Department of Electrical and Information Engineering
ELECTRICAL AND INFORMATION ENGINEERING
Ph.D. Program

SSD: ING-INF/04 Automatica

Final Dissertation

Robust Optimal Demand-side Management in Smart Grids

by

Seyed Mohsen Hosseini

Supervisor: Prof. Mariagrazia Dotoli

Co- Supervisor: Dr. Raffaele Carli

Coordinator of Ph.D. Program:

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33rd Cycle, 01/11/2017-31/12/2020

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A thesis submitted to the Department of Electrical and Information Engineering in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Electrical and Information Engineering

Abstract

Smart grids (SGs) are experiencing an increasing growth due to their economic, social and environmental benefits. The concept of SG has recently gained significant attention from the research community due to its ability to effectively integrate distributed energy resources (DER) including renewable energy sources (RES), energy storage systems (ESS) and the demand side management (DSM) programs. A SG can change the operation paradigm of the electric grid to ensure an efficient and sustainable electricity supply with lower losses and greater reliability and security. Despite these potential benefits, the massive penetration of DERs in SGs may impose new challenges to the system design and functioning. A substantial challenge arises from system uncertainties due to forecast errors. For instance, the inherent intermittency of RESs, the unpredictable changes in users' electricity demand, and the volatility of the dynamic electricity price in electricity markets can inject considerable amounts of uncertainty into the electric grid.

Facing these challenges, this thesis investigates the integration of DERs and DSM programs as great sources of flexibility and essential elements for effective supply-demand balancing into SGs in the presence of uncertainty. Firstly, we present a comprehensive classification, review and analysis of existing approaches and findings for DSM to highlight key features and components of energy management systems for more flexible and intelligent grids. We provide a definition of DSM and introduce the reader to the functionalities and achievements of DSM applications in SGs. We then focus on the state-of-the-art decision-making and control

approaches for DSM, followed by a comprehensive description of demand side applications detailed for smart users, distribution networks and transmission networks.

Afterwards, we characterize our novel methodologies presented in this thesis in two main parts including centralized and decentralized/distributed approaches.

In the first part, we present five novel robust centralized DSM approaches for the optimal scheduling of residential microgrids (MGs) comprising a number of interconnected end-use consumers with various types of electrical loads, RESs, ESSs, and plug-in electric vehicles (PEVs). The general objective of the optimal scheduling is minimizing the expected electricity cost while satisfying device/comfort/contractual constraints of the system under the uncertainties on RES generation and users' electricity demand. In addition, we deal with the conservativeness of the proposed approaches for different scenarios in terms of the cost saving, the peak-to-average ratio (PAR), and the constraints' violation rate. The proposed robust DSM approaches allow the decision maker (i.e., the energy manager of the system) to make a satisfactory trade-off between the electricity cost and constraints' violation rate considering the system technical limits and the users' comfort. We validate the effectiveness of the proposed approaches on several simulated case studies and provide comparisons and discussions on the results.

In the second part, we explore decentralized and distributed DSM approaches for the coordinated optimal charge control of PEVs in SGs. In particular, we develop a novel fully distributed control strategy for the optimal charging of large-scale PEV fleets aiming at the minimization of the aggregated charging cost and battery degradation, while satisfying the PEVs' individual load requirements and the overall grid congestion limits. The proposed resolution algorithm requires a minimal shared information between PEVs that communicate only with their neighbors without relying on a central aggregator. Thus, it guarantees the PEV users' privacy. We validate the proposed approach on numerical experiments with a large number of PEVs to demonstrate the ability of the approach in finding a global optimum solution with a favorable computational efficiency. Moreover, we present a new robust decentralized framework for day-ahead charge control of PEV fleets under uncertainties on the dynamic electricity price and the inelastic loads demand. The main objective of this work is minimizing both the overall charging cost and the aggregated battery degradation cost of PEVs while preserving the robustness of the solution against perturbations in the uncertain parameters. In addition, power congestion limits of the overall capacity of the distribution network and the PEVs' individual needs such as charge level requirements and battery degradation cost are taken into account.

Thesis Supervisor: Mariagrazia Dotoli

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1. Introduction

1.1. Background and motivation

The electric grid is going through a great technological evolution with the development of the SG concept. This evolution impacts the whole electricity supply chain (i.e., electricity generation, distribution, consumption, storage, and load management) and all the involved actors, allowing an effective integration of RESs and more interaction between the supply side and the demand side of the electric grid [1]. The development of SGs as a result of the integration of control, information and communication technologies has provided a unique opportunity for energy companies and consumers to effectively communicate with each other for the management of the energy demand [2]. This ability, which is called demand-side management (DSM) and is known as a key property of the SG, is widely acknowledged as an important source of flexibility and an essential element to balance supply and demand more effectively. DSM programs are adopted to use the available energy more efficiently without the need to expand new generation and transmission infrastructure [3]. In this context, demand-side flexibility can be described as an extend of the energy demand that could be reduced, increased or shifted in a specific period [4]. Demand-side flexibility sources, such as DERs, can effectively participate in DSM programs to profit different power system stakeholders in transmission, distribution and end-use levels of the electric grid. Whereas end-use consumers have conventionally been a passive part of the electric grid, DSM technologies now enable them to be actively involved in the energy sector renovation process. Traditionally, DSM programs were applied to large electricity users to make them more active contributors by encouraging them economically. However, it has by now become evident that small end users such as smart homes can be seen as key enablers for the transition toward a low-carbon, low-electricity cost and self-controllable energy sector, ensuring the efficient and sustainable use of natural resources from the electricity provider and consumer perspectives. Letting the consumers automatically control and manage their individual consumption patterns, combined with mechanisms for the electricity price management, results in an electric grid that is more secure and efficient, easier to operate, and that simultaneously facilitates the integration of DERs and ESSs. Despite the broad benefits of DSM programs for both electricity providers (the supply side) and consumers (the demand side), in the field test environment, the dynamic behavior of the energy system components and the presence of unexpected disturbances in some electricity resources and users' demand impose many challenges to the optimal design of a DSM program. For instance, the inherent intermittency of RES generation (e.g., photovoltaic systems (PVSs) or domestic wind turbines (DWTs)) enforces significant forecast uncertainty to the supply side [5]. On the other hand, the users' electricity demand is largely affected by demand-side uncertainty, due to the unpredictable changes in users' preferences. In this context, the presence of forecast errors may endanger the security of the system operation [6]. Therefore, there is an emerging need to define advanced energy management strategies to tackle the issue of forecast uncertainty. Accordingly, this thesis aims to propose several centralized and distributed/decentralized DSM approaches which are robust, generic and flexible as they can be applied to different structures of energy systems considering various types of uncertainty in local energy generation or demand.

1.2. Thesis objectives and research contributions

This research is divided into three main parts, which are briefly explained in the sequel.

In the first part of the thesis, we present a comprehensive classification, review and analysis of DSM approaches and findings to highlight key features and components of energy management for more flexible and intelligent grids. We provide a definition of DSM and introduce the reader to the functionalities and achievements of DSM applications in SGs. We then present a critical review of the decision-making and control approaches for DSM, followed by a comprehensive description of demand-side applications detailed for smart users, distribution networks and transmission networks. We conclude this part by discussing and suggesting relevant and promising future research directions in each domain.

In the second part of the thesis, we focus on exploring centralized techniques for the energy management of smart residential users under forecast uncertainty. We present several novel day-ahead and online energy scheduling approaches for residential MGs. The main elements of novelty and original contributions of this part can be summarized as follows:

1) We present several models and systematic robust methodologies to state and solve the optimal energy scheduling problem of residential MGs with multiple components incorporating controllable loads (CLs), non-controllable loads (NCLs), RESs, energy ESSs and PEVs. Furthermore, we investigate the cases when the smart users can share

a given number of RESs and ESSs under dynamic linear or quadratic pricing, and when the MG is further able to sell its extra power back to the electric grid.

2) We deal with the forecast uncertainty caused by the RESs energy profiles, as well as the users' energy demand. The uncertainty in both the objective function and some corresponding contractual constraints is addressed. The problem includes uncertain terms both in the objective function and in the left-hand side (LHS) and the right-hand side (RHS) of the inequality constraints. To the best of our knowledge, no robust quadratic programming approach for the energy scheduling of the residential MGs has ever been proposed to tackle the uncertainties associated with RES energy generation and users' energy demand under quadratic pricing.
3) We propose frameworks which are generic and flexible as they can be applied to different structures of MGs considering various types of uncertainty in energy generation or demand.
4) We deal with the conservativeness of the proposed approaches for different scenarios and quantify the effects of the budget of uncertainty on the cost saving, the PAR and the constraints' violation rate. Our proposed robust approaches enable the decision maker (i.e., the energy manager of the MG) to make a trade-off between the users' payment and constraints' violation rate by adjusting the values of the budget of uncertainty.

In the third part of the thesis, we focus on exploring novel decentralized/distributed techniques for the energy management of PEV fleets in a SG. Firstly, we present a distributed approach for the charge control of PEV fleets considering grid congestion and battery degradation. The main elements of novelty and original contributions of the proposed approach can be summarized as follows:

1) we address the optimal charging of PEV fleets tackling both the power capacity limits related to the distribution network and the impact of charging strategies on battery degradation, in order to preserve the reliability and efficiency of both the electric grid and the individual PEVs.
2) we establish a novel fully distributed control strategy for the optimal charging of large-scale PEV fleets, in order to coordinate PEVs and eliminate the need for a central coordinator, reducing the computational complexity and guaranteeing the PEV users' privacy. Our objective is obtaining a global optimum solution which minimizes the aggregated charging cost and battery degradation cost based on the PEVs' individual satisfactions and requirements. Considering a realistic quadratic cost function for the energy purchased from the electric grid, and a quadratic PEVs battery degradation model as well, we formulate the optimization problem as a convex quadratic programming (QP) problem, where all the PEVs' decision variables are coupled both

via the objective function and some grid resource sharing constraints. Hence, we adopt the distributed control algorithm for waterfilling of Networked Control Systems (NCSs) with coupling constraints to solve our iterative distributed strategy effectively.

Secondly, we propose a novel robust decentralized charge control approach for large-scale PEV fleets in a system incorporating multiple PEVs as well as inelastic loads connected to the power grid under power flow limits. We aim at minimizing both the overall charging energy payment and the aggregated battery degradation cost of PEVs in the presence of data uncertainty. We take into account the power congestion limits of the overall capacity of the distribution network and the PEVs' individual needs such as charge level requirements and battery degradation cost. The main elements of novelty and original contributions of the proposed approach can be summarized as follows:

1) We present a novel mathematical model and an iterative coordinated framework, without relying on a central decision-maker, using an extended Jacobi-Proximal Alternating Direction Method of Multipliers (ADMM) algorithm [7] to minimize the aggregated charging cost of large-scale PEV fleets under both PEVs' individual requirements and grid power flow limits.
2) We account for the data uncertainties associated with the dynamic electricity price and the inelastic load demand by formulating a robust counterpart of the charge scheduling problem using the so-called uncertainty set-based robust optimization where uncertain parameters are assumed to take their values from different domain sets independently.
3) We define suitable robustness factors to mitigate the conservativeness of the proposed approach and we investigate the effects of such robustness factors on the robustness of the solution against variations of the uncertain parameters within the given uncertainty sets.

1.2.1. List of publications by the author

Journal Articles:

I. S. M. Hosseini, R. Carli and M. Dotoli, "Robust Optimal Energy Management of a Residential Microgrid Under Uncertainties on Demand and Renewable Power Generation," in *IEEE Transactions on Automation Science and Engineering*, 2020. doi: 10.1109/TASE.2020.2986269.
II. S. M. Hosseini, R. Carli, G. Cavone, M. Dotoli, "Distributed Control of Electric Vehicle Fleets Considering Grid Congestion and Battery Degradation," in *Internet Technology Letters*, vol. 3, no. 3, pp. 1-6, 2020. doi: 10.1002/itl2.161.

III. S. M. Hosseini, A. Parisio, R. Carli and M. Dotoli, “Decision and Control Approaches for Demand-side Management in Smart Grids: A Survey,” in *IEEE Transactions on Control Systems Technology* – under submission.

Conference Proceedings:

I. S. M. Hosseini, R. Carli, A. Parisio and M. Dotoli, “Robust Decentralized Charge Control of Electric Vehicles under Uncertainty on Inelastic Demand and Energy Pricing,” *IEEE International Conference on Systems, Man, and Cybernetics (SMC),* Toronto, Canada, Oct 11-14, 2020.

II. S.M. Hosseini, R. Carli, M. Dotoli, “Robust Day-ahead Energy Scheduling of a Smart Residential User under Uncertainty,” *IEEE European Control Conference (ECC),* Naples, Italy, June 25-28, 2019.

III. S.M. Hosseini, R. Carli, M. Dotoli, “Robust Energy Scheduling of Interconnected Smart Homes with Shared Energy Storage under Quadratic Pricing,” *IEEE International Conference on Automation Science and Engineering (CASE)*, Vancouver, Canada, August 22-26, 2019.

IV. S.M. Hosseini, R. Carli, M. Dotoli, “A Residential Demand-Side Management Strategy under Nonlinear Pricing Based on Robust Model Predictive Control,” *IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Bari, Italy, October 6-9, 2019.

V. S.M. Hosseini, R. Carli, M. Dotoli, “Model Predictive Control for Real-Time Residential Energy Scheduling under Uncertainties,” *IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Miazaki, Japan, October 7-10, 2018.

VI. S.M. Hosseini, R. Carli, G. Cavone, M. Dotoli, “Distributed Control of Electric Vehicles Charging Considering Grid Congestion and Battery Degradation,” *International Workshop on Smart Mobility in Future Cities (SMFC)*, Bari, Italy, October 6, 2019.

VII. S.M. Hosseini, R. Carli, M. Dotoli, “A Model Predictive Control Based Scheduling of Energy Systems with Shared Energy Generation and Storage”, *Extended Research Abstract*, Poliba PhDays, Bari, Italy, December 11-12, 2017

1.3. Thesis structure

The rest of this thesis is structured as follows: Chapter 2 presents an overview of the key features and components of DSM for flexible and intelligent grids, with a particular focus on decision-making and control aspects. In order to provide readers an exhaustive overview of the SG development and DSM routemap within the last decade, we conduct a detailed analysis of the various decision-making and control approaches available in the literature. We categorize them in three main application domains, namely smart end users, transmission network and distribution network. We cluster all surveyed publications according to these three domains to present a systematically structured survey. In Chapter 3, we present five centralized DSM approaches aiming at providing a cost-effective solution for energy management of residential MGs under different technical/operational/contractual/ constraints in presence of both generation and demand uncertainties. Firstly, we propose a day-ahead robust approach based on a box uncertainty set model for the optimal scheduling of a residential MG. Then, we present an online approach based on model predictive control (MPC) and another online approach based on robust MPC (RMPC) regarding the cardinality-constrained uncertainty set model for the DSM of residential MG. Finally, we present a comprehensive model and a systematic robust methodology to state and solve the optimal energy scheduling problem of a grid-connected residential MG with several users incorporating individually owned RESs, NCLs, energy-based and comfort-based CLs, and PEVs. In Chapter 4, we firstly address the problem of coordinated energy management of PEVs in SGs considering grid congestion and battery degradation, then we present a fully distributed control strategy for the optimal charging of large-scale PEV fleets aiming to minimize the aggregated charging cost and battery degradation, while satisfying the PEVs' individual load requirements and the overall grid congestion limits. Furthermore, we propose a novel robust control algorithm to optimally control the battery charging of electric vehicles under grid resource sharing constraints in a decentralized fashion. We tackle the uncertainties on the dynamic electricity price and the inelastic load demands to preserve the robustness of the approach against the disturbances. The thesis ends with conclusions and future work proposals presented in Chapter 5.

2. Demand-side Management in Smart Grids; Background, Opportunities and Challenges

2.1. Introduction

DSM refers to *technologies, actions and programmes on the demand-side of energy metres that seek to manage or decrease energy consumption, in order to reduce total energy system expenditures or contribute to the achievement of policy objectives such as emissions reduction or balancing supply and demand* [8]. Another well accepted definition states that *Demand-side management is 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, that is, changes in the time pattern and magnitude of a utility's load* [9],[10].

DSM encompasses a broad range of programs, from classical direct consumer load control to ancillary service provision, and can include energy conservation, energy efficiency, costumer generation, and demand response (DR) programs [8],[10]. In particular, DR is defined *as changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized* by the U.S. Department of Energy (DOE) and the Federal Energy Regulatory Commission (FERC) [11],[12].

DSM is widely acknowledged as an important source of flexibility and then as an essential element to balance supply and demand more effectively in intelligent and sustainable power grids. The implementation of DSM programs can aid in improving stability and reliability of the grid, in addition to the many advantages for consumers. For instance, DERs, especially local RESs and ESSs, can provide consumer's demand in hours of high energy prices, which reduces the dependence of consumers on the grid. The shifting of the consumers' demand from high energy price periods to lower energy price periods reduces consumers' energy costs and reduce the amount of peak demand on the network. Reducing unnecessary loads at the certain periods (peak demand period or at the request of the system operator) will lead to further savings in energy consumption and cost reduction.

Demand-side flexibility sources can effectively participate in DSM programs to profit various power system stakeholders in transmission, distribution, and costumer levels of the power grid. Several flexibility sources are expected to be increasingly available in power systems, such as:

- dispatchable energy resources (i.e., distributed generation and distributed storage, including multi-energy generation such as cogeneration or combined heat and power (CHP));
- flexible loads (e.g., smart appliances, heating, ventilation, and air conditioning (HVAC) systems, heat pumps (HPs) and electric vehicles (EVs) with smart charging);
- technical and commercial aggregation structures (e.g., virtual power plants (VPP), microgrids (MGs), aggregators, virtual storage plants (VSP));
- local markets for balancing and demand-side services.

Novel control and decision-making frameworks will be the backbone of a more intelligent and sustainable power system, and control is the cornerstone of an efficient DSM as well [13],[14]. The advances in information and communication technologies and control can make DSM a viable and attractive solution to increase the power system flexibility and the penetration of RESs. To this end, future power systems are expected to integrate these intelligent technologies across the entire system, from electric power generation, transmission, and distribution to final electricity consumers.

Taking advantages of the demand-side flexibility sources, the development of DSM aims at contributing to 1) reduce the costs of energy consumption, system operation, maintenance, and planning; 2) guarantee the controllability, observability and stability of the power system; 3) enhance the sustainability, reliability and security of the grid support services [15].

Significant research has been devoted to the design and implementation of control and decision-making frameworks for DSM, with particular focus on energy efficiency and DR. Researchers have explored the application of DSM to diverse areas, such as frequency control [16], peak demand shaving in datacenters coupled with battery storage systems [17], capacity credit of renewable energy sources [18], transmission expansion and investment deferral [19]. However, a review of the extensive body of studies on control and decision-making frameworks for DSM is missing. Hence, a thorough exploration of this timely and relevant topic, with a particular emphasis on the current barriers, concerns and possible control solutions for an efficient and holistic design of DSM programs is a great matter of importance to spotlight the pathway of ongoing and future research.

2.2. Motivation and Contributions

Several review papers and surveys can be found in the literature focusing on DSM and its classification from different perspectives. For instance, a group of papers overview the existing literature on the role of DSM in open electricity markets [20],[21],[22],[23]. The authors in [23] discuss the state-of-the-art on electricity retail decision-making schemes, including long-term retailer load forecasting, energy procurement strategies, retail pricing schemes, and risk management in the retail market. Other studies only focuses on the application of DSM in specific sectors, for instance, in residential area, where DSM optimization strategies aim to reduce the operational costs and the peak load demand [24],[25],[26]. In particular, the authors in [25] review the literature on the home energy management systems (HEMS) that integrate DR programs, smart technologies, and load scheduling controllers. They compare the effectiveness of various heuristic optimization techniques in terms of computational speed and complexity. The survey [27] overviews DR programs applying on end-users in SGs. The authors focus on two major branches of DR programs, namely incentive-based DR programs where customers are paid by utilities for participating in demand reduction in the case of emergencies, and price-based DR programs where customers change their demand in response to time-varying electricity price signals in different time periods. They also explore some commonly used mathematical models and problem formulations in the context of DR. The authors in [28] classify DR models and characterize them according to six different features including thematic properties referring to the research content, methodological properties including models and mathematical perspectives, temporal properties regarding models' temporal perspective and resolution, spatial properties including geographic location, technological properties according to energy demand sectors and practical properties referring to the type of DR activity such as price- and incentive based measures. Furthermore, in [29] the state-of-the-art on modeling, operation strategy and market behavior of integrated DR programs in multi-energy systems (MES) as well as their applications throughout the world is investigated.

The previous survey and review papers mostly focus on DR and on individual power-related aspects as well as on electricity markets. Hence, there is a lack of a comprehensive survey on decision-making and control strategies for DSM, which not only covers the impacts of DSM programs on the actors in downstream power network, i.e., individual energy consumers, but also takes thoroughly into consideration the benefits to the upstream power network i.e., to the aggregation of generators and consumers/prosumers connected to the distribution network (DN) as well as to the transmission network and to the network as a whole, through the provision of adequate ancillary services.

Aiming at filling this gap, this work reviews the key features and components of DSM for more flexible and intelligent grids, with a particular focus on decision-making and control aspects. In order to provide to the readers an exhaustive overview of the SG development and DSM routemap within the last decade, we conduct a detailed analysis of the various optimization and control approaches available in the literature. They can be categorized in three main domains, namely smart end-users, transmission level and distribution level. We cluster all surveyed publications according to these three domains to present a systematically structured survey. We conclude this survey by discussing and suggesting relevant and promising future research directions in each domain.

In the remainder of the paper the existing studies on the decision-making and control approaches for DSM applications are classified and reviewed. The background information of the main decision-making/control structures in SGs is firstly introduced in Section 2.3. Section 2.4 gives a summary of existing studies on uncertainty consideration in DSM strategies. Section 2.5 outlines some important DSM research categories applied to the power system. Section 2.6 comprehensively illustrates the main decision-making and control strategies focusing on individual smart users, whilst Sections 2.7 and 2.8 explore the related works at distribution and transmission levels, respectively. Section 2.9 presents the current research gaps and the future research directions. Finally, the paper ends with conclusions in Section 2.10.

2.3. Methodology: selection and classification of the papers for the review

In order to provide a comprehensive overview of the research topic, we adopted a systematic search strategy by following some critical steps for finding the most relevant and principal research papers to the topic. Firstly, we selected a large sample of related papers from two important databases of high quality and innovative papers, i.e., *Science Direct* and *IEEE Xplore* databases, which have various advanced search options for a precise search, as well as from some important technical reports databases such as *Pacific Northwest National Laboratory (PNNL)* and *Energy Policy Acts*. Then, we used a list of research terms including "*demand-side management*", "*demand response*", "*energy efficiency*" and "*energy management*", also once alongside the keywords "*decision making*", "*control*" as well as "*smart users*", "*distribution network*" and "*transmission network*" to search for the relevant articles. In total, we selected 1034 scientific publications in this step.

Then, for the sake of filtering the sheer number of extracted papers and selecting the most updated, cited and relevant researches in the context, we firstly considered a time/citation filtering frame for the resulting papers consisting of three sub-frames as: (*f.1*) the papers published during the last two years from 2019 to January 2021, (*f.2*) the papers published from 2016 to the end of 2018 and were cited more than 5 times, and (*f.3*) the papers published from 2013 to the end of 2015 and were cited at least 15 times. Accordingly, the review totally covers the last 8 years of related literature with threshold criteria of being updated and/or being highly cited. In the next step, we deeply reviewed the remaining papers according to the topics of focus in terms of conceptual, theoretical, and methodological aspects to organize the structure of the review, intended sections and sub-sections. Within this step, we also applied a further filter on the publications to only keep the related papers with a special focus on the decision-making and control while clustered them according to their applications to the different power levels from transmission to distribution and consumption levels as well. After distinguishing authoritative and critical perspectives to the topic and defining a precise structure for the review, we launched a new search in the same databases considering all defined topics and sub-topics to achieve a highly comprehensive dataset of various related research efforts. A final filtering was made to remove duplicate papers or unrelated papers to the topics. Lastly, we analyzed each group of papers to include logical research patterns, and to provide a degree of analysis and conceptual information while identifying research gaps and pointing the way for future work.

In total, we reviewed 295 publications, of which 38% were placed within the frame *f.1*, 37% within the frame *f.2*, and the remaining 25% within the frame *f.3*.

