_{u,y}^s)} \lambda_{CIP}(t) \cdot P_{u,y}(t) \cdot \Delta t \quad (5.2)$$

$$c_{u,y}^0 = \sum_{t=t_{u,y}^s}^{t=t_{u,y}^e} \lambda_{RTP}(t) \cdot P_{u,y}(t) \cdot \Delta t \quad (5.3)$$

where $\lambda_{CIP}(t)$ and $\lambda_{RTP}(t)$ are the CIP and utility RTP prices; and $t_{u,y}^{sch}$ is the aggregator-defined start time of an asset.

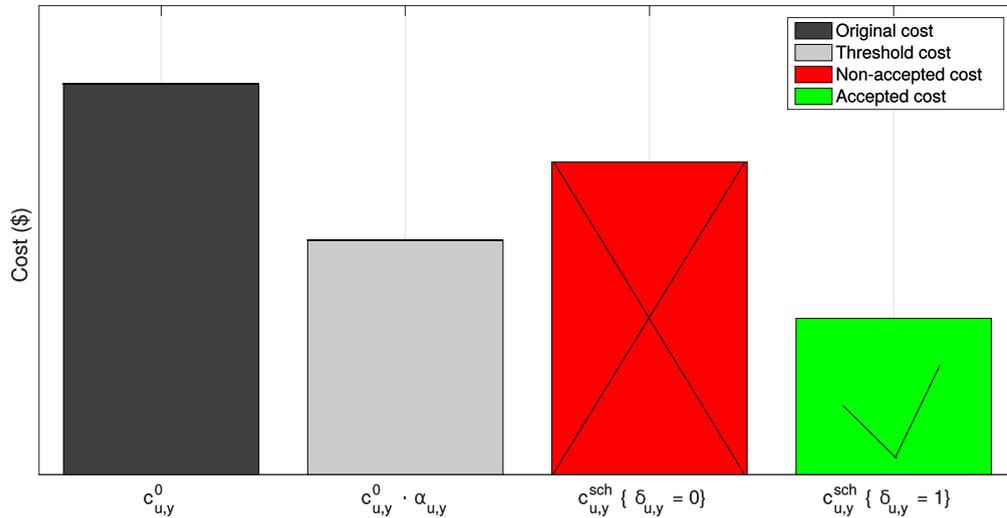


Figure 5.4: $\alpha_{u,y}$ modeling for appliance scheduling.

According to (5.1) (also see Fig. 5.4), the aggregator can only schedule an asset if the cost reduction satisfies the threshold condition. Otherwise, the aggregator is disallowed from controlling the asset. Based on this principle, the aggregator aims to maximize its own profit \mathbf{A}_p by offering the CIP and controlling assets. The optimization problem is then formulated by:

$$\begin{aligned} & \text{maximize } \left\{ \mathbf{A}_p = \sum_{u=1}^{\mathcal{U}} \sum_{y=1}^{\mathcal{Y}_u} \delta_{u,y} \cdot (S_{u,y} + N_{u,y} - B_{u,y}) \right\} \\ & \text{s.t. } (3.1), (3.2), (3.16), (5.1) \end{aligned} \quad (5.4)$$

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

where $S_{u,y}$ is the income from selling energy for appliance consumption; $N_{u,y}$ is the income from selling negative load (i.e., the deferred peak) to the spot market; and $B_{u,y}$ is the expense for buying energy from the spot market. In both cases (with and without PV), the aggregator calculates its profit using the same parameters for (5.4). However, due to local generation, parameters ($S_{u,y}$, $N_{u,y}$, and $B_{u,y}$) are formulated differently. Therefore, we first introduce the optimization problem of SGRA without PV from [120], and then re-formulate the $S_{u,y}$, $N_{u,y}$, and $B_{u,y}$ parameters based on the local generation in the neighborhood area.

5.2.1/ SGRA WITHOUT CONSIDERING RESIDENTIAL PV GENERATION

Originally, the SGRA optimization problem was formulated without considering PV generation, hence there is no negative load (PV generation can be considered as a negative load) in the neighborhood electricity profile, as shown in Fig. 5.5. The power flow is unidirectional, and assets operation times are only displaced in time due to the DR event. Thereby, the neighborhood electricity load is always positive. According to that, $S_{u,y}$, $N_{u,y}$, and $B_{u,y}$ are calculated as follows:

$$S_{u,y} = \Delta t \cdot \delta_{u,y} \sum_{t=t_{u,y}^{sch}}^{t=t_{u,y}^{sch}+(t_{u,y}^e-t_{u,y}^s)} \lambda_{CIP}(t) \cdot P_{u,y}(t) \quad (5.5)$$

$$N_{u,y} = \Delta t \cdot \delta_{u,y} \cdot \sum_{t=t_{u,y}^s}^{t=t_{u,y}^e} \lambda_{spot}(t) \cdot P_{u,y}(t) \quad (5.6)$$

$$B_{u,y} = \Delta t \cdot \delta_{u,y} \cdot \sum_{t=t_{u,y}^{sch}}^{t=t_{u,y}^{sch}+(t_{u,y}^e-t_{u,y}^s)} \lambda_{spot}(t) \cdot P_{u,y}(t) \quad (5.7)$$

where $\lambda_{spot}(t)$ is the spot market electricity price. The aggregator profit \mathbf{A}_p only depends on the scheduled asset profiles. According to (5.5)-(5.7), the aggregator profit \mathbf{A}_p only depends on the asset consumption profiles before and after solving the SGRA optimization problem. Therefore, the aggregated net electricity profile \mathbf{P}_{agg}^n has no influence on the aggregator profit, hence the calculation of the base appliances consumption profiles is unnecessary for the scenario where there is no PV penetration. Overall, according to (5.7), the aggregator aims to decrease the electricity consumption of the neighborhood during high electricity price hours (most probably during high consumption hours) by scheduling assets to low price hours (most probably during low consumption hours).

5.2.2/ SGRA WITH CONSIDERING RESIDENTIAL PV GENERATION

In this part, the SGRA optimization problem is formulated while considering residential PV generation in the neighborhood area, hence there can be negative load (surplus PV generation based on the daily irradiance and PV system penetration) in the neighborhood, as shown in Fig. 5.6. In this case, the power flow is bidirectional, so the changed asset consumption profile can increase or decrease the consumption profile as well as the generation profile of the neighborhood. Therefore, the neighborhood net profile must be taken into account during the optimization process.

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

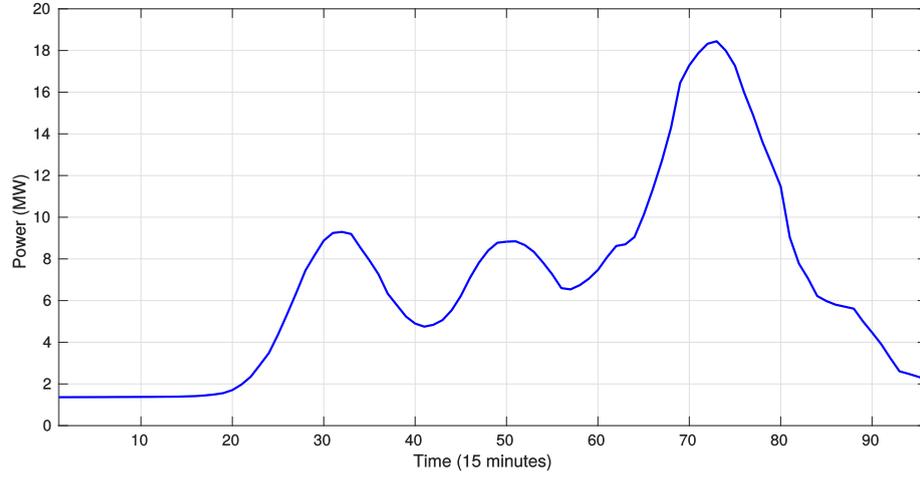


Figure 5.5: Aggregated electricity profile of the neighborhood without considering residential PV generation.

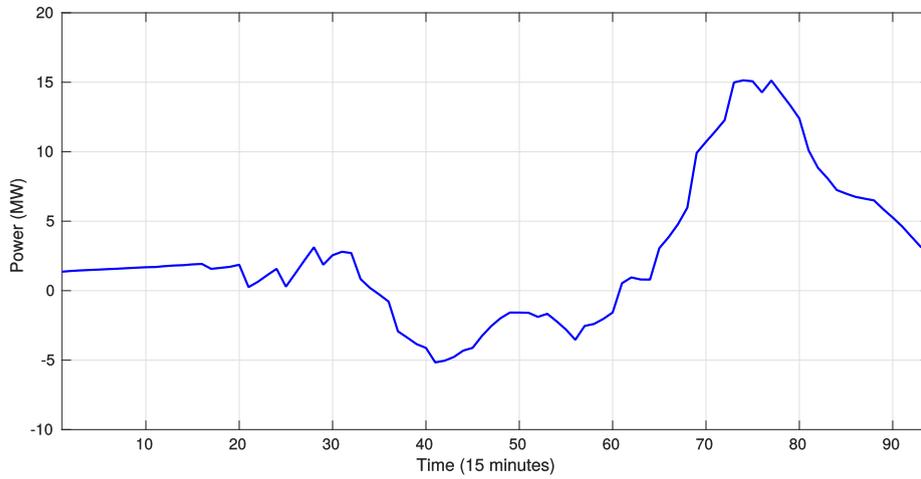


Figure 5.6: Aggregated electricity profile of the neighborhood considering residential PV generation.

According to that, at the beginning of the procedure, the aggregator clusters the electricity profiles according to the type of units in three groups: base consumption $P_{u,x}(t)$, PV generation $P_u^g(t)$ and asset consumption $P_{u,y}(t)$. After that, as shown in Fig. 5.7, the sum of the base and generation electricity profiles are calculated to create the aggregated net profile $\mathbf{P}_{agg}^a(t)$ of the neighborhood with:

$$\mathbf{P}_{agg}^a(t) = \sum_{u=1}^{\mathcal{U}} \left[\left(\sum_{x=1}^{X_u} P_{u,x}(t) \right) - P_u^g(t) \right] \quad (5.8)$$

Note that PV generation is a negative load in the distribution system. In the next step, the consumption of assets (based on the customer willingness $\delta_{u,y}$) are divided into two groups: consumption of scheduled and non-scheduled assets, as shown in Fig. 5.8.

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

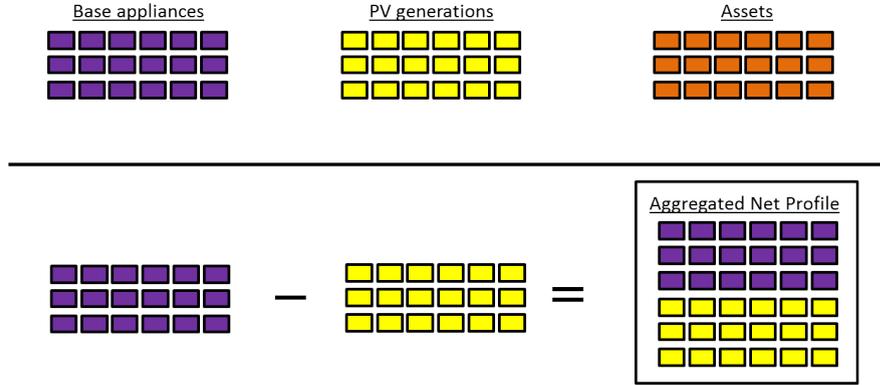


Figure 5.7: Aggregated electricity profile of the neighborhood with base loads and PV generation (PV generation is a negative load).

Non-scheduled assets consumption is included in the aggregated net profile by:

$$\mathbf{P}_{agg}^a(t) = \sum_{u=1}^{\mathcal{U}} \left[\left(\sum_{x=1}^{X_u} P_{u,x}(t) \right) - P_u^g(t) + \left(\sum_{y=1}^{Y_u} \begin{cases} P_{u,y}(t) & , \text{if } \delta_{u,y} = 0 \\ 0 & , \text{else } \delta_{u,y} = 1 \end{cases} \right) \right] \quad (5.9)$$

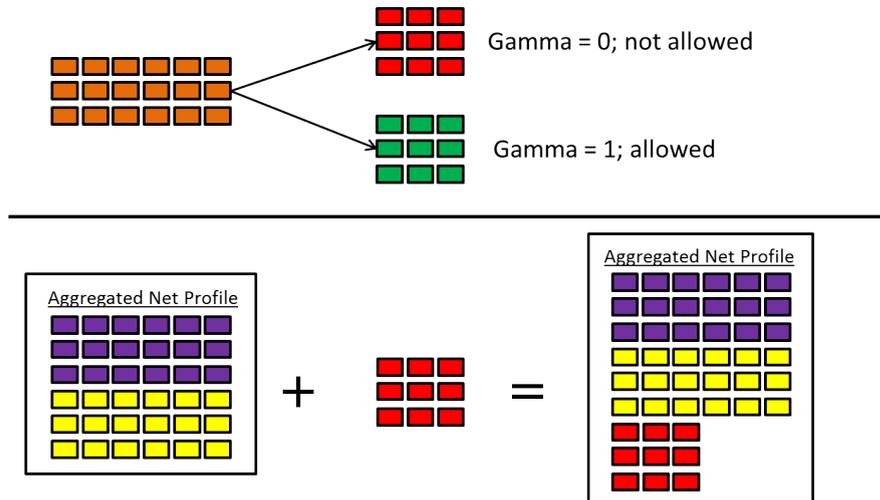


Figure 5.8: Aggregated electricity profile of the neighborhood with base loads, PV generation and non-scheduled assets.

After that, the aggregator starts to calculate its own profit by calculating the $S_{u,y}$, $N_{u,y}$ and $B_{u,y}$ terms for each scheduled asset, one after another, as shown in Fig. 5.9. Firstly, $S_{u,y}$ is formulated as:

$$S_{u,y} = \Delta t \cdot \delta_{u,y} \sum_{t=t_{u,y}^{sch}}^{t=t_{u,y}^{sch} + (t_{u,y}^e - t_{u,y}^s)} \lambda_{CIP}(t) \cdot P_{u,y}(t) \quad (5.10)$$

According to (5.10), the $S_{u,y}$ term is not effected by PV generation (as in (4.2)). Thus, the consumption power of the asset (after scheduling) is provided by the aggregator using

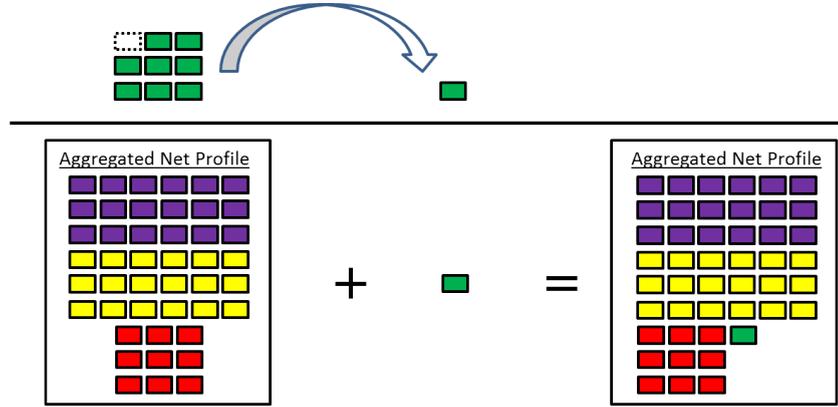


Figure 5.9: Aggregated electricity profile of the neighborhood with base loads, PV generation, non-scheduled assets and a scheduled asset.