Looking at all publications investigated in this review, on the one hand, the decision-making and control approaches for DSM in terms of methodological perspective were clustered into the following categories:

- Optimization techniques/algorithms
- Transactive control
- Artificial intelligence approaches
- Optimal control and dynamic programming
- Model predictive control
- Game theory
- Multi-agent systems

On the other hand, we classify the applications of decision-making and control approaches for DSM regarding the following stakeholders:

- Smart users (i.e., residential/commercial/industrial consumers, electric transport, and public facilities)
- Distribution network
- Transmission network

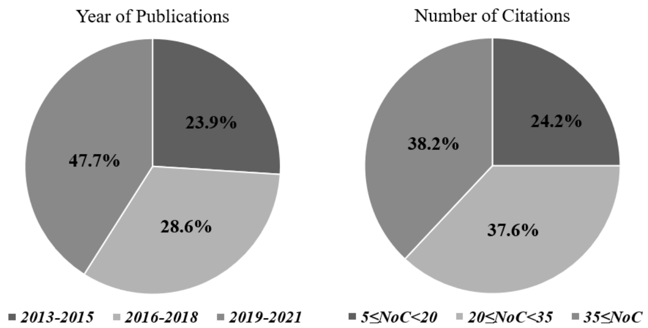


Fig. 1. Statistical percentage of reviewed publications in terms of (a) year of publications, and (b) number of citations

A statistical report of all surveyed articles in this work in terms of years of publication and number of citations is shown in Fig. 1. The general overview on the methodological-based content cluster as well as the application-based content cluster of the research topics investigated in this review are depicted in Fig. 2 and Fig. 3, respectively.

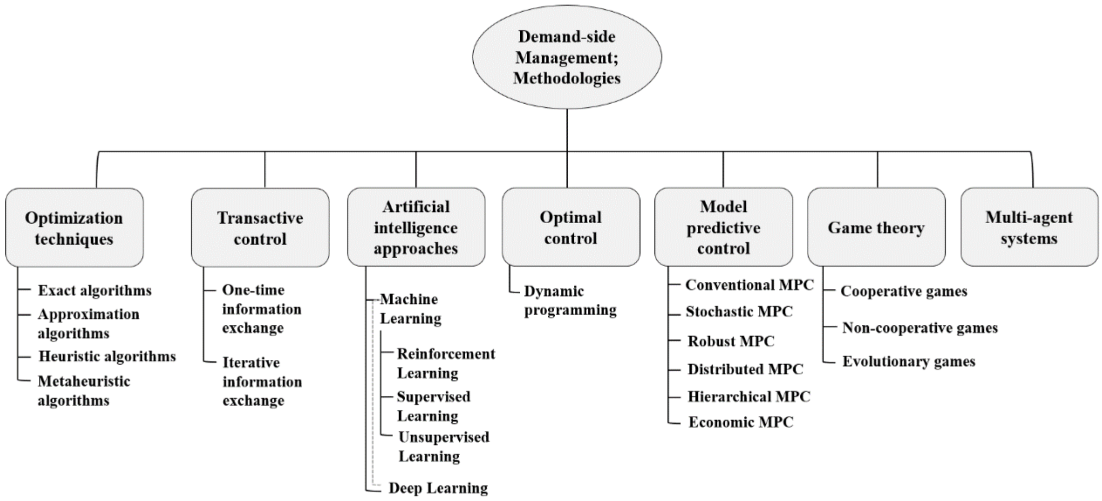


Fig. 2. An overlook on the state of the art on DSM topic in terms of methodologies

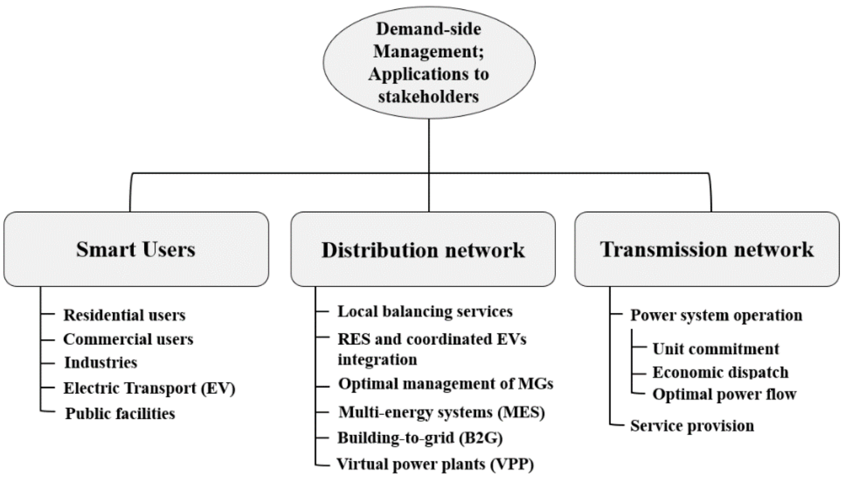


Fig. 3. An overlook on the state of the art on DSM topic in terms of applications to the main power system stakeholders

2.4. Decision-making/control structure

In this section we introduce main decision-making/control structures regarding physical, interaction and communication architectures of control, information units and system components. In this regard, three main architectures can be distinguished: centralized, decentralized, and distributed systems. Although a full exploration of these three architectures is beyond the scope of this paper, we aim at identifying some of their key characteristics, advantages, and drawbacks together with recent developments within the context.

2.4.1. Centralized systems

Indeed, in a centralized system, a central server is in charge of collecting all the information from individual subsystems and forecasting systems to centrally perform the decision-making/control task of all subsystems [30]. The centralized architecture has been a prevalent and effective control schema that has dominated control systems for years. In the context of energy management, analytical and conceptual models of centralized decision-making and control for smart systems' operation are widely provided in the literature with various objectives such as reducing total energy costs and enhancing energy savings [31],[32], declining peak-to-average ratio (PAR) of demand profiles with beneficial impacts on the efficiency of generation, transmission and distribution systems [33],[34], and maintaining grid stability [35],[36]. In all aforementioned works, customers send a request as subsystems to a central authority and receive the response decision. From an important perspective, centralized decision making and control approaches can be further categorized into so called *offline algorithms* such as day-ahead or multiple-day-ahead approaches [32]-[38] where the decision-making/control task is executed once upon a defined time window, and so called *online algorithms* such as iterative real-time approaches [31],[39],[40] where the decision-making/control task is repeatedly performed over a time window while gathering data, processing them, and updating the system at each time slot. Whereas the former group usually ignores the dynamic behavior of the system as well as the intermittency and variability of parameters (except for stochastic and robust methodologies [34],[36]), the latter group frequently monitors the system in real time for responding to the sudden change of system inputs. Although most of decision-making and control techniques for DSM in literature has been developed in a centralized setting, this paradigm has evident limitations which overshadow its potential benefits. The centralized techniques generally show effective results and are usually easy to implement. However, they suffer from poor privacy protection of users, for instance in the energy scheduling of appliances where users may not be comfortable with the idea of seeing their appliances controlled by someone else. Moreover, centralized techniques have limited communication capability among the subsystems and limited computation ability in one single controller for large-scale systems. Indeed, the practical realization of energy management techniques, in particular for large-scale power systems consisting of various interconnected DER or subsystems with more complicated processing of measurements and control computation, necessitates more systematic approaches with more advanced information interfaces. Motivated by this necessity, most recent studies are alternatively oriented toward decentralized and distributed approaches.

2.4.2. Decentralized systems

In a decentralized system, the computation is distributed across several local servers, but a centralized authority oversees collecting information from each subsystem and transmitting updates to all of them [41]. In such systems, users are considered as independent decision-makers/controller under the influence of the central authority and/or other users. For instance, in [42] a decentralized control structure based on genetic algorithm is proposed for the energy management of smart homes with RES and ESS aiming to minimize the daily electricity bill of the users. The authors define a multi-agent system to model the entities of the power grid where the utility company, the smart homes and a central authority are considered as agents. They consider the central authority as a third-party entity that can receive electricity profiles data from the smart homes, determine the aggregated neighborhood profile and dynamic price, and finally send the updated data back to the smart homes. The work of [43] deals with a similar problem but by employing a decentralized online algorithm to minimize total energy bills of smart homes within a neighborhood, while further taking into account the uncertainty on RES generation. They assume a central authority that is responsible for purchasing enough electricity from wholesale electricity markets. The central authority only requires the total grid energy usage for all smart homes to preserve the privacy of the users. However, the algorithm ignores the possibility of two-way electricity transfers between smart homes and the power grid. The authors in [44] propose an agent-based decentralized decision-making approach based on a reinforcement learning (RL) for a cluster of non-residential buildings to minimize the energy use and to maximize the buildings' comfort. An example of a decentralized DSM strategy for the optimal control of large-scale plug-in hybrid electric vehicles (HEVs) is presented in [45] aiming at minimizing the charging cost and the battery degradation for each user. The most aforementioned studies have addressed only one single type of energy, optimizing either electrical or thermal energy. However, other group of DSM techniques are also implemented for enhancing the efficiency, the flexibility and the scalability of the whole energy system including different sources of energy (i.e., electricity, heat, and gas) [46],[47]. For instance, the authors in [47] suggest a fully decentralized decision-making approach for a multi-energy system (MES) comprising various types of flexible and hybrid energy appliances. The authors further compare the performance of the proposed decentralized approach with a centralized approach using a test case study. They demonstrate that although the decentralized approach might end up in a local minimum in some cases, but it offers an efficient performance for dealing with scalability as well as flexibility due to smaller local optimization problems. It is worth noting that a drawback of such decentralized systems is that each local controller is generally operate by ignoring the interactions from other subsystems and by solely using its locally available information. Therefore, the controllability of the system is restricted, deteriorating the system control performance. One typical example of such deficiency in power grids is the widespread blackout in North American in August 2003, where each subsystem only focused on preserving its own stability and transferred the extra load to other subsystems and eventually caused a severe overload and cascading corruption [48]. These challenges can be tackled by letting the local controllers communicate with their neighboring controllers to establish a distributed control system.

2.4.3. Distributed systems

Differently from a decentralized system, in a distributed system not only the computation but also the communication between subsystems is distributed, and local controllers can exchange information with neighboring controllers [41]. A distributed system usually consists of many interconnected users, which are required to cooperate for obtaining a desirable global objective [49]. In such systems, each user is considered as a local controller which performs local computation based on its own information and those received from its neighboring users through the underlying communication network. The associated benefits with distributed approaches, such as high privacy protection, high flexibility and scalability, reduced communication overhead and robustness to failures, have recently led scholars to further develop distributed decision-making and control approaches for DSM applications. Various methods can be found in literature for the realization of distributed DSM techniques in SGs. Among them, the most prominent approaches are based on dual decomposition [50]-[52] and alternating direction method of multipliers (ADMM) [53]-[56]. For instance, the dual decomposition, where the original large-scale problem is broken up into smaller sub-problems and the coupling between sub-problems is relaxed using Lagrange multipliers, is adopted in [50] for the distributed energy management of a MG with high penetration of RES. The objective is to reduce the cost of conventional generation while maintaining the constraint of the supply-demand balance affected by the intermittency of RES. Instead, the ADMM approach, which is another advanced method for splitting the original large-scale problem into smaller sub-problems with a property of high accuracy, convergency and decomposability, is proposed in [53] for multi-agent system (MAS) based MGs. In the proposed approach, the agents (i.e., local controllers) can defer/skip the computation and transmission of updates. It means that each agent can update its local information and communicate with their neighbors relying on its own local timer without a global synchronization, leading to an efficient and fully distributed solution for saving the overall energy cost of MGs. Due to the great scalability feature of distributed approaches, a bunch of distributed algorithms are proposed for coordinated optimal charging of large-scale EVs fleets in SGs. For example, the work of [57] introduce a distributed EVs' charging strategy to smooth the daily grid load profile concerning communication and computational overhead as well as EV users' privacy. In addition, a distributed approach, so called waterfilling algorithm, subject to individual constraints and coupled waterlevels is developed in [58] and implemented on EVs' fleets for the optimal charging. More recent distributed DSM approaches tackling data uncertainties in the system's parameters using distributed robust methods [59], distributed robust real-time methods [60], and distributed stochastic methods [61]. Summing up, the research on the development of distributed approach for DSM applications are still ongoing to overcome some of its limitations such as challenging set up and developments as well as the presence of uncertainty in the final consensus-based solutions.

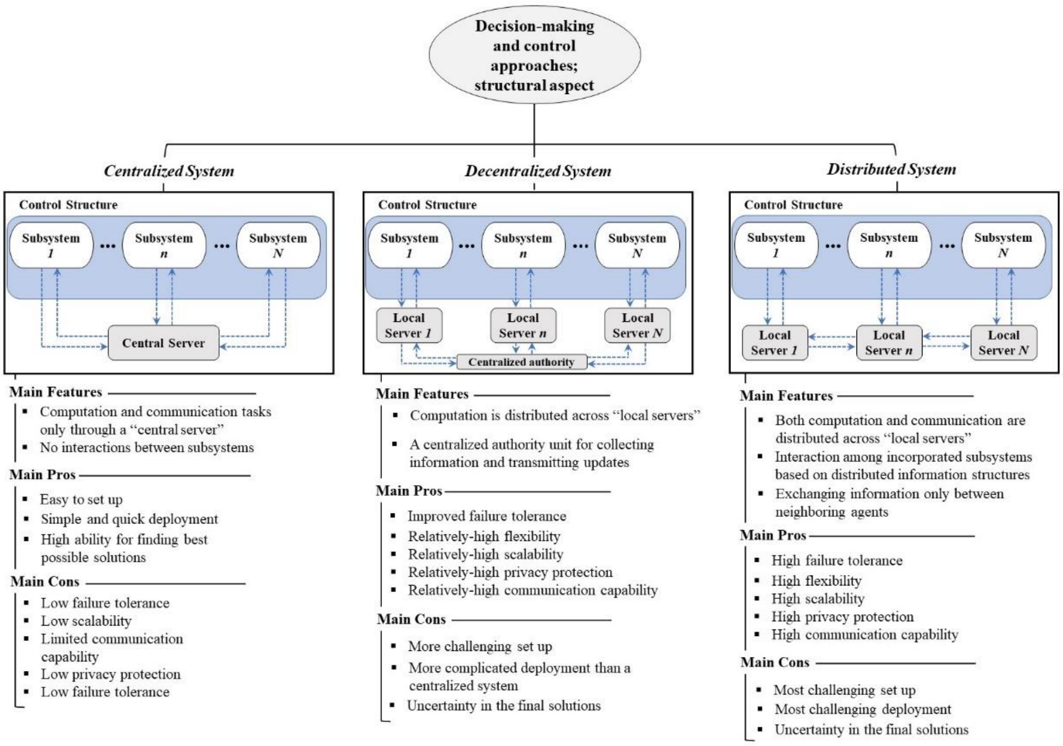


Fig. 4. An overview on the features, pros, and cons of the main decision-making/control structures

2.5. Uncertainty consideration in demand-side management

Real engineering systems are vulnerable to external disturbances and noises, and mathematical models used for the design and the actual system are mostly inconsistent [62]. A crucial challenge in energy management of SGs is to account for the intermittency and variability of uncertain parameters of the system. In fact, an efficient DSM strategy is required to satisfy certain performance levels in the presence of disturbance signals, unmodeled power system dynamics and parameter forecast variations. The deterministic DSM approaches, which do not consider the effects of uncertainties, only focus on finding the best possible system response. However, this response is usually estimated from a limited historical dataset and therefore may be far from the true model with actual parameters [63]. In contrast, uncertainty-based DSM approaches tend to optimize the responses of the system while minimizing the variability of the responses to assess the impact of input uncertainty on the estimated performance measures in a statistically valid and computationally efficient way. Owing to the massive and ever-growing penetration of RES linked to transmission or distribution systems, in particular photovoltaic (PV) systems and wind turbines with intermittent and unpredictable nature, as well as inadvertent users' energy demand (e.g., electricity and heat demands), a considerable amount of uncertainty can be imposed to the power grid design and functioning. Regarding relevant research to the context, the major sources of uncertainty in SGs can be distinguished as the forecast uncertainties in RES generation profiles [34],[36],[43],[59]-[61],[65] users' energy behavior [36],[59], [60],[64] energy price signals [34],[59], and devices' usage times [34]. Coping with these challenges, two widely used sets of approaches for DSM of SGs in uncertain environments including *robust techniques* [50],[59],[60],[64],[66] and *stochastic techniques* [34],[36],[43],[61],[65] are introduced. More specifically, the robust techniques deal with the inconsistency of uncertain parameters by modeling uncertainty sets for guaranteeing the robustness of the solutions against the worst-case outcomes within these sets. For instance, the work of [66] deals with the uncertainty of RES generation in the energy cost minimization problem for a SG by establishing a robust counterpart problem relying on the uncertainty sets of possible realizations of the uncertain parameters. More widely, the authors in [67] consider an optimal energy scheduling problem of a grid-connected MG under uncertainties on both RES generation and users' energy demand trough a cardinality-constrained uncertainty set approach where decision makers can flexibily adjust the level of conservativeness. On the other hand, the stochastic techniques tackle uncertainties by modeling probability distribution functions of uncertain parameters based on statistical data for their successive unknown changes. A comprehensive example of such methodology to deal with the uncertainty in SGs is presented in [34] where a scenario-based stochastic modeling approach is proposed to tackle uncertainties in electricity prices, RES generation and users' behavior in using different types of appliances in a residential environment. In general, while stochastic DSM approaches often show effective performance facing uncertainty, they suffer from some limitations such as the necessity for the knowledge of the probability distribution of uncertain parameters, insufficient historical data for new cases, dependence between some uncertain parameters, and high computational effort due to high number of scenarios.

2.6. Approaches for Demand-side Management

In this section the development of approaches for energy management in different sectors of power systems with ever-increasing complexities and dynamics is surveyed. The main decision-making and control approaches for DSM applications are illustrated and critically reviewed. We present a general overview of the most popular topics of research on DSM in power grids, in particular the optimization techniques, market-based, learning-based, dynamic, and predictive-based control approaches as well as game-theoretical and multi-agent strategies.

2.6.1. Optimization Techniques/Algorithms

Optimization techniques seek to effectively solve the problem of maximizing/minimizing particular functional or operational objectives in a finite dimensional Euclidean space under relevant technical, operational and contractual constraints [68]. Within the SG domains, the main objective of optimization for energy management is to compute a feasible optimal solution for maximizing the overall benefits in terms of the performance criteria and target properties of the system.

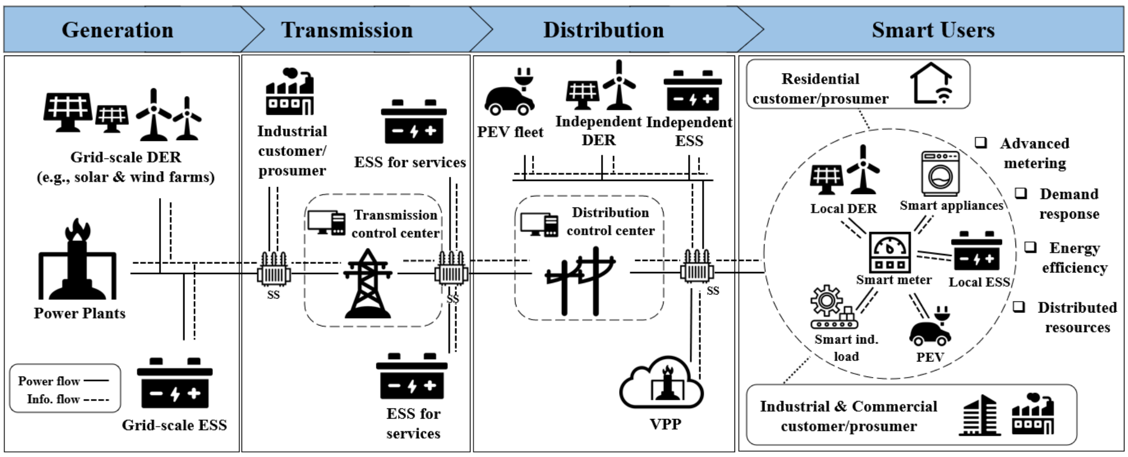


Fig. 5. Different levels of SG architecture including generation, transmission, distribution, and smart users based on two-way power and information flows.

In this regard, optimization techniques mainly provide optimal or near-optimal operational plans for smart loads (e.g., smart appliances [33],[34],[66],[67],[69], HVACs [37],[70], CHPs and HPs [37],[38],[67],[69],[71]), storage systems [32],[66],[67],[69] and EVs [34],[67] aiming at, for instance, minimizing the total energy costs [32]-[34],[37],[38],[66],[69],[71], shaving high-peak demands [33],[34], maximizing costumers' comforts [37],[72] and environmental benefits [69],[71]. The topic of optimization for energy management for different applications is well studied in the technical literature, and in general, the applied methods can be distinguished as exact (also, it is called as deterministic), approximation, heuristic, and metaheuristic algorithms. Within this context, a wide class of studies deal with the optimization problems using exact algorithms that guarantee to find an optimal solution for the optimization problem. For example, the work of [72] presents a technical approach for the energy management of multiple buildings in a MG using a mixed-integer nonlinear programming (MINLP). This paper presents the economic advantages of optimizing the operation of heating, ventilation, and air conditioning units, lighting appliances, PV generation and ESS of each building. The authors solve the cost function via a set of linearization techniques and equivalent representations to convert the original MINLP into a simplified MILP problem. An example of optimization approaches for providing ancillary services is presented in [73] to leverage the participation of EVs for secondary frequency regulation by formulating the problem of frequency support as a MILP problem. The main challenge in the implementation of such algorithms arise when the size and complexity of the problem grow. In more complex large-scale problems, it is generally hard to solve the problem within a rational time by using the exact algorithms. For instance, the optimal energy management of large-scale EVs fleets is usually a large-size multi-objective, nonconvex, and nonlinear optimization problem, which is difficult to be solved by conventional exact algorithms [74]. To this end, recent research efforts are rapidly moving toward finding alternative approaches that can support and capture efficiently the solution of the optimization problems that may not be optimal but are fully acceptable in terms of computation time, such as approximation, heuristic, and metaheuristic algorithms. Approximation algorithms provide an approximate solution with a guarantee of performance in both computation time and solution quality. For instance, the authors in [75] address a multiobjective optimization problem to manage frequency deviations, to handle EV's charge demand, to maximize the vehicle-to-grid (V2G) support to EV users while minimizing EV's battery degradation. This paper adopts an approximation algorithm to decompose the complex multiobjective optimization problem into subproblems, and then to solve the formulated subproblems iteratively using interior point method. In [76] an approximation approach based on search-swapping algorithm (SSA) is proposed for the charging coordination of EVs. The method results in minimizing charging cost, reducing computational cost, improving final state-of-charge (SOC) uniformity, and eliminating charging interruption. Such approximation algorithms crucially require a mathematical proof guaranteeing that the quality of the obtained solutions is within worst-case boundaries. In contrast, heuristic and metaheuristic algorithms such as particle swarm optimization (PSO) and genetic algorithm (GA) try to find reasonably good solutions but generally without a clear indication at the outset on when they may succeed or fail. For example, the authors in [74] present a population-based heuristic approach based on a particle swarm optimization (PSO) for the large-scale utilization of EVs in power systems aiming at minimizing total charging cost, reducing power loss and voltage deviation of the power grid. In [77] a heuristic algorithm is proposed to reduce peak demand on the power grid by intelligent management of electric water heaters (EWHs) with thermal storage capacity. Aiming at reducing electricity cost, PAR, carbon emission, and ensuring users' comfort in residential buildings with huge number of appliances, the recent work of [78] adopt multiple efficient heuristic approaches including hybrid genetic particle swarm optimization (HGPO) algorithm, genetic algorithm (GA), binary particle swarm optimization algorithm (BPSO), ant colony optimization (ACO), wind-driven optimization algorithm (WDO) and bacterial foraging algorithm (BFA) to efficiently schedule smart appliances to obtain the desired objectives. They demonstrate by the simulation results that their proposed optimization technique reduces the electricity cost by 25.55%, PAR by 36.98%, and carbon emission by 24.02% in comparison to the case of without scheduling. The authors in [79] address the energy scheduling problem of smart appliances in residential area by a heuristic approach, and then they evaluate the performance of the method in terms of cost and computation time compared to an exact algorithm. They demonstrate that the cost obtained by the heuristic algorithm is within 5% of the one obtained by the exact algorithm while the computation time is exponentially reduced in the heuristic case.

The common heuristic optimization algorithms, such as PSO, are usually exposed to be easily trapped in certain local minima. Moreover, they are computationally complex, and they show difficulty in selecting optimal control parameters. The author in [80] show that the heuristic energy management algorithm based on binary PSO is relatively inefficient regarding computational time, demonstrating that it is unsuitable for the application in real-time energy scheduling. The other group of research develop metaheuristic algorithms for optimization problems which can be defined as high-level heuristic algorithms with an improved evolution in the search space. An important feature of such metaheuristic approaches is that they do not require particular knowledge on the optimization problems to be solved, then they can be considered as general problem-solving models for other related optimization problems. This feature is interesting in the context of decision-making for energy management of power systems with ever-increasing complexities and dynamics. For instance, metaheuristic algorithms have been recently used for the optimization of ancillary services in power systems. For instance, the authors in [81] propose a metaheuristic optimization algorithm based on a variant of PSO to tackle the problem of energy resource management in MGs. They aim to minimize operating costs and to maximize the revenue of the energy aggregator that accumulate different available energy resources from the MG. The work of [82] compares the performance of three metaheuristic algorithms, namely harmony search algorithm (HSA), an improved harmony search (IHS) algorithm, and biogeography-based optimization (BBO) algorithm (see [82] for more details regarding these three algorithms), for solving the problem of economic dispatch of the power grid, i.e., the economic operation of generation facilities, under various technical power constraints. The author reveal that the HIS algorithm shows a more effective performance than others in terms of lower fuel cost and higher convergence characteristics response.