CIP without being affected by local PV generation. Secondly, $N_{u,y}$ is calculated with:

$$N_{u,y} = \Delta t \cdot \delta_{u,y} \cdot \sum_{t=t_{u,y}^s}^{t=t_{u,y}^e}$$

$$\begin{cases} \lambda_{spot}(t) \cdot P_{u,y}(t) & , \text{ if } \mathbf{P}_{agg}^a(t) + \sum_{i=1}^{y-1} \delta_{u,i} \cdot P_{u,i}(t) > 0, \mathbf{P}_{agg}^a(t) + (\sum_{i=1}^{y-1} \delta_{u,i} \cdot P_{u,i}(t)) - P_{u,y}(t) \geq 0 \\ \lambda_{spot}(t) \cdot (\mathbf{P}_{agg}^a(t) + P_{u,y}(t)) & , \text{ elseif } \mathbf{P}_{agg}^a(t) + \sum_{i=1}^{y-1} \delta_{u,i} \cdot P_{u,i}(t) \leq 0, \mathbf{P}_{agg}^a(t) + (\sum_{i=1}^{y-1} \delta_{u,i} \cdot P_{u,i}(t)) - P_{u,y}(t) < 0 \\ 0 & , \text{ else } \mathbf{P}_{agg}^a(t) + \sum_{i=1}^{y-1} \delta_{u,i} \cdot P_{u,i}(t) \leq 0, \mathbf{P}_{agg}^a(t) + (\sum_{i=1}^{y-1} \delta_{u,i}) \cdot P_{u,i}(t) - P_{u,y}(t) < 0 \end{cases} \quad (5.11)$$

where i is a temporary index to refer to all calculated assets until asset y (i.e., $i < y < Y_u$). In (5.11), if there is surplus generation in the neighborhood (reverse power flow) at the original operation time of the asset (before scheduling), the aggregator is not able to decrease the electricity consumption by scheduling the asset at that time. Hence, the earning of $N_{u,y}$ is decreased due to PV generation, as shown in Fig. 5.10. Lastly, $B_{u,y}$ is

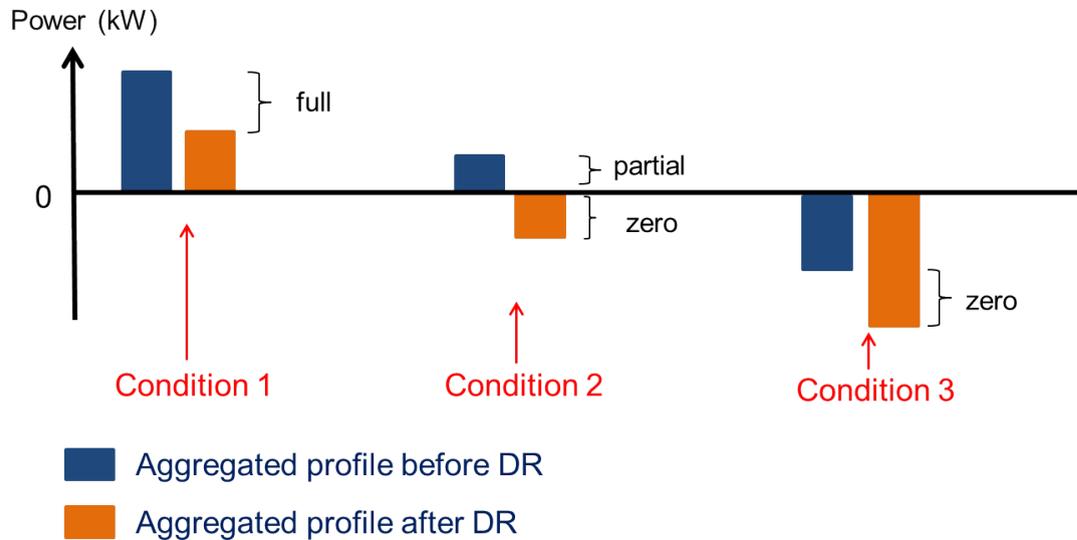


Figure 5.10: Calculation of parameter $N_{u,y}$.

calculated as follows:

$$B_{u,y} = \Delta t \cdot \delta_{u,y} \cdot \sum_{t=t_{u,y}^{sch}}^{t=t_{u,y}^{sch} + (t_{u,y}^e - t_{u,y}^s)}$$

$$\left\{ \begin{array}{l} \lambda_{spot}(t) \cdot P_{u,y}(t) \\ \lambda_{spot}(t) \cdot (\mathbf{P}_{agg}^a(t) + P_{u,y}(t)) + \lambda_{RTP}(t) \cdot \mathbf{P}_{agg}^a(t) \\ \lambda_{RTP}(t) \cdot \mathbf{P}_{agg}^a(t) \end{array} \right. , \text{ if } \left\{ \begin{array}{l} \mathbf{P}_{agg}^a(t) + \sum_{i=1}^{y-1} \delta_{u,i} \cdot P_{u,i}(t) \geq 0 \\ \text{elseif } \mathbf{P}_{agg}^a(t) + \sum_{i=1}^{y-1} \delta_{u,i} \cdot P_{u,i}(t) < 0, \\ \mathbf{P}_{agg}^a(t) + (\sum_{i=1}^{y-1} \delta_{u,i} \cdot P_{u,i}(t)) + P_{u,y}(t) \geq 0 \\ \text{else } \mathbf{P}_{agg}^a(t) + \sum_{i=1}^{y-1} \delta_{u,i} \cdot P_{u,i}(t) < 0, \\ \mathbf{P}_{agg}^a(t) + (\sum_{i=1}^{y-1} \delta_{u,i} \cdot P_{u,i}(t)) + P_{u,y}(t) < 0 \end{array} \right. \quad (5.12)$$

If there is surplus generation at the scheduled asset operation time, the aggregator buys energy from the neighborhood, not from the spot market, as shown in Fig. 5.11. Therefore, the aggregator has to buy energy with the utility RTP. The reason for this is that the utility RTP is used for both selling and buying energy in the smart homes. Thereby, the aggregator solves (5.4) using (5.10)-(5.12) to maximize its profit.

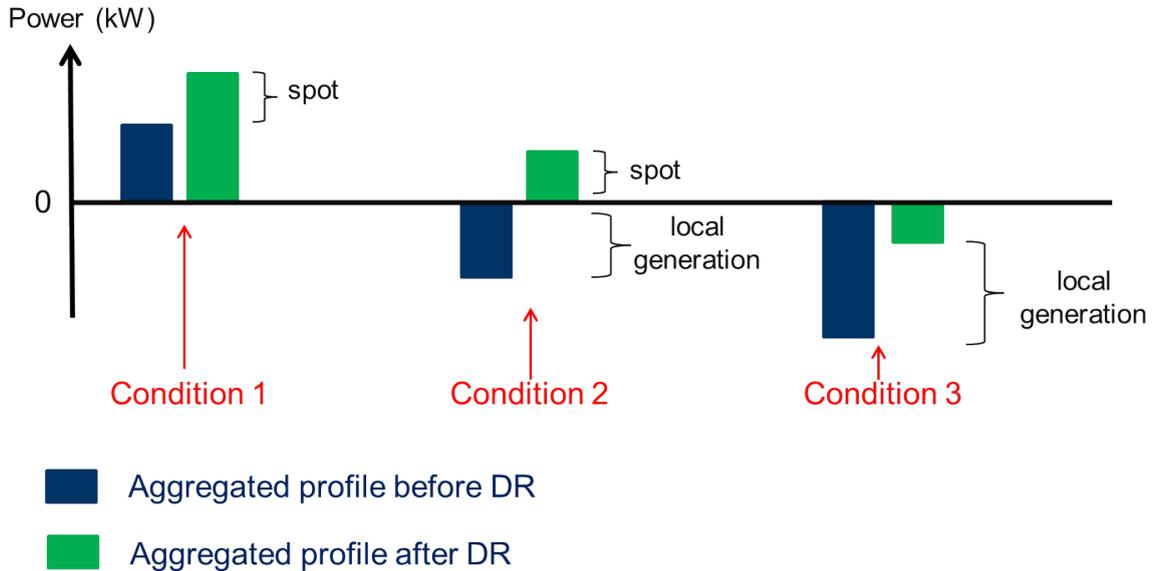


Figure 5.11: Calculation of parameter $B_{u,y}$.

5.3/ PARALLEL PROCESSING METHODS

Any new control technique proposed for aggregation should be tested with extensive simulations for long periods of times (i.e., days, weeks, etc.) before real-world implementation. However, testing such an aggregator-based (centralized) control problem may take long simulation times depending on the test case duration and the number of controlled

resources. Therefore, parallel processing techniques with multi-core computers is essential for reducing simulation and computation time. Parallel processing is used for dividing a large optimization problem into smaller sub-problems and to solve them simultaneously using multi-core computers. It should be noted that the result of a sub-problem must not affect the result of any other sub-problem; thus each sub-problem must be modeled independently.

Open Multi-Processing (OpenMP) and Message Passing Interface (MPI) are the most commonly used programming styles in various applications for parallel processing [19]. The basic difference between these two styles is that the former uses a shared-memory architecture and the latter uses a distributed-memory architecture. Although OpenMP and MPI have their own qualities, both are effective and efficient for reducing computation time. In this section, the basics of parallel programming using the OpenMP and MPI programming approaches are discussed. Further, we use the above-mentioned approaches in three parallelization schemes for solving the multi-day SGRA problem.

5.3.1/ PARALLEL PROCESSING WITH OPENMP

OpenMP is an application programming interface that provides a parallel processing framework using multi-threading (T threads $\rightarrow T$ cores) on a shared-memory architecture [150]. The set of threads/cores run simultaneously, i.e., in parallel, to execute sub-tasks or solve sub-problems. It is important to note that the specified task is divided among the threads and each thread has access to the same information (e.g., variable, parameter, objects) in the shared-memory. OpenMP supports multi-processing programming in C, C++ and Fortran languages on most platforms [47]. The OpenMP flow model is shown in Fig. 5.12.

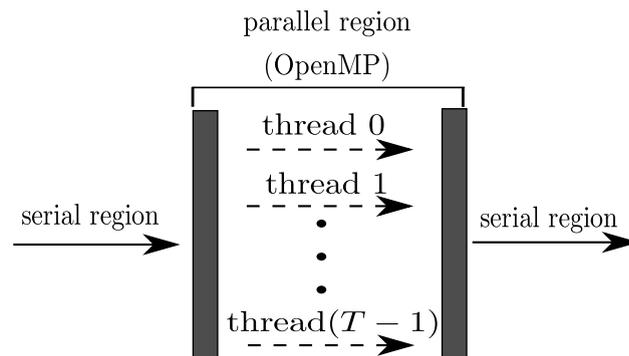


Figure 5.12: OpenMP flow model.

In the SGRA study, to solve the optimization problem with the OpenMP parallelization, the smart appliances are distributed among T threads to determine the profit of the aggregator. Fig. 5.13 depicts the implementation of OpenMP programming for SGRA.

In the shared-memory, each thread (associated with a computer core) accesses a certain number of assets and individually determines $N_{u,y}$, $S_{u,y}$, and $B_{u,y}$ for each asset. After that, the aggregator profit, \mathbf{A}_g , is determined for every scheduled asset and then each thread sums the determined \mathbf{A}_g values with every other thread to create one cumulative result for the aggregator profit.

5.3.2/ PARALLEL PROCESSING WITH MPI

MPI is a specification for message-passing library interface that addresses parallel programming models on a distributed-memory architecture [149]. MPI is a communication protocol that supports both point-to-point and collective communication routines. It was developed for cooperative parallel computing among computer cores running on distributed memory. With MPI, multiple tasks run simultaneously on separate cores defined by the user and each core has its own private memory. MPI programming does not use a shared-memory architecture; thus, cores are not able to access the same information stored in the memory. Therefore, cores need to use a messaging protocol, standardized by MPI, if information from other cores are needed. Language bindings of MPI are defined for C, C++ and Fortran. Fig. 5.14 depicts the MPI application model. The basic difference between OpenMP and MPI is that the written code is run for a defined number of MPI task times simultaneously while OpenMP solves optimization problems in parallel according to a user-defined method (in this case, assets parallelization) inside the task.

To implement the parallel processing of SGRA using MPI, the total number of days (in the multi-day SGRA problem) is distributed among cores. The goal of this effort is to determine the aggregator profit for each day using a single core. For each day, the optimization problem (representing the same application albeit with different daily input) is solved simultaneously by cores in a distributed memory for each task. Message passing is not needed in this implementation because each day’s optimization is totally independent from the other days; hence, no core has the need to wait for a message from another. The implementation of the MPI parallelization for the SGRA problem is shown in Fig. 5.15.

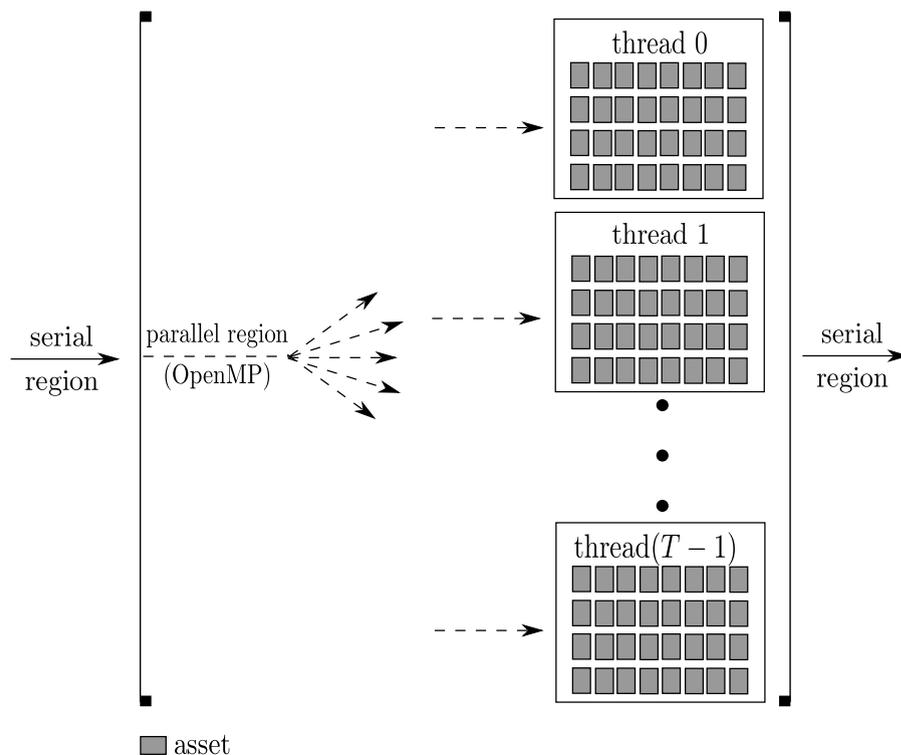


Figure 5.13: OpenMP implementation of SGRA (T cores).

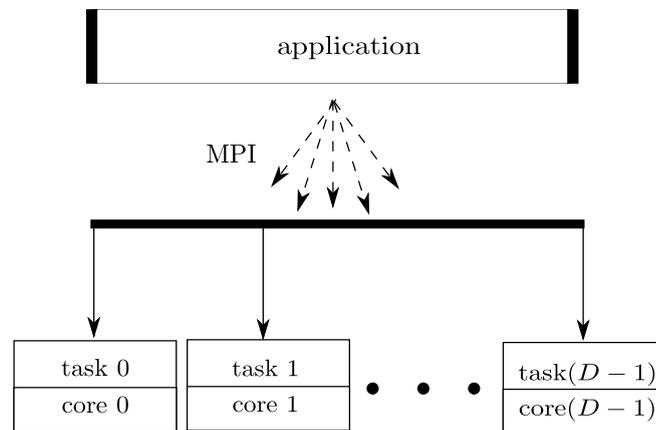


Figure 5.14: MPI application utilization model.

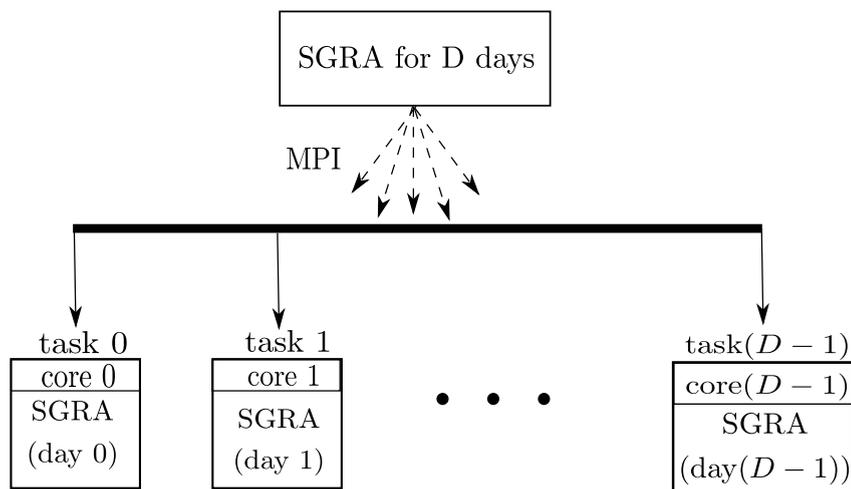


Figure 5.15: MPI implementation of SGRA (D cores).

5.3.3/ PARALLEL PROCESSING WITH OPENMP/MPI

Hybrid applications use both the OpenMP and the MPI models together for parallelism. A hybrid model requires a more sophisticated programming paradigm than either type of the constituents so as to manage shared and distributed memory allocations with multiple cores. We aim to use a higher number of cores in the HPC system and reduce the computation time. It is worthwhile to mention again that we are not dealing with the technical challenges of using these parallelization methods. In this paper, we are simply aiming to provide information on basic programming models and compare their performances in terms of computation time. In Fig. 5.16, the hybrid parallelization model for the SGRA study is presented.

With the hybrid model, D tasks are created for separating and solving days simultaneously, and T threads are used for each task to distribute the assets among threads to determine the aggregator profit for each day. In this way, $T \times D$ cores are used through hybrid parallelization. For example, consider that five MPI tasks are defined and each task is deployed on three OpenMP threads to solve an optimization problem, thus totally 15 cores are utilized at the same time.

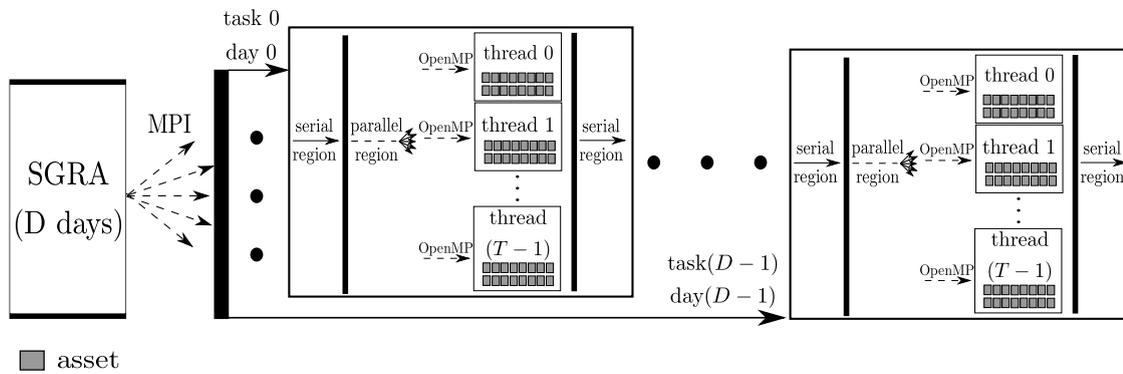


Figure 5.16: OpenMP plus MPI implementation of SGRA ($T \times D$ cores).

5.3.4/ PERFORMANCE OF PARALLEL PROCESSING TECHNIQUES

The implementation of the above parallel processing techniques is strictly dependent on the formulated optimization problem. We would like to emphasize that the optimization problem of SGRA with PV is not suitable for implementation with the OpenMP style parallel processing technique. The reason is that each scheduled asset affects the results of the next scheduled asset results through terms $N_{u,y}$ and $B_{u,y}$ (using i index). Hence, dividing the main problem into an asset based sub-problem is not implementable. Therefore, only the MPI style parallel processing technique can be used to reduce the computation time of the multi-day SGRA problem with PV.

However, the OpenMP, the MPI and the hybrid parallelization methods can be implemented on multi-day SGRA problem with no PV as the aggregated net profile is always positive $\mathbf{P}_{agg}^a(t) \geq 0$ due to the absence of PV generation, so there is no dependency among scheduled asset profits. Therefore, we analyze the performance of the parallel processing methods by testing them on SGRA problem.

To determine the full performance of the parallel processing techniques, we used the Summit Colorado State University (CSU) and the University of Colorado Boulder high performance computing (HPC) system [15, 16]. Summit is a heterogeneous supercomputing cluster with 380 Haswell CPU nodes with 9,120 cores, ten GPU nodes, five hi-mem nodes, two storage gateway nodes, two Omnipath Architecture (OPA) interconnect fabric management nodes, with 100 GB/sec OmniPath interconnect, one Petabyte DDN SFA14K scratch storage, and a 40Gb uplink to the Science Ethernet Network. The Summit HPC uses a batch queuing system for execution. Finally, the SGRA problem was programmed in C++ and compiled with the gnu-c++-compiler on Summit.

The above-mentioned parallel processing techniques for the SGRA problem with no PV are performed on a test system with 5,555 customers, 56,605 controllable assets, and 151,773 base loads. For the spot market and utility electricity prices, real data corresponding to July 1-7, 2011 are used from PJM and ComEd, respectively [37], [35]. To solve the SGRA problem, which is heuristic in nature, Genitor—a modular genetic algorithm (GA) package [46]—is used as an optimization solver. Genitor creates two children from the initially generated population (100 members) at each iteration by applying crossover and mutation operations. We assume that the optimization is completed when the result of the best fitness function does not change for 10,000 consecutive iterations or if the total number of iterations reaches 500,000.

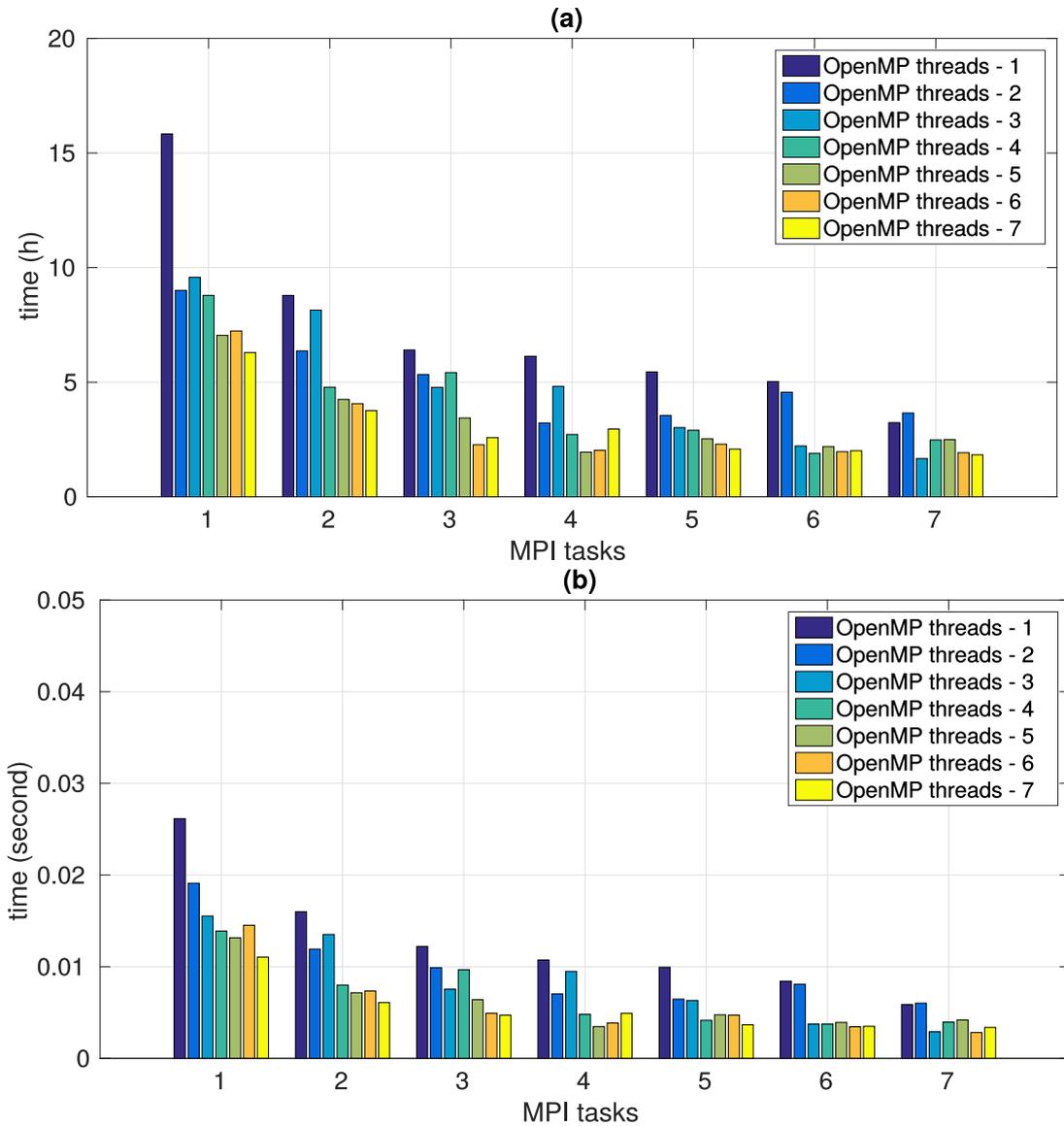


Figure 5.17: Number of hybrid threads and tasks versus (a) total simulation time and (b) computation time of per-GA-iteration.

In Fig. 5.17, the results in terms of simulation time (hours) and computation time of per-GA-iteration (seconds) are given for all three parallelization methods, with a varying number of OpenMP threads and MPI tasks combinations. Firstly, the effect of the number of OpenMP threads are analyzed (MPI tasks: 1, OpenMP threads: variable). The computation time is recorded over the range of (6, 15) hours; where the maximum time occurs when one thread (i.e., the base case with one core) is used and the minimum time of 6.5 hours occurs when seven threads are used; thus, a 60.24% reduction in computation time is achieved. Note that there is an exponential relation between the computation time and the number of OpenMP threads. Therefore, the biggest reduction in computation time between two OpenMP cases—43.12%—is achieved among thread numbers one and two. Beyond that, when the thread number is increased from two to seven, only 17.12% additional reduction in computation is achieved as compared to the base case.

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

However, the reduction in computation time can be misleading for accurate comparison because of the difference in the total number of iterations. When the computation times of per-GA-iteration are compared, a 57.74% reduction compared to one thread in computation time is achieved with seven threads. It should be noted that more than seven threads—up to a theoretical maximum number equaling the number of assets—can be defined for the studied case. For fair comparison with the MPI case, we limited the number of threads to seven.

After that, the results of the MPI model for a varying number of tasks are analyzed (MPI tasks: variable, OpenMP threads: 1). The minimum simulation time recorded was 197 minutes when seven MPI tasks are utilized. Here, we see a reduction of 79.57% in simulation time and 77.56% in computation time of per-GA-iteration achieved. This indicates a better performance when compared to the previous case of OpenMP with seven threads. In other words, when the same number of cores are considered, MPI outperforms OpenMP in executing the SGRA problem due to the absence of any serial parts. Note that we used a maximum of seven MPI tasks to match the number of days in the multi-day example defined in the test case.

Lastly, the results of the hybrid OpenMP/MPI model are presented and compared for a varying number of OpenMP threads and MPI tasks combinations. When combining the two methods in a hybrid mode, more cores can be used (such as seven threads times seven tasks) with greater efficiency based on the problem formulation. In our case, the core numbers can be increased when using OpenMP only, which is less efficient than MPI. On the other hand, the number of cores used by MPI to solve the SGRA problem is defined by the number of days in the multi-day SGRA. For instance, even though there are 9,120 general purpose Haswell CPU cores available in the Summit HPC, the multi-day SGRA problem (for seven days) uses a smaller subset of those cores (i.e., a maximum of 49 cores). In Fig. 5.17, the classic SGRA problem from the above examples is solved in 100 minutes—corresponding to a 89.46% reduction using 49 cores. By using 42 extra cores, approximately 10% additional simulation time reduction is achieved as compared to the seven MPI tasks-one OpenMP thread case (see Fig. 5.17(a)).

These results can however not be generalized, but they provide an insight into the use of the three parallelization methods for the SGRA problem. As we embark on the task of parallelizing the SGRA problem for larger test systems for longer time horizons, this effort should serve as an early indicator for the choice of the technique.

5.4/ PERFORMANCE EVALUATION

For evaluating the performance of the methods, the same test system as described for the comparison of parallel processing techniques in Section 5.3.4 is used (5,555 customers, 56,605 controllable assets, and 151,773 base loads with price data corresponding to July 1-7, 2011). Irradiance data corresponding to July 1-7, 2010 is taken from the National Solar Radiation Data Base [25]. Simulations are performed for five different PV penetration levels (0%, 25%, 50%, 75%, and 100%) in the same neighborhood. The penetration level is given according to smart homes with PV over the total number of smart homes. For parallel processing, due to the dependency among scheduled assets, the MPI-based parallel processing model is used with seven MPI tasks. Simulations are performed on same desktop computer as in Chapter 3. Lastly, the impact of PV penetration is analyzed

in two part: daily and weekly simulation results.

5.4.1/ DAILY RESULTS OF SGRA WITH/WITHOUT PV

Simulations are performed for July 1st, 2011 (price data) and 2010 (irradiance data). In Fig. 5.18, the aggregator forecast and actual profits are given for each PV penetration level. The deviation between forecast and actual results are due to the forecasting error on the price profile. As a reminder, note that the forecast and the actual price data are gathered from PJM [37] and ComEd [35]. The maximum aggregator profit is determined when there is no PV penetration in the neighborhood area, and the aggregator profit is decreased in direct proportion to the increase on the PV penetration level. Hence, the aggregator earns less when the local generation is increased in the neighborhood area, which is not a desirable solution for the aggregator.

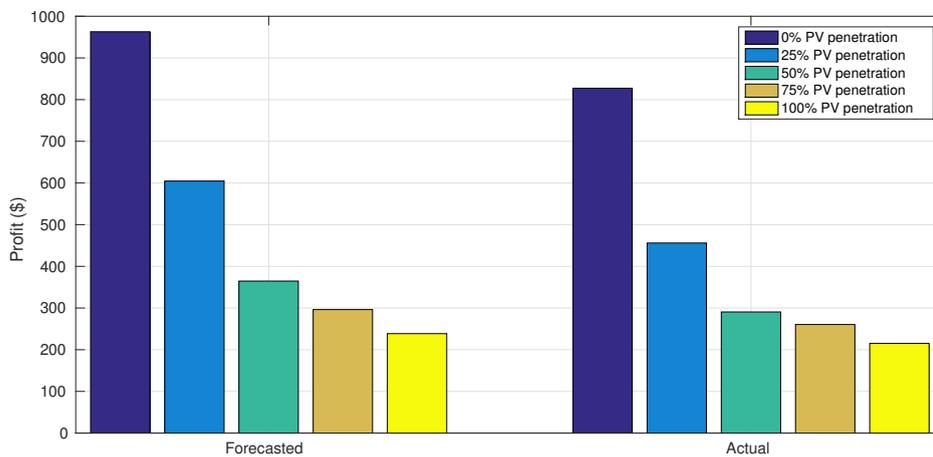


Figure 5.18: Aggregator profits on July 1st for each PV penetration level.

In Fig. 5.19, the total profits of the customers are given for each PV penetration level. The profits of the customers from the DR program significantly decrease when they invest in a residential PV system. However, it should be noted that customers pay less compared to the case with no PV integration due to self-consumption and selling energy to the main grid. However, they achieve to gain less by participating to the DR program when they install PV in their smart home.

In Fig. 5.20, the number of controlled assets by the aggregator is given in the neighborhood. With no PV integration, the aggregator controls 45,017 of 56,605 assets (79.53%), while it is only 41.19% with 100% PV penetration. Although the same α modeling techniques with the same parameters is used in each case, the controlled number of appliances decrease when the PV penetration increases. Therefore, the aggregator and the total customers profits decrease as less assets are scheduled. As a result, besides α modeling, the PV generation is an obstacle for the scheduling ability of the aggregator with a DR program.

In Fig. 5.21, the total neighborhood electricity profiles before and after DR are given for each PV penetration case. When PV is installed in smart homes, the consumption from the main grid is decreased during sunny hours. As long as the PV penetration

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

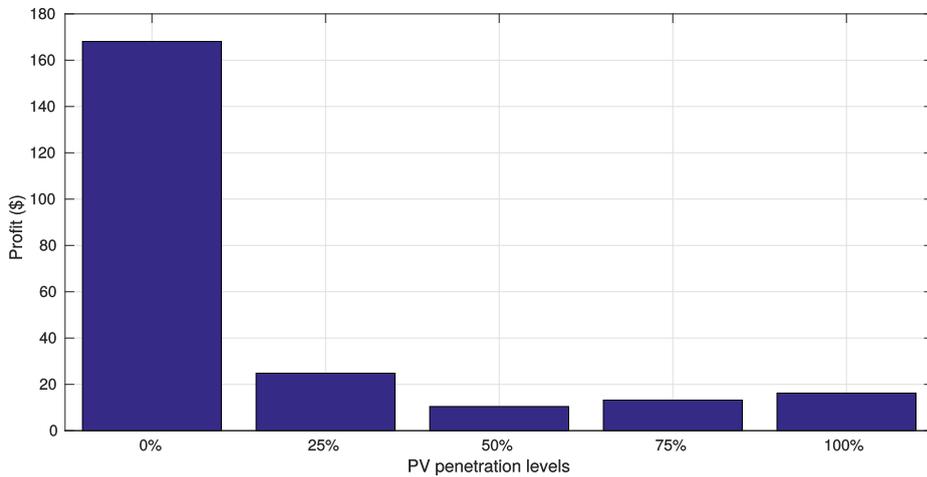


Figure 5.19: Total profits of customers on July 1st for each PV penetration level.

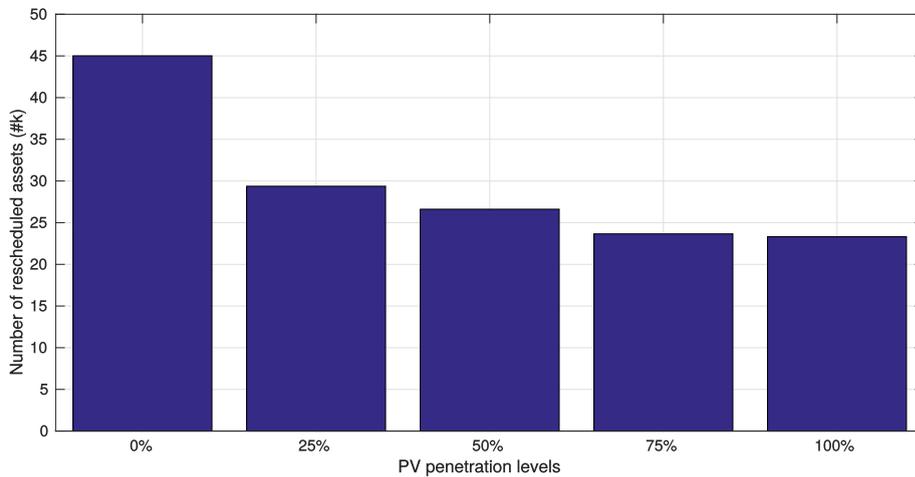


Figure 5.20: Total controlled assets number on July 1st for each PV penetration level.

increases, reverse power flows from neighborhood to main grid increases with surplus PV generation. Moreover, the range of the surplus generation over the time horizon increases with the increased PV penetration.

In Fig. 5.22, the total assets consumption profiles before and after DR are given for each case. The aggregator is able to reduce the two peaks of assets consumption, one in the morning and one at night, by scheduling the assets to the early morning, noon and/or late night hours. However, the morning peak slightly increases instead of decreasing. The reason is that there is high PV consumption on the total electricity profile during the morning hours (for example, around $30 \times 15/60 \rightarrow 7 : 30$), hence reducing consumption is not possible (there is none). Therefore, the aggregator is not scheduling the assets that start at those times, which explains the decrease in controlled asset numbers shown in Fig. 5.20.