2.6.2. Transactive Control

Transactive control (TC) is one of the leading control approaches relying on an interaction among agents by economic signals to optimize the allocation of resources. The initial idea of TC was firstly introduced in [83],[84] where it was defined as a type of market-based distributed control to change the operational state of responsive assets so as to obtain an equilibrium between supply and demand through economic incentive signaling. In a transactive DSM, various agents, such as consumers, prosumers, and distributed generation units, automatically negotiate their actions with each other and with the utility system through efficient and scalable electronic market algorithms [85]. Scholars have extensively studied and discussed the benefits of incentive price mechanisms to control electricity demands, alleviate congestions and service provision in electric power systems (see, e.g., [85],[86] and references therein). The applications of TC in the SG domain range from the realization of DR programs in residential and commercial buildings considering grid operational constraints [70],[87],[88],[89] to frequency regulation and control [90] and voltage and congestion management in distribution networks [91]. One way to categorize the methodologies of TC in literature can be elicited from how the methods find an equilibrium among the users and complete the transactions. Accordingly, TC approaches can be differentiated according to their information exchange timing as the approaches with one-time information exchange [70],[88],[89],[91] or iterative information exchange [87],[90]. In the former, participants send the bid of their available flexibility to a coordinator in order to enable the coordinator to find the clearance price through price discovery mechanisms and control the devices accordingly. While in the latter, which mostly relies on the concept of dual decomposition, an upper-level entity repeatedly sends the price signals to a lower-level entity containing all participants and receives the corresponding responses from them. After specific iterations, the clearance price is set by the upper-level entity after meeting operational objectives. An important example of TC applications within DSM paradigm relates to their wide use in different buildings. Various works for TC in residential and commercial buildings offer a special focus on HVAC and Thermostatically Controlled Loads (TCLs) [70],[87],[88],[89]. Two demonstration projects launched by Pacific Northwest National Laboratory implemented on the Olympic Peninsula and the American Electric Power, Ohio (AEP Ohio) are presented in [87],[88] to evaluate the market-based coordination strategies for residential loads. These projects demonstrate the effectiveness of the TC approach in an energy market to efficiently resolve the allocation of HVAC loads during operating interval, and they provide valuable insights for the coordination of residential loads from the practical point of view. A TC mechanism for HVACs in commercial buildings is further proposed in [89] for DR targets. The authors develop the transactive market structure, the distributed transactive market mechanism, and the agents bidding strategies aiming at social welfare maximization and load peak shaving. In [70], a bidding and market clearing strategy based on the coordination of a group of TCLs is presented to maximize a team objective, i.e., the social welfare, with incomplete information (due to the users' privacy) subject to a peak energy constraint. The authors assume a system with a coordinator, which obtains energy from the wholesale market. A potential concern in the formulated problem of this work is that a clearing price may not always exist for an arbitrarily given team optimal solution. To cope with this issue, they present a novel bidding and clearing strategy to guarantee that the cleared price realizes the team optimal solution. The work of [90] develop a hierarchical TC approach in SGs and apply it to an IEEE 30-bus sample system. The control strategy combines market transactions at the higher levels with inter-area and unit-level control at the lower levels aiming to ensure frequency regulation using optimal allocation of resources in the presence of uncertainties in RES and demand, to reduce the cost of reserves, and to increase the social welfare. In [91], a market-based control approach for the DSM of EVs taking the grid constraints into account to avoid voltage drops or overloading of the distribution transformers.

2.6.3. Artificial intelligence approaches

Decision-making and control for DSM targets require intelligent solutions that flexibly address an increasing complexity of the system operation and management in future power systems due to cyber-physical nature and high penetration of heterogeneous components in an unknown, dynamic, and uncertain environment. Analyzing the large deal of data generated by the technologies such as internet-of-Things (IoT) and advanced metering infrastructures (AMI) implemented in such energy systems is sometimes unmanageable for human operators, especially in more complex and scalable systems. This emerges an essential need for automated approaches to analyze the resulting data [92]. Such challenge can be addressed by Artificial Intelligence (AI) technology thanks to its great ability for developing computer programs to perform a variety of tasks, and to simulate the intelligent way of problem solving by humans [93]. Recently, AI approaches are employing to forecast electricity or thermal demands [94]-[99], system protection device errors [100] and electricity pricing [95],[101], to optimize decisions of EVs [102],[103], and to provide better stability and efficiency of the power grid [101]. The work of [92] presents a comprehensive and detailed overview on the trend of AI approaches for DR applications, and it shows the growing interest of the research and industrial communities for AI approaches in the DR sector between 2009 and 2019. A wide look at the research works going on the topic of control and energy management in power grids shows that a vast research is being conducting on two core subsets of AI, namely *machine learning (ML)* [94]-[99],[101],[105] and *deep learning (DL)* [102],[103],[106],[107],[108]. ML relies on working on datasets to learn a group of actions from data by examining and comparing them to automatically identify common patterns, employ these patterns for prediction, and solve control/decision making problems in an uncertain and dynamic environment [104]. Depending on the type of the data and the model to be created, ML-based approaches can be broadly categorized into *supervised learning (SL)* [94],[95], *unsupervised learning (USL)* [96],[97] and *reinforcement learning (RL)* [98],[99],[101],[105] approaches (see [104] for more details). A SL assumes an available labelled set of input-output pairs for all training samples to train an algorithm with a known set of input data and known responses to make predictions. SL-based approaches have been extensively adopted to predict the users' demand [94], distributed generation and electricity prices [95]. For example, the work of [94] presents two ML-based approaches for enhancing the accuracy of load prediction in a large-scale residential area. The authors develop a multi-layer neural network architecture to increase the prediction accuracy. A case study is investigated based on a dataset of 8-week electricity consumptions at 1-hour resolution from 2337 residential customers, where the first 7 weeks' data was devoted to train the model and the last week data was used to validate the results. They demonstrate that their proposed SL approach allows multiple residential customers to obtain an acceptable load prediction over 94%. Unlike SL-based approaches, a USL-based approach only uses a series of input values without any corresponding target value. In this case, the goal is to detect clusters of similar examples in a dataset. An advantage of USL-based approaches compared to SL-based approaches is that they can be applied to a more extensive types of problems as they do not require labelled data which are usually difficult to gain. The wide use of USL-based approaches for DSM targets can be observed in finding typical shapes of users' load profiles, identifying potential group of users for DR targets, and discovering the loads which are contributing to the DR programs. A UCL-based clustering approach applied to smart meters energy consumption is proposed in [96] to extract critical information from data aiming at achieving efficient energy demand management while considering users' behavior uncertainty in orders, times, and frequencies of appliances usage. The work of [97] deals with one of the major challenges with the application of USL in energy monitoring process of smart homes, i.e., high computational complexity, through a fuzzy clustering algorithm. The authors provide an experimental evaluation of the method to demonstrate the great ability of the algorithm to learn useful appliance models in unseen energy data. RL is another subset of ML that enables an agent to learn through interacting with an uncertain environment. In contrast to the USL, it trains the machine through a trial-and-error process using a feedback from its actions and experiences instead of sample data. The dominant applications of RL in decision-making and control programs is related to energy scheduling of EVs and appliances relying on interactions with users to take the users' preferences into account. RL-based approaches have also adopted for DR targets at consumer and service provider levels [98],[99],[105], as well as for learning DR pricing mechanisms [101]. For example, a RL technique is proposed in [98] to obtain the optimal electricity and natural gas consumptions in residential areas. The authors devise a new configuration of smart energy hub (for more detail about energy hubs, see Section VI(E)) based on a cloud computing system and they show that the method can incentivize customers to participate in DR programs by both shifting their energy consumption and changing their energy resources. A RL scheme is further developed in [101] for service providers, which allows them to adaptively calculate the retail electricity price in a hierarchical electricity market. An extension of the fitted Q-iteration as a variant of the batch RL technique is proposed in [99], which can provide a more effective decision-making process for DR programs, when some prior expert knowledge about the system dynamics and the monotonicity of the solution are available. A more detailed overview of the studies with the focus on the applications of RL for DSM at the building level is discussed in [105]. The authors review the state-of-the-art on the applications of RL to control energy systems such as DG, PV systems, EVs, electrical energy storage and HVAC in buildings. They show that most of the relevant papers only focus on single-agent systems with demand-independent electricity prices and a stationary environment, and there is still a need to further explore and develop RL to coordinate multi-agent systems that can participate in DSM programs under demand-dependent electricity prices. Moreover, they propose a standardized evaluation framework for future research to improve the analyzability, comparability, and reproducibility of the results in the diverse problems within the area. DL is another subset of AI, which is also a subset of ML. However, we investigate it separately from other types of ML-based approaches due to its important characteristic for discovering new features to be used for detection and classification in a completely automated manner using deep neural networks. DL relies on a number of processing layers in the neural network to enable the learning of complicated and highly non-linear relationships and correlations. These outstanding features of DL -also sometimes in combination with RL as deep reinforcement learning (DRL)- have been widely adopted in DSM of smart systems to obtain load profile prediction and feature extraction in household- and building-level SGs [106],[107], decision-making tasks for EVs charging [102],[103], and optimal energy management policy for industrial facilities [108]. For instance, a spatial-temporal load forecasting approach is proposed in [106] for household loads taking advantage of a combination of compressive sensing and data decomposition. The authors aim to exploit the low-dimensional structures governing the interactions among the nearby houses. However, a potential challenge may arise when the length of receding horizon and the number of houses increase, so that the size of datasets significantly grows. The interesting work of [107] argue that direct implementation of DL in household load forecasting cannot necessarily improve the obtained results due to more parameters and relatively fewer data in more complex systems. This issue may result in the occurrence of overfitting. To tackle this issue, they a pooling-based DL for forecasting of household loads under high uncertainty and volatility which facilitate learning spatial information shared between interconnected customers to compensate insufficient temporal information. In [102] a deep neural network charging strategy for EV users is proposed to minimize the overall EVs energy cost. The method trains a decision-making model to obtain real-time optimal decisions for smart EVs charging without any knowledge of the future energy prices and the car usage.

Even though a growing interest can be observed in the application of learning-based approaches to address decision-making and control problems, there are still associated downsides which may limit their applicability in real physical systems. For example, these techniques usually require massive data sets and computation which is not always available or expensive in current energy systems, they suffer from curse of dimensionality in large-scale systems such as grid-scale RES adoption or EVs fleets, and they are basically not robust against perturbations in the data sets, which may cause the algorithm not to perform as per the expectation. These aspects should be further explored in future studies.

2.6.4. Optimal Control and Dynamic Programming

Optimal control (OC) is the process of finding a control for a dynamical system given some objective criteria relying on the optimization of an objective function containing state and control variables over a time horizon [109]. The OC is one of the most used approaches for DSM problems which concerns with modelling and solving sequential decision-making/control problems in smart energy systems mostly in an uncertain environment. The most used applications of OC within the energy system area can be identified for regulation service provision for the power grid, in particular, frequency regulation and optimal power flow [110]-[115], buildings' thermal management [111],[116],[117], energy management and control of ESS [115],[118],[119] minimizing the energy usage and cost in MGs [118]. For example, in [110] a probabilistic programming approach based on a variant of Monte Carlo method, as a computer–driven sampling method for estimating posterior distributions, is developed to reduce the imbalance energy, i.e., the energy gap between contracted supply and actual demand, and its associated cost. Load-side participation in frequency control is tackled in [111] by a distributed primary/secondary frequency regulation approach to rebalance supply and demand after disturbances, to restore the nominal frequency, and to preserve the inter-area power flows and the thermal limits of the power system. Stochastic dynamic programming is further utilized in [112] for regulation service provision in smart buildings. The authors develop an optimal dynamic pricing policy for a smart building operator to obtain an effective provision of regulation service reserves through flexible loads. The work of [117] provides an overview on optimal control approaches applied to HVAC systems for buildings' thermal management. The authors argue the great potential of optimal controllers for energy saving realization leading to the development of energy efficient and sustainable buildings. In [118] a robust OC strategy for an ESS of a grid-connected MG is proposed where a MILP-based rolling horizon controller of the energy management system periodically updates the control schedule by solving an optimization problem. The proposed method aims to maintain a high level of economic benefit even under demand prediction error conditions. OC approaches are shown to provide a high-performance multivariable control with rapid responses which is beneficial for the control of smart energy systems. However, a challenge of OC approaches is the necessity to identify an appropriate model of the system. Moreover, the evaluation and real-time implementation of the control in more complicated problems with nonlinear objective functions and constraints can be challenging in terms of computational burden.

Dynamic programming (DP) provides an alternative approach to design OCs for solving more complex optimization problems that can be discretized and sequenced. In this case, the original problem is split into simpler subproblems and the obtained solutions of subproblems are used to achieve an optimal solution for the original problem. DP approaches can be implemented in various energy management applications. A DP approach is presented in [120] for the optimal energy management of an improved elevation system with energy storage capacity. The authors validate the method in a real test tower with an ESS to show its capability in reducing grid power peaks by 65% and braking resistor energy losses up to 84%. DP in combination with RL employing two neural networks is presented in [121] to provide an optimal control policy and an approximate cost-to-go function for MG operation under uncertainty. The interesting concept of stochastic dynamic programming (SDP), a prevalent type of DP where the system behavior is described statistically, is employed for optimal dispatch of energy hubs [122] and for energy management of smart homes with EV energy storage [123].

2.6.5. Model Predictive Control

Model predictive control (MPC) is known as an advanced intuitive model-based approach for real-time process control which repeatedly solves an optimal control problem over a finite prediction horizon [124]. It uses the concept of receding horizon feedback as it solves a new optimal control problem at the beginning of each time interval by updating all the measured states in that point of time. MPC is increasingly gaining ground for optimal decision making and control of smart energy systems, in particular owing to its capability to tackle system parameters uncertainty such as RES generation profiles and unpredictable costumers' energy demands. It has been shown in literature that by handling problems with multiple variables through future prediction of control actions, MPC is one of the most promising approaches to address large and complex power system problems [125]. So far, there have been presented many versions of MPC approaches for decision-making/control tasks in power systems. Finite control set MPC is the most used one due to its simplicity and accuracy. For example, an interesting application of MPC in combination with MILP is presented in [126] for the optimal operation planning of MGs. The authors aim at minimizing the overall MG operating costs while taking into account unit commitment and economic dispatch of all generation and storage units, buying and selling of energy from/to the power grid, and curtailment schedule of internal generations. An MPC approach is further proposed in [127] to optimize the operation of MGs by decomposing an original MINLP problem into two separated unit commitment (UC) and optimal power flow (OPF) problems which are solvable in more efficient way. The models proposed in recent works [128] and [129] are particularly interesting as they develop stochastic MPC (SMPC) using Markov chains for the predictive optimal energy management of hybrid EVs. The advantage of this model is that the closed-loop system can effectively adjusts to the uncertainty that arises from the environment around the vehicle. In [69] a two-stage stochastic framework for the optimal economic/environmental operational planning of a MG is proposed, and the optimization problem is solved by a combination of MPC and MILP. In [130] a MPC-based coordination framework for a cement plant is proposed, based on a combination of industrial loads and on-site energy storage, aiming to provide power regulation or load following ancillary services. The authors consider the number of active machines and the charging power of the energy storage as decision variables, where the optimal control provides a high-performance regulation service in a cost-effective way. In [64] a robust MPC scheme integrated with the design-then-approximate (DTA) method, where the controller is first designed by developing the governing differential equation and the system model is solved through approximate methods, is introduced for aggregated thermostatically controlled loads (TCLs), to provide a robust tracking of a desired power trajectory under uncertainty in the TCLs' parameters. A robust MPC (RMPC) scheme based on a data-driven stochastic approach is presented in [131] to optimize the operation of energy hubs and district buildings. Among more recent MPC-based approaches, distributed MPC (DMPC) has also recently received a great deal of interest in the development of DSM. In DMPC, there are multiple MPC controllers, each for a particular system, where local controllers with partial system-wide information receive state information and cooperatively solve a constrained optimal control problem in a receding horizon fashion. For instance, DMPC is adopted in [132] and [133] for the cooperative energy management and supply-demand balancing between distribution network operators (DNOs) and MGs. Alternatively, hierarchical MPC (HMPC) approaches with multilayer/multilevel control structures are implemented in some prior research, where the system is composed by a number of subsystems placed at different layers. For example, HMPC is employed in [134] for optimal power balance and critical load avoidance in MGs, and in [135] for fuel saving of power-split hybrid EVs. Furthermore, in [136] and [137], economic MPC (EMPC) schemes are devised for DSM programs, as a predictive feedback control integrating economic optimization and process control. Summing up, the applications of MPC is rapidly increasing in literature during recent years due to its unique features. For instance, as it employs a feedback mechanism, it provides a high level of robustness against uncertainty. Moreover, its operation depends on predictions and future behavior of the system, which is of great interest for the systems relying on RES generation and energy demand forecasts. Furthermore, it can address various system constraints such as generator capacity and ramp rate limits (i.e., the rate that a generation unit can increase or decrease generation to match with demand variations).

2.6.6. Game Theory

The essential need for an effective coordination of large communities of consumers/prosumers for an optimal energy management of the whole system necessitates an intelligent interaction among all involved actors. Game theory has drawn great attention recently as a method for steering and effectively promoting this interaction. Game theory can be generally viewed as a set of analytical tools which provides an insight on existing events observed when decision makers interact [138]. Game theory is extensively employed to enhance the flexibility and adaption of decision-making and control to energy systems as game environments under dynamical changes and limited information [20],[139]. Game-theoretic approaches generally model a DSM problem considering the consumers as *players*, the consumers' strategies for optimizing the utility function as *actions*, and the optimal outcome of the utility function as the *solution*. A survey on the application of game theory for DSM targets in the context of the open electricity market is provided in [20]. The existing state-of-the-art on game-theoretic approaches for DSM is mainly based on *non-cooperative* games with competition between individual players [140]-[142], *cooperative* games where groups of players may enforce cooperative behavior [143], and *evolutionary* games where the players constantly adjust their own strategies according to environmental changes and the strategies of other players [144],[145]. A Nash equilibrium is a determined solution of a non-cooperative game in which each player lacks any incentive to change his/her own initial strategy. This concept is used in [140] to obtain the solution of a non-cooperative differential game in a smart heterogeneous network, as the authors describe the dynamic of each users' energy state based on a differential equation. The objective is to minimize the energy costs and to control the energy consumption automatically. The study in [142] presents a DR market framework based on game theory to achieve an optimal bidding strategy for each DR aggregator to sell its stored energy in storage devices, aiming at maximizing its own payoff. A bargaining-based cooperative game where the players bargain over how to divide the gains from trade is proposed in [143] for the systems with overlapping consumers who enroll and participate in DSM programs planned by multiple aggregators. A hierarchical comparison algorithm is used to find the Nash equilibrium. The evolutionary game theory is adopted in [144] to solve the problem of minimizing overall energy cost of networked SGs, where players can switch between grid power and local power according to strategies of their neighbors. The authors introduce a new binary optimal control to optimize the transient performance of the networked evolutionary game. A multi-follower bilevel programing for optimal energy management of CHP-based MGs is presented in [146], where the framework constitutes a Stackelberg game as a hierarchical-based game theory which includes just one leader, in which a MG owner (MGO) is the leader and CHPs owners (CHPOs) are the followers. The target of this work is to guarantee profits to both MGO and CHPOs. Among the most prevalent game-theoretic approaches for decision-making and control in SGs, we can further mention the multi-leader-follower games [147] as a class of hierarchical games in which leaders participate in a Nash game based on the Nash equilibrium constrained by the equilibrium conditions of the follower. Moreover, we can denote Bertrand games [148], where all players are considered as leaders, as well as stochastic games [149], where players repeatedly interact and the underlying state of the environment changes stochastically in response to players' behavior.

It can be concluded from the related literature that game theoretic approaches can relatively address the interactions and interdependencies among participants for optimal energy management in power systems. However, the high complexity of future power systems due to, for example, growing number of participants with various locations, repeated auctions in the electricity market and intermittency nature of new electricity sources can be a major obstacle for standard game theoretic techniques to be conveniently modeled. In particular, participants or players should be able to repeatedly change and adapt their strategies to achieve a common goal, which may result in further computational complexity and burden that is difficult to represent by conventional techniques. An appealing extension to the traditional approaches includes the use of agent-based modeling to study complex large-scale systems.

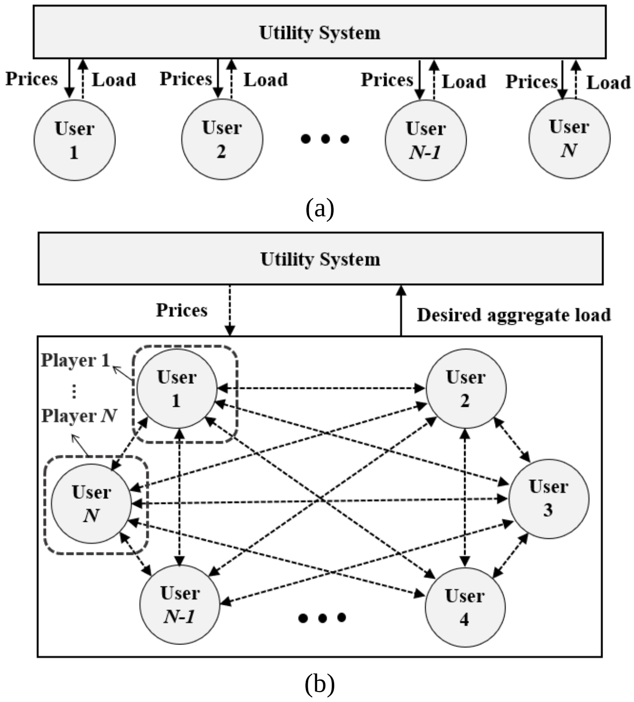


Fig. 6. DSM strategy relying on: (a) individual interactions between users and the utility (a TSO, DSO, or real-time energy markets), (b) cooperative interactions among users and the utility

2.6.7. Multi-agent Systems

A promising decision-making/control process for the energy management of complex energy systems with diverse energy careers can be realized by integrating a network of multiple interacting agents, called as multi-agent systems (MAS). An agent is an entity which acts within an embedded environment either for solving a problem by itself, or coordinately finding a solution together with other entities [150]. Indeed, a MAS can be defined as a group of networked agents which interact and coordinate their activities through some agent-communication languages to achieve specific global objectives [151]. Two contributions [150] and [152] presented by the IEEE Power Engineering Society's (PES) Intelligent System Subcommittee explore the potential benefits of MAS to power engineering applications, and offer guidance and technical recommendations on the design and implementation of MAS in the power and energy sectors. A MAS can be particularly applied to power systems in the roles of monitoring, control, protection, forecasting, trading, and planning. Recent studies have proved that MAS is a powerful tool to deal with an extensive variety of DSM problems in the power system ranging from power quality enhancement [153], security, economic and environmental benefits to MGs [53],[154], energy management of smart buildings and smart cities [44],[155], optimal control and charging of EVs and distributed ESS units [156] and energy market planning [157],[158]. For example, in [153] a MAS is introduced to effectively address the decentralized frequency control of an autonomous MG. The authors show that the proposed strategy based on average consensus algorithm can improve the convergence speed of the solution independently from the system configuration, and consequently, can enhance the frequency stability of the MG. In [154] a MAS for distributed hierarchical control of MGs is proposed to realize a reliable and efficient penetration of RES in MGs. Three agents are considered including the generation unit agent, the energy switch agent at the interconnection point between the main grid and the MG, and the main grid agent. The authors analyze the effect of communication delay on the convergence rate of consistency algorithm. Instead, the work of [53] deals with the minimization of the total energy cost of a MAS-based MG by considering a collection of DG agent, ESS agent, and DR agent which can update their local information and communicate with their neighbor agents asynchronously. The focus on the scope of smart buildings is considered in [44] where an agent-based decentralized decision-making approach based on RL is presented for a cluster of buildings. The authors establish a multi-objective problem with two conflicting objective functions, i.e., energy consumption minimization and comfort maximization. A weighted aggregation method along with particle swarm optimization (PSO) is adopted to solve the optimization problem. Other group of studies apply the concept of MAS to the energy market. As an example, the authors in [158] present a two-level agent-based decision-making framework, where at the top level a retailer agent purchases energy from the wholesale market and sells it to the consumers. Instead, at the lower level, the consumer agents optimize their consumption patterns independently using their local controllers after receiving the retail prices from the retailer agent. Recent technological developments allow designing power systems to include multiple energy carrier systems, such as electricity, natural gas and heat aiming to improve energy utilizing efficiency, to decrease CO2 emission, and to increase the operation economy and flexibility. In such systems, different energy carriers and systems can be planned as agents which interact together in an efficient and synergistic way [47],[159]. Accordingly, an energy hub, i.e., a functional unit for conversion and storage of different energy carriers, needs to be properly employed as a promising option for integrated management of such systems and to balance different types of energy demands. An example of this is presented in [159] considering a large-scale multiple energy carrier system with RES, gas turbine and CHP units including several energy hubs as agents. The authors introduce a multi-agent bargaining learning approach to minimize the total energy costs and the total energy losses simultaneously, while meeting the constraints related to the RES generation, the capacity limits of all energy sources, the energy balance, the prohibited operating zones of thermal generating units for faults prevention, and a limit for the dispatch factor.

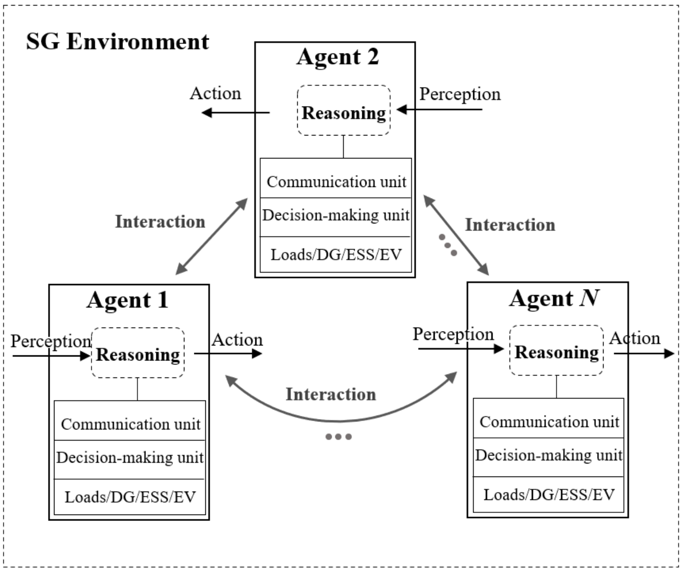


Fig. 7. A framework of MAS in the SG

Summing up, the development of MAS technology improves several functionalities inherent to SGs, such as fast problem-solving by parallel computations, efficient distributed and real-time monitoring, individual learning ability for each agent, fast response to condition changes, reconfigurability support, diagnosis, self-maintenance, and negotiation capability in the system, leading to realizing a flexible, interoperable, and scalable solution to the DSM programs. However, despite a large number of related research, the wide real-life implementation of MAS-based decision-making/control systems in the SG domain is quite slow. As MAS is a relatively new technology in the SG domain, several technical challenges need to be resolved for realizing their wide and effective usage. For instance, the implementation of MAS-based approaches generally requires enormous investments on the evolution process of many levels of the existing power grid infrastructure. Also, there is a lack of standardized agent architectures as well as mature and well accepted design methodologies for MAS in SGs. Moreover, the cooperation of agents results in the creation of a nonstationary environment that naturally makes it very difficult to achieve a convergence. Further, the adaptation of agents to the dynamic behavior of other agents is another challenge [155]. To obtain a systematic application of agent-based architectures, the future research works need to focus on defining suitable and well accepted methodologies, agent architectures, and tools that are clearly specific to the energy management of smart energy systems. Finally, a more study on the convergence features of cooperative MAS strategies to obtain an equilibrium is necessary.

Table 2. 1. Comparative summary of decision-making and control approaches for DSM investigated in this subsection

Methods	Type of load (n.o.p)	Main objectives (n.o.p)	System components (n.o.p)	Main constraints (n.o.p)	Solution methods (n.o.p)
Optimization techniques for energy scheduling	Residential (17) Industrial (5) Communal (4) Commercial (3) N.S. (17)	Energy cost min. (28) Utility profit/User comfort max. (10) ESS degradation min. (4) DER penetration max. (3) Emissions min. (3) Privacy protection (2) Frequency regulation (2) PAR min. (2) Forecast error min. (1) Charging loss min. (1) Power fluctuation min. (1)	RES (16) ESS (14) PEV (10) DG (8) TES (4) CHP (3) Boiler (2) HVAC (1)	Technical power limits (23) SOC (12) Power balance (9) Demand fulfilment (8) Power feasibility constraint (4) Battery degradation (3) SOH (2) Price fluctuation (2) Input gas limits (2) DG generation limits (2) Temperature range (1)	Cooperative mechanism (17) Robust optimization (5) PSO (3) IPM (3) SDP (4) Lyapunov technique (3) ANN (2) GA (2) Fuzzy-logic (1) Artificial immune system (1)
Transactive control	Residential (3) Commercial (1) N.S. (3)	Energy cost min. (5) Social welfare max. (2) Power market reg. (1) Frequency regulation (1) Peak shaving (1) Voltage control (1)	HVAC (2) PEV (1) TCL (1)	Technical power limits (4) Power balance (2) SOC (1) Peak energy constraint (1) Conditioned air limits (1) Power flow constraints (1)	Cooperative mechanism (3) MPC to clear TM (1)
Learning-based control	Residential (1) Communal (1) N.S. (3)	Energy cost min. (5) Comfort max. (2) Energy usage min (2) Utility profit max. (1)	CHP (1) Boiler (1) ESS (1) TES (1) TCL (1) HP (1) EV (1)	Technical power limits (4) Thermal capacity (2) Congestion constraint (1)	RL (3) ANN (1) Expectation–max. (EM) (1) Anal. of variance (ANOVA) (1) Service-oriented app. (SOA) (1) Markov decision proc. (MDP) (1)
Optimal control and dynamic programming	Residential (1) Industrial (1) N.S. (5)	Energy cost min. (5) Valley-filling (2) Privacy protection (2) Imbalance energy min. (1) Frequency control (1) Regulation service (1) ESS degradation min. (1)	ESS (3) PEV (2) TCL (1)	Technical power limits (4) SOC (4) Energy balance (3) Usage schedule const. (2) Demand deviation (1) Temperature limits (1) Battery degradation (1) Battery terminal volt. const.(1)	Price leveling algo. (2) SDP (2) Markov decision proc. (MDP) (1) Hierarchical cooperative (1)
Model Predictive Control	Residential (7) Industrial (1) Communal (1) N.S. (5)	Energy cost min. (11) Power balancing (3) RES penetration max. (3) Energy saving (3) Power regulation (2) PAR min. (2) Emissions min. (1) On/off cost of DG min. (1) Critical load avoidance (1) Comfort max. (1) Demand flexibility (1)	ESS (7) RES (6) PEV (4) TCL (1) TES (1) HP (1) Boiler (1) Chiller (1) CHP (1) DG (1)	Technical power limits (10) SOC (8) Energy balance (6) Battery charging rate (4) Demand fulfilment (3) Thermal capacity (2) Thermal balance (2) Switching limitation (1) Comfort constraint (1) Temperature limits (1)	Cooperative MPC (2) DMPC (2) HMPC (2) EMPC (2) Game theoretic MPC (1) RMPC (1) Data-driven RMPC (1) MPC to clear TM (1) Stochastic MPC (1) Conventional MPC (1)
Game theory	Residential (2) Commercial (1) N.S. (8)	Energy cost min. (7) Aggregator payoff max. (5) Opt. bidding strategy (3) Opt. power flow (2) Agents' profit max. (2) Privacy protection (1) Peak shaving (1) Social welfare max. (1) ESS maintenance min. (1)	ESS (2) DG (2) RES (1) PEV (1) WH (1) AC (1) TES (1) CHP (1)	Technical power limits (4) Energy balance (3) Voltage limit (2) DG generation limits (2) Demand fulfilment (1) Temperature limits (1) Bidding price constraint (1) Exchangeable power limit (1) Power flow limits (1)	Non-cooperative game (3) Evolutionary game (2) Bargaining cooperative game (1) Stackelberg game (1) Multi-leader-follower game (1) Bertrand game (1) Stochastic game (1) Differential game (1)
Multi-agent system	Residential (2) Commercial (2) Communal (2) N.S. (3)	Energy cost min. (11) Utility profit/User comfort max. (6) RES penetration max. (2) Volt./freq. regulation (2) Emissions min. (2) Efficiency max. (1) Social welfare max. (1) Peak shaving (1)	RES (4) ESS (3) DG (3) TCL (1) CHP (1) SH (1) AC (1) PEV (1)	Technical power limits (6) DG generation limits (3) DG ramp rate limit (3) Battery charging capacity (2) Hot/chilled water limit (1) Comfort constraint (1) Temperature limits (1) RES generation limit (1) Gas emission limits (1)	MA distributed hierarchical (1) MA reinforcement learning (1) PSO (1) MA bargaining learning (1) MA decentralized (1) ADMM (1) MA multi-layered hierarchical (1)

Note-The list of new acronyms used: *AC* (Air conditioner), *CHP* (Combined heat and power), *HP* (Heat pump), *HVAC* (Heating, ventilation, and air conditioning), *IPM* (Interior-point method), *MA* (Multi agent), *PSO* (Particle swarm optimization), *SDP* (Stochastic dynamic programming), *SOC* (State of charge), *SOH* (State of heat), *TCL* (thermostatically controlled load), *TES* (Thermal energy storage), *WH* (Water heater).

2.7. Demand-side Management for Smart Users

As DSM is not a one-size-fit-all program, its design, development, and performance can directly depend on the detailed data of consumers' nature and behavior. The effectiveness of a DSM program can be significantly increased by taking into consideration the types of consumers that are applied to. This section reviews some essential aspects of DSM focusing on different end-use sectors (e.g., individual apartments with smart appliances, buildings - single owner with behind the meter onsite generation and/or storage, commercial buildings, individual EVs or storage systems, single industrial consumers/plan/facility).

2.7.1. Introduction

The growing tendency towards the development of the small-scale SGs and MGs stems from the potential of DSM programs to fundamentally change the social dynamics of electrical systems [160]. The recent advances in information and communication technologies (ICTs), smart sensors, smart meters and monitoring systems enable the consumers to behave as an active energy actor and to be widely engaged in DSM programs. By integrating information on the users' preferences and activities, a DSM program helps end-users to modify their level and pattern of electricity demand leading to mitigation of excessive grid loading from "peak periods". A DSM program provides to end users suggestions and information about when and how to optimally buy/sell their required/locally-generated electricity from/to the power system. By doing so, a DSM program can play an essential role in the optimized utilization of the available power generation capacity and in ensuring a real-time balance between supply and demand [67]. To date, a considerable body of research has been conducted on decision making and control of smart end users in SGs. In this context, in following subsections we investigate the existing state-of-the-art on DSM programs for smart end-users by categorizing them into different categories. As illustrated in Fig. 8, four different end-use sectors are the major electricity consumers, namely residential, industrial, transportation and commercial users, which are thoroughly reviewed in this section in terms of DSM targets. We further make an overlook at the application of DSM for energy management of public facilities as they recently account for a large share of the urban electricity consumption.

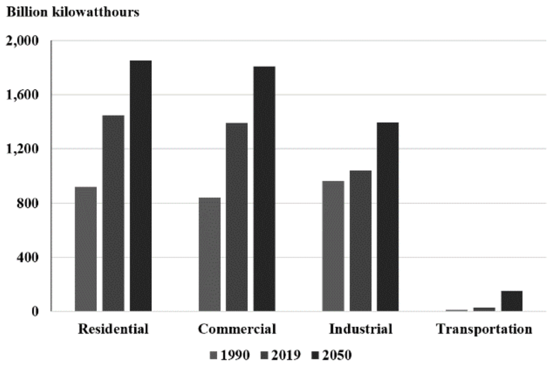


Fig. 8. Electricity use growth by end-use sectors from 1990 to 2050 in the Annual Energy Outlook (AEO) 2020 [161]

2.7.2. DSM for Residential Users

A residential SG can be generally considered as a number of interconnected smart homes equipped with domestic electrical (and thermal) appliances such as controllable loads (CLs) such as dishwasher and washing machine with flexible and programmable operation, non-controllable loads (NCLs) such as televisions and computers with inflexible and fixed power curve, and non-interruptible loads (NILs) such as refrigerators which must operate continuously until the end of their task. These interconnected smart homes also commonly include local DERs (e.g., photovoltaic system or micro-CHP) and onsite small-scale battery storage units which can be autonomously controlled for interacting with each other and the power grid [162],[163]. Household energy consumption can be effectively monitored by energy consumption controllers (ECCs) integrated in the home energy management system (HEMS) through internet protocols and local area networks (LANs) [164]. As households account for a considerable portion of total energy consumption worldwide, the residential sector should be a major component of a DSM strategy which can be realized through energy efficiency or DR programs. Moreover, it offers cost-effective opportunities with the lowest investment needs [165]. However, the design of an efficient DSM strategy for residential users is significantly more complicated than one for industrial or commercial sectors. The reason behind this fact is that residential consumption patterns are highly subject to volatility and intermittency due to random users' behavior which necessitates a more intelligent design and modelling [36],[59],[60],[64]. The promotion of DSM strategies for the residential sector has been of interest to numerous scholars [162]-[172]. In the literature, the most prevalent aspect of DSM implementation within the residential sector is related to the DR application [25],[139]. In particular, DR programs are adopted to reduce or shift electricity consumption of smart homes for cost reduction and peak shaving [167],[168],[169]. This can be realized either by incentive-based schemes where the management of consumers' loads during emergency or peak periods is controlled by utility companies based on a mutual agreement (e.g., as in [167] and [168] for direct load control (DLC) of large-scale residential buildings), or price-based schemes where consumers are encouraged to reduce or shift their energy consumption from peak periods in response to different price signals provided by the utility (e.g., as in [169] through adaptive pricing scheme for residential DSM). In [170], the authors classify residential consumers for DSM based on different categories: a) long range consumers, who can shift their consumption pattern over a wide range of time in response to changes in prices, b) real world-postponing consumers, whose perception only depends on current and future prices, c) real world-advancing consumers, which are similar to postponing consumers except that the consumer perception only depends on current and past periods, d) real-world mixed consumers, who are a mix of postponing and advancing customers, and e) short range consumers, who do not care about optimizing their loads, and only take care about the electricity price at the current time instant. In [67], three types of loads including NCLs (e.g., TV), energy-based CLs (e.g., dishwasher) and comfort-based CLs (e.g., a heat pump system) are modeled in a residential MG. The authors develop a DSM approach to provide the decision maker a tradeoff between electricity payment minimization and the contractual power constraint satisfaction, which is advantageous for both the residential MG and the power grid. However, they do not insert NILs into the system modeling. There are other important considerations that should be included during the design of a DSM strategy for residential users. One is the exploitation of local power generation such as rooftop PVSs or DWTs. For instance, the interesting work of [34] includes wind turbine and solar panel in the structure of residential users. The authors adopt a stochastic optimization approach to find the optimal scheduling for a HEMS while dealing with the uncertainties on electricity prices, RES generations, and consumers' behavior. As mentioned before, a large body of related studies essentially take the effect of uncertainty in costumers' behavior [34],[60],[67],[96] or distributed generations [34],[43],[60],[65] into account when modeling a residential MG. Another consideration arises from the integration of individual EVs into smart homes [34],[67],[98],[171]. For example, a two-stage real-time DSM for a residential MG incorporating EVs with V2G option is proposed in [171], which aims at minimizing the daily total cost and maintaining the supply-demand balance in an uncertain environment. The authors examine several test cases to confirm the effectiveness of the method for achieving economic benefits, and for improving the system net load characters of the MG system. Although the most taken objectives of DSM applications in residential sector are cost minimization and PAR reduction, other groups of studies utilize the potential of residential SGs for maintaining power quality, reliability and sustainability [169],[172]. In [169], an adaptive pricing scheme is presented for residential DSM programs, which not only motivates users to manage their energy consumption for cost saving, but also allows the utility system to maintain grid reliability and sustainability. Instead, in addition to users' cost minimization, reactive power compensation is further addressed in [172] to enhance the power factor (PF) of home-to-grid integration points in a residential energy system incorporating RES, E V and energy storage systems.

Most popular used software for implementing and simulating DSM strategies in the residential sector are MATLAB, GAMS, CPLEX and LINGO. It can be concluded from the existing literature that most important challenges ahead of residential DSM programs are to ensure an effective and robust strategy for tackling uncertainty, to provide a safe exploitation of locally generated powers, and to fulfill diverse technical and comfort constraints of multiple electrical appliances with various energy requirements, operational times, and arrival rates of power requests.

2.7.3. DSM for Commercial Buildings

As one of the major electricity consumers, commercial sector accounts for a significant share of the total energy consumption worldwide. For instance, commercial sector consumes more than one third of the total electricity consumption in the United States which is almost the same as the one for the residential sector [161]. According to the 2018 Commercial Buildings Energy Consumption Survey (CBECS) [173], the main energy consumers in the commercial sector are offices, supermarkets, shopping malls, educations, healthcare, and warehouses. Heat ventilation and air conditioning (HVAC), lighting, appliances and electronics are the major electricity consuming end-users in commercial buildings [174]. So far, commercial sector has drawn only minor attention of researchers for DSM applications due to its different load demand patterns which cannot be generalized as opposed to the residential load demand. Nevertheless, recent study of [175] demonstrates that commercial consumers have a great potential to participate in the DSM programs. It is stated in [176] that the most promising segments for contributing to DSM programs can be ranked as universities and schools, hospitals, malls, hotels, and offices. Recently, scholars are identifying commercial consumers as important potential players to DSM. Focusing on load reduction and cost savings, the work of [177] presents an energy management scheme for HVAC systems in a university building. The authors formulate the energy management problem as a MILP problem which is solved through a heuristic-based algorithm. In [89] a TC market structure is proposed for commercial HVAC systems aiming at peak shaving, load shifting, and strategic energy conservation. DSM programs are further applied to HVAC systems in [178] for frequency regulation and balancing services and in [179] for optimizing energy cost and costumers' comfort level through an economic MPC approach in commercial buildings. By a similar way, an economic MPC is employed in [180] to develop a building-aggregator-grid contract for the energy management of HVAC systems to not only reduce the grid operating costs and emissions, but also to enhance the grid reliability and market efficiency by maximizing the penetration level of RES and reducing the need of ancillary services provided by generators. Most of the relevant works disregard the importance of ESS and EV integration, as well as some appliances such as the lighting system, which is the second major electricity consumer in commercial buildings. In this regard, along with the energy management of a HVAC unit, an integration of lighting appliances, PV system and ESS is further considered in [72] to minimize the total energy cost and to manage the energy demand and generation of buildings while meeting operational constraints of the power grid. The authors in [181] serve a building air conditioning and mechanical ventilation (ACMV) as a virtual storage system in combination with a priority-based load shedding and an ESS to deal with the fluctuation of PV generation in commercial buildings. The presented method maintains users' thermal comfort while lowering the computational burden and the ESS activities cost. It may be inferred from the technical literature that cost saving, load reduction and thermal comfort enhancement are the most taken objectives for the commercial DSM. The approaches have commonly used CPLEX, MATLAB and EnergyPlus for modeling and solving the commercial DSM programs.

It is worth noting that the consumption level of individual customers in the commercial sector is significantly higher than one in the residential sector. Therefore, compare to the residential sector, applying an effective DSM program on the same number of consumers in the commercial sector can yield much greater impacts on the power grid, and consequently, would affect the overall system significantly.

2.7.4. DSM for Industries

Diverse energy-intensive industries such as manufacturing, mining, and construction (e.g., steel, aluminum, cement, and chemicals industries) use electricity for processing, producing, or assembling goods. The industrial sector consumes less than a third of the total electricity consumption, however, it is still recognized as one of the main electricity consumer sectors. Thus, it can potentially contribute to the optimal management of several hundred megawatts of electricity [182]. The largest share of electricity in the industrial sector goes to supply diverse machine drives, to use for heating and cooling, and to serve electro-chemical processes. The rising cost of electricity drives small- and medium-sized industrial enterprises to change their energy consumption behavior and move toward executing DSM strategies in return for financial rewards [183]. As opposed to residential and commercial loads which usually operate independently and not necessarily in cooperation or sequence, industrial loads are generally interdependent and many manufacturing processes have critical temporal dependencies, which must be scheduled with high timing precision. Thus, they usually need to follow specific operational sequences with millisecond monitoring and control [139], [184]. For instance, a real-time energy management and smart manufacturing for the industrial process of extracting olive oil from raw olives is presented in [185]. The process includes several sequential stages such as cleaning, washing, and milling where all these steps require a certain amount of electricity use. The authors adopt an economic MPC to perform an optimal power scheduling and an optimal multi-carrier power dispatch aiming at minimizing the energy costs. In [183], the authors present a discrete manufacturing production model and design a real-time demand bidding (DB) program -as a type of incentive-based DR- to obtain the optimal load-reduction bid and generate dynamic adjusted production and effective energy plans. Instead, a combination of low-temperature thermal energy storage (TES) and off-grid PV system is proposed in [186] together with an optimization-based time-of-use DSM to shift the peak demand and reduce the annual electricity consumption costs of industrial consumers. Minimizing electricity-derived carbon emissions and costs are tackled in [187] by optimally rescheduling the production process of a cement plant in the UK while satisfying its overall production targets and meeting the constraints of the available inventory storage. Industrial customers can also effectively participate in the energy markets to buy or sell electricity within a market environment [183],[188]. For instance, an optimized energy purchase allocation in the forward market, day-ahead market, and real-time market for an industrial costumer is addressed in [188] to minimize the procurement cost and the associated volatility risk.

An important challenge in DSM of large-scale industrial customers is that they only concur to change their production schedule if it is economically viable. In general, the amount of residential electricity demand varies depending on the season and the time of day due to increased air conditioning and the lighting uses. In the commercial sector, the electricity demand tends to be highest during operating business hours, and to significantly decrease during nights and weekends. However, the industrial electricity demand is not subject to a drastic change over the day or seasons as in the residential and commercial sectors. Moreover, due to confidentiality and competitive reasons, industrial loads are usually not willing to share their information and their operational models with their customers and other industrial units. To cope with these challenges a significant attention has been recently drawn to distributed algorithms for DSM of industrial sectors. For example, a distributed framework based on ADMM for cooperative DSM of industrial loads is proposed in [189], where the industrial load and its customers only exchanges minimal information about agreed product demand profiles and prices, which meets data privacy considerations. A multi-agent deep RL-based approach for the DSM of industrial manufacturing systems is proposed in [190] to obtain the optimal schedule of different machines with the aims of minimizing the electricity costs and fulfilling the production tasks. Scholars have mostly used CPLEX, LINGO and MATLAB to simulate DSM algorithms in the industrial systems. Whereas the residential and commercial DSM programs mainly pursue the cost minimization and the comfort maximization as two main objectives, the decision-making in industrial loads is highly associated with more complexity, and is concerned with further challenges such as meeting sequential industrial process needs, capturing the physical characteristics of different machines, maintaining production tasks as well as interdependencies and correlations between industrial loads and their customers. Therefore, realizing an effective industrial energy management requires a detailed understanding of the whole industrial system and process. Other barriers ahead of an extensive implementation of DSM programs in the industrial sector arise from the lack of sufficient incentives for industry owners. For instance, industrial companies are usually producing at their maximum capacity with no extra capacity in process sections, they need several hours to regain a stable production after a stop, the cost of electricity accounts for a small percentage of their total cost of production, they usually have fixed price contracts with utility companies for their required electricity, and they commonly see the implementation of DSM programs complicated and uneconomical. Therefore, stronger short- and medium-term incentives are required to encourage such industries to participate in DSM programs.

2.7.5. DSM for electric transportation (EVs)

The expansion of EVs (including electric passenger cars, taxicabs and buses) has been broadly accepted as a vital technology for supporting the decarbonization of the transport sector and thus a more sustainable urban logistics. However, it may cause significant technical challenges to the reliability, the security, and the efficiency of power systems such as equipment and lines congestion [191]. More precisely, uncontrolled simultaneous charging of a cluster of EVs, in addition to the other loads, may cause a peak demand in the power grid, resulting in the need for additional power generation capacity and electricity infrastructure. To manage these issues and to exploit the potential of EVs for demand-side flexibility, the design and assessment of intelligent optimal charging strategies for EVs have become a timely and important topic of research. An intelligent coordinated communication of EV networks possibly benefits all types of participants in a power grid. The applications of DSM approaches for EVs range from the simple optimal EVs' charge/discharge scheduling problems [58],[192] to more complex problems with diverse constraints and settings such as costumer's preferences, deadlines and mobility constraints [45],[57],[102],[103], grid power congestion constraints [91],[171], technical, safety, state-of-charge (SoC) and dynamic constraints of EVs' batteries [45],[135], the presence of uncertainty on forecast data [128],[129], optimal location of charging stations [193], and providing grid services like regulation [73],[74].