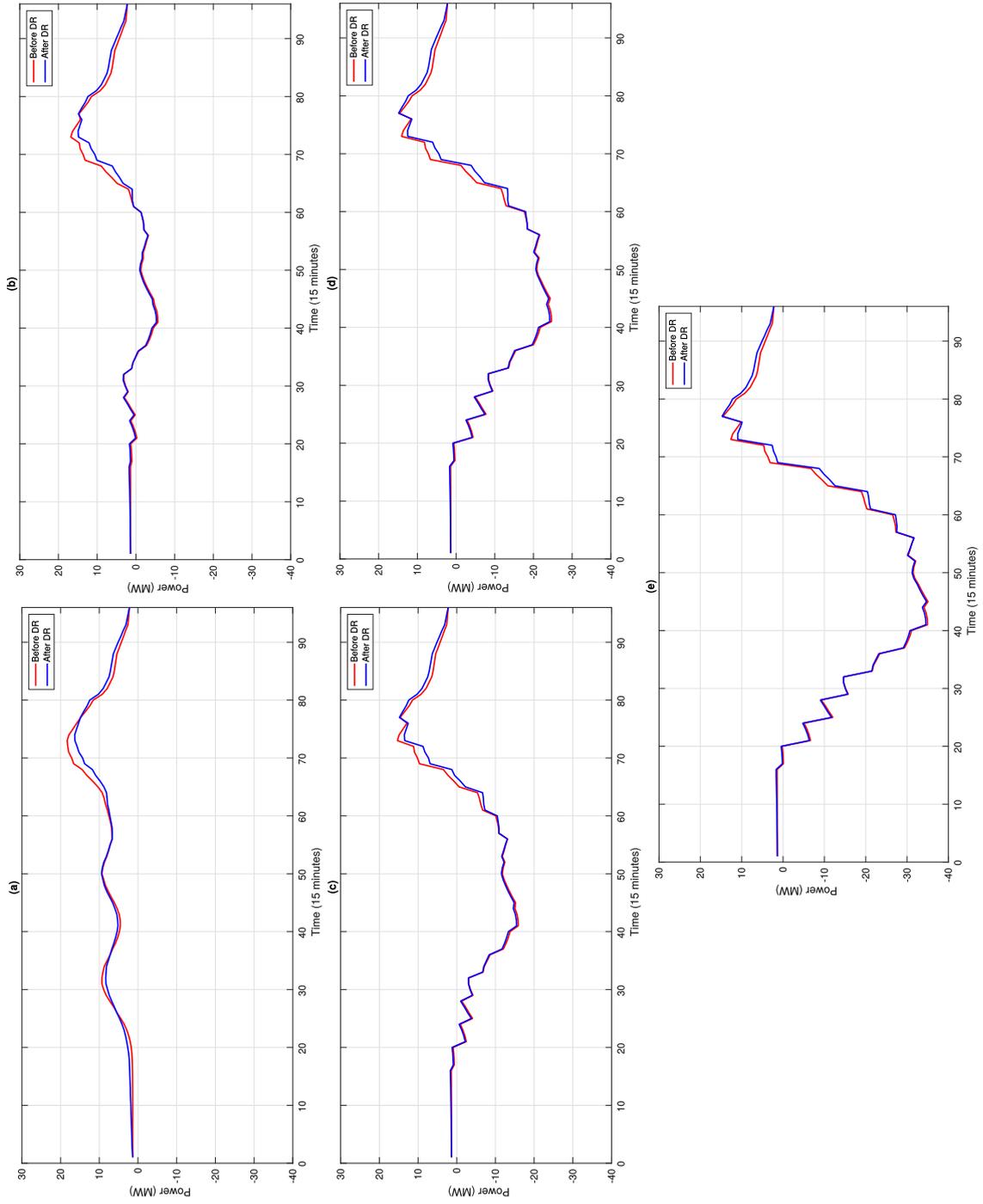


Figure 5.21: Aggregated electricity profiles of the neighborhood before and after scheduling: (a) 0% (b) 25% (c) 50%, (d) 75% and (e) 100% PV penetration levels

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

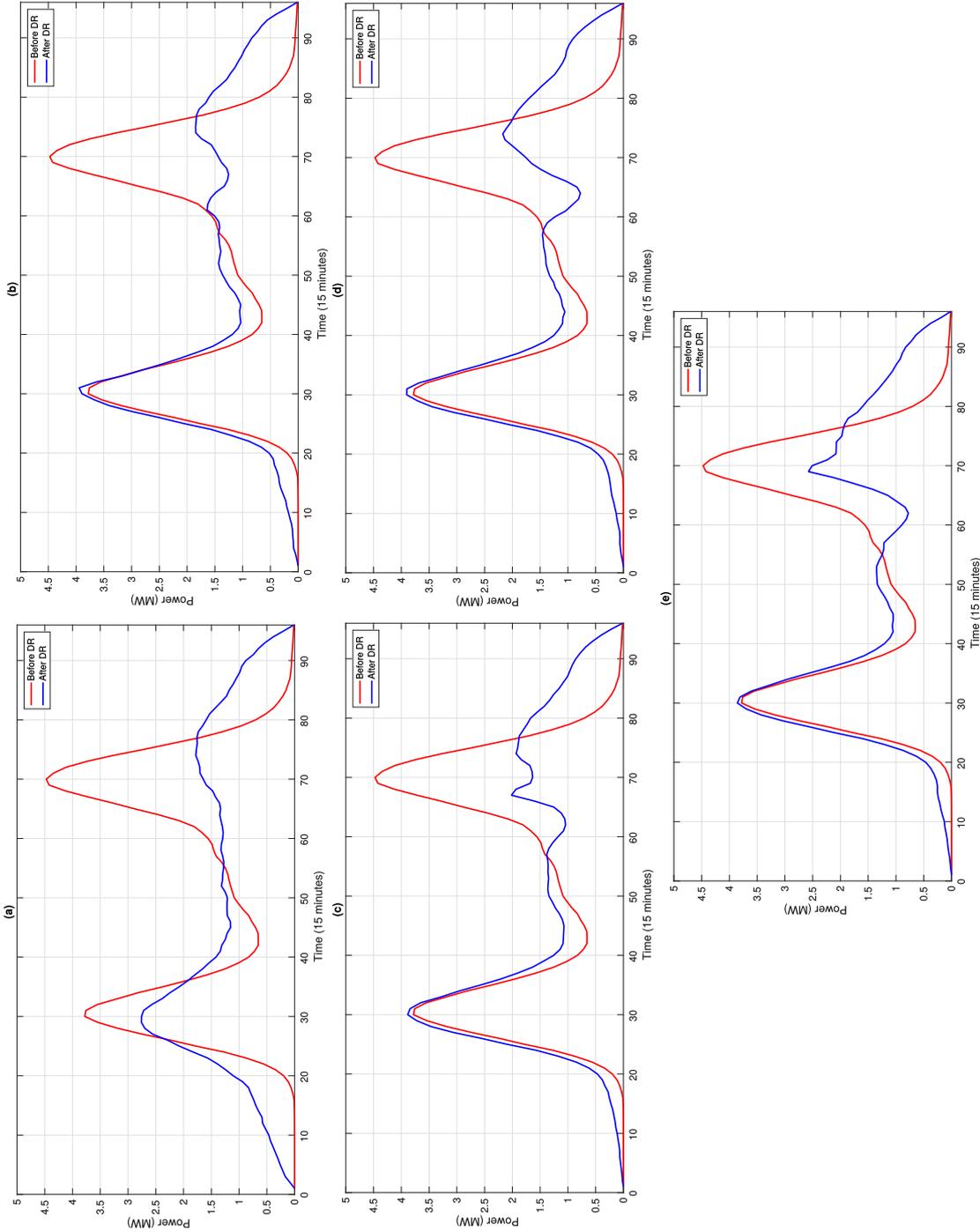


Figure 5.22: Total asset electricity profiles of the neighborhood before and after scheduling: (a) 0% (b) 25% (c) 50%, (d) 75% and (e) 100% PV penetration levels

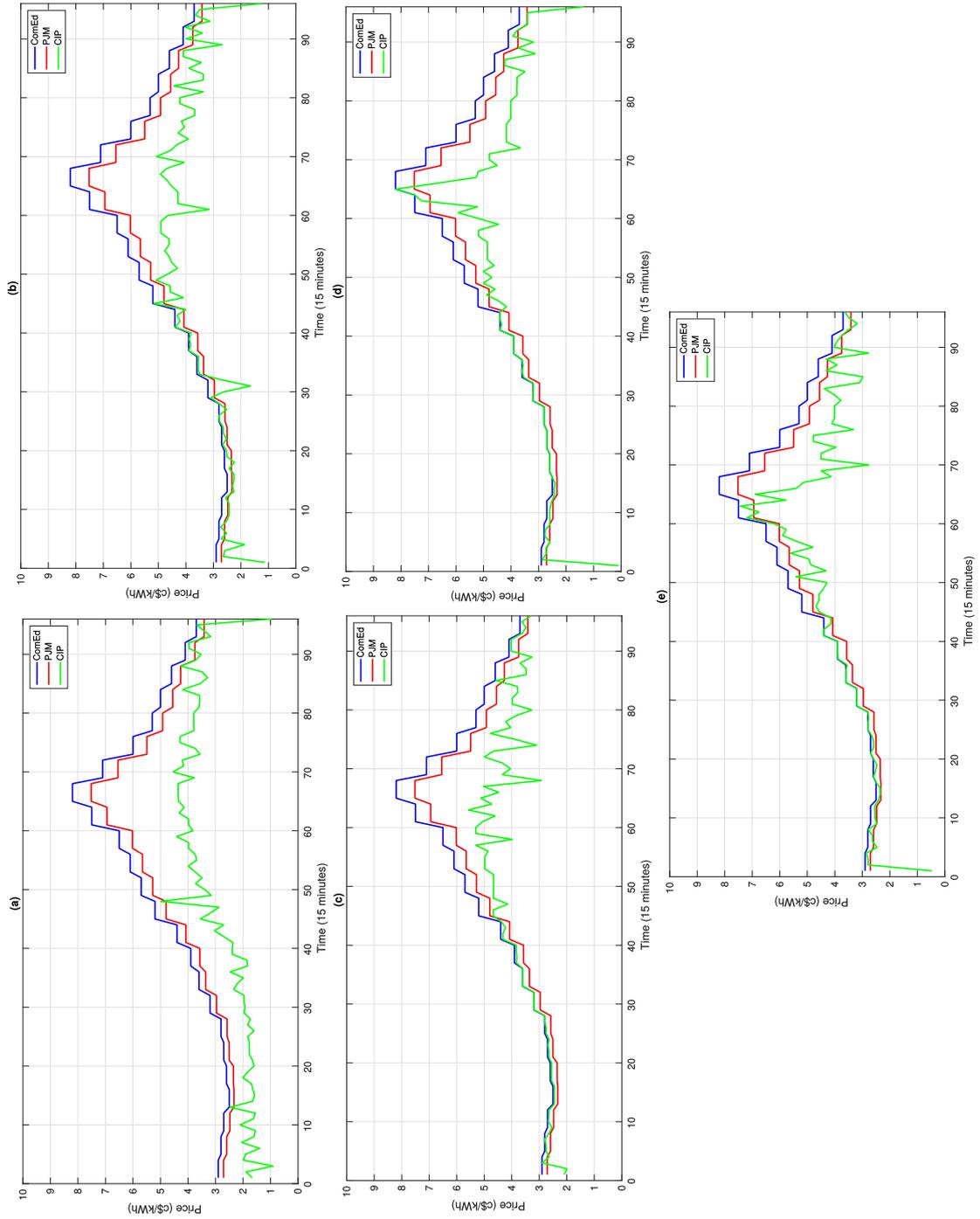


Figure 5.23: Forecast price profiles (ComEd, PJM and CIP): (a) 0% (b) 25% (c) 50%, (d) 75% and (e) 100% PV penetration levels

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

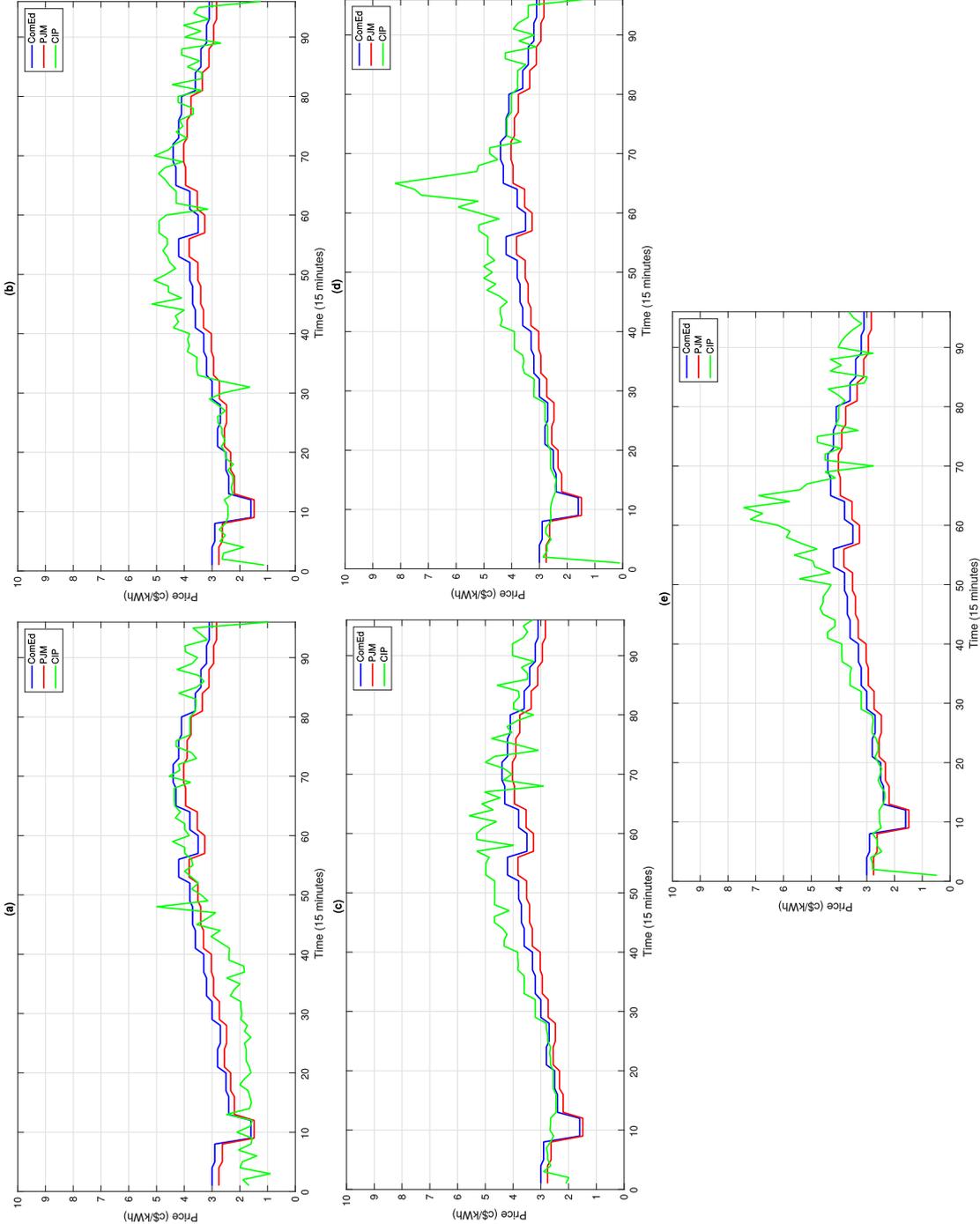


Figure 5.24: Actual price profiles (ComEd, PJM and CIP) : (a) 0% (b) 25% (c) 50%, (d) 75% and (e) 100% PV penetration levels

Lastly, in Figs. 5.23 and 5.24, the forecast and actual price profiles (ComEd, PJM and CIP) are shown, respectively. Firstly, the actual profit of the aggregator is lower than the forecast profit, because the actual price is lower than the forecast price. The lower actual price has a negative impact, due to the decreasing $S_{u,y}$ term. Recall that $S_{u,y}$ is the parameter that describes how the aggregator gains profit with λ_{spot} after scheduling the assets. Therefore, the gained profit decreases when λ_{spot} decreases, hence the expected profit is lower than what is actually obtained. Secondly, the CIP is decided higher by the aggregator for hours when PV generation is higher. Normally the aggregator should offer a lower price than the utility to convince the customers, but also as high as possible to increase its revenue (see Fig. 5.23(a)). However, scheduling of some assets is not profitable anymore when PV integration is considered, hence the aggregator no longer needs to take them into account during the optimization. Therefore, it offers the maximum CIP (i.e., equal to the RTP) to increase its revenue as much as possible with limited controlled assets.

5.4.2/ WEEKLY RESULTS OF SGRA WITH/WITHOUT PV

The impact of the PV is analyzed by simulating the SGRA problem with different PV penetration levels, and by using MPI programming to simulate each day optimization problem simultaneously on a multi-core computer. For each case, seven MPI tasks are defined (equal to the number of days) for solving the multi-day SGRA problem. In Fig. 5.25, the total simulation time of each PV penetration case is given for solving the optimization problem formulated in 5.4 with equations listed in Section 5.2.2. Simulation times vary between 6 and 7 hours, which is much less than the initial 16 hours (see Fig. 5.17). However, the simulation took more time than expected (3 hours more) due to the use of a different formulation and processor.

In Figs. 5.26 and 5.27, the aggregator forecast and actual profits are given for one week. Based on the ComEd and PJM prices, the gained aggregator profits show differences from one day to another, and the profit still decreases when the PV penetration is increased in the neighborhood. The total actual profit is decreased by 76.58% when all smart homes are equipped with a PV system.