An overview on the energy management of EVs focusing on economic and incentive aspects considering unidirectional and bidirectional energy flows in the electricity market is provided in [194]. The authors argue the total benefits earned by the presence of EVs in the society and the importance of proper market design since the market structure directly impacts the actors' behaviors. Ma *et al*. [192] present a leading work for developing the optimal charging control of a large number of EVs which selfishly share electricity resources on a finite collection of charging intervals. The authors form the problem as a non-cooperative game which converges to a Nash equilibrium where all EVs simultaneously update their strategy regarding the average charging strategy of all EVs. However, this work does not consider local considerations such as users' preferences, availability time and deadline constraints, or battery state of health concerns. Instead, studies such as [195] and [196] not only pursue economic benefits to EVs users but also consider users' preferences for charging EVs to a required level by a specified time. In [197] and [198] power grid congestion management is further taken into account alongside overall cost minimization through an optimal EVs charging control. A cost minimization algorithm for vehicle-to-grid (V2G) EV energy activities is proposed in [199], which combines an offline demand shaping and an online demand response to day-ahead and real-time markets for the aggregated demand. Although the EV behavior may depend on different parameters, it can be generally parameterized in terms of time of charge, connection charge location and charge magnitude. With this in mind, the authors in [200] develop an online algorithm to estimate the maximum and minimum adjustable power limits of EVs and to contribute to the power system dispatch. The algorithm uses an accurate knowledge of the real-time initial SoC and the available time duration parameters through mobile phone applications and vehicle's interface system for obtaining optimal charge scheduling. The authors in [201] employ a fuzzy logic controller for optimal charging of EVs at different points of connection, where voltage conditions may not be the same. The proposed controller is decentralized and makes all the decisions at the local level to ensure a minimum real-time communication and to preserve the users' privacy. Differently, the work of [45] develop a decentralized control of large-scale hybrid EVs (HEVs) using the theory of mean filed (MF) game aiming at minimizing the energy cost and the battery degradation for each user. The authors take into account both the gasoline and the battery modes, the charging and discharging modes, the traveling time and the distance limitations. Although a majority of studies on DSM of EVs are based on simulation, some studies have been carried out experimentally. It is argued in [202] that in a real system, some dynamics with respect to the inherent behavior of EVs such as unknown energy demand, transitions between operation modes or voltage and current drops may not be properly and evidently modelled in detail. The authors of [202] present a comparison between the experimental results obtained from two energy management strategies for hybrid electric buses on a test-bench platform, and then they demonstrate that there can be a gap between the simulation-based and the experiment-based energy management of EVs. Instead, in [203] an online dynamic programming approach is implemented on a prototype HEV under development at Renault to optimally control the power flows between the fuel and electricity sources, which ensures high efficiency and acceptable drivability of the energy management approach.

2.7.6. DSM for Public Facilities

The energy consumption of public facilities such as public transport (e.g., train and bus), water supply, sanitation and public buildings has recently attracted interest from researchers. Scholars have been studying energy management frameworks mostly to obtain sustainable and optimal energy plans. The key reason for this tendency is that such parties are centrally possessed and controlled. Moreover, although they account for a large share of the urban energy consumption and carbon emissions, they need a minor modification in their electrical and communication system and facilities to allow optimized operation. Besides, they have a great potential to involve large-scale distributed energy resources such as wind and solar plants at the distribution network. A related example is provided in [204], where the public water supply is considered as an excellent candidate for DSM applications owing to its great potential for various operating modes and a high degree of flexibility over the timing of pumping. The authors propose a market-driven DSM for water networks benefiting both the water utility by reducing the energy cost as well as the power system by increasing the wind power utilization. Among other prominent studies, the authors in [205] present an approximate dynamic programming (DP) approach for energy scheduling of subway trains that simultaneously considers service quality and energy consumption issues. They provide a comparison between the results obtained by GA and differential evolution algorithm with the proposed DP-based algorithm to ensure that a faster tradeoff among the utilization of trains, adequate comfort level, and energy efficiency can be achieved with the proposed approach.

Table 2. 2. Comparative summary of DSM approaches for smart users investigated in this subsection

Smart user type	**Main objectives (n.o.p)**	**System components (n.o.p)**	**Main constraints (n.o.p)**	**Solution methods (n.o.p)**	**Math. type (n.o.p)**
Residential users	Energy cost min. (9) Peak shaving (2) PAR min. (2) Reactive power compensation (1) Supply-demand balance (1) Load prediction (1) Power factor improvement (1)	PEV (7) ESS (5) RES (4) DG (1)	Technical power limits (8) Active power balance (7) SOC (5) Charging/discharging power limits of PEVs (3) Task deadline (2) Demand fulfilment (2) Energy transaction limits (2) Battery charging capacity (1) Reactive power balance (1)	Cooperative mechanism (3) Markov Chain (2) DLC (1) Adaptive pricing (1) MPC (1)	MILP (5) MIQP (2) LP (1) QP (1)
Commercial Buildings	RES penetration max. (2) Energy cost min. (1) Load shedding (1) ESS cost min. (1) ESS\PEVpenetration max. (1) Peak shaving (1)	ESS (3) RES (3) ACMV (1) Virtual storage (1) HP (1) PEV (1)	Technical power limits (2) Battery charging capacity (2) Temperature limits (1) Power balance (1) Thermal comfort (1) Battery degradation (1) SOC (1) Charging/discharging power limits of PEVs (1)	SP (1) Elitist GA (1)	MILP (1) LP (1) NLP (1) Heuristic (1)
Industries	Energy cost min. (6) Manufacturer's profit max. (2) Total revenue max. (2) Peak shaving (2) High sustainable business model (1) Social benefit max. (1) Load reduction (1) Optimal power dispatch (1) Emissions min. (1) Procurement cost min. (1) Volatility risk min. (1)	ESS (3) Manufacturing machine (1) TES (1) Boiler (1) EM (1) Mill (1)	Technical power limits (3) Battery charge/discharge rate (2) Battery charging capacity (2) Buffer storage capacity (1) RES (1) SOC (1) Production timing (1) power balance (1) Line voltage/current limits (1) Risk constraints (1)	EMPC (1) Value mapping tool (1) SP (1) Cooperative mechanism (1) ADMM (1)	MILP (2) LP (1) MIP (1) LP (1) QP (1) MINLP (1)
Public facilities	RES penetration max. (1) Energy cost min. (1)	WP (1)	Water volume limits (1) Service reservoirs levels (1)	GA (1)	Heuristic (1)
Electric vehicles	Energy cost min. (4) Battery degradation min. (2) Privacy protection (2) Social welfare max. (1) Procurement cost min. (1) PEVdispatch (1) Voltage regulation (1) Peak shaving (1)	PEV (6)	Charging/discharging power limits of PEVs (6) SOC (6) Power balance (3) Battery degradation (2) Technical power limits (2) Grid congestion limits (2)	DWA (1) Lagrangian Relaxation (1) Cooperative mechanism (1) FL (1) Mean filed game (1)	SQP (2) QP (1) MILP (1) LP (1)

Note-The list of new acronyms used: *ACMV* (Air conditioning and mechanical ventilation), *DLC* (Direct load control), *EM* (Electric motor), *FL* (Fuzzy logic), *HP* (Heat pump), *HVAC* (Heating, ventilation, and air conditioning), *SP* (Stochastic programming), *SOC* (State of charge), *TES* (Thermal energy storage), *WP* (Water pump).

2.8. Demand-side Management at Distribution Level

A distribution network (DN) manages the transfer of bulk electricity received from the transmission or sub-transmission system to end users. In this section we review decision-making and control strategies focusing on aggregation of generators, consumers/prosumers connected through the distribution network (DN), including, or not including network constraints. Both technical and commercial aggregation structures are included, e.g., aggregators, MGs, virtual power plants (VPP), community of consumers as a whole.

2.8.1. Introduction

DNs account for over 90% of the total electrical network length while a major portion of all electrical demand and distributed power generation is connected to DNs as well [206]. As DNs comprise more than half of the total capital expense and a significant percentage of total system losses and power outages, they have a great potential for extensive modifications and savings. The growing size and complexity of most DNs call for between 65% and more than 80% of all the network investments to maintain and establish DNs to 2050 [206]. These challenges create an essential need for a targeted consideration of DNs in the energy management planning and expansion. In recent years, significant benefits for DNs are known to be realized through carefully planned DSM programs, including notable impacts on asset utilization, operational efficiency, sustainability and flexibility of overall power systems. Whereas the objectives of DSM strategies at consumption level (i.e., smart users) mainly focus on minimizing the electricity bills and maximizing the users' comfort, the adoption of DSM programs for distribution utilities further concerns about the DN's operational objectives [207]. These objectives can be sorted as power grid efficiency (e.g., managing feeder losses), safety/reliability/security (e.g., improving power quality and mitigating power outages), economic benefits (e.g., reducing operating and maintenance costs), environmental benefits (e.g., reducing CO2 emissions by shifting peak loads and integrating low-carbon technologies) as well as large-scale RES and coordinated EVs integrations (e.g., integrating distributed generation and providing opportunities for consumer/prosumer involvement). The importance of such objectives is further felt considering that in modern power systems with broad numbers and diversity of the actors and assets, the distribution security and reliability events such as overload-related outages constitute around 90% of the total sustained interruptions, which represent the largest portion of the customer's annual interruption [208]. The reliability enhancement is typically sought by continuous infrastructure investment and maintenance. However, the investment required to establish and maintain a DN will be significant. Instead, as an alternative way, incorporating DSM programs (including DR, energy efficiency and strategic load growth strategies) into DNs can defer the network investment and result in economic, sustainability and reliability opportunities. For instance, peak shaving as a result of DSM programs not only significantly reduces the needs for purchasing electricity by the utility during peak hours resulting in economic benefit to the utility, but also provides capacity margin to the power system assets. Consequently, the system upgrades for future endeavors can be deferred [209]. However, there are still various challenges to an effective and optimal design of such programs for the DN operation. A significant consideration is with respect to the interface between DN and TN operation. In other words, evolutions in the power grid operation toward the SG concept will require a closer cooperation between TN and DN stakeholders. For example, voltage instability in the DN can spread to the TN and cause a major blackout [210]. Thus, network flexibility and stability achieved by a DSM plan in the DN level can also play a crucial role in supporting the TN operation. This fact highlights the significance of a continuous coordination between TN and DN stakeholders during all steps of planning and road mapping process for development of a DSM program. More discussion and assessment on the need for a coordination between TN and DN operation in SGs is provided in [211]. Another challenge arises from the integration of DSM and distributed power generation going together with other energy sectors such as thermal and transport. The main concern is to effectively maintain a balance between demand and generation in a distributed energy supply system dominated by different forms of RES, and in particular, in multi-energy systems (MES) with various types of energy sources. Besides, a number of technical challenges related to the infrastructure of communications, the metering infrastructure, integrated thermic/electric storage technologies and micro-CHP installations needs to be properly resolved. A technology roadmap focusing on SG deployment in DNs at the national, regional or municipal level is presented in [206]. This roadmap aims to define a series of milestones in a predetermined timeline for the sustainable deployment of SGs at the DN level spanning from the short-term (i.e., up to five years) to the long-term (e.g., up to 2050) efforts. Regarding significant potentials for a rapid deployment of demand-side participation in the DN sector to support the overall development and transformation of the electricity system, an overview and classification of DSM resources for maintaining or enhancing the system reliability, efficiency and sustainability is provided in [212]. The authors further discuss and compare the status of the energy management contribution in U.S. electricity markets offered by different Independent System Operators (ISOs) and regional transmission organizations (RTOs). As mentioned before, applying DSM strategies to single energy carrier systems (e.g., only electricity) cannot fully utilize the demand side resources when the number of inelastic and must-run loads in an energy system is high. This concern motivates scholars to promote the concept of MES which can be introduced as the integration of various forms of energy such as electricity, thermal energy, and natural gas.

The MES provides new insights into energy management systems by allowing all the energy users to actively participate in the DSM program (this will be further discussed in subsection VI(E)). As to that, the authors [29] provide a review of the state-of-the-art of integrated DSM in the MES and of related engineering projects within this field worldwide. Another relevant overview of the existing research on the deployment of DR aggregators in DNs is conducted in [213]. The authors explore the values of aggregators in DNs and divide their potential values into three categories including: *fundamental values*, which are independent of the market or regulatory context in permanent or near permanent conditions, *transitory values*, which are under current and future regulatory and technology contexts in the present and near-future conditions, and *opportunistic values*, which are in response to regulatory or market design flaws and may harm power system economic efficiency. The work investigates the role of the aggregators in power systems under different technological and regulatory scenarios. An alternative way for the DSM of some large-scale and power-intensive costumers which are typically connected to the DN is to instantly migrate power consuming activities among various locations instead of temporal flexibility approaches such as load shedding and load shifting. Data center (DC) is a great example of such loads, since the processing of information goods is not necessarily tied to a specific location, and the information goods can be conveniently transferred through communication networks. The work of [214] focuses on the spatial load migration of power-intensive process information goods in DCs. The authors state that the transferability feature of the information activities through communication networks enables the economic feasibility of spatially migrating loads between different locations of DCs.

Differently from the above-mentioned overview studies, in the following subsections we provide a review on the current state-of-the-art for the application of DSM programs in the DN domain, with a particular focus on their contributions to local balance services (e.g., voltage support), large-scale RES and coordinated EVs integration into the DN, as well as to the optimal management of MGs, MESs, building to grid (B2G) services and VPPs.

2.8.2. DSM for local balancing services in DNs

Realizing the full benefits of DSM programs at the DN level requires proper knowledge and identification of spatial and functional features of system loads in the specific area where the DSM strategy is designed to be applied. Most DSM strategies are basically designed to reshape load profiles at the system level. Accordingly, such strategies can effectively impact the requirements of a DN as they may bring significant changes in the total load curve of an area. Spatial distribution of different customer classes which can be realized by for instance, estimating future load profiles through load growth factor applied to existing loads, is another important consideration in designing an efficient DSM strategy in the DN. Knowing the appropriate information of the desired system, DSM programs can be used to provide effective local balancing services at aggregated levels for distribution network operators (DNOs). These services not only contribute to the enhancement of the DN operation, but also are effective in supporting the TN operation. These local services can range from voltage stability [74],[91],[170],[201],[202],[215], DN congestion management [91],[170], equipment preventive maintenance [216], investment defer and improvement of system sustainability [217], flexibility [89],[201] and reliability [73],[74],[89]. Plenty of research focus on local services provided by DSM in ensuring voltage stability, which is known as one of the major concerns in power system planning and operation, at the DN domain. Voltage stability refers to the ability of the power system to automatically maintain acceptable voltage levels over the system buses under normal or disturbed operating conditions. Voltage instability at DNs can be a consequence of the growing number of single-phase distributed generation units and EVs charging stations. In [170] and [215], promising results are obtained from DSM strategies in reducing voltage instability. The authors of [215] design a DSM algorithm for TCLs to compensate the voltage unbalance in power systems through voltage sensitivity analysis. The method controls minimum number of TCLs by detecting the most effective bus that affects point of common coupling (PCC) voltage. Consequently, they achieve more effective voltage regulation with less TCL control. Instead, the authors of [170] not only examine the impact of DSM on the voltage profile improvement, but also analyze the potential of the DSM in mitigation congestion in the network. The contribution of DSM programs to congestion management is generally due to flattening the overall load profile and reducing the duration of peak load periods. On the other hand, the proven ability of DSM for the reliability and flexibility of the DN operation is shown as a real-world case study on an urban Finnish distribution network in [218] and [219]. The results from these studies verify that by negligible adjustments in the operation of responsive loads, great reliability and flexibility benefits can be achieved from the implementation of DSM strategies at DNs. An optimal DSM plan can further contribute to postpone the preventive maintenance of system components by developing security-constrained preventive maintenance scheduling [216]. Moreover, it can defer investment needs in new generation units and the expansion of DN capacities [217]. Although relevant studies in recent years have yielded positive results for the participation of DSM programs in the provision of services to the DN, many challenges and issues still remain unsolved, and many potential benefits of DSM have not been yet explored. For instance, there can be observed a shortage in the thorough assessment of the required considerations and impacts of DSM programs in providing balancing services to different DN topologies (e.g., meshed and radial network structures) and ever-increasing DC distribution networks (DCDNs), to assess the compromise between the cost of implementing DSM programs and achieved service benefits, the potential benefits of energy efficiency programs for reliability improvement, the performance of DSM strategies under different types of uncertainty (e.g., load profiles, DSM measures, energy price, distributed generation and failure rates) and an in-depth analyze and assessment of existing approaches as well as a practical instruction for supporting decision makers to choose between running DSM programs or building new structures during distribution system expansion planning. Future studies should be directed toward a thorough investigation and consideration of such issues within the DN domain.

2.8.3. DSM for RES and coordinated EVs integration

Low-to-moderate penetration of RESs in the DN can profit both the utility and customers in different ways such as supplying local loads [42], minimizing network losses [61], deferring investments in network upgrades [217], and providing flexibility and stability to the network [47]. However, such benefits may be undermined in the case of large penetration of RESs, in particular when the power generation exceeds the load and the DN starts to export power [154]. This is because the traditional DNs have been typically designed for top-down energy flows and not to properly face generation features with the opposite direction of power flow [220], [221]. In this case, RES may introduce operational challenges to DSOs. The most common challenges arising from large penetration of RES in the DN include voltage violation, increased power loss and power quality issues, increased grid congestion, and additional stress on DN equipment [222]. The main reason for these issues is the discrepancy between RES generation time periods (e.g., in PV systems the maximum generation capacity is from mid-morning to the afternoon) and the high demand time periods (the daily peak demands is usually from the late-afternoon to early-evening) leading to excessive power flow into or from the area through feeding transformers [32],[221]. Moreover, the intermittent nature of RES can impose a serious challenge to supply the demand in a reliable way [34],[36],[43],[59]-[61],[65]. These challenges should be addressed through coordinated operation between different RESs, bulk ESSs and loads through efficient DSM strategies. Plenty of research have focused on developing novel DSM strategies to mitigate the negative impacts of RES penetration on the DN, and to maintain a safe operation of the whole power system. Coordinated DSM strategies for the integration of large-scale RESs in DNs is studied in either centralized [67],[223],[224] or decentralized/distributed manners [50],[53],[59]-[61],[159]. A group of studies have dealt this problem in a centralized way (e.g., in [224] where the optimal scheduling of distributed energy resources including RES is stated in the form of MINLP problem for a 33-bus test system and a 180-bus test system which is centrally solved through a metaheuristic algorithm). However, due to some challenges in these centralized strategies such as slow convergence rate and curse of dimension, the decentralization is recently identified as a more promising and efficient way for addressing such integration. Several decentralized/distributed approaches have been introduced to optimize the high RES penetration at the DN level including dual decomposition approach with challenging constraint of the supply–demand balance raised by the intermittent nature of RES [50], MAS-based energy management via ADMM approach [53],[59], MPC-based approaches via artificial intelligence [60], distributed stochastic programming for optimal power flow problem in DNs considering both real and reactive power control of RESs [61], and learning-based approach applied to distributed energy hubs [159]. In most of the aforementioned approaches, an intelligent combination of RES generation and ESS capabilities (e.g., as bulk battery storage or large-scale EVs) is utilized as a key strategy to prevent RES generation wastage.

Apart from the large integration of RES into the DN, the broad deployment of EVs connected to DNs, responding to the increasing fuel demand and greenhouse gas emissions, imposes another significant challenge to the secure operation of DNs, and to the quality of the power supply. On the one hand, the storage potential of EV batteries can support the peak demand at local areas and thus postpone the need for the infrastructure upgrades [91]. Moreover, smart charging/discharging of large-scale EVs has potential to balance some variability issues associated with intermittent RES utilization [225],[226], and to provide local services such as voltage and frequency regulations to the DN [73],[74],[201],[202]. On the other hand, the significant population of EVs will bring about the astonishing change in DN power flow. Uncontrolled penetration of EVs may cause many issues in the DN such as increasing phase imbalance due the large connection of single-phase EVs charger to the grid, voltage dip and voltage fluctuation, harmonics due to the power conversion in EVs' chargers, and magnitude of real power leading to more power losses [191]. Thus, it is advisable that coordinated charging of EVs considering the operational requirements of customers and the DN as well as optimum place and charging capacity of charging stations can enhance the load factor and reduce power losses of the DN. A detailed discussion of the impacts of an uncoordinated EV charging on DNs in terms of power losses, power quality (e.g., voltage profile, unbalance, harmonics), peak loads and system efficiency is provided in [227]. Over recent years, a broad spectrum of works has explored advanced schemes for an intelligent coordination of EV charging, mostly integrated with RES, either in centralized or decentralized/distributed fashion. For instance, Tesla has developed a Solar City to meet the required electricity for supplying Tesla EVs using solar energy [225]. A representative study for the large integration of EVs is [226], where a distributed decision-making approach relying on a real-time interaction between aggregators and EV users is proposed. The authors take into account the impacts of low and high EV penetration on the voltage unbalance, and interactively employs a PV system and EVs to mitigate the unbalance in low-voltage DNs. The authors in

[228] examine the contribution of smart EV charging stations integrated within the DN operation framework. They adopted a queuing model followed by a supervised neural network learning to obtain optimal charging profiles aiming at minimizing the feeder losses while maximizing the number of EV charged during a day. The proposed approach benefits both local distribution companies and EVs' owners. In [229] a DSM approach through EVs for a cloud-based energy management service is proposed, which provides financial incentives to customers with a higher participation level compared to those with a lower participation level within the same community. The fluctuation in the EV penetration is constrained and smoothed to meet the local constraints and technical/operational requirements of the DN such as the capacity of the power distribution line, and consequently, to provide a grid-friendly operation of DERs and EVs within the community. Instead, a coordinated charging process for EVs in the context of energy hubs is presented in [230], where the authors develop a multi-objective optimization framework for identifying optimal charging patterns while addressing both EV's owners needs and system operator requirements.

2.8.4. DSM and Optimal Management of Microgrids

MGs are subsystems of DNs that widely accepted as captivating and emerging solutions for integrating electrical loads, distributed generation, ESS and EV, operating as coordinated systems [40]. MGs can operate either connected to the main power grid [133],[153] or operated independently in the stand-alone mode [127] and can both purchase and sell power to and from their energy suppliers. The optimal performance of an MG is extremely important as it can manage the coordination among different components of the system in a more decentralized way reducing the need for the centralized coordination and management [126]. However, an effective decision making and control of MGs while guaranteeing a reliable, secure and economical operation of the whole power network is still a challenging and complicated task in both theory and practice [13]. One reason for this complication appears from the complicated modeling of vast MG's components including ESSs (with continuous decision variables such as storage charge/discharge rates and discrete decision variables such as storage charging/discharging mode) [118], CLs (with discrete decision variables such as ON/OFF states of controllable HVACs or EVs) [72], as well as the modeling of power exchange with the DN (in the form of linear or quadratic models along with discrete decision variables for buying/selling energy from/to the power grid) [67],[103]. Hence, the problem is generally formulated as a MINLP which is hard and computationally expensive to solve [126]. Another aspect which complicates the control and management of MGs comes from the high amount of uncertainty in the load demand, RESs generation and energy prices [59],[63],[66]. Coping with these challenges, an increasing research interest toward the engagement of efficient DSM strategies in MGs can be observed in literature, where various decision-making and control strategies have been proposed. An overview of the existing technologies, developments, and remaining challenges of MG design is provided in [231]. In this survey the authors classify the reviewed control strategies based on the three levels of the MG control hierarchical structure, namely primary, secondary, and tertiary, according to the speed-of-response and the infrastructure requirements. The authors in [232] review the classification of the control techniques and the objectives of DERs interconnected to MGs in terms of voltage and frequency stability. Differently, the authors in [233] review and categorize the various power sharing control and inverter output control strategies of DERs substantially focusing on primary control in islanded MGs. An interesting review on features and characteristics of distributed control and management strategies for MGs along with corresponding challenges and opportunities is provided in [234].An in-depth look at the relevant studies conducted can conclude that a MG may be generally modelled based on a number of modeling components: 1) load energy demand, 2) RESs generation (e.g., PV and wind generation), 3) non-RESs generation (e.g., DG and micro turbine (MT)) 4) ESS and EV activities, 5) internal and external power flows, 6) control unit, 7) information flows, and 8) DSM programs (e.g., DR strategies). Considering the importance and popularity of the objectives of DSM programs in MGs, the first-priority objective is to minimize the short- to long-term operational costs such as the cost of generation, storage, load shedding strategies, and energy purchased from the grid [50],[53]-[56],[67],[72],[118],[121],[126],[127],[154],[171],[235]. For instance, effective distributed strategies based on ADMM is proposed in [53] and [54] for the optimal energy management of MGs with high penetration of RESs, aiming to minimize the cost of power generation while maintaining the constraint of the supply-demand balance affected by the intermittency of RES. The interesting work of [235] addresses the problem of interactions between DNO and clusters of MGs through a bi-level stochastic formulation which benefits both DNO and MG owners in terms of operation costs. The next prominent objective of DSM programs within MG domain can be stated as guaranteeing the quality of service for DNOs and customers [115],[153],[215],[236]. An example of this is provided in [236] where different energy supply constraints in the form of power outages are taken into consideration, and a game-theoretical DSM using the blockchain technology is employed to achieve security and privacy protection in the MG operation. Another critical objective for the implementation of DSM programs in MGs is with respect to network power loss minimization subject to various technical and operational constraints such as load constraints, DER constraints, and power flow constraints [237],[238]. For example, minimizing power losses in the DN in the case of large-scale penetration of hybrid EVs in a MG is pursued in [237] through a two-stage optimization method with low computational complexity. A wide review on relevant published works can conclude that although numerous efforts have been conducted to improve the planning, operation and control of MGs, there is still plenty of room for further studies to develop various modern control strategies for MG energy management. For instance, potential future developments of DSM strategies for MGs should include more innovative and efficient control strategies for developing control of flexible multi-MG systems focusing on more decentralized and agent-based coordination techniques, tackling reliability issues such as voltage harmonies, overvoltage and overcurrent protections, stability and uncertainty issues due to intermittent PV systems and wind turbines, as well as detailed investigation of the ESS management systems to reduce the costs of DERs integrated within MGs.

2.8.5. DSM for Multi-energy Systems

Most studies on energy management systems address only one single form of energy, e.g., electrical or thermal, whereas a tight and growing interaction is observed between various energy sectors recently [29]. Multi-energy systems (MES) wherein multiple forms of energy vectors (e.g., electricity, heating, and cooling) interact with each other at different levels of aggregation (e.g., in a district, city or region) can enhance the system efficiency, economic and environmental performance, and rise the reliability and flexibility of the energy supply [247]. The MES provides new insights into the energy management systems by allowing all the energy users to actively participate in the DSM program. Flexibility and complementary features of MESs enable them to efficiently accommodate high penetration of RESs, and to be an interesting option for applying integrated DSM programs [248]. The prevalent components of a MES can be listed as RESs, ESSs, combined heat and power (CHP) plants, heat pumps (HPs), micro-turbines (MTs), gas furnaces (GFs), thermal energy storage (TES) systems, hydrogen storages (HSs), air conditioning (AC) systems, hydrogen production plants (HPPs), fuel cell (FCs), and refrigeration systems [29],[122],[249]. However, most of the studies incorporate electricity, heat and gas energies in the presence of RESs and ESS. A major challenge for developing sustainable MESs is to construct or upgrade the multi-energy infrastructures and facilities to enable consumers flexibly switch between various energy sources [250]. This requires a tight interaction among different sources of energy at DN level. In this context, DSM programs are the most suggested solutions in the technical literature for moderating coupling between different energy sectors [29]. The development of advanced metering infrastructure (AMI) on the demand side enables consumers in a MES to implement DSM programs thorough different energy carriers [251]. The consumers are able to take advantage of this flexibility to actively interact within the MES not only by shifting their time of energy usage but also switching the sources of energy to meet their requirements [29]. A sample effort for the large integration of RES into CHP-based MESs using the flexibility provided by a DSM program is presented in [248]. The authors develop a two-stage optimization problem to jointly optimize the placement of AMIs, the installation of RESs as well as the relevant pricing strategy for demand side to achieve lower total costs and higher RES utilization. In addition, in [249] a DSM approach is detailed for the decentralized energy management of a neighboring area including smart houses with flexible and inelastic electricity, heating, and cooling power demands. The authors consider a comprehensive MES comprising CHPs, HPs, ACs, EVs and RESs which optimally interact with each other to minimize total energy costs. Another interesting decentralized decision-making approach for a MES comprising various types of flexible and hybrid energy appliances is proposed in [47]. The authors evaluate the performance of decentralized approach compared to a centralized approach to demonstrate that the decentralized energy management of MESs offers more efficient performance for dealing with scalability as well as flexibility due to smaller local optimization problems. Promising results for multi-energy conversion in MESs can be achieved through energy hubs [46],[98],[122],[131],[159],[230]. An energy hub is a multi-carrier energy unit which can convert, regulate, and store different sources of energy and satisfy different varieties of energy demands [29]. The energy management of an energy hub is addressed in [46] through a probabilistic approach to achieve the optimal energy carriers to be purchased, then to be converted or stored in a MES, in order to fulfill the energy requests of the consumers. The authors establish an objective function consisting of the cost of electricity and gas purchased from the grid as well as the number of startups and shutdowns of the gas furnace and the CHP unit. The authors of [98] demonstrate that a respective reduction of up to 30% and 50% can be obtained in the total energy cost and electrical peak load of a residential energy hub by applying a RL-based DSM strategy. The risk consideration for the accumulated operational cost in the energy management of an energy hub with various sources of energy is tackled in [122]. The uncertainties associated with energy hub's input parameters (in particular, in load demand and prices of different energy sources) is the matter of significant importance, needing to be properly modeled in the optimal scheduling problem to reduce the risks of violation from the optimal solution. Dealing with these uncertainties have been discussed in studies such as [46],[122].

It can be inferred from the relevant research that the energy management of MESs is often a large-size problem in the form of MILP or MINLP with multiple continuous and integer variables along with many technical and operational constraints. Thus, the development of heuristic/metaheuristic as well as decentralized/distributed strategies for applying to such systems is becoming the most remarkable way for dealing with their computational complexity and convergence issues efficiently. The most frequently considered constraints in DSM of

MESs can be sorted as energy demand constraints (e.g., balancing constraints of electricity, heat and natural gas), conversion capacity constraints (e.g., power limits of energy converters), startup and shutdown constraints (e.g., safety and cost constraints for changing ON and OFF states of HPs and hydrogen production plant) and energy storage constraints (e.g., electrical, thermal and hydrogen storages). The room for future work can be exploring the optimal operation schedules of energy hubs participating in transactive energy markets, and study on more realistic limitations in the energy conversion between different energy carriers to involve more types of consumers into DSM programs (e.g., the consumers with must-run loads where the only available form of energy is electricity).

2.8.6. Building-to-grid and DSM for Multiple Electrical Loads

Building sector is an ideal source of cost-effective demand flexibility as it accounts for consuming the largest portion of the total electricity worldwide (e.g., over 70% of all U.S. electricity consumption) [161]. Building electricity consumption also drives a large share of peak power demand so that integrating them into the smart grid concept is critical for flexible load control and enhancing associated infrastructure costs and safety [252]. Moreover, buildings have a potential to reduce their consumption by 20–38% through advanced metering and controls while almost 90% of the commercial buildings can be aggregated to connect to the power grid [253]. Hence, exploring and understanding the coupling between buildings and power grids has emerged as a promising strategy for energy management and control targets [252]. The idea of building-to-grid (B2G) integration refers to the interface of buildings and power grids by allowing smart buildings to actively contribute to the seamless and reliable operation of the whole system by changing their overall demand patterns in response to grid operations. A B2G mode is developed in [254] for integrating the power systems economic dispatch with the buildings' thermal dynamics and end-use constraints. The authors formulate B2G model as an optimization problem to minimize the daily electricity generation cost including the fuel and carbon emissions costs while satisfying power system operational constraints and the power balance constraint. A B2G integration is provided in [134], where a hierarchical MPC is proposed for load control to redistribute power consumption in the grid to avoid critical operating conditions and regulate the voltage and the line current. Regulation and balancing service provisions through smart buildings have been a focus of [112] and [178]. More than 41% of energy consumption in building sector is directly related to HVAC systems [207]. Besides, HVAC systems are flexible to provide DSM service to the power grid [255] (for more detail on optimal control approaches applied to buildings' HVAC systems, see [117] and references therein). Promising results are obtained from DSM of buildings incorporating HVAC systems which benefits both entities involved in the B2G system, i.e., the operations of the buildings and the DN [89],[177],[179],[180],[207],[255]-[257]. In this regard, the application of MPC has been a focus of many research works for the optimal DSM of buildings' HVAC systems [179],[180],[207],[255],[256]. Razmara et al. [255] employ MPC to control the power flow of the power grid, RES, and ESS to a commercial building with HVAC systems. They demonstrate that their MPC-based framework applied on a B2G system can provide DSM service to the system by reducing the maximum load ramp-rate of the power grid which prevents high peak demand issues while increasing the penetration of RES in the grid. The scope of [256] is to investigate the impact of model uncertainty on MPC controllers for a building HVAC system, and to develop a robust MPC utilizing uncertainty knowledge to enhance the nominal MPC performance for the control of the HVAC system. In [180] an economic MPC is introduced to develop a building-aggregator-grid contract for the DSM of buildings' HVAC systems to minimize the grid operating costs and emissions, and to improve the grid reliability and market efficiency. The authors of [207] develop a bilevel optimization framework in B2G interaction and apply it on a cluster of commercial buildings connected to a 33-node distribution test feeder with the actual parameters obtained from an office building at Michigan Technological University. The results reveal that compared to the unoptimized case, MPC-based DSM can reduce commercial buildings' monthly electricity costs by 25% in Winter while enhancing the system load factor. Differently, the authors of [257] argue that by implementing DLC mechanism for buildings' HVAC systems, a reduction of up to 60% in the peak demand can be achieved while the indoor temperature can be maintained within the defined limits. Two works of [167] and [168] further utilize DLC-based approaches for DSM of large-scale residential buildings. Load peak shaving, load shifting, and strategic energy conservation are pursued in [89] through the distributed transactive market mechanism for HVACs in commercial buildings. A more interaction between residential, commercial, and industrial buildings with the DNs can be expected in the future modernized power grids due to the recent advances in the information and communication technologies and in control and automation systems. However, some challenges may slow the large-scale deployment of B2G integration. One is with regard to infrastructural challenges such as interoperability between devices at building levels, compatibility issues related to the diversity of data with different resolution and communication standards, and bandwidth limitation. Another challenge comes about mechanism barriers such as lack of appropriate models to provide incentive to consumers for participating in DSM programs, uncertainty in weather and price forecasts, and scale ability and computational limits for real-time applications in practical sized systems.

2.8.7. DSM for VPPs

A Virtual power plant (VPP) is an aggregation of several independent small- and medium-scale DERs, ESSs and flexible loads interacting with each other and with supervisory entities (e.g., MG controllers) through a cloud-based control system as a single virtual power plant with the aim of optimizing the energy resources [258]. A VPP can participate in the energy trading within the wholesale electricity markets while operating its own devices to provide a reliable power and services for its consumers [147]. An energy management strategy for the optimal operation of integrated components in the VPP is of a vital importance for its effective integration into the power grid [259]. Two recent studies of [260] and [261] investigate the potential impacts of VPPs on RES integration and power system dynamic response, respectively. So far, the optimization and control of VPPs have been topics of numerous research activities. These studies can be clustered in terms of different perspectives such as problem-solving approaches, formulation types, and uncertainty modeling [262]. Regarding problem solving, the related approaches for DSM of VPP systems are implemented in centralized [262],[263],[264],[267] or decentralized/distributed fashions [265],[266]. In centralized modes, the VPP employs a central coordination entity to integrate and manage diverse DSM resources. For instance, references [263] and [264] present centralized models that maximize benefits for DSM participant consumers of VPPs participating in energy markets. The authors of [263] detail a DSM model for a VPP where a central aggregator participates in a wholesale market while further managing an internal market for VPP participants who are able to buy or sell electricity with the aim of minimizing total electricity cost. In [264] the infrastructure of a VPP is used to provide flexible demand in low-voltage DNs by optimizing the power consumption of a number of electric space heaters. The concept of VPP can be expanded to diverse geographical areas, in which decentralized/distributed approaches can provide more efficient solutions [260]. For example, a recent work of [265] proposes a decentralized aggregation strategy for a MES through bi-level interactive transactions of VPP to efficiently utilize distributed resources for participating in the market while maximizing the VPP benefits. In [266] optimal dispatch of geographically distributed components of a VPP are conducted hierarchically through a distributed optimization algorithm based on the MAS concept. The formulation types regarding DSM problems in VPPs are commonly based on MILP [263],[264], MINLP [265],[266], stochastic programming [262],[267],[268], and intelligent algorithms [147]. The operation of VPPs is particularly affected by uncertainty due to the intermittency of large-scale distributed resources, energy prices in day-ahead and real-time markets, and retail customers' demand [267]. This reason motivates a group of works to devise strategies for estimating the effects of the uncertainties on such systems. Of all the related approaches, stochastic programming is the most frequently used approach to capture the uncertainties in VPP systems [259]. In [267] and [268], multi-stage stochastic programming models are proposed to achieve the optimal bidding strategies of

VPPs under system uncertainties. Reference [262] presents a stochastic scheduling model for a VPP to maximize the net profit of the VPP and to fulfill the thermal and electrical loads considering the constraints of network security and uncertainties in RESs, loads and market price. Although stochastic programming can effectively model uncertainties in stochastic parameters of the VPP, it typically suffers from the poor scalability when the number of stochastic parameters increases (see Section III), which is an important issue for VPP systems with diverse distributed components. Another group of approaches handle uncertainties in the VPP through fuzzy optimization. A major benefit of fuzzy optimization in comparison to other approaches is that it avoids increasing the problem size notably as the number of uncertain parameters increases. A fuzzy day-ahead optimization model is proposed in [269] for a VPP that serves multiple DERs affected by uncertainty aiming to optimize the day-ahead bidding strategy of the VPP and to maximize the VPP's profit in the day-ahead and the real-time markets. The authors further compare the fuzzy-based approach with a deterministic and a probabilistic day-ahead optimization in terms of real-time market performance considering uncertainty to validate that the highest realized profits can be obtained through fuzzy optimization. However, this work ignores to include ESSs as an important source of flexibility in VPPs. Instead, the work of [260] employs a fuzzy optimization to maximize the daily profit of the VPP that aggregates various energy resources including storage facilities with their corresponding constraints. Summing up, it can be advised that in order to make the realization of VPPs more convinced and reliable, the corresponding energy management strategies and policies should still mature strategically. This aim can be obtained by planning toward broader decentralization of control and optimization structures -as one of the insufficiently explored strategies for the VPP integration- which can beneficially change the role of the DN from a central controller to only a supervisor and coordinator of the different transactive actions among the involved stakeholders. By doing so, a more active, reliable and economically justifiable system design can be resulted. Moreover, in the realization of DSM for VPPs, handling the operational constraints of the DN and TN under VPP observation is of crucial importance, otherwise, the results may cause the network operational constraints to violate and may be practically infeasible. In addition, it is worth denoting that bidding of a VPP in the market is exposed to high risks because of potential imbalances in energy due to the high fluctuations in RES outputs, market prices and energy demands. Accordingly, the identification and assessment of potential risks should be further considered in network security management. Therefore, future research should broadly take these challenges into consideration.

Table 2. 3. Comparative summary of DSM approaches at distribution level investigated in this subsection

DSM application	Main objectives (n.o.p)	System components (n.o.p)	Main constraints (n.o.p)	Solution methods (n.o.p)	Math. type (n.o.p)
EVs coordination and RES integration	Energy cost min. (2) Power loss min. (1) Load factor max. (1) Voltage deviations min. (1) Voltage unbalance min. (1) Feeder loss min. (1) EVs simultaneous charging max. (1) PV power fluctuation min. (1) Costumers' comfort max. (1)	PEV (5) ESS (2) RES (2) CHP (1)	Charging/discharging power limits of PEVs (4) Voltage/current limits (2) Technical power limits (2) SOC (2) RES production capacity (2) Power balance (1) Transformer capacity limits (1) Parking lot power limits (1) Charge facility rates (1) EVs simultaneous charging (1) Trading price ranges (1) Thermal constraints (1)	SP (1) Multi-stage real-time approach (1) Neural network (1) Cloud-based approach (1) Multiobjective PSO (1)	QP (2) NLP (1) MILP (2)
Optimal management of MGs	MG operating cost min. (3) Emission min. (2) Reliability improvement (2) Privacy protection (1) PAR min. (1) MG payoff max. (1) Costumers' comfort max. (1) Utility profit max. (1) Energy cost min. (1) Economic dispatch (1) Power quality improvement (1) Line congestion management (1)	RES (5) ESS (5) PEV (3) DG (3) FC (1)	ESS capacity limits (4) Technical power limits (4) Power balance (3) DG output limits (2) ESS Charging/discharging limits (2) SOC (2) Energy supply constraints (1) Demand fulfilment (1) Contracted load reduction limits (1) DG timing constraints (1)	PSO (2) SP (1) Game theory (1) IPM (1) Robust control (1) MPC (1) Stochastic MPC (1)	MINLP (3) QP (1)
Multi-energy systems	Electricity cost min. (2) Gas cost min. (1) Peak shaving (1) Demand/supply matching (1) DG startups/shutdowns cost min. (1)	CHP (2) ESS (2) HP (1) RES (1) TES (1) DG (1) GF (1)	ESS capacity limits (4) ESS Charging/discharging limits (2) Technical power limits (2) Participation factor limit (1) CHP ramp-up/down rates (1) Thermal limits (1) CHP capacity limit (1) Gas furnace capacity limit (1) SOC (1) Energy balance (1)	Cooperative mechanism (1) Approximation approach (1)	MIQP (1) MINLP (1)
Building-to-grid and multiple electrical loads	Energy cost min. (3) Peak shaving (2) Load factor max. (1) Thermal comfort (1) Voltage/current regulation (1) Costumers' comfort max. (1)	HVAC (2) WH (2) DG (2) CB (1) CHP (1) ESS (1) RES (1) PEV (1) Boiler (1) FC (1) TCL (1)	Temperature rates (4) Thermal capacity (3) Voltage limits (2) Technical power limits (2) Energy balance (2) Building power penetration limits (1) Capacitor bank limits (1) Transformer capacity limits (1) SOC (1) ESS Charging/discharging limits (1) ESS capacity limits (1) Energy transaction limits (1) HVAC capacity (1) Demand fulfilment (1) DG output limits (1)	Hierarchical MPC (2) Bilevel programming (1) SP (1) Greedy algorithm (1) Binary search algorithm (1) Differential evolutionary algorithm (1)	LP (3) HP (2)
Virtual power plants	VPP operator's profit max. (3) Costumers' comfort max. (1) RES penetration max. (1) Social welfare max. (1) Voltage regulation (1)	RES (3) DG (2) ESS (1) HVAC (1) PEV (1)	DG output limits (2) Temperature rates (1) Line capacity (1) HVAC capacity (1) Temperature rates (1) HVAC heat rate (1) Energy balance (1) SOC (1) ESS Charging/discharging limits (1) ESS capacity limits (1) DG ramp limits (1)	FL (2) Data mining technique (1)	NLP (1) MILP (1) MINLP (1)

Note-The list of new acronyms used: *AC* (Air conditioner), *CB* (Capacitor bank), *CHP* (Combined heat and power), *FC* (Fuel cell), FL (Fuzzy logic), GF (Gas furnace), *HP* (Heat pump), *HVAC* (Heating, ventilation, and air conditioning), *IPM* (Interior-point method), *MA* (Multi agent), *PSO* (Particle swarm optimization), *SP* (Stochastic programming), *SOC* (State of charge), *SOH* (State of heat), *TCL* (thermostatically controlled load), *TES* (Thermal energy storage), *WH* (Water heater).

2.9. Demand-side Management at Transmission Level

In a transmission network (TN), bulk energy products are transferred from the location of production to distribution lines that carry the energy products to end users. In this section we analyze and discuss the decision-making and control strategies for utilizing the potential of DSM programs for the enhancement of the TN operation and support focused on the electric transmission planning, the power system economic operation including the integration of DSM into *unit commitment (UC)*, *economic dispatch (ED)* and *optimal power flow (OPF)* problems, and flexibility service provision to the TSO, mainly ancillary services such as frequency control and voltage support in transmission level, congestion management, load following and shedding.

2.9.1. Introduction

Contrary to the well-recognized impacts of DSM resources on the DN and the end-use customers, the contribution of such resources, including the energy efficiency and the DR, still requires a wider technical investigation and long-term system assessment [270]. In general, identifying the impacts of DSM implementation at the TN are more challenging to quantify and are not possible to be characterized by simple metrics [271]. The most important question is whether DSM programs will have short- to long-term impacts on the TN operation, infrastructure and capacity expansion, and further how significant will these impacts be? As a quick answer, cancellations of several major upgrade projects for the TN due to the reduction in demand growth can inspire that there is a connection (e.g., two upgrade projects of PJM's Mid-Atlantic Power Pathway and Potomac-Appalachian Transmission Highline were cancelled as analyses no longer demonstrate a need for the new capacities to maintain grid reliability [272]). Generally, building and expanding the TN infrastructures are very difficult and costly. Diverse transmission constraints may further result in suboptimal investments, such as inducing utilities to buy energy from geographically near generation sources without considering extra resulting costs and environmental impacts [273]. Accordingly, exploring alternatives for reducing, shifting or shedding demands is of greater priority to maximize the possibility of using the existing transmission capacity. This is where the DSM resources can play a crucial role. Whereas potentials of DSM resources can provide excellent values to TSOs as well as additional sources of revenue for other market players, it is still surprisingly underdeveloped in most research programs [274]. One of the most prominent topics for the TSO is regarding TN expansion planning. It refers to the location, the time, the capacity and the type of reinforcements, i.e., the new power transmission lines and the associated electrical facilities, that need to be placed in the TN in order to meet the predicted demand and the security, reliability and quality criteria while minimizing the total investment and operational costs [275]. US Department of Energy (DOE) and the Edison Electric Institute identify four main drivers for building new transmission capacities, namely interconnection, reliability, economics and replacement [276]. According to that, Oak Ridge National Laboratory published an interesting report on the impacts of DSM resources on TN expansion planning where the role of DSM on these four drivers in addition to a further introduced driver, i.e., policy, is discussed [270]. This report argues that DSM resources can beneficially affect all these drivers. Firstly, a less interconnection of new loads or generations may be required due to the reduced demand or the increased local generation at the end-user locations. Secondly, a more reliable system can be achieved with the reduction of operational stresses on the TN while a less need for planning reserves is required as a result of the lower peak demand. Thirdly, deployment of distributed generations can substantially reduce the capital cost of transmission as well as the transmission line losses of distant plants. Fourthly, the reduced peak demand due to the implementation of DSM programs may delay or reduce the need to replace aged assets. Lastly, utilizing the environmentally friendly demand resources can reduce the emissions, land and water impacts and consequently, can affect the relevant policies such as renewable portfolio standards, reduced emissions, esthetics and grid resilience. Thus, seen from the perspective of the TN planning, DSM programs can be considered as an effective non-network solution providing supplementary options for transmission expansion. However, many issues may inevitably arise from inaccuracies in the DSM design and implementation [277],[278]. For instance, the work of [279] indicates that a significant RES capacity has been recently connected to the TN in Central Europe to achieve the unique brought by the clean generation. However, the intermittent nature of RES is posing emerging challenges to the network planners. Moreover, the involvement of DSM in both TNs and DNs (as DN is becoming actively engaged in TN operations) can pose additional constraints and considerations into the TN design and operation which necessitates the need for deep interactions between TSOs and DSOs (we refer to [279] for more detail about opportunities of TSO/DSO interaction). These interactions have been the scope of some technical literature for different targets such as network congestion management [281] and service provisions [282]. Hence, TN development planning has become a complex decision-making process which mostly requires further risk analyses. An interesting example of such analyses is provided in [283] where the authors propose a decision-making support tool to TN expansion planning considering a risk constraint and the uncertainty in the RES in order to obtain optimal planning schemes with a minimum probability of load curtailment within a threshold, and to establish a trade-off between the cost, the reliability and the risk. In [278] an incentive-based DSM supporting utilities is described, which manages a targeted negotiation with corresponding load aggregators for contributing to peak load reduction. This feature can provide utilities with a flexible TN expansion planning so as to achieve an optimal trade-off between the transmission investment and the DSM expenses. Summing up, an optimal carefully designed DSM program at TN level can substantially contribute to maintaining the whole system balance, complying with the transmission limits and reaching the required reliability level. This also increases the bulk electric system flexibility by providing additional dispatchable resources, which can potentially mitigate the imbalances due to the RES generation. In the following subsections we review the decision-making and control strategies for DSM targets supporting the economic operation of a flexible and sustainable TN.

2.9.2. Power System Operation

In large power systems, the mismatch between loads and generation may cause various problems such as voltage instability, cascaded failures of transmission lines, and wide area blackouts [284]. The integration of DSM resources into the TN can be successfully realized to provide the power system a more efficient, secure, and economic operation [271]. A good example of this is the automatic optimal control of demand as a source of flexibility to enhance the system controllability. This cannot be easily achieved by conventional generators due to their various flexibility limits such as ramp rates and generation levels [285]. Flexible demand controlled through DR is a great candidate to remove these limitations, and to provide a fast ramping by quickly changing the demand to balance the grid [255]. However, such new DSM opportunities and potential benefits may be also accompanied by new challenges to the power system operation while enforcing additional constraints and modelling requirements to the system which must be carefully addressed. While the TSO pursues a reliable operation of the power grid by solving fundamental operational problems, including UC, ED and OPF, incorporating DSM into these problems may increases their complexities [286]. In this subsection, we review the integration of DSM into the classical power system economic operation problems.

2.9.2.1. Unit Commitment

The UC consists in selecting a set of available generation units for a predefined time period aiming to minimize the overall generation cost (including fuel cost, startup/shutdown cost and maintenance cost) while supplying the entire system load subject to some operational and technical constraints of each generation unit (e.g., ramp rate limits) [287]. UC is typically seen as a large-scale, non-convex and mixed-integer optimization problem which is hard to be solved (see [288] for more detail regarding conventional UC problem formulation and constraints).