Lastly, in Figs. 5.28 and 5.29, the total customer profits and the total controlled asset numbers are given for each day and each PV penetration level. As for daily results, the total customer profits and the total controlled asset numbers are decreased as PV penetration increases. However, another important results is that customer savings on July 5th are much higher than savings on the other days (the same trend is observed for all PV penetration cases), although almost the same number of assets is controlled. The reason of this outcome is related the utility and spot market prices and the difference between the forecast and actual price profiles.

5.4.3/ SCALABILITY ANALYSIS

In this section, a scalability analysis is performed by varying the number of the smart homes in the neighborhood area. The simulations are performed for five different neighborhood area sizes (1111, 2222, 3333, 4444, and 5555), and run for two PV penetration levels (0% and 50%) for July 1st. The results are given for forecast and actual aggregator profiles in Figs. 5.30 and 5.31. According to the figures, the aggregator increases its

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

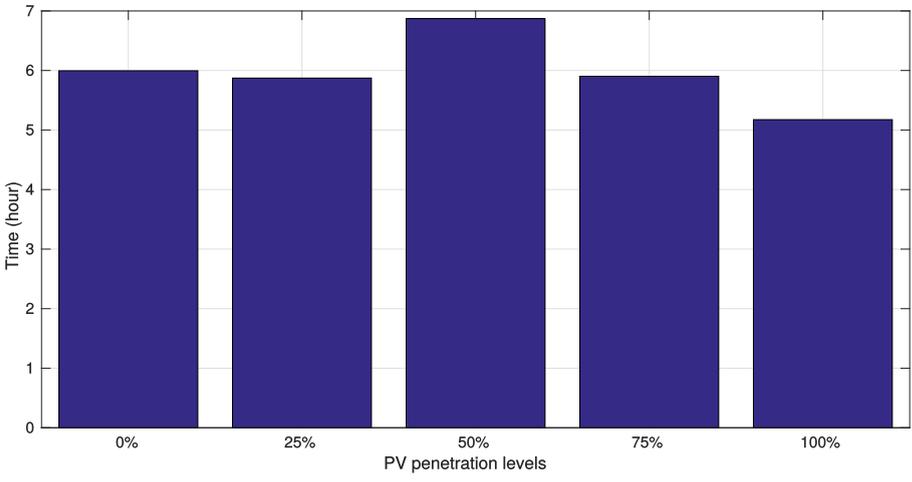


Figure 5.25: Total simulation time for each PV penetration level.

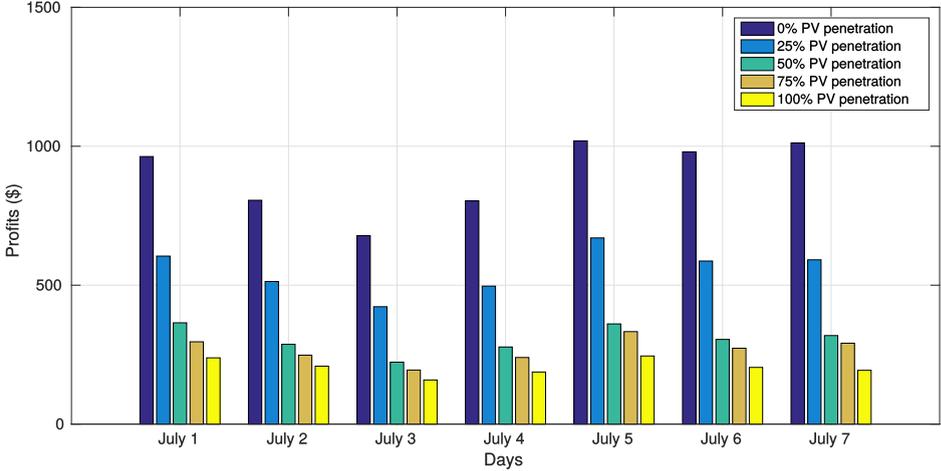


Figure 5.26: Weekly forecast aggregator profits for each PV penetration level.

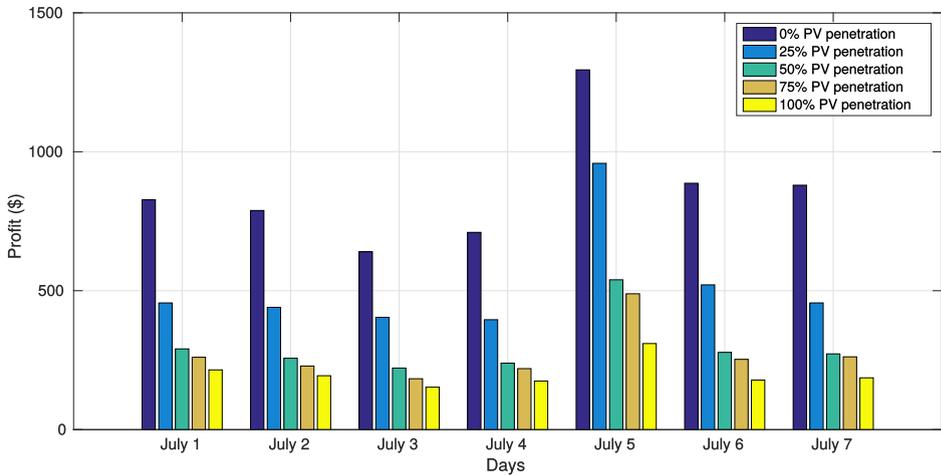


Figure 5.27: Weekly actual aggregator profits for each PV penetration level.

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

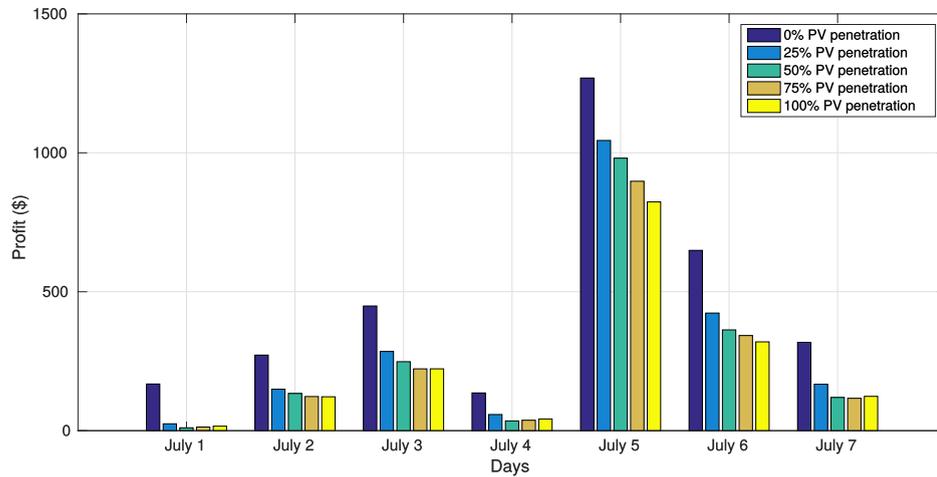


Figure 5.28: Weekly total profits of customers for each PV penetration level.

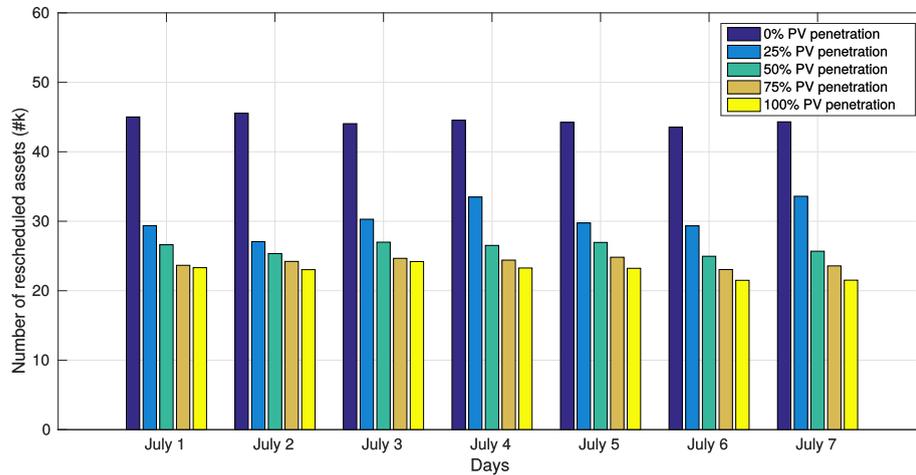


Figure 5.29: Weekly total controlled assets numbers for each PV penetration level.

profit when it serves more smart homes and controls more assets in the neighborhood. Thus, the aggregator revenue depends on the number of smart homes located in the neighborhood, and simulation results show that the presented SGRA algorithm can keep working efficiently in various neighborhood areas.

5.5/ CONCLUSION

This chapter has presented an aggregator-based (centralized) coordination mechanism for scheduling the assets of users by taking into account the impact of residential PV penetration on the SGRA problem. The aggregator interacts with users as well as the utility and the spot market to determine and to offer cost-beneficial consumption strategies to users by scheduling their assets with CIP. The focus of the aggregator is to increase its own revenue by scheduling the assets of users. The aggregator achieves to schedule the assets of users as long as it provides the threshold benefit for each asset scheduling defined with α modeling. The impact of residential PV integration is investigated for dif-

CHAPTER 5. AGGREGATOR-BASED ASSET CONTROL WITH RESIDENTIAL PV GENERATION

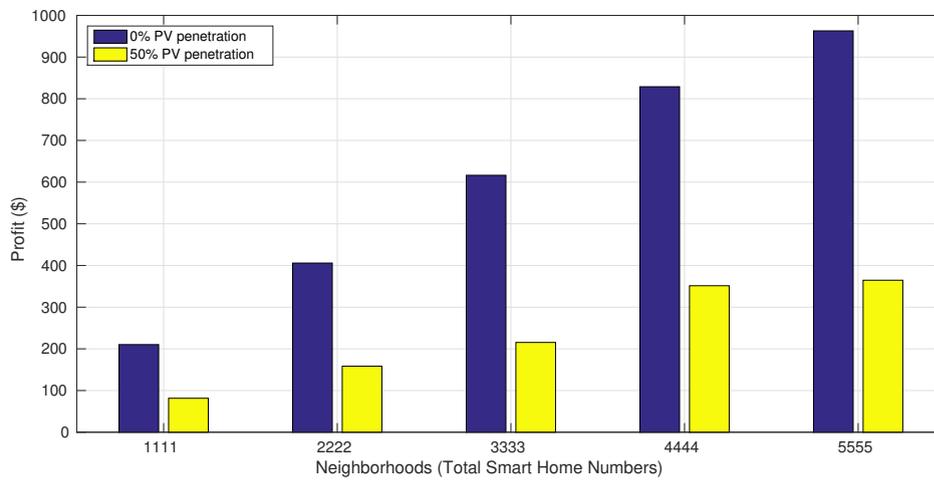


Figure 5.30: Weekly total forecast aggregator profits.

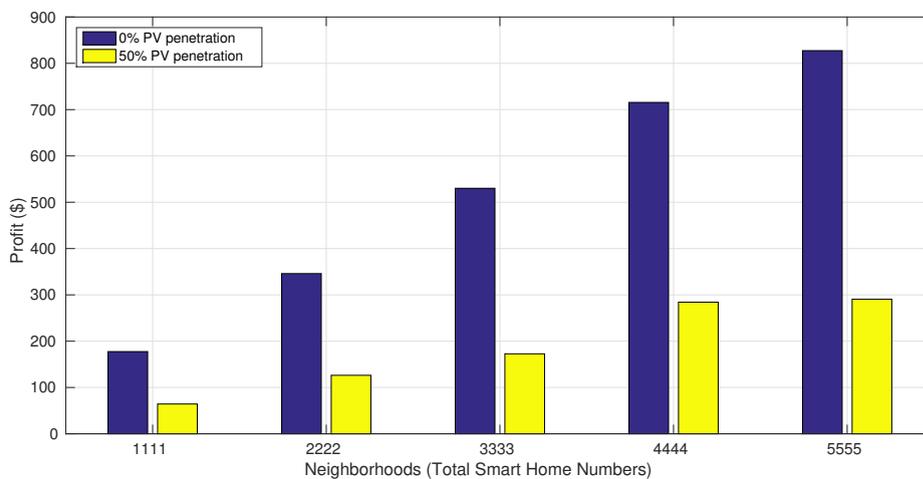


Figure 5.31: Weekly total actual aggregator profits.

ferent PV penetration levels and results are compared with the no-PV case. Simulation results show that the aggregator and customer profits are highly dependent on PV generation in smart homes (as well as utility and spot market prices, user preferences and the size of the neighborhood area), and PV integration has a negative impact. The reason is that local PV generation is an obstacle in front of the presented control algorithm as it reduces the net consumption and decreases the ability of the aggregator to schedule assets. Thereby, it proves that the aggregator profit is also dependent on local generation in the smart homes.

Secondly, this chapter has presented three parallel processing methods to reduce the computation time of the optimization problem. The parallelization procedure of each technique is demonstrated for the SGRA problem. Due to dependency in the profit of each asset schedule on SGRA with the PV case, the performance of three parallel processing techniques is evaluated on the SGRA problem with no PV. The performance of the methods is quantified in terms of reductions in simulation time and computation

time per-GA-iteration, and the results are compared against the number of cores utilized. The results show that all parallelization methods can significantly affect the computation time for solving the SGRA problem. The computation time appears to fall exponentially with the number of utilized core number. Among the parallelization methods, the hybrid OpenMP/MPI model showed the best performance when a higher number of cores are available, and the MPI model was the second best. However, it should be noted that the performance of the methods is highly dependent on the programming of the optimization problem and the solver.



CONCLUSIONS

CONCLUSION

As the previous chapters have shown, SG technology is enabling new local energy management strategies, for example for neighborhoods, that can benefit both electricity providers (utilities) and end-users if adequate coordination is enabled. This chapter reviews the contributions of this dissertation, discusses its results, and lists several possible avenues for future works.

6.1/ CONTRIBUTIONS

This dissertation has focused on the coordination of smart homes in neighborhood areas, and has presented several centralized and decentralized control methods for electric energy management. Its key contributions are summarized as follows:

1. A thorough literature review has proposed an overview of the state-of-the-art on the topic. The studied scientific works were categorized according to their characteristics, and the advantages and disadvantages of each approach were listed.
2. The presented coordination methods do not only consider appliance scheduling with DR programs, but also include PV and battery systems in the process. Advanced control algorithms are introduced for enabling energy trading or sharing.
3. An adaptive time resolution process is used to reduce computation burden in the optimization problem, as well as the required communication bandwidth. A high time resolution is used for modeling electricity appliances, and a lower one is used for controlling battery output in decentralized algorithms.
4. User privacy concerns are taken into account, in that another time resolution is introduced to mask actual high resolution data by taking average values of home electricity profiles over a given period.
5. The performance of the proposed decentralized algorithms is compared with baseline and selfish scenarios to emphasize the importance and effectiveness of the coordination mechanisms, not only in terms of costs but also on peak reduction values.
6. Three novel metrics are introduced to evaluate the performance of the control algorithms for annual simulations.

CHAPTER 6. CONCLUSION

7. The aggregator performance is investigated under different penetration levels of residential PV generation.
8. Finally, three parallel processing methods based on two programming techniques are introduced to reduce the computation time of simulations by using multi-core processors.

Overall, it is hoped that this work can serve as a basis for utilities and researchers to develop community-scale energy management systems or microgrids, where energy can be locally generated, shared and utilized. With the development of DG, such approaches can be expected to gain further momentum in the future.

6.2/ SUMMARY OF WORKS

This dissertation has outlined that the coordination of energy consumption of multiple households equipped with HEMS can benefit both sides of the electricity distribution grid, i.e., the utility and the end-users. Several coordination mechanisms were proposed, tested, and analyzed. Results have then shown that while utilities can reduce the peak consumption of the neighborhood and thus the associated generation costs, users can also potentially reduce their daily electricity bills by enabling the control of their assets, such as appliances and batteries.

At first, a state-of-the-art review of the literature was presented to cluster studies according to the used coordination structures and techniques. DSM and DR were first introduced by reviewing energy management studies in single smart homes. Then coordination mechanisms were divided into two groups: centralized and decentralized, based on the communication and decision-making structure in the neighborhood area. The decentralized coordination structure is further subdivided into three groups: fully-dependent, partially-dependent and fully-independent. As a result, it has been shown that neighborhood-level coordinated home energy management is a timely and increasingly popular subject that needs to be studied in SG. Moreover, the review also showed that there was room for further contributions, especially for decentralized coordination techniques.

At the second step, two coordination mechanisms (centralized and fully-dependent decentralized) were developed for controlling assets and battery units in smart homes by combining TOU, FIT and an incentive. The incentive is used to increase renewable energy utilization inside the neighborhood area. MAS are used for modeling neighborhood entities as agents through home and aggregator agents. While home agents receive the full incentive for self-consumption, they share the offered incentive with others when they trade with each other. Thereby, home agents are more interested in selling and buying surplus generation than in selling and buying from the main grid. The results are compared with those of the baseline and selfish scenarios, where home agents optimize without sharing data and energy. While the centralized method aims to reduce the neighborhood cost, home agents focus on decreasing their electricity bill in the decentralized one. As a result, the fully-dependent decentralized method seems more appropriate and promising, as it can increase the overall benefit of the neighborhood while increasing renewable energy usage and coordinating home agent actions in reasonable time.