Furthermore, despite beneficial contributions of DSM resources into the power system operation, the trend of incorporating DSM programs along with DERs related modelling and constraints in the grid makes UC problems even more complicated and computationally challenging [289]. The major reason contributing to this additional complication is the uncertain availability of DSM resources (e.g., inaccuracies in the forecast of RES generations) and imperfect controllability over DSM resources (e.g., unexpected behavior of the consumers and limited information on the state, constraints, and dynamics of the loads) [290]. Hence, additional analyses may be necessary to accommodate these issues in an optimal UC. The value and impact of integrating DSM resources on UC in the power grid has been assessed in several studies [126],[127],[291]-[296]. Reference [291] proposes a UC model which is robust to the uncertainty in the DR resource (i.e., in uncertain price elasticity of demand) intending to minimize the cost of generators, opportunity cost of reduced demand due to the DR program, startup cost of generators, and spinning reserve cost. The authors in [292] determine the value of residential DSM resources on operating cost savings under stochastic RES generation and limited controllability of the loads, stated as a UC problem with probabilistic reserve constraints, using a model inspired by the Belgian power system. Their results demonstrate that average operating cost savings amount to over 6% for short-term load shifting (arbitrage) and over 7% for combined arbitrage and regulation. Instead, a stochastic UC model with several flexibility resources is developed in [293] and tested on two large-scale case studies of the IEEE 300-bus and IEEE 118-bus test systems to determine the minimum daily operation cost. To this aim, the authors combine DR, ESS and network reconfiguration by the transmission switching actions while considering the uncertainties in RESs and equipment failures. The detailed impacts of ESS unit with its energy shifting and fast-ramping capabilities on system operating cost saving are evaluated in [294]. The use of ESS in UC problems is a prominent option to satisfy the transmission constraints, but installation cost of high-capacity ESSs is very high. The case study in [295] shows that ESS capacity can be drastically reduced by incorporating DSM system. Rather, interesting work of [296] details the potential of energy efficiency and DR programs coordination in handling the UC problem through a two-stage scheme covering short term and midterm scheduling for cost-effective operation of power plants. While the midterm scheduling over a one-year horizon determines the level of the energy efficiency investment, its obtained results is adopted for the short-term scheduling over a one-day horizon to minimize operation cost and total incentive cost of consumers. Published results from the investigated relevant studies implies a properly managed incorporation of DSM resources distributed across different load buses into the UC problem not only can result in significant reduction of the startup/shutdown and fuel cost of the power plants, in alleviating the network congestion, and in reduction of electricity prices in electricity markets but also keeping robustness of the solution against various types of forecast uncertainty. For instance, reference

[285] reports that by involving DSM strategies in market clearing problem formulation, a notable reduction in market prices can be achieved. It further argues that due to the non-convexity of the UC problem, some price spikes can be observed in the large-scale DSM implementation, which needs to be evaluated before incorporating DSM programs into UC in an electricity market environment. In addition, numerical and simulation results of the UC problem on several case studies with and without the integration of DSM programs are discussed in [297] which confirm considerable values of DSM programs as a cos-effective and energy-efficient tool in the UC problem.

2.9.2.2. Economic Dispatch

ED is a sub-problem of the UC and is a step that generally needs to be done after completing the UC process. It aims at optimally allocating demands and transmission losses to the power generation units to reliably supply the entire system load with the lowest cost whilst complying with the various technical constraints of the TN and the generation units [286]. Typically, technical constraints of the TN such as the transmission capacity limits are considered in ED problems [287].

Recent studies demonstrate that an effective ED model should address nonlinear and non-smooth nature of input-output characteristics of modern generators which is due to some factors such as valve point effect (i.e., the ripples induced by the valve point loading to generating units causing ripples to the fuel-cost curve), discontinuous prohibited zones and ramp rate limits of generation units, as well as intermittency in both generations and consumptions [298]. Hence, conventional derivative-based ED approaches such as lambda iteration, dynamic programming and gradient method are mostly unreliable and computationally inefficient to solve ED problems as they often obtain a local optimum for the highly nonlinear and non-convex optimization problems [82],[159]. More recent studies have moved toward other sorts of priority techniques such as heuristic/metaheuristic algorithms [82],[159],[299], artificial intelligence approaches [300] or predictive-based approaches [126] to tackle these challenges. The authors of [301] use a genetic algorithm to address both DSM and ED problems through two complementary optimization stages. In [302] the optimal dispatch of DSM units alongside conventional generating units is presented, but without integrating RESs and with some simplifying assumptions neglecting the presence of any uncertainty in the system parameters. An interesting transmission level energy management for the balancing market ED is developed in [303] where the authors solve the problem in a decentralized fashion while considering flexible demand characteristics as well as network constraints (i.e., TN and DN constraints such as bus power balance, voltage magnitude constraints, and line capacity constraints), generation constraints (e.g., generation limits and ramp rate limits), demand constraints (including end-users' devices, small-scale RES and EVs) as well as coupling constraints (related to concatenation of active power, reactive power and voltage constraints). A group of studies solve the ED problem as static ED (SED) when only looking at a single interval of time, e.g., half an hour. A SED simplistically assumes that the power output of the generation units can be adjusted instantaneously. However, this assumption cannot reflect the actual operating processes of the generating units due to their ramp rate limits. In addition, the uncertainties associated with the large intermittency of the customers' demand RES generation cannot be efficiently handled through the SED [304]. Other group of research focus on the dynamic ED (DED) which provides a look-ahead capability to meet the predicted demand and the possible uncertainties while considering the dynamic constraints of the generation units [82],[299],[300],[305]. In [305] a dynamic coordination between ED and DSM is stated and solved through a distributed algorithm while taking advantage of an ESS unit to mitigate the effect of RES uncertainty. In general, as a DED problem consists of multiple objectives with several equality and inequality constraints, an increase in the system size can make it a complicated optimization problem. More recent studies cope with this issue by adopting other classes of algorithms such as heuristic/metaheuristic algorithms and AI-based algorithms. For instance, the authors in [299] propose a DSM approach which integrates a DED problem with a price-based DR program. They apply a metaheuristic algorithm to solve the problem aiming to minimize the generation costs and the customers' costs while maximizing the network reliability. In [159] a multi-agent learning based solution for the ED of distributed energy hubs is developed, however, it ignores important energy network constraints. Rather, AI-based approach based on a dynamic online learning is proposed in [300] for optimal ED of networked MGs. The authors show that an optimal DSM program not only helps to reduce long-term operation cost of the system but also supports the stable operation of system components (in this case, ESS unit and flexible loads).

2.9.2.3. Optimal Power Flow

The concept of OPF is introduced as a more general approach than ED for producing acceptable flows which simultaneously satisfies power flow balance and constraints related to the network operating limits such as nodal voltages, line flows and apparent power in feeders [306]. OPF problem is generally solved as a large-scale MINLP problem with a large number of mixed-integer variables. As for UC and ED problems, high penetration of uncertain RESs in transmission and distribution networks along with unpredictable behavior of energy demands make this problem more complex [284]. While ED usually ignores some network constraints and the topology of the power system, e.g., the location of the generating units and loads, OPF usually considers actual network location along with voltage, thermal, and fault level constraints. This is important as the characteristics of the loads and their host networks may vary from one location to another and ignoring such aspect may lead to unacceptable flows or voltages into power networks [307] (see also [284] for more detail regarding the most common objectives and constraints in the OPF problem). Many scholars have studied the incorporation of DSM programs in the OPF problem. Reference [307] investigates an OPF approach to determine where the application of DSM resources would be of most benefit to the network operation regarding their ability to alleviate critical upstream network contingencies (e.g., relieving grid supply transformer overload and voltage instability). Stochastic optimizations are employed in [61] and [308] to model the uncertainty of RES generation into the OPF problem through generating a finite number of possible scenarios. However, in large OPF problems, stochastic OPF algorithms may result in very high computational burden while requiring probability distributions of uncertain variable which are not easily available in the power system. Instead, interval-based robust optimization approaches can tackle these limitations as proposed in [309] using non-probabilistic quantification of uncertainty in wind generation to manage network congestion. Cost-effective capability of DSM resources in OPF problems is assessed in [284] considering diverse system operational constraints such as bus voltage magnitude and angle bounds, active/reactive power generation constraints, active/reactive load-generation balance constraint, transmission power flow calculation and limits, ramp rate limits. Differently, OPF techniques have also been applied to determine the optimal buses and times for implementing DSM programs. For instance, the authors in [310] develop an algorithm based on power transfer distribution factors, available transfer capability and dynamic OPF to alleviate the network congestion and enhance the system reliability. The works of [114] and [311] present a combination of a real-time OPF and a day ahead OPF. The real-time OPF aims to minimize the cost of all generation units and to supply the load demand while considering the voltage, reactive power limit and line flow constraints. On the other hand, the day-ahead OPF accounts for maximizing the social benefits, i.e., the customer benefits minus the generation costs, considering ramp rate limits while taking care of the RES generation and the demand uncertainties.

2.9.3. Service provision

Grid services are all support services for the reliable and high-quality generation, transmission, and distribution of electricity from the utility to the consumer [252]. In particular, ancillary services refer to a range of functions that system operators (TSOs) contract so as to guarantee the power system security [312]. They are vital support services to the operation of whole power system for ensuring a continuous flow of electricity to meet electricity demand uninterruptedly even during contingency events. Ancillary services at transmission level are typically divided into *frequency* and *non-frequency* services. Frequency response service are used to maintain the system frequency to the nominal value with automatic and very fast responses. Non-frequency services include black start capability, i.e., the ability to restart a grid following from a blackout, reserve services to provide additional energy when needed and voltage support through the provision of reactive power [282].

Traditionally, ancillary services have been provided by generators, storage resources or reactive power control equipment. However, as an example of the exorbitant costs exerted by service provision on electricity suppliers, a total amount of £33.90 million have been spent by National Grid in Great Britain on ancillary services in January 2020 [313]. These significant costs justify the emerge of new plans for utilizing the potential of DSM resources for the service provision in the power system. DSM mechanisms in control services not only reduce such costs considerably, but also maintain the security and support of the system more efficiently. The integration of DERs such as DGs, RESs, ESSs, the wide-spread deployment of EVs, the development of SG and MG technologies, and applying DR programs have prompted the provision of ancillary services for future power systems. DSM systems can perform similar functions as a traditional ancillary service provider (e.g., a fossil fueled thermal power plants) with a very quick response less than a second or within minutes [220]. Many recent studies have focused on the potential of DSM for providing ancillary services at the transmission level. In particular, they focus on the role of DSM strategies on maintaining grid frequency [73],[75],[113],[178],[314]-[316] and transmission-level voltage [318] at desired levels, transmission congestion management [317], load following service [130],[321] and provisioning operating reserves [112],[319],[320] for any contingency event or disruption to the power supply. For instance, a distributed active DSM relying on a stochastic control algorithm is proposed in [314] for the provision of both primary and secondary load frequency regulation in power systems. Load participation in frequency control of SGs is assessed in [113] for restoring the frequency to its nominal value after a disturbance by dynamically adapting the loads. The interesting results of a field experiment from a demonstration project in [315] demonstrates that the use of demand side flexibility can provide a considerable frequency reserve in the power system. In addition, experimental tests of DSM resource participation on a 30000 m^2 commercial office building are provided in [316] to investigate the ability of a commercial HVAC system to provide frequency regulation services. Instead, relieving congestion in transmission lines using DSM programs and generation rescheduling is the focus of [317]. By establishing a multi-objective problem based on a heuristic approach, the authors minimize total operation costs, DR costs and emission while managing the power system transmission lines congestion. Other cluster of studies address load following services which is currently known as a major ancillary service for the grid to regulate frequency and voltage [130],[255]. According to that, the demand side should be able to follow the supply side. For instance, the potential of the predictive B2G controller is studied in [255] for delivering load following services. The authors establish probabilistic analysis accounting for forecast uncertainty aiming at decreasing the maximum load ramp-rate of the power grid while ensuring maximum RES penetration. In [318] the participation of smart appliances in response to the network voltage and frequency drop is examined to effectively contribute to maintaining the power balance and preventing frequency or voltage collapse. The authors propose an under frequency load shedding combined with a under voltage load shedding to restore the system voltage to the normal range, i.e., between 0.945~1.045p.u, and system frequency back to more than 49.9Hz after contingencies. As discussed before, ever-growing large-scale penetration of RESs can crucially increase regulation and load following needs with regard to capacity and ramping capability, and the conventional regulating generators hold serious limitations and drawbacks such as ramp-rate constraints, efficiency loss due to the ramping, inaccurate tracking of the area control error signal as well as operating and maintenance costs. Hence, DSM can play a further promising role in exploiting the flexible demand side resources to bear a more efficient and fast-response regulation reserve. For instance, in [319] the potential of flexible HVAC power in smart commercial buildings as regulating power is investigated. The strategy is based on storing excess RES generation as thermal energy in the buildings, so that the flexible central HVAC loads can be used to effectively compensate the variability of the RES. An interesting utilization of thermostatically controlled appliances such as aggregated electric water heaters is introduced in [320] to provide balancing reserves for the utility. The authors argue that this DR resource can provide desired balancing reserves in the presence of wind generation for a high percentage of the operating time.

Currently, a potential sector which can actively participate as a DSM tool into service provisions such as spinning reserve, load following, and demand-side regulation is industrial plants which are often already equipped with control, measurement, and communication infrastructures. A good example of this participation is presented in [321] where a MPC-based coordination method enables industrial loads as DSM resources to provide regulation or load following with the support of an onsite ESS. This study shows that the cooperation of the industrial machines and the ESS can provide an accurate regulation or load following command in a very wide range.

Although valuable efforts are being made to involve DSM resources into network service provisions, more accurate and comprehensive studies on the various aspects of this incorporation have remained insufficient which can be interesting directions for future investigations. A precise assessment of the interactions between TN, DN, DERs alongside DSM programs for providing services is possible only if accurate and realistic models of DERs and other flexibility resources (such as flexible loads and ESSs) connected to the network are incorporated. In addition, increased cost of serving DSM resources should be included into the cost of providing regulation services as this cost can be significant. Moreover, while holistic and standardized solutions within this research area are still unavailable, the lack of a standard test platforms, diversity of protocols and performance metrics precludes a proper comparative analysis of different methodologies. A comparative summary of DSM approaches at transmission level investigated in this subsection is provided in Table 2.4.

Table 2. 4. Comparative summary of DSM approaches at transmission level investigated in this subsection

DSM application	Main objectives (n.o.p)	Main constraints (n.o.p)	Solution methods (n.o.p)
Power transmission development planning	Investment cost min (3) Reliability improvement (3) Planning risk management (2) System security improvement (1) Peak demand reduction (1) Operation cost min. (1)	DG output limits (3) Power balance (3) Technical power limits (3) Risk constraint (2) Network flow (2) System reliability const. (1) Transmission capacity (1) Stability requirement (1)	Decomposition approach (2) Differential evolution (1) Mont Carlo simulation (1)
Power systems operations (ED/ UC/ OPF)	Cost min. (13) Emission min. (4) Demand fulfillment (3) Reliability improvement (2) Congestion management (2) Power regulation (1) Peak demand reduction (1) Utility profit max. (1)	Power balance (11) DG output limits (9) DG ramp rate limits (9) Technical power limits (5) Thermal limits (5) Network flow (4) Bus voltage/current limits (4) RES power const. (2) Spinning reserve constraints (2) SOC (1) SOH (1) User's incentive limits (1) DG startup/shutdown const. (1)	Cooperative mechanism (3) Imperialist competitive algorithm (1) Discrete compromise programming (1) Stochastic programming (1) Decomposition approach (1) Chance constrained programming (1) Robust approach (1) Closed loop hierarchical (1) Heuristic method (1) Two-point estimate method (1) Real-time approach (1)
Ancillary services	Voltage/frequency stability (8) Reliability improvement (4) Cost min. (5) Risk management (3) Profit/return max. (3) Investment/maintenance cost min. (2) Power quality improvement (2) RES utilization max. (1) Balancing reserve (1) Load following (1) DG generation cost (1) Primary/secondary frequency control (1) Power flow control (1) RES penetration max. (1) Load ramp-rate max. (1) Reliability improvement (1) Voltage unbalance min. (1)	Frequency/voltage limits (6) Power balance (6) Temperature limits (5) Technical power limits (4) ESS capacity limits (4) Thermal limits (2) SOC (2) Voltage/current limits (2) Transformer capacity limits (2) DG output limits (1) DG ramp rate limits (1) Energy demand limits (1) Line capacity (1) Feeder capacity limits (1) DR timing constraints (1) Charging/discharging capacity (1) Load curtailment timing (1)	Cooperative mechanism (6) Stochastic programming (4) Real-time approaches (3) MPC (2) PQ controller (1) Heuristic method (1) Bilevel programming (1) Voltage sensitivity method (1)

2.10.Conclusions and Recommendations

This chapter provided a multi-directional understanding of the recent advances in the area of DSM to several domains of the electric grid from smart end-users to distribution level and transmission level. Investigating a broad spectrum of related research theoretically showed a vast potential economic and technological benefits due to DSM programs. However, their real-word implementation is still minimal owing to numerous barriers, in particular from the perspective of decision-making and control. Despite positive attempts, significant effort is still required to explore DSM potential regarding necessary consideration of the impact of DSM programs on the electric grid in long-term planning.

Although DSM programs offer promising solutions to the increasing load level and can considerably improve the reliability and financial performances of electric grid, one of the main challenges is to effectively maintain a balance between demand and generation in a distributed energy supply system dominated by different forms of DERs, and in particular, in multi-energy systems with various types of energy sources and associated uncertainties. Another significant consideration is with respect to the interface between TN and DN operation. This can be addressed by continuously coordinating TN and DN stakeholders during all steps of planning and road mapping process for development of DSM programs. Moreover, a number of technical challenges related to the infrastructure of communications, the metering infrastructure, integrated thermic/electric storage technologies and micro CHP installations needs to be resolved.

Some important assumptions on the behavior of the electric grid in the case of, for example, ageing effect, partial outage of generation units, intermittent operating units and natural disasters is necessary for a sustainable deployment of DSM in SGs, which have not been considered in most of the surveyed research. Furthermore, forecast uncertainties such as the intermittency of RES generation, electricity price, failure rate and users' behavior in the presence of DSM are poorly investigated. Future works should concern a more in-depth analysis of these issues for the implementation of DSM programs.

Finally, the potential for considerable amount of electric power from local generation and storage fed back into the electric grid is evident and will require greater examination to understand the true impact to the grid.

From the findings and contribution of the research in this chapter, the following paper is under submission:

- S. M. Hosseini, A. Parisio, R. Carli and M. Dotoli, "Decision and Control Approaches for Demand-side Management in Smart Grids: A Survey," in *IEEE Transactions on Control Systems Technology* – under submission.

3. Robust Centralized Approaches for Demand-side Management in Residential Microgrids

3.1. Introduction

In this section, we present several original centralized DSM approaches aiming to provide a cost-effective solution for energy management of residential MGs under different technical/operational/contractual constraints in presence of both generation and demand uncertainties. The features of the considered microgrid are defined according to residential microgrid architectures commonly used in the most recent studies. We define on this chapter a residential microgrid as a locally controlled system to promote the integration of distributed generation sources, energy storage systems, interconnected users with household loads, plug-in electric vehicles along with smart meters and home energy consumption controllers, in which households' energy demands can be supplied by local generations while their extra required/surplus energy can be bought/sold from/to the power grid. We define a relatively comprehensive architecture for the residential microgrid including household loads (i.e., elastic controllable and critical non-controllable appliances), micro generation resources (i. e., several photovoltaic systems and domestic wind turbines), an energy storage system, and plug-in electric vehicles. Firstly, we propose a day-ahead robust approach based on box uncertainty set model for optimal scheduling of a residential MG. Then, we explore a novel online approach based on MPC, and a robust online approach based on robust MPC (RMPC) regarding the cardinality-constrained uncertainty set model for the DSM of a residential MG. Finally, we present a comprehensive model and a systematic robust methodology to state and solve the optimal energy scheduling problem of a grid-connected residential MG with several electric components and various types of uncertainty.

3.2. A Robust Day-ahead Approach for Energy Management of Residential Microgrids

3.2.1. Introduction

In this section, we develop a robust optimization framework for the day-ahead energy scheduling of a grid-connected residential user. The system incorporates a RES, an ESS as well as elastic controllable and critical non-controllable electrical appliances. The proposed approach copes with the fluctuation and intermittence of the RES generation and non-controllable load demand by a tractable robust optimization scheme requiring minimum information on the sources of uncertainty. The main objective is minimizing the total energy payment for the user considering operational/technical constraints and a contractual constraint penalizing the excessive use of energy. The presented framework allows the decision maker to define different robustness levels for uncertain variables, and to flexibly establish an equilibrium between user's payment and price of robustness. To validate the effectiveness of the proposed framework under uncertainty, we simulate the dynamics of a residential user as a case study. A comparison between the proposed robust approach and the same method with deterministic RES and loads profiles is carried out and discussed.

3.2.2. Related Works and Contributions

Over the past decades, a wide spectrum of optimization techniques has been developed to minimize the energy payment and optimizing the system performance of residential MGs. However, most of the studies assume perfect knowledge of all coefficients, which is hardly realistic and not necessarily valid for many real-world cases due to the randomness involved with RESs and poor forecast accuracy [322],[323]. Thus, other researchers have proposed methods considering uncertainty to achieve a more practical, robust and efficient energy scheduling [324]-[330]. For example, [324] presents a two-stage framework to minimize the expected operation cost of a distribution company considering future load and real-time prices as two sources of uncertainty. In [325], the RES generation and the demand load are considered as the uncertain variables for the day-ahead energy scheduling of a smart MG. The proposed models in [324] and [325] both use two-stage scenario-based stochastic programming. In addition, a robust approach to schedule the operation of smart home appliances and ESS for obtaining a robust solution under load uncertainty is presented in [326], even though the uncertainty associated with the RES unit is ignored. A robust day-ahead scheduling of a smart residential user under uncertainty is also provided in [327] using an energy service decision-support tool. Although the presented approach effectively results in a lower expected cost than traditional deterministic approach, it suffers from computational complexity as the robust schedule is derived using a stochastic programming approach over a set of scenarios for modeling the range of uncertainty. Moreover, the probability of the occurrence of each scenario has to be known in advance. In [328], a robust optimization method is proposed addressing the uncertainty of the RES by setting up a collaborative scheduling of the ESS with direct load control (DLC). The robust day-ahead energy management of smart homes in the presence of uncertainty of the RES is also tackled in [329], but without pursuing uncertainty in loads, and without incorporating the ESS in the MG. A robust strategy for minimizing the total energy exchange cost and simultaneously maximizing social benefits is presented in [330]. Although both forecast uncertainties in RES and loads are considered in [330], the authors use probabilistic scenario-based uncertain sets imposing high computational complexity. Moreover, the method is based on optimization of the worst-case scenario without providing robustness flexibility and resulting in a too conservative formulation.

To the best of the authors' knowledge, and as shown by previous literature review, there is no contribution in the related literature proposing a robust optimization approach under bounded uncertainty sets dealing with intermittency in both RESs and loads in residential smart users including ESS units. Thus, filling this gap, this section develops a robust optimization framework for the day-ahead scheduling of residential smart user under uncertainties of forecast parameters. Unlike stochastic scenario-based techniques, our proposed method takes advantage from a robust optimization scheme including minimum information on the sources of uncertainty - namely only the deterministic range of the uncertain variables and the resistance against any disturbance in the uncertainty set - and characterized by a lower computational burden than stochastic optimization that normally utilizes time consuming Monte Carlo sampling [331].

3.2.3. Aims and Objectives

The main objective of the energy scheduling is minimizing the total energy payment for the user considering a contractual constraint with penalized cost for excessive use of energy. We also deal with the conservatism of the robust control algorithm and flexibility of the method for application to different settings. Our approach allows the decision maker to establish a trade-off between user’s payment and level of conservatism. We apply a contractual constraint with adjustable robustness factors to make the problem statement closely representative of the practical system and increase the flexibility of conservatism. We simulate the dynamics of a residential user as a case study to validate the effectiveness of the proposed framework under uncertainties both in the forecast of the RES and non-controllable loads. Finally, a comparison between the proposed approach and the same method with deterministic forecast profiles is carried out and discussed.

3.2.4. The Residential User Mathematical Model

The scheme of the system under consideration is illustrated as Figure 3.1. The system is composed by a residential user with a controllable load, a non-controllable load, a local RES, and a ESS that may charge/discharge energy during each time slot. The leading actor is a HEMS. It oversees autonomously managing the interactive operation of home appliances, RES, ESS and distribution grid while considering operational/technical constraints as well as contractual grid regulations imposed by the main distribution grid [332]. We consider a time window $\boldsymbol{\mathcal{H}} \triangleq \{1, \dots, h, \dots, H\}$ including H equally spaced time intervals. The modeling of system components is discussed as follows.