At the third step, two fully-dependent decentralized coordination mechanisms (group-based and turn-based) are presented by improving the previously proposed decentralized method. Compared to previous method, home agents share less information during communication, and the algorithm does not require offering an incentive to coordinate the actions of home agents. However, electric energy management is obtained by scheduling users assets and controlling their batteries. To bill users, a dynamic price structure is used by merging grid TOU and a dynamic price associated to the neighborhood electricity profile. Home agents solve the same formulated optimization problem in both methods (group-based and turn-based), but in a different order. While all home agents solve the optimization problem simultaneously in the group-based method, they do the same one-by-one in the turn-based method. Furthermore, the forecasting errors are considered in base appliance consumption and PV generation profiles, and algorithms are simulated over a horizon of one year. Accordingly, three novel metrics are introduced to evaluate the success rate of the proposed algorithms. Algorithms are compared with baseline and selfish scenarios, and provided better results in terms of cost and peak reduction, as well as on the three proposed success metrics. Although the same optimization problem is used, the turn-based method performs better than the group-based method. However, the turn-based method is not suitable for use in larger neighborhoods, as it requires more computation time to achieve convergence.

At the last step, the aggregator interactions with upper-level entities were taken into account. The coordination of smart home actions in the neighborhood by asset scheduling considering residential PV integration is achieved while studying the performance of an aggregator serving the area. In this work, the optimization problem that was previously formulated in [120] was updated by considering residential PV integration in the neighborhood. The aggregator interacts with the utility and the spot market to receive the RTP and spot market price, and offers a CIP to customers for controlling their assets. The impact of residential PV is investigated for different PV penetration levels. Simulation results show that residential PV penetration has a negative impact on the performance of the control algorithm. When PV penetration is increased the aggregator performance decreases as well as the number of controlled assets. For this study, parallel processing methods were studied to use multi-core processors for reducing simulation time of the optimization. Three parallelization techniques were modeled using two programming approaches (OpenMP and MPI). The presented parallelization methods were then tested on the case without PV. Simulation results show that MPI gives better performance compared to OpenMPI. Moreover, more processor cores can be used with the hybrid model (OpenMP/MPI) to significantly reduce computation time, if core utilization efficiency is not neglected.

6.3/ FUTURE WORKS

This dissertation has shown that the coordination of multiple smart homes in neighborhoods is both a useful and interesting subject, which can help ensure economic, efficient and reliable electric energy management in neighborhood areas. However, there are a number of challenges, listed below, that still need to be considered in future works:

1. *Two-way battery charging*: battery systems were only allowed to charge from local, self-generated electricity, due to the specific focus on increasing renewable energy

CHAPTER 6. CONCLUSION

utilization in the neighborhood. However, batteries could also be allowed to charge from upper-level grid resources, which may provide even better efficiency in the coordination.

2. *Integration of EV:* over the past few years, interest in EV has increased steadily due to environmental issues. However, high EV penetration rate can significantly affect residential load profiles, with low very load during the day (due to PV generation) and high loads in the evening (due to EV charging). Therefore, coordinating EV charge is another research avenue for the future. Additionally, EV can also be used as secondary storage units in smart homes when they are parked, for example to provide energy to the smart home and/or the neighborhood via vehicle-to-home (V2H) and vehicle-to-grid (V2G) paradigms.
3. *Payback time of the investments:* although the presented methods return higher profit or savings than the base scenarios, the capital cost of RES and energy storage units were not considered. By integrating the (age and use-related) degradation of RES and storage units, the payback times of these resources can be calculated. This would provide a complete picture to end-users, showing the costs and expected benefits from such investments.
4. *Constraints on the distribution system:* the presented coordination algorithms do not consider distribution system constraints, such as congestion due to line and transformer capacity. For example, although the algorithms decrease the neighborhood peak consumption at the PCC with trading and sharing, there can still be high stress on the distribution lines due to energy transfers among smart homes. Therefore, these constraints should be considered in the optimization problem.
5. *Penetration of central energy resources:* the penetration rates of central energy resources (such as wind turbines, community-scale battery storage, large PV systems, etc.) are increasing in distribution systems. The utilization of these utility or third party-owned resources can provide opportunities for consuming even cheaper and cleaner energy in smart homes.
6. *Coordination of multiple aggregators:* multiple aggregators can connect to the same distribution grid to serve different neighborhoods or customers. Thereby, the smart homes of each aggregator may be located in different geographic areas, hence they could have different consumption and generation profiles. To ensure adequate coordination, aggregators would thus need to share information and energy, for example through an upper level coordination approach, so as be able to profit both neighborhoods and the utility while generating profit.
7. *Transactive energy:* the concept of transactive energy has emerged recently to describe decentralized economic and control approaches used to manage power flows. While this work matches several of the properties of existing transactive energy frameworks, further work could also focus on creating local, short-lived and reconfigurable markets at the neighborhood scale, or integrating blockchain technologies.
8. *Coordination in islanded MG:* MG can equipped with DER (conventional and/or RES), and can operate while connected to the main grid or disconnected from it (i.e., they operate in islanded mode). Reasons for islanding include reliability and power quality requirements in the face of critical conditions on the distribution

system, the need to reduce costs (assuming local generation is cheaper than grid power), minimizing emissions, supplying a remote area, etc. In this case, the MG energy management system could integrate a coordination mechanism to integrate DER use and energy sharing among smart homes.

BIBLIOGRAPHY

- [1] NASH, J. F., AND OTHERS. **Equilibrium points in n-person games.** *Proc. Nat. Acad. Sci. USA* 36, 1 (1950), 48–49.
- [2] HOLLANDS, K., AND HUGET, R. **A probability density function for the clearness index, with applications.** *Solar Energy* 30, 3 (1983), 195 – 209.
- [3] BJORK, C. O., AND KARLSSON, B. G. **Load management applications for industrial loads.** *IEEE Transactions on Power Apparatus and Systems PAS-104*, 8 (Aug 1985), 2058–2063.
- [4] DOUBLIGERIS, C., AND MAZUMDAR, R. **A game theoretic approach to flow control in an integrated environment with two classes of users.** In *Proceedings of the 1988 Computer Networking Symposium* (1988), IEEE, pp. 214–221.
- [5] OSBORNE, M. J., AND RUBINSTEIN, A. **A course in game theory.** MIT press, 1994.
- [6] ASHOK, S., AND BANERJEE, R. **Load-management applications for the industrial sector.** *Applied Energy* 66, 2 (2000), 105 – 111.
- [7] MACKENZIE, A. B., AND WICKER, S. B. **Game theory in communications: Motivation, explanation, and application to power control.** In *IEEE Global Telecommunications Conference (GLOBECOM'01)* (2001), vol. 2, IEEE, pp. 821–826.
- [8] ROUGHGARDEN, T., AND TARDOS, É. **How bad is selfish routing?** *Journal of the ACM* 49, 2 (2002), 236–259.
- [9] KIRSCHEN, D., AND STRBAC, G. **Fundamentals of Power System Economics.** John Wiley & Sons, 2004.
- [10] ELZABADANI, H., HELAL, A., ABDULRAZAK, B., AND JANSEN, E. **Self-sensing spaces: smart plugs for smart environments.** In *Proceedings of the 3rd International Conference on Smart Nomes and Health Telematics* (2005), pp. 91–98.
- [11] U.S. DEPARTMENT OF ENERGY. **Benefits of demand response in electricity markets and recommendations for achieving them. a report to U.S. congress,** 2006. Available: <http://eetd.lbl.gov/ea/EMS/reports/congress-1252.pdf> (Accessed Dec. 2014).
- [12] McARTHUR, S. D., DAVIDSON, E. M., CATTERSON, V. M., DIMEAS, A. L., HATZIARGYRIOU, N. D., PONCI, F., AND FUNABASHI, T. **Multi-agent systems for power engineering applications—part I: Concepts, approaches, and technical challenges.** *IEEE Transactions on Power Systems* 22, 4 (2007), 1743–1752.
- [13] NORTH AMERICAN ELECTRIC RELIABILITY CORPORATION. **Demand response discussion for the 2007 long-term reliability assessment,** 2007. Available: <http://www.naesb.org/pdf2/dsmee052407w4.pdf> (Accessed Dec. 2014.).

BIBLIOGRAPHY

- [14] PIER DEMAND RESPONSE RESEARCH CENTER. **Understanding customer behavior to improve demand response delivery in California**. Tech. rep., 2007.
- [15] THE INFORMATION SCIENCE & TECHNOLOGY CENTER - COLORADO STATE UNIVERSITY. **Summit - high performance computing system: User's guide**, 2007. Available: <https://www.acns.colostate.edu/hpc/> (Accessed Apr. 2017).
- [16] UNIVERSITY OF COLORADO BOULDER. **Summit: Research computing - university of colorado boulder**, 2007. Available: <https://www.rc.colorado.edu/resources/compute/summit> (Accessed Apr. 2017).
- [17] VON NEUMANN, J., AND MORGENSTERN, O. **Theory of games and economic behavior**. Princeton university press, 2007.
- [18] AALAMI, H., YOUSEFI, G., AND MOGHADAM, M. P. **Demand response model considering EDRP and TOU programs**. In *IEEE/PES Transmission and Distribution Conference and Exposition (2008)*, IEEE, pp. 1–6.
- [19] BRUNST, H., AND MOHR, B. **Performance Analysis of Large-Scale OpenMP and Hybrid MPI/OpenMP Applications with Vampir NG**. Springer Berlin Heidelberg, Berlin, Heidelberg, 2008, pp. 5–14.
- [20] SURYANARAYANAN, S. **Techniques for accommodating unscheduled flows in electricity networks and markets**. In *Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE* (July 2008), pp. 1–6.
- [21] MCDANIEL, P., AND MCLAUGHLIN, S. **Security and privacy challenges in the smart grid**. *IEEE Security & Privacy* 7, 3 (2009), 75–77.
- [22] POPULAR MECHANICS. **Smart house: Your so-called sci-fi life**, 2009. Available: <http://www.popularmechanics.com/technology/gadgets/a4109/4216434/> (Accessed May. 2015).
- [23] SWAN, L. G., AND UGURSAL, V. I. **Modeling of end-use energy consumption in the residential sector: A review of modeling techniques**. *Renewable and Sustainable Energy Reviews* 13, 8 (2009), 1819 – 1835.
- [24] WOOLDRIDGE, M. **An introduction to multiagent systems**. John Wiley & Sons, 2009.
- [25] **National solar radiation data base**, 2010. Available: http://rredc.nrel.gov/solar/old_data/nsrdb/ (Accessed Jun. 2017).
- [26] AALAMI, H., MOGHADDAM, M. P., AND YOUSEFI, G. **Demand response modeling considering interruptible/curtailable loads and capacity market programs**. *Applied Energy* 87, 1 (2010), 243–250.
- [27] HAN, S., HAN, S. H., AND SEZAKI, K. **Design of an optimal aggregator for vehicle-to-grid regulation service**. In *Innovative Smart Grid Technologies (ISGT)* (2010), IEEE, pp. 1–8.
- [28] KISHORE, S., AND SNYDER, L. V. **Control mechanisms for residential electricity demand in smartgrids**. In *First IEEE International Conference on Smart Grid Communications (SmartGridComm)* (2010), IEEE, pp. 443–448.

- [29] LEE, S.-S., LEE, H.-C., YOO, T.-H., NOH, J.-W., NA, Y.-J., PARK, J.-K., AND YOON, Y. T. **Demand response prospects in the south korean power system.** In *IEEE Power and Energy Society General Meeting* (2010), IEEE, pp. 1–6.
- [30] MOHSENIAN-RAD, A.-H., WONG, V. W., JATSKEVICH, J., SCHOBER, R., AND LEON-GARCIA, A. **Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid.** *IEEE Transactions on Smart Grid* 1, 3 (2010), 320–331.
- [31] NEWSHAM, G. R., AND BOWKER, B. G. **The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: a review.** *Energy Policy* 38, 7 (2010), 3289–3296.
- [32] SURYANARAYANAN, S., MANCILLA-DAVID, F., MITRA, J., AND LI, Y. **Achieving the smart grid through customer-driven microgrids supported by energy storage.** In *IEEE International Conference on Industrial Technology (ICIT)* (2010), pp. 884–890.
- [33] SURYANARAYANAN, S., RIETZ, R., AND MITRA, J. **A framework for energy management in customer-driven microgrids.** In *IEEE Power and Energy Society General Meeting* (2010), IEEE, pp. 1–4.
- [34] **A basic interface between matlab and jade agents using TCP/IP**, 2011. Available: <https://github.com/robinroche/mat2jade> (Accessed Apr. 2014).
- [35] **Comed real-time and day-ahead hourly prices**, 2011. Available: <https://hourlypricing.comed.com/live-prices/> (Accessed Apr. 2017).
- [36] **Commonwealth edison company - ComEd**, 2011. Available: <https://www.comed.com> (Accessed Apr. 2017).
- [37] **PJM daily real-time locational marginal pricing (LMP)**, 2011. Available: <https://goo.gl/r5ppJk> (Accessed Apr. 2017).
- [38] **PJM interconnection**, 2011. Available: <https://www.pjm.com> (Accessed Apr. 2017).
- [39] CHEN, C., KISHORE, S., AND SNYDER, L. V. **An innovative RTP-based residential power scheduling scheme for smart grids.** In *2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (May 2011), pp. 5956–5959.
- [40] EROL-KANTARCI, M., AND MOUFTAH, H. T. **Wireless sensor networks for cost-efficient residential energy management in the smart grid.** *IEEE Transactions on Smart Grid* 2, 2 (June 2011), 314–325.
- [41] GRIJALVA, S., AND TARIQ, M. U. **Prosumer-based smart grid architecture enables a flat, sustainable electricity industry.** In *ISGT 2011* (Jan 2011), pp. 1–6.
- [42] GUNGOR, V. C., SAHIN, D., KOCAK, T., ERGUT, S., BUCCELLA, C., CECATI, C., AND HANCKE, G. P. **Smart grid technologies: Communication technologies and standards.** *IEEE Transactions on Industrial Informatics* 7, 4 (Nov 2011), 529–539.

BIBLIOGRAPHY

- [43] JIANG, L., AND LOW, S. **Multi-period optimal energy procurement and demand response in smart grid with uncertain supply**. In *Decision and Control and European Control Conference (CDC-ECC), 2011 50th IEEE Conference on* (2011), IEEE, pp. 4348–4353.
- [44] LEE, M., ASLAM, O., FOSTER, B., KATHAN, D., KWOK, J., MEDEARIS, L., PALMER, R., SPORBORG, P., AND TITA, M. **Assessment of demand response and advanced metering**. Tech. rep., Federal Energy Regulatory Commission, 2011.
- [45] QURESHI, W. A., NAIR, N.-K. C., AND FARID, M. M. **Impact of energy storage in buildings on electricity demand side management**. *Energy Conversion and Management* 52, 5 (2011), 2110 – 2120.
- [46] WHITLEY, D. L. **Genitor: Modular GA package with floating-point support.**, 2011. Available: <https://goo.gl/i8kPCg> (Accessed Apr. 2017).
- [47] YANG, C.-T., HUANG, C.-L., AND LIN, C.-F. **Hybrid cuda, openmp, and mpi parallel programming on multicore gpu clusters**. *Computer Physics Communications* 182, 1 (2011), 266 – 269. Computer Physics Communications Special Edition for Conference on Computational Physics Kaohsiung, Taiwan, Dec 15-19, 2009.
- [48] ZHU, Z., TANG, J., LAMBOTHARAN, S., CHIN, W. H., AND FAN, Z. **An integer linear programming and game theory based optimization for demand-side management in smart grid**. In *IEEE GLOBECOM Workshops* (2011), IEEE, pp. 1205–1210.
- [49] BOYLE, G. **Renewable electricity and the grid: the challenge of variability**. Earthscan, 2012.
- [50] BOZCHALUI, M. C., HASHMI, S. A., HASSEN, H., CANIZARES, C. A., AND BHATTACHARYA, K. **Optimal operation of residential energy hubs in smart grids**. *IEEE Transactions on Smart Grid* 3, 4 (2012), 1755–1766.
- [51] CHEN, Z., WU, L., AND FU, Y. **Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization**. *IEEE Transactions on Smart Grid* 3, 4 (Dec 2012), 1822–1831.
- [52] COSTANZO, G. T., ZHU, G., ANJOS, M. F., AND SAVARD, G. **A system architecture for autonomous demand side load management in smart buildings**. *IEEE Transactions on Smart Grid* 3, 4 (Dec 2012), 2157–2165.
- [53] FAZAL, R., SOLANKI, J., AND SOLANKI, S. K. **Demand response using multi-agent system**. In *North American Power Symposium (NAPS)* (2012), IEEE, pp. 1–6.
- [54] GIORGIO, A. D., AND PIMPINELLA, L. **An event driven smart home controller enabling consumer economic saving and automated demand side management**. *Applied Energy* 96 (2012), 92 – 103. Smart Grids.
- [55] GRANDJEAN, A., ADNOT, J., AND BINET, G. **A review and an analysis of the residential electric load curve models**. *Renewable and Sustainable Energy Reviews* 16, 9 (2012), 6539 – 6565.

- [56] HANSEN, T., ROCHE, R., SURYANARAYANAN, S., SIEGEL, H. J., ZIMMERLE, D., YOUNG, P. M., AND MACIEJEWSKI, A. A. **A proposed framework for heuristic approaches to resource allocation in the emerging smart grid.** In *IEEE International Conference on Power System Technology (POWERCON)* (2012), IEEE, pp. 1–6.
- [57] LI, Y., NG, B. L., TRAYER, M., AND LIU, L. **Automated residential demand response: Algorithmic implications of pricing models.** *IEEE Transactions on Smart Grid* 3, 4 (2012), 1712–1721.
- [58] LOGENTHIRAN, T., SRINIVASAN, D., AND SHUN, T. Z. **Demand side management in smart grid using heuristic optimization.** *IEEE Transactions on Smart Grid* 3, 3 (2012), 1244–1252.
- [59] METS, K., D’HULST, R., AND DEVELDER, C. **Comparison of intelligent charging algorithms for electric vehicles to reduce peak load and demand variability in a distribution grid.** *Journal of Communications and Networks* 14, 6 (2012), 672–681.
- [60] NGUYEN, H. K., SONG, J. B., AND HAN, Z. **Demand side management to reduce peak-to-average ratio using game theory in smart grid.** In *IEEE Conference on Computer Communications Workshops* (2012), IEEE, pp. 91–96.
- [61] RASTEGAR, M., FOTUHI-FIRUZABAD, M., AND AMINIFAR, F. **Load commitment in a smart home.** *Applied Energy* 96 (2012), 45–54.
- [62] ROCHE, R. **Agent-based Architectures and Algorithms for Energy Management in Smart Grids.** PhD thesis, Univ. Technol. Belfort-Montbéliard, Belfort, France, 2012.
- [63] ROOZBEHANI, M., DAHLEH, M. A., AND MITTER, S. K. **Volatility of power grids under real-time pricing.** *IEEE Transactions on Power Systems* 27, 4 (2012), 1926–1940.
- [64] SAAD, W., HAN, Z., POOR, H. V., AND BAŞAR, T. **Game-theoretic methods for the smart grid: An overview of microgrid systems, demand-side management, and smart grid communications.** *Signal Processing Magazine, IEEE* 29, 5 (2012), 86–105.
- [65] WANG, D., PARKINSON, S., MIAO, W., JIA, H., CRAWFORD, C., AND DJILALI, N. **Online voltage security assessment considering comfort-constrained demand response control of distributed heat pump systems.** *Applied Energy* 96 (2012), 104–114.
- [66] ZEHIR, M. A., AND BAGRIYANIK, M. **Demand side management by controlling refrigerators and its effects on consumers.** *Energy Conversion and Management* 64 (2012), 238 – 244. IREC 2011, The International Renewable Energy Congress.
- [67] **Special issue: The smart home.** *Proceedings of the IEEE* 101, 11 (2013).
- [68] AGNETIS, A., DE PASCALE, G., DETTI, P., AND VICINO, A. **Load scheduling for household energy consumption optimization.** *IEEE Transactions on Smart Grid* 4, 4 (2013), 2364–2373.

BIBLIOGRAPHY

- [69] CELIK, B., KARATEPE, E., GOKMEN, N., AND SILVESTRE, S. **A virtual reality study of surrounding obstacles on BIPV systems for estimation of long-term performance of partially shaded PV arrays.** *Renewable Energy* 60 (2013), 402 – 414.
- [70] CHANG, T.-H., ALIZADEH, M., AND SCAGLIONE, A. **Real-time power balancing via decentralized coordinated home energy scheduling.** *IEEE Transactions on Smart Grid* 4, 3 (2013), 1490–1504.
- [71] CHEN, C., WANG, J., HEO, Y., AND KISHORE, S. **Mpc-based appliance scheduling for residential building energy management controller.** *IEEE Transactions on Smart Grid* 4, 3 (2013), 1401–1410.
- [72] CHEN, X., WEI, T., AND HU, S. **Uncertainty-aware household appliance scheduling considering dynamic electricity pricing in smart home.** *IEEE Transactions on Smart Grid* 4, 2 (June 2013), 932–941.
- [73] CHEN, Y., LU, J., YU, X., AND HILL, D. J. **Multi-agent systems with dynamical topologies: Consensus and applications.** *IEEE Circuits and Systems Magazine* 13, 3 (2013), 21–34.
- [74] DAI, R., AND MESBAHI, M. **Optimal power generation and load management for off-grid hybrid power systems with renewable sources via mixed-integer programming.** *Energy Conversion and Management* 73 (2013), 234–244.
- [75] EUROPEAN ENVIRONMENT AGENCY. **Final energy consumption by sector, 2013.** Available: <https://www.eea.europa.eu/data-and-maps/indicators/final-energy-consumption-by-sector-5/assessment> (Accessed Jul. 2017).
- [76] FAN, Z., KULKARNI, P., GORMUS, S., EFTHYMIIOU, C., KALOGRIDIS, G., SOORIYABANDARA, M., ZHU, Z., LAMBOTHARAN, S., AND CHIN, W. H. **Smart grid communications: Overview of research challenges, solutions, and standardization activities.** *IEEE Communications Surveys & Tutorials* 15, 1 (2013), 21–38.
- [77] FUSELLI, D., ANGELIS, F. D., BOARO, M., SQUARTINI, S., WEI, Q., LIU, D., AND PIAZZA, F. **Action dependent heuristic dynamic programming for home energy resource scheduling.** *International Journal of Electrical Power & Energy Systems* 48 (2013), 148 – 160.
- [78] GKATZIKIS, L., KOUTSOPOULOS, I., AND SALONIDIS, T. **The role of aggregators in smart grid demand response markets.** *IEEE Journal on Selected Areas in Communications* 31, 7 (2013), 1247–1257.
- [79] GUO, Y., PAN, M., FANG, Y., AND KHARGONEKAR, P. P. **Decentralized coordination of energy utilization for residential households in the smart grid.** *IEEE Transactions on Smart Grid* 4, 3 (2013), 1341–1350.
- [80] GYAMFI, S., KRUMDIECK, S., AND URMEE, T. **Residential peak electricity demand response—highlights of some behavioural issues.** *Renewable and Sustainable Energy Reviews* 25 (2013), 71–77.
- [81] HU, Q., AND LI, F. **Hardware design of smart home energy management system with dynamic price response.** *IEEE Transactions on Smart Grid* 4, 4 (2013), 1878–1887.

- [82] KUNWAR, N., YASH, K., AND KUMAR, R. **Area-load based pricing in DSM through ANN and heuristic scheduling**. *IEEE Transactions on Smart Grid* 4, 3 (2013), 1275–1281.
- [83] KYRIAKARAKOS, G., PIROMALIS, D. D., DOUNIS, A. I., ARVANITIS, K. G., AND PAPADAKIS, G. **Intelligent demand side energy management system for autonomous polygeneration microgrids**. *Applied Energy* 103 (2013), 39–51.
- [84] LAN, T., KANG, Q., AN, J., YAN, W., AND WANG, L. **Sitting and sizing of aggregator controlled park for plug-in hybrid electric vehicle based on particle swarm optimization**. *Neural Computing and Applications* 22, 2 (2013), 249–257.
- [85] MURATORI, M., ROBERTS, M. C., SIOSHANSI, R., MARANO, V., AND RIZZONI, G. **A highly resolved modeling technique to simulate residential power demand**. *Applied Energy* 107 (2013), 465–473.
- [86] NIRO, G., SALLES, D., ALCÂNTARA, M. V., AND DA SILVA, L. C. **Large-scale control of domestic refrigerators for demand peak reduction in distribution systems**. *Electric Power Systems Research* 100 (2013), 34–42.
- [87] OZTURK, Y., SENTHILKUMAR, D., KUMAR, S., AND LEE, G. **An intelligent home energy management system to improve demand response**. *IEEE Transactions on Smart Grid* 4, 2 (2013), 694–701.
- [88] ROCHE, R., IDOUMGHAR, L., SURYANARAYANAN, S., DAGGAG, M., SOLACOLU, C.-A., AND MIRAQUI, A. **A flexible and efficient multi-agent gas turbine power plant energy management system with economic and environmental constraints**. *Applied Energy* 101 (2013), 644–654.
- [89] ROCHE, R., LAURI, F., BLUNIER, B., MIRAQUI, A., AND KOUKAM, A. **Multi-agent technology for power system control**. Springer, 2013, pp. 567–609.
- [90] SHAO, S., PIPATTANASOMPORN, M., AND RAHMAN, S. **Development of physical-based demand response-enabled residential load models**. *Power Systems, IEEE Transactions on* 28, 2 (2013), 607–614.
- [91] ZHAO, P., SURYANARAYANAN, S., AND SIMOES, M. G. **An energy management system for building structures using a multi-agent decision-making control methodology**. *IEEE Transactions on Industry Applications* 49, 1 (2013), 322–330.
- [92] ZIPPERER, A., ALOISE-YOUNG, P. A., SURYANARAYANAN, S., ROCHE, R., EARLE, L., CHRISTENSEN, D., BAULEO, P., AND ZIMMERLE, D. **Electric energy management in the smart home: Perspectives on enabling technologies and consumer behavior**. *Proceedings of the IEEE* 101, 11 (2013), 2397–2408.
- [93] ADIKA, C. O., AND WANG, L. **Non-cooperative decentralized charging of homogeneous households' batteries in a smart grid**. *IEEE Transactions on Smart Grid* 5, 4 (2014), 1855–1863.
- [94] BAI, L., XU, G., AND ZHENG, Q. P. **A game theoretical approach to modeling energy consumption with consumer preference**. In *2014 IEEE PES General Meeting — Conference Exposition* (July 2014), pp. 1–5.

BIBLIOGRAPHY

- [95] BEAUDIN, M., ZAREIPOUR, H., BEJESTANI, A. K., AND SCHELLENBERG, A. **Residential energy management using a two-horizon algorithm**. *IEEE Transactions on Smart Grid* 5, 4 (July 2014), 1712–1723.
- [96] CHAVALI, P., YANG, P., AND NEHORAI, A. **A distributed algorithm of appliance scheduling for home energy management system**. *IEEE Transactions on Smart Grid* 5, 1 (2014), 282–290.
- [97] CHEN, C., WANG, J., AND KISHORE, S. **A distributed direct load control approach for large-scale residential demand response**. *IEEE Transactions on Smart Grid* 29, 5 (2014), 2219–2228.
- [98] CHEN, H., LI, Y., LOUIE, R. H., AND VUCETIC, B. **Autonomous demand side management based on energy consumption scheduling and instantaneous load billing: An aggregative game approach**. *IEEE Transactions on Smart Grid* 5, 4 (2014), 1744–1754.
- [99] DENG, R., YANG, Z., CHEN, J., ASR, N. R., AND CHOW, M.-Y. **Residential energy consumption scheduling: A coupled-constraint game approach**. *IEEE Transactions on Smart Grid* 5, 3 (2014), 1340–1350.
- [100] FAKHRAZARI, A., VAKILZADIAN, H., AND CHOOBINEH, F. F. **Optimal energy scheduling for a smart entity**. *IEEE Transactions on Smart Grid* 5, 6 (Nov 2014), 2919–2928.
- [101] FRIZELL, S. **This startup is trying to create—and control—the internet of your home**, 2014. Available: <http://time.com/2926400/at-your-service/> (Accessed Jul. 2014).
- [102] GIUSTI, A., SALANI, M., DI CARO, G. A., RIZZOLI, A. E., AND GAMBARDELLA, L. M. **Restricted neighborhood communication improves decentralized demand-side load management**. *IEEE Transactions on Smart Grid* 5, 1 (2014), 92–101.
- [103] HOMAEE, O., ZAKARIAZADEH, A., AND JADID, S. **Real time voltage control using emergency demand response in distribution system by integrating advanced metering infrastructure**. *Journal of Renewable and Sustainable Energy* 6, 3 (2014).
- [104] JUELSGAARD, M., ANDERSEN, P., AND WISNIEWSKI, R. **Distribution loss reduction by household consumption coordination in smart grids**. *IEEE Transactions on Smart Grid* 5, 4 (2014), 2133–2144.
- [105] KAHROBAEE, S., RAJABZADEH, R. A., SOH, L.-K., AND ASGARPOOR, S. **Multi-agent study of smart grid customers with neighborhood electricity trading**. *Electric Power Systems Research* 111 (2014), 123–132.
- [106] MAO, M., JIN, P., HATZIARGYRIOU, N. D., AND CHANG, L. **Multiagent-based hybrid energy management system for microgrids**. *IEEE Transactions on Sustainable Energy* 5, 3 (2014), 938–946.
- [107] MIGUEL, P., NEVES, L., AND MARTINS, A. G. **Methodology to simulate the impact of a large deployment of a residential energy management system in the electricity grid**. *Electric Power Systems Research* 116 (2014), 399 – 407.

- [108] MURATORI, M., SCHUELKE-LEECH, B.-A., AND RIZZONI, G. **Role of residential demand response in modern electricity markets.** *Renewable and Sustainable Energy Reviews* 33 (2014), 546 – 553.
- [109] NGUYEN, D. T., AND LE, L. B. **Joint optimization of electric vehicle and home energy scheduling considering user comfort preference.** *IEEE Transactions on Smart Grid* 5, 1 (2014), 188–199.
- [110] NIU, W., AND LI, Y. **Uncertain optimization decision of interruptible load in demand response program.** In *IEEE Innovative Smart Grid Technologies Asia (ISGT Asia)* (2014), IEEE, pp. 675–679.
- [111] PAVLAK, G. S., HENZE, G. P., AND CUSHING, V. J. **Optimizing commercial building participation in energy and ancillary service markets.** *Energy and Buildings* 81 (2014), 115–126.
- [112] SAMADI, P., MOHSENIAN-RAD, H., WONG, V. W., AND SCHOBER, R. **Real-time pricing for demand response based on stochastic approximation.** *IEEE Transactions on Smart Grid* 5, 2 (2014), 789–798.
- [113] SETLHAOLO, D., XIA, X., AND ZHANG, J. **Optimal scheduling of household appliances for demand response.** *Electric Power Systems Research* 116 (2014), 24 – 28.
- [114] TAN, Z., YANG, P., AND NEHORAI, A. **An optimal and distributed demand response strategy with electric vehicles in the smart grid.** *IEEE Transactions on Smart Grid* 5, 2 (March 2014), 861–869.
- [115] TUSHAR, M. H., ASSI, C., MAIER, M., AND UDDIN, M. F. **Smart microgrids: Optimal joint scheduling for electric vehicles and home appliances.** *IEEE Transactions on Smart Grid* 5, 1 (2014), 239–250.
- [116] TUSHAR, W., ZHANG, J. A., SMITH, D. B., POOR, H. V., AND THIÉBAUX, S. **Prioritizing consumers in smart grid: A game theoretic approach.** *IEEE Transactions on Smart Grid* 5, 3 (May 2014), 1429–1438.
- [117] WU, Z., ZHOU, S., LI, J., AND ZHANG, X. P. **Real-time scheduling of residential appliances via conditional risk-at-value.** *IEEE Transactions on Smart Grid* 5, 3 (2014), 1282–1291.
- [118] CELIK, B., KARATEPE, E., SILVESTRE, S., GOKMEN, N., AND CHOUDER, A. **Analysis of spatial fixed pv arrays configurations to maximize energy harvesting in bipv applications.** *Renewable Energy* 75 (2015), 534 – 540.
- [119] COMED. **The ComEd residential real-time pricing program,** 2015. Available: <https://www.comed.com/Documents/HomeSavings-ProgramsIncentives/RRTPGuide200904.pdf> (Accessed Feb. 2015).
- [120] HANSEN, T. M., ROCHE, R., SURYANARAYANAN, S., MACIEJEWSKI, A. A., AND SIEGEL, H. J. **Heuristic optimization for an aggregator-based resource allocation in the smart grid.** *IEEE Transactions on Smart Grid* 6, 4 (2015), 1785–1794.
- [121] HU, Z., KIM, J.-H., WANG, J., AND BYRNE, J. **Review of dynamic pricing programs in the US and Europe: Status quo and policy recommendations.** *Renewable and Sustainable Energy Reviews* 42 (2015), 743–751.

BIBLIOGRAPHY

- [122] KHAN, A. A., RAZZAQ, S., KHAN, A., KHURSHEED, F., AND OTHERS. **HEMSs and enabled demand response in electricity market: an overview**. *Renewable and Sustainable Energy Reviews* 42 (2015), 773–785.
- [123] MACEDO, M., GALO, J., DE ALMEIDA, L., AND LIMA, A. D. C. **Demand side management using artificial neural networks in a smart grid environment**. *Renewable and Sustainable Energy Reviews* 41 (2015), 128–133.
- [124] MEYN, S. P., BAROOAH, P., BUSIC, A., CHEN, Y., AND EHREN, J. **Ancillary service to the grid using intelligent deferrable loads**. *IEEE Transactions on Automatic Control* 60, 11 (2015), 2847–2862.
- [125] ROCHE, R., SURYANARAYANAN, S., HANSEN, T. M., KILICCOTE, S., AND MIRAQUI, A. **A multi-agent model and strategy for residential demand response coordination**. In *IEEE PowerTech Eindhoven* (2015), IEEE, pp. 1–6.
- [126] SHAFIEI, S. E., KNUDSEN, T., WISNIEWSKI, R., AND ANDERSEN, P. **Data-driven predictive direct load control of refrigeration systems**. *IET Control Theory & Applications* 9, 7 (2015), 1022–1033.
- [127] VARDAKAS, J. S., ZORBA, N., AND VERIKOUKIS, C. V. **A survey on demand response programs in smart grids: Pricing methods and optimization algorithms**. *IEEE Communications Surveys Tutorials* 17, 1 (Firstquarter 2015), 152–178.
- [128] ZHANG, N., YAN, Y., AND SU, W. **A game-theoretic economic operation of residential distribution system with high participation of distributed electricity prosumers**. *Applied Energy* 154 (2015), 471–479.
- [129] ZHOU, K., AND YANG, S. **Demand side management in China: The context of china’s power industry reform**. *Renewable and Sustainable Energy Reviews* 47 (2015), 954–965.
- [130] ZHU, Z., LAMBOTHARAN, S., CHIN, W. H., AND FAN, Z. **A game theoretic optimization framework for home demand management incorporating local energy resources**. *IEEE Transactions on Industrial Informatics* 11, 2 (April 2015), 353–362.
- [131] CELIK, B., ROCHE, R., BOUQUAIN, D., AND MIRAQUI, A. **Coordinated energy management using agents in neighborhood areas with RES and storage**. In *IEEE International Energy Conference (EnergyCon)* (2016).
- [132] CELIK, B., ROCHE, R., BOUQUAIN, D., AND MIRAQUI, A. **Increasing renewable local energy use in smart neighborhoods through coordinated trading**. IET, London, 2016, pp. 217–252.
- [133] CUI, Y., AND LIU, N. **Emergency energy management strategy for commercial building microgrid consisting of PV and energy storage**. In *2016 IEEE 11th Conference on Industrial Electronics and Applications (ICIEA)* (June 2016), pp. 2049–2054.
- [134] INTERNATIONAL ENERGY AGENCY. **Renewable energy feed-in tariffs (iii)**, 2016. Available: <https://www.iea.org/policiesandmeasures/pams/france/name-24112-en.php> (Accessed Jul. 2017).

- [135] MEDIWATHTHE, C. P., STEPHENS, E. R., SMITH, D. B., AND MAHANTI, A. **A dynamic game for electricity load management in neighborhood area networks.** *IEEE Transactions on Smart Grid* 7, 3 (May 2016), 1329–1336.
- [136] MHANNA, S., CHAPMAN, A. C., AND VERBIČ, G. **A fast distributed algorithm for large-scale demand response aggregation.** *IEEE Transactions on Smart Grid* 7, 4 (July 2016), 2094–2107.
- [137] MOON, S., AND LEE, J. W. **Multi-residential demand response scheduling with multi-class appliances in smart grid.** *IEEE Transactions on Smart Grid PP*, 99 (2016), 1–1.
- [138] ONTARIO ENERGY BOARD. **Electricity prices**, 2016. Available: <http://www.naesb.org/pdf2/dsmee052407w4.pdf> (Accessed Mar. 2016).
- [139] OUAMMI, A. **Optimal power scheduling for a cooperative network of smart residential buildings.** *IEEE Transactions on Sustainable Energy* 7, 3 (July 2016), 1317–1326.
- [140] PATERAKIS, N. G., ERDINÇ, O., PAPP, I. N., BAKIRTZIS, A. G., AND CATALÃO, J. P. S. **Coordinated operation of a neighborhood of smart households comprising electric vehicles, energy storage and distributed generation.** *IEEE Transactions on Smart Grid* 7, 6 (Nov 2016), 2736–2747.
- [141] SAFDARIAN, A., FOTUHI-FIRUZABAD, M., AND LEHTONEN, M. **Optimal residential load management in smart grids: A decentralized framework.** *IEEE Transactions on Smart Grid* 7, 4 (July 2016), 1836–1845.
- [142] SAURAV, K., BANSAL, H., NAWHAL, M., CHANDAN, V., AND ARYA, V. **Minimizing energy costs of commercial buildings in developing countries.** In *2016 IEEE International Conference on Smart Grid Communications (SmartGridComm)* (Nov 2016), pp. 637–642.
- [143] SDGE. **Electricity price**, 2016. Available: <http://www.sdge.com/business/demand-response/cpp> (Accessed Apr. 2016).
- [144] CELIK, B., ROCHE, R., BOUQUAIN, D., AND MIRAQUI, A. **Decentralized neighborhood energy management with coordinated smart home energy sharing.** *IEEE Transactions on Smart Grid PP*, 99 (2017), 1–1.
- [145] CELIK, B., ROCHE, R., SURYANARAYANAN, S., BOUQUAIN, D., AND MIRAQUI, A. **Electric energy management in residential areas through coordination of multiple smart homes.** *Renewable and Sustainable Energy Reviews* 80 (2017), 260–275.
- [146] CELIK, B., SURYANARAYANAN, S., MACIEJEWSKI, A. A., SIEGEL, H. J., SHARMA, S., AND ROCHE, R. **A comparison of three parallel processing methods for a resource allocation problem in the smart grid.** Available: <https://www.engr.colostate.edu/~aam/pdf/conferences/191.pdf>, 2017.
- [147] ENEDIS. **L’électricité en réseau**, 2017. Available: <http://www.enedis.fr/classes-temporelles> (Accessed Jul. 2017).

BIBLIOGRAPHY

- [148] EUROPEAN TECHNOLOGY & INNOVATION PLATFORMS. **ETP smart grids: Vision and strategy**, 2017. Available: <http://www.etip-snet.eu/publications/reference-publications/> (Accessed Jul. 2017).
- [149] MESSAGE PASSING INTERFACE FORUM. **MPI: A message-passing interface standard**, 2017. Available: <http://mpi-forum.org/docs/> (Accessed Apr. 2017).
- [150] OPENMP ARCHITECTURE REVIEW BOARD. **OpenMP application program interface**, 2017. Available: <http://www.openmp.org/specifications/> (Accessed Apr. 2017).
- [151] THE SMARTGRIDS EUROPEAN TECHNOLOGY PLATFORM. **What is a smartgrid?**, 2017. Available: <http://ftp.smartgrids.eu/ETPSmartGrids> (Accessed Jul. 2017).
- [152] ZHANG, Y., CHEN, W., AND GAO, W. **A survey on the development status and challenges of smart grids in main driver countries**. *Renewable and Sustainable Energy Reviews* 79 (2017), 137 – 147.

LIST OF FIGURES

1.1	Conceptual model of the SG.	5
1.2	DSM approaches, adapted from [123]: (a) load shifting, (b) peak shaving, (c) strategic conservation, (d) strategic load growth, (e) valley filling, (f) flexible load.	6
1.3	Types of DR programs.	7
1.4	DR pricing shemas: (a) TOU, (b) CPP, (c) RTP.	9
1.5	Total energy and electric energy breakdown for each sector.	10
1.6	Smart home architecture.	10
1.7	Rebound peak effect with uncoordinated DR.	14
2.1	System architecture with neighborhood area networks (CES: Community energy storage).	23
2.2	Principle of centralized coordination (DM: decision making).	24
2.3	Fully-dependent decentralized coordination (DM: decision making).	26
2.4	Fully-independent decentralized coordination (DM: decision making).	26
2.5	Partially-independent decentralized coordination (DM: decision making).	27
3.1	Smart home model (SM: smart meter).	42
3.2	PV system structure.	45
3.3	Neighborhood agent model with power and communication structures.	46
3.4	TOU, FIT and neighborhood pricing.	47
3.5	Representation of the appliance control interval over 24 hours. Each block represents a 60-minute time interval.	49
3.6	Representation of the battery control interval (15 minutes) in one hour.	50
3.7	Flowchart of the decentralized coordination method.	51
3.8	Actual and communication data of a consumption profile.	52
3.9	Flowchart of the centralized coordination method.	59
3.10	Installation capacity of the resources in the neighborhood. (a) PV capacities, (b) battery capacities in smart homes.	60
3.11	Rolling horizon approach principle.	60
3.12	Co-simulation platform.	61

LIST OF FIGURES

3.13 Smart home 01 (with PV and battery) electricity consumption profiles: (a) baseline, (b) selfish, (c) decentralized (d) centralized. 63

3.14 Smart home 03 (with PV and without battery) electricity consumption profiles: (a) baseline, (b) selfish, (c) decentralized (d) centralized. 64

3.15 Smart home 04 (without PV and battery) electricity consumption profiles: (a) baseline, (b) selfish, (c) decentralized (d) centralized. 65

3.16 State-of-charge of the battery system for each case. 66

3.17 Energy analysis of the smart homes in the decentralized coordination. 66

3.18 Energy analysis of the smart homes in the centralized coordination. 67

3.19 Determined neighborhood profits for each control method and neighborhood size. 68

4.1 Breakdown of the probability values of the different consumption rates among smart homes. 71

4.2 Start time probability of lights. 73

4.3 Start time probability of the kettle. 73

4.4 Start time probability of the microwave. 73

4.5 Start time probability of the vacuum cleaner. 73

4.6 Start time probability of the television. 74

4.7 Start time probability of the computer. 74

4.8 Start time probability of the iron. 74

4.9 Start time probability of the hair dryer. 74

4.10 Start time probability of the coffee maker. 74

4.11 Start time probability of the toaster. 74

4.12 Start time probability of the washing machine. 74

4.13 Start time probability of the clothes dryer. 74

4.14 Start time probability of the dish washer. 75

4.15 Neighborhood agent model with PCC. 76

4.16 Full dynamic price in the neighborhood (condition 1: when surplus generation is increased, condition 2: when electricity consumption is increased). 77

4.17 Neighborhood net load profile. 77

4.18 Base and full dynamic electricity pricing. 78

4.19 Communication diagram of the neighborhood agents. 80

4.20 Coordination diagram of the group-based mechanism. 81

4.21 Coordination diagram of the turn-based mechanism. 82

4.22 Assets and non-controllable appliance numbers in smart homes. 84

4.23 PV installation capacities in smart homes. 84

LIST OF FIGURES

4.24 Battery installation capacities in smart homes.	84
4.25 Smart home electricity profile example.	85
4.26 Comparison of the energy consumption breakdown for the different strategies.	86
4.27 Smart home electricity profile example, using the different strategies.	87
4.28 Annual neighborhood cost profiles.	87
4.29 Annual neighborhood peak consumption profiles.	88
5.1 Electric and communication systems architecture.	93
5.2 Forecast spot-market (PJM) and utility prices (ComEd) for July, 20 2017.	94
5.3 Actual spot market (PJM) and utility prices (ComEd) for July, 20 2017.	94
5.4 $\alpha_{u,y}$ modeling for appliance scheduling.	95
5.5 Aggregated electricity profile of the neighborhood without considering residential PV generation.	97
5.6 Aggregated electricity profile of the neighborhood considering residential PV generation.	97
5.7 Aggregated electricity profile of the neighborhood with base loads and PV generation (PV generation is a negative load).	98
5.8 Aggregated electricity profile of the neighborhood with base loads, PV generation and non-scheduled assets.	98
5.9 Aggregated electricity profile of the neighborhood with base loads, PV generation, non-scheduled assets and a scheduled asset.	99
5.10 Calculation of parameter $N_{u,y}$	99
5.11 Calculation of parameter $B_{u,y}$	100
5.12 OpenMP flow model.	101
5.13 OpenMP implementation of SGRA (T cores).	102
5.14 MPI application utilization model.	103
5.15 MPI implementation of SGRA (D cores).	103
5.16 OpenMP plus MPI implementation of SGRA ($T \times D$ cores).	104
5.17 Number of hybrid threads and tasks versus (a) total simulation time and (b) computation time of per-GA-iteration.	105
5.18 Aggregator profits on July 1 st for each PV penetration level.	107
5.19 Total profits of customers on July 1 st for each PV penetration level.	108
5.20 Total controlled assets number on July 1 st for each PV penetration level.	108
5.21 Aggregated electricity profiles of the neighborhood before and after scheduling: (a) 0% (b) 25% (c) 50%, (d) 75% and (e) 100% PV penetration levels	109

LIST OF FIGURES

5.22 Total asset electricity profiles of the neighborhood before and after scheduling: (a) 0% (b) 25% (c) 50%, (d) 75% and (e) 100% PV penetration levels . 110

5.23 Forecast price profiles (ComEd, PJM and CIP): (a) 0% (b) 25% (c) 50%, (d) 75% and (e) 100% PV penetration levels 111

5.24 Actual price profiles (ComEd, PJM and CIP): (a) 0% (b) 25% (c) 50%, (d) 75% and (e) 100% PV penetration levels 112

5.25 Total simulation time for each PV penetration level. 114

5.26 Weekly forecast aggregator profits for each PV penetration level. 114

5.27 Weekly actual aggregator profits for each PV penetration level. 114

5.28 Weekly total profits of customers for each PV penetration level. 115

5.29 Weekly total controlled assets numbers for each PV penetration level. . . . 115

5.30 Weekly total forecast aggregator profits. 116

5.31 Weekly total actual aggregator profits. 116

LIST OF TABLES

2.1	Residential energy consumption modeling approaches [23].	18
2.2	Comparison of coordination structures.	36
2.3	Summary of the reviewed studies.	37
3.1	Amount, power rating and controllability of appliances (✓: controllable, -: non-controllable)	43
3.2	Start time and operation duration parameters of appliances.	44
3.3	Electricity grid and neighborhood trading tariffs.	47
3.4	Comparison of the algorithms (✓: used, -: not used).	48
3.5	Smart homes and total neighborhood electricity costs (**: smart home with PV and battery, * smart home with PV).	61
3.6	Neighborhood area number of resource owners.	67
4.1	Comparison of proposed methods in Chapters 3 and 4.	69
4.2	Number of smart home appliances and corresponding probabilities.	72
4.3	Appliance operation duration and mode.	73
4.4	PV and battery systems ownership and ratings.	75
4.5	Daily electric energy management results with (WE) and without (WoE) forecasting errors.	85
4.6	Annual electric energy management with (WE) and without (WoE) forecasting errors.	88
4.7	Neighborhood area number of resource owners.	89
4.8	Determined neighborhood profits and peak reductions for each control method and neighborhood size.	90
5.1	Modeling parameters of assets [120].	93

IV

APPENDICES

PUBLICATIONS

Journal Papers:

- J.1. (Accepted) **B. Celik**, R. Roche, D. Bouquain, and A. Miraoui, "Decentralized neighborhood energy management with coordinated smart home energy sharing," *IEEE Transactions on Smart Grid*. DOI: 10.1109/TSG.2017.2710358.
- J.2. **B. Celik**, R. Roche, S. Suryanarayanan, D. Bouquain, and A. Miraoui, "Electric energy management in residential areas through coordination of multiple smart homes," *Renewable and Sustainable Energy Reviews*, 80, 260-275, 2017.

Book Chapters:

- B.1. **B. Celik**, R. Roche, D. Bouquain, and A. Miraoui, "Increasing renewable local energy use in smart neighborhoods through coordinated trading," In: S. Suryanarayanan, R. Roche, and T. Hansen (eds.), *Cyber-Physical-Social Systems and Constructs in Electric Power Engineering*, chapter 9, pp. 217- 252, IET, summer 2016. ISBN 978-1-84919-936-0.

Conference Papers:

- C.1. (Accepted) S. Sharma, V. Durvasulu, **B. Celik**, S. Suryanarayanan, T. M. Hansen, A. A. Maciejewski, and H. J. Siegel, "Metrics-based assessment of sustainability in demand response," In: *The 15th IEEE International Conference in Smart City (SmartCity 2017)*, 2017 Bangkok, Thailand.
- C.2. (Presented) **B. Celik**, S. Suryanarayanan, A. A. Maciejewski, H. J. Siegel, S. Sharma, and R. Roche, "A comparison of three parallel processing methods for a resource allocation problem in the smart grid," In: *North American Power Symposium (NAPS)*, 2017 Morgantown, West Virginia, USA.
- C.3. **B. Celik**, R. Roche, D. Bouquain, and A. Miraoui, "Coordinated home energy management in community microgrids with energy sharing among smart homes," In: *ELECTRIMACS*, 2017 Toulouse, France, p. 6p.
- C.4. **B. Celik**, R. Roche, D. Bouquain, and A. Miraoui, "Coordinated neighborhood energy sharing using game theory and multi-agent systems," In: *Power Tech*, 2017 IEEE Manchester, UK, pp. 1-6.

APPENDIX A. PUBLICATIONS

- C.5. **B. Celik**, R. Roche, D. Bouquain, and A. Miraoui, "Coordinated energy management using agents in neighborhood areas with RES and Storage," *In: International Energy Conference (ENERGYCON)*, 2016 IEEE Leuven, Belgium, pp. 1-6.
- C.6. R. Roche, **B. Celik**, D. Bouquain, and A. Miraoui, "A framework for grid-edge resilience improvement using homes and microgrids coordination," *In: Power Tech*, 2015 IEEE Eindhoven, Netherlands, pp. 1-6.

Workshops and Seminars:

- P.1. **B. Celik**, R. Roche, D. Bouquain, and A. Miraoui, "Coordinated neighborhood energy sharing using game theory and multi-agent systems," *In: FEMTO-ST Seminar-Poster*, 2017 Besançon, France.
- P.2. **B. Celik**, S. Sharma, V. Durvasulu, S. Suryanarayanan, T. M. Hansen, A. A. Maciejewski, and H. J. Siegel, "Metric-based assessment of sustainability in demand response," *In: International Conference and Workshop REMOO - Presentation*, 2017 Venice, Italy.
- P.3. **B. Celik**, R. Roche, S. Surayanarayanan, D. Bouquain, and A. Miraoui, "Cyber physical systems in the smart grid: electric energy management through smart homes coordination," *In: French-American Doctoral Exchange (FADEX 2016) - Poster*, 2016 Grenoble/Paris/Rennes, France.
- P.4. **B. Celik**, R. Roche, S. Surayanarayanan, D. Bouquain, and A. Miraoui, "CPS for energy management in smart homes through coordination," *In: French-American Doctoral Exchange (FADEX 2016) - Presentation*, 2016 Grenoble/Paris/Rennes, France.

SPIM

■ École doctorale SPIM - Université de Technologie Belfort-Montbéliard
F - 90010 Belfort Cedex ■ tél. +33 (0)3 84 58 31 39
■ ed-spim@univ-fcomte.fr ■ www.ed-spim.univ-fcomte.fr