3.2.4.1. Controllable and Non-controllable Loads

In the present work, we assume the user is equipped with two types of electrical home appliances, called controllable and non-controllable loads. Indeed, the operation time of some appliances such as dishwasher, dryer, and washing machine can be controlled and deferred to other time slots of the time horizon based on user's priority with neglectable effect on the user's comfort. We denote the consumption profile of the controllable load by a vector $\boldsymbol{x} = [x(1), \dots, x(h), \dots, x(H)]$ with H non-negative decision variables. The required energy level for the operation of the controllable load at each time slot should be defined between a minimum and a maximum range. Therefore, we state two parameter vectors $\boldsymbol{x_{lb}} = [x_{lb}(1), \dots, x_{lb}(h), \dots, x_{lb}(H)]$ and $\boldsymbol{x_{ub}} = [x_{ub}(1), \dots, x_{ub}(h), \dots, x_{ub}(H)]$ for minimum and maximum energy consumption level, respectively. Also, the cumulative consumption needs to reach a given threshold X_T by the deadline to complete the task in the considered time horizon. Thus, the controllable load decision variables vector at each time instant is subject to the following constraints:

$$\boldsymbol{x}_{lb} \leq \boldsymbol{x} \leq \boldsymbol{x}_{ub} \tag{1}$$

$$\sum_{h=1}^{H} x(h) = X_T, \ \forall h \in \mathcal{H}. \tag{2}$$

Another type of home appliance is categorized as non-controllable load, whose action is critical, so that its standard operation time cannot be shifted. We denote the non-controllable load consumption profile for each time slot by a vector of H input parameters $\tilde{\boldsymbol{b}} = \left[\tilde{b}(1), \dots, \tilde{b}(h), \dots, \tilde{b}(H)\right]$. We assume that this vector is computed by a forecast sub-module of the HEMS (see Figure 3.1), using a prediction algorithm based on historical data [333]. In next section we show that only a minimum/maximum range for non-controllable load profile is enough for our robust framework:

$$\tilde{b}_{lb}(h) \leq \tilde{b}(h) \leq \tilde{b}_{ub}(h), \qquad \forall h \in \mathcal{H}. \tag{3}$$

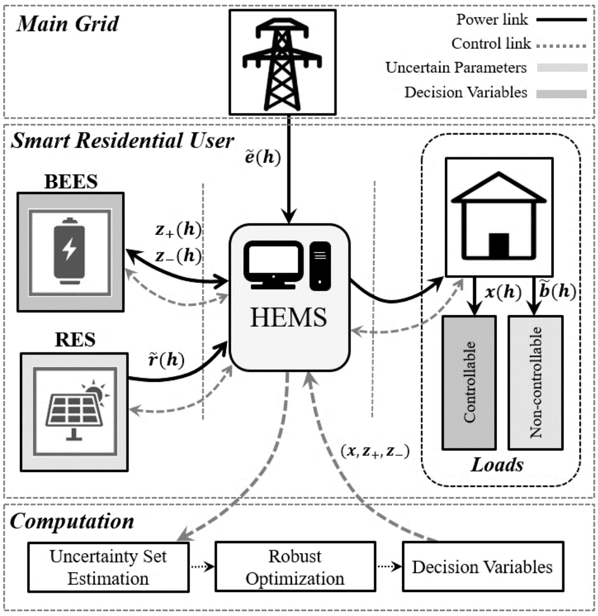


Figure 3. 1. Scheme of the considered smart residential user

3.2.4.2. Renewable Energy Source

The RES generation profile within the prediction horizon for each time slot can be represented as a vector of H input parameters $\tilde{\boldsymbol{r}} = [\tilde{r}(1), \ldots, \tilde{r}(h), \ldots, \tilde{r}(H)]$. This vector is also assumed to be calculated by a forecast sub-module of the HEMS by a prediction algorithm based on weather data [334]. We later show that, to solve the scheduling problem, our approach only requires knowledge of the lower and upper bounds that are typically available based on historical data:

$$\tilde{r}_{lb}(h) \leq \tilde{r}(h) \leq \tilde{r}_{ub}(h), \qquad \forall h \in \mathcal{H}. \tag{4}$$

3.2.4.3. Energy Storage System

The HEMS is also in charge of implementing the charging/discharging strategies of the ESS. The ESS has to optimally store the energy harvested from the distribution grid and/or the RES unit. Then, it can supply the MG loads in peak demand periods. We define vectors $\boldsymbol{z} = [z(1), \ldots, z(h), \ldots, z(H)]$ with H decision variables to model the charge/discharge energy profiles of the ESS in the prediction horizon. The mentioned decision variables should be technically constrained as follows:

i) the rate of charging/discharging of the stored energy is bounded between zero and a maximum charging/discharging rate Z_{+}^{BESS} /Z_{-}^{BESS}:

$$Z_{-}^{BESS} \leq \ z(h) \leq \ Z_{+}^{BESS} , \forall h \in \mathcal{H} \tag{5}$$

ii) a first order discrete time model is used to model the dynamics of the charge/discharge level of the small-scale ESS for $h \in \mathcal{H}$:

$$s(h) = s(h-1) + z(h), \forall h \in \mathcal{H} \tag{6}$$

where $s(h)$ denotes the charge level of the storage device in time slot $h \in \ \mathcal{H}$. Note that in the present work we do not take the charging/discharging efficiencies. This is a simplified model for the dynamics of ESS. However, from the next subsection, we further take charging and discharging efficiencies into account. In the whole chapter, we assume that the battery degradation and leakage effects are negligible.

iii) we assume that the charge level at the last time slot $s(H)$ and at the beginning of the prediction horizon $s(0)$ are equal. Hence, the following constraint holds:

$$s(0) = s(H) = \sum_{h=1}^{H} z(h)\,; \tag{7}$$

iv) the maximum charge level is limited by the maximum storage capacity Z_{max}^{BESS} (that is non-negative):

$$-\,s(h-1) \ \leq \ z(h) \leq Z_{max}^{BESS} - \ s(h-1), \ \forall h \in \mathcal{H}. \tag{8}$$

3.2.4.4. Grid Energy Flow with Corresponding Constraint and Cost

The total purchased energy by the user is calculated on a time slot basis by a scalar aggregation of energy demand, required energy for charging the ESS, generated energy of RES and released energy of ESS. We denote the energy profile exchanged between user and the distribution grid within prediction horizon by a vector of $\tilde{\boldsymbol{e}} = [\tilde{e}(1), \dots, \tilde{e}(h), \dots, \tilde{e}(H)]$. Hence, the following energy balance equation should be always satisfied:

$$\tilde{e}(h) = x(h) + \tilde{b}(h) - \tilde{r}(h) + z(h), \forall h \in \mathcal{H}. \tag{9}$$

A contractual obligation imposed by the distribution grid should also be considered as an additional constraint: the user's energy consumption cannot exceed a maximum which is defined by the energy supplier. We assume that the total energy exchanged with the grid is always non-negative. If we denote by $\boldsymbol{E_{max}} = [E_{max}(1), \dots, E_{max}(h), \dots, E_{max}(H)]$ the vector of maximum permissible energy consumptions at each time slot, the value of the exchanged energy should be subject to the contractual/technical constraints as follows:

$$x(h) + \tilde{b}(h) - \tilde{r}(h) + z(h) \leq E_{max}(h), \forall h \in \mathcal{H}. \quad (10)$$

Furthermore, we consider a linear pricing function for the energy bought from the grid, so that the total cost for the user in the time window $\mathcal{H}$ is simply computed as the summation of all costs in each time slot:

$$\mathcal{C}(\tilde{\boldsymbol{e}}) = \sum_{h=1}^{\mathrm{H}} c(h)\tilde{e}(h), \ \ \forall h \ \in \ \mathcal{H}, \quad (11)$$

where $\boldsymbol{c}(h)$ is the known cost coefficient at the time slot h provided by the distribution grid operator to the end user.

3.2.5. Problem Formulation

3.2.5.1. The Optimization Problem

The user energy scheduling is stated as an optimization problem where the objective function (to be minimized) is the cost of the total exchanged energy with the grid over the prediction horizon. We intend to find the optimal energy consumption profile of the controllable loads and the optimal charging/discharging strategy of the ESS, while satisfying the related constraints and considering the RES generation and demand uncertainties. Thus, the optimization problem is formulated by the following linear programming problem:

$$\min_{\boldsymbol{x},\boldsymbol{z}} \boldsymbol{\mathcal{C}}(\tilde{\boldsymbol{e}}) \text{ s.t. (1), (2), (5), (6), (7), (8), (10).} \quad (12)$$

Note that (12) is an uncertain optimization problem due to the presence of $\tilde{\boldsymbol{b}}$ and $\tilde{\boldsymbol{r}}$, whose values are affected by uncertainties. Conversely, in case of absence of uncertainty in the parameters, the energy scheduling problem (12) turns into the so-called nominal optimization problem.

3.2.5.2. Uncertainty Modeling

We assume that the sources of uncertainties affecting the RES generation and the load consumption forecasts are known and the corresponding maximum/minimum data are available. Hence, we adopt the box uncertainty set model that relies on the approach proposed in [335], which is an effective approach to obtain robust solutions to uncertain optimization problems. However, differently from [335], in this work the conservatism of the approach can be selected by the decision maker. Following the box uncertainty set definition [336], vectors b˜ and r˜ indicating the actual values of the uncertain non-deferrable load and RES generation are expressed as (13). We adopt the so-called set-based uncertainty model that is very practical in many applications with parameters' uncertainty. Another motivation for using this model is its computational tractability [336]. The box uncertainty set is defined as follows:

$$\begin{gathered}\mathcal{U} = \{\widetilde{\boldsymbol{b}} = \boldsymbol{b} + 0.5\boldsymbol{\xi}_b^T \boldsymbol{I}_H \Delta\boldsymbol{b},\ \tilde{\boldsymbol{r}} = \boldsymbol{r} + 0.5\boldsymbol{\xi}_b^T \boldsymbol{I}_H \Delta\boldsymbol{r} \mid \\ \|\boldsymbol{\xi_b}\|_\infty \leq \boldsymbol{\Gamma_b}, \|\boldsymbol{\xi_r}\|_\infty \leq \boldsymbol{\Gamma_r}\}\end{gathered} \tag{13}$$

where $\boldsymbol{b} = [b(1), \ldots, b(h), \ldots, b(H)]$ and $\boldsymbol{r} = [r(1), \ldots, r(h), \ldots, r(H)]$ are the vectors of the nominal predicted values of uncertain parameters, $\Delta\boldsymbol{b} = [\Delta b(1), \ldots, \Delta b(h), \ldots, \Delta b(H)]$ and $\Delta\boldsymbol{r} = [\Delta r(1), \ldots, \Delta r(h), \ldots, \Delta r(H)]$ are the vectors of the difference values between lower and upper bounds of the uncertain parameters, $\boldsymbol{\xi}_b = [\xi_b(1), \ldots, \xi_b(h), \ldots, \xi_b(H)]$ and $\boldsymbol{\xi}_r = [\xi_r(1), \ldots, \xi_r(h), \ldots, \xi_r(H)]$ are the vectors of random and independent coefficients which are subject to uncertainty, and $\boldsymbol{I}_H$ is the H-dimensional identity matrix. In (13) the absolute values of $\xi_b(h)$ and $\xi_r(h)$ in each time slot are respectively bounded by Γ_b and Γ_r, which are called robustness factors. In our model, the level of conservatism is adjusted to make a trade-off between user's payment and the so-called price of robustness (PoR). Note that PoR is defined as the percentage of relative difference between the costs achieved by a robust solution and a nominal solution [337]. Finally, we recall that a solution of the optimization model under uncertainty set $\mathcal{U}$ is robust if the value of all uncertain variables $\widetilde{\boldsymbol{b}}$ and $\tilde{\boldsymbol{r}}$ perturbs not more than Γ_b and Γ_r, respectively.

3.2.5.3. The Robust Counterpart

Having defined uncertainty on non-deferrable loads and RES generation through the introduction of $\boldsymbol{\mathcal{U}}$, we now provide the robust counterpart of the nominal energy scheduling problem (12). Hence, we implement the uncertain linear optimization problem based on box uncertainty set based on the following robust counterpart formulation:

$$\min_{\boldsymbol{x},\boldsymbol{z}}\{\ \mathcal{C}(\tilde{\boldsymbol{e}}) \text{ s.t. (1), (2), (5), (6), (7), (8), (10) }\}_{(\widetilde{\boldsymbol{b}},\tilde{\boldsymbol{r}})\in\mathcal{U}}. \tag{14}$$

By setting the values of the robustness factors (Γ_b, Γ_r), the decision maker can adjust the diameter of the uncertainty set. Therefore, the constraint (10) can be modified as follows:

$$\begin{gathered}x(h) + b(h) + 0.5\Gamma_b \Delta b(h) - r(h) + 0.5\Gamma_b \Delta r(h) \\ +z(h) \leq E_{max}(h), \qquad \forall h \in \mathcal{H}.\end{gathered} \tag{15}$$

Equation (15) has the effect of "robustifying" the solutions to the linear problem (12). Moreover, replacing in objective function (11) the definition of vectors $\widetilde{\boldsymbol{b}}$ and $\tilde{\boldsymbol{r}}$ provided in (13), it may be demonstrated that the robust counterpart (14) can be re-written as follows [336]:

$$\min_{\boldsymbol{x},\boldsymbol{z}} \left\{ \sum_{h=1}^{\mathrm{H}} c(h)\big(x(h) + z(h) + b(h) - r(h)\big) \right\} \quad (16)$$

s.t. (1), (2), (5), (6), (7), (8), (15).

The resulting optimization problem (16) consists of $2H$ decision variables in $\boldsymbol{x}, \boldsymbol{z}$ that minimize the objective function regarding $5H$ bounding constraints, $3H$ inequality constraints, and 2 equality constraints.

By solving the robust optimization problem (16) and the corresponding constraints, the load scheduling with different predefined robustness factors can be obtained. For $\Gamma_r = \Gamma_b = 0$, the problem is solved in the nominal case without considering forecast uncertainties. In this case, the results are obtained in the most optimistic case. Instead, for $\Gamma_r = \Gamma_b = 1$, the greatest amount of uncertainty is considered. Thus, uncertainties are fully addressed during the operation, but the problem goes into the most conservative case (i.e., worst case over all the possible realization of uncertain variables). To reduce the level of conservatism in the solution, the decision maker can set the value of these two parameters between 0 and 1 based on the user's preference. The decision maker is able to run various simulations and observe the optimization results over different robustness factors to choose the best solution in terms of an acceptable trade-off between cost and conservatism. In all simulations we assume that the feasible set of problem (16) is not empty.

3.2.6. Simulation Results and Discussion

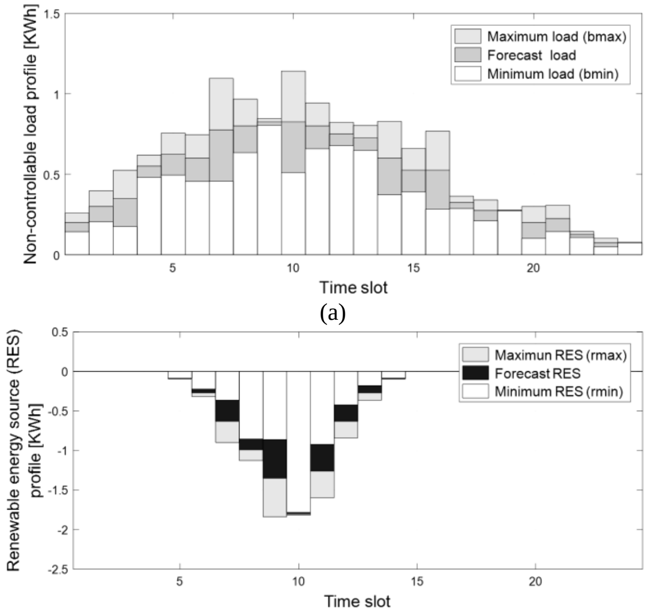
3.2.6.1. The Simulation Setup

We refer to a residential user composed of a local controllable and a non-controllable load, a RES and an ESS. All the computations in this work are performed by Matlab R2016a equipped with the Optimization Toolbox on a desktop PC with an Intel i7-7500U core processor with 2.70 GHz (4 CPUs) and 12 GB RAM memory. The run time for all the algorithm simulations is less than 10ms. For our simulations, we consider a prediction horizon of $H = 24$ hours and a sampling time of 1 hour. Moreover, other parameters related to the controllable load, ESS, and hourly cost coefficients of purchased energy from the distribution grid are presented in Table 3.1. The forecast RES and non-controllable load profiles are illustrated in Figure 3.2.

Table 3. 1. Simulation Parameters

Quantity	Value	Unit
Controllable load range per slot	[0, 3]	kWh
Controllable load daily cumulative threshold	25	kWh
Length of prediction horizon (H)	24	hours
Length of each time slot	1	hour

Quantity	Value	Unit
Charging/discharging rate of ESS per slot	1	kWh
Maximum storage capacity of ESS	30	kWh
Charging/discharging efficiency of the ESS	1	-
Initial storage charge level of the ESS	0	kWh
Peak demand hours	[9, 11], [16, 21]	hours
Off-Peak demand hours	[1, 8],[12, 15], [22, 24]	hours
Peak demand hours payment coefficient	0.07	€/kWh
Off-Peak hours payment coefficient	0.04	€/kWh
Penalty cost coefficient	0.21	€/kWh
Robustness parameters (Γ_b, Γ_r)	[0, 1]	-
Maximum permissible energy consumption per time slot ($E_{max}(h)$)	2.4	kWh



(b)

Figure 3. 2. Forecast energy profiles in terms of nominal, minimum, and maximum values for: (a) controllable load consumption, (b) RES generation.

3.2.6.2. Results Analysis and Discussion

Figures 3.3 and 3.4 depict the results of the energy scheduling of the controllable load x and storage charging/discharging activities z obtained by applying the method for $\Gamma_r = \Gamma_b = 0$ (i.e., the so-called nominal solution) and for $\Gamma_r = \Gamma_b = 1$ considering exact forecast profiles of RES and load without uncertainties (i.e., the most conservative case). From the results, it can be found that the scheduling moves the operation time of controllable appliances to off-peak time slots for minimizing the energy payment. Also, the maximum utilization of the RES should be ensured by energy optimization. The presence of the ESS provides the possibility to store the surplus energy when the available RES is greater than the demand. It can supply the load when the required aggregate demand is larger than the available renewable energy. The method adopts the best strategies of the ESS based on a trade-off between the forecasted RES over the prediction horizon and energy's tariffs at different time slots.

To examine the quality of the robust solution, we run a Monte Carlo simulation over 5000 experiments with different patterns for the uncertain variables, and compare the robust solutions generated by changing the robustness factors. For both uncertain variables, the actual profile at each Monte Carlo iteration is obtained by adding a normally distributed random sequence with zero mean and standard deviation equal to 0.2 [kWh] to the nominal predicted value. The scheduled energy profiles exchanged with the distribution grid compared to the maximum permissible energy per slots (E_{max}) are reported in Fig. 5 for a single Mont Carlo iteration. It is obvious that the energy consumption profile by the nominal approach ($\Gamma_r = \Gamma_b = 0$) exceeds this limit (Figure 3.5a); conversely, the robust approach for $\Gamma_r = \Gamma_b = 1$ can fully satisfy this limitation (Fig. 3.5b).

We then present the average results to assess the performance of our approach. We compare the performance of the method from the worst-case to the nominal-case to get some insight on the conservatism of the approach. To this aim, we define a merit function – that we denote as scheduling cost – as follows:

$$\mathcal{C}'(\tilde{e}) = \sum_{h=1}^{\mathrm{H}} c'(h)\tilde{e}(h) \qquad (17)$$

where we introduce a higher cost coefficient ($c_p(h) >> c(h), \forall h \in \mathcal{H}$) for the energy consumption beyond the limit to achieve a trade-off between cost and conservatism:

$$c'(h) = \begin{cases} c(h), if\, \tilde{e}(h) \leq E_{max}(h) \\ c_p(h), if\, \tilde{e}(h) > E_{max}(h) \end{cases}, \forall h \in \mathcal{H}. \qquad (18)$$

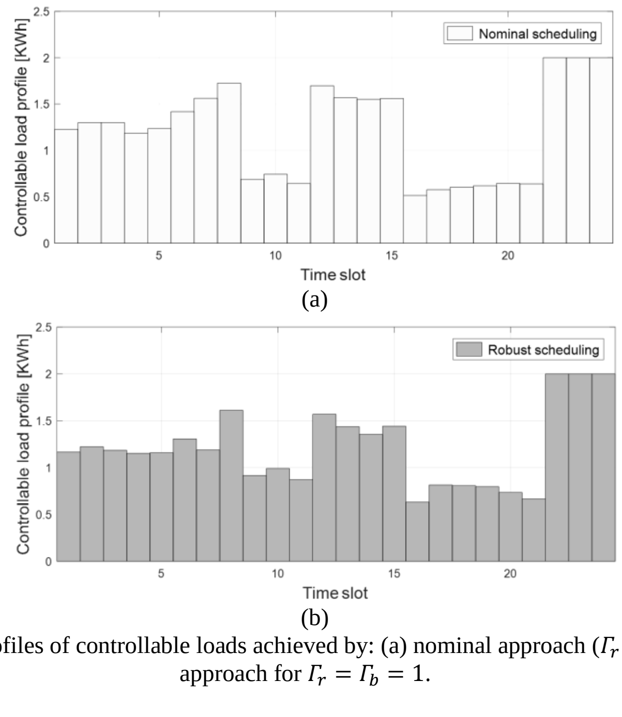
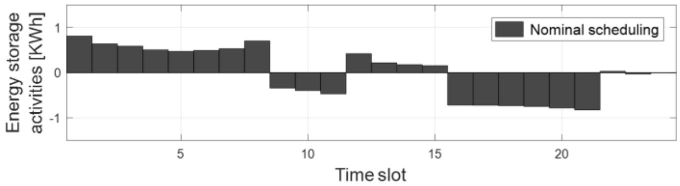
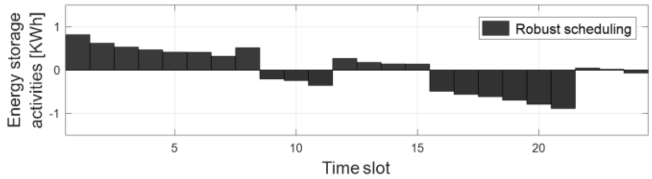


Figure 3. 3. Energy profiles of controllable loads achieved by: (a) nominal approach ($\Gamma_r = \Gamma_b = 0$), (b) robust approach for $\Gamma_r = \Gamma_b = 1$.

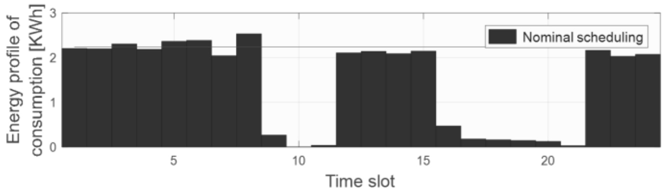


(a)

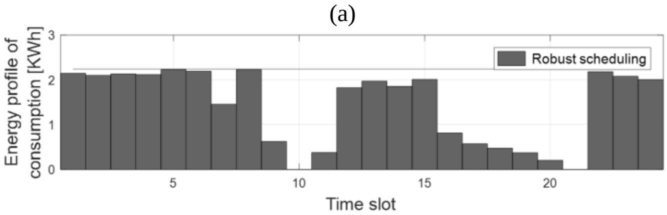


(b)

Figure 3. 4. Energy charging/discharging strategies of the ESS achieved by: (a) nominal approach ($\Gamma_r = \Gamma_b = 0$), (b) robust approach for $\Gamma_r = \Gamma_b = 1$.



(a)



(b)

Figure 3. 5. Profiles of energy exchanged with the grid versus maximum permissible energy consumption (red line) for a specific Monte Carlo run: (a) nominal approach ($\Gamma_r = \Gamma_b = 0$), (b) robust approach for $\Gamma_r = \Gamma_b = 1$.

Figure 3.6 indicates the variation trend of the scheduling cost while varying the parameters' values (for $\Gamma_r = \Gamma_b \in [0, 1]$). It can be observed that, by increasing the values of robustness factors, the scheduling cost firstly decreases, but then it increases again continuously for parameters' values higher than 0.4, since the system goes into over-conservative state which tends to deviate the scheduling from the optimal solution. The results show that, although setting the values of robustness factors in the maximum levels ($\Gamma_r = \Gamma_b = 1$) allows the highest protection, it also leads to the most conservative results in practice, since the cost value in this case is even 1.15% worse than the nominal optimization solution. For $\Gamma_r = \Gamma_b = 0$, we obtain the nominal optimal value equal to 1.1932 €. The contour plot of the scheduling cost for variations of robustness factors in the permissible range [0,1] is presented in Figure 3.7 for a better evaluation of the results. For our case study with a discrete optimization problem, the minimum cost is achieved in the point (Γ_r =0.2, Γ_b =0.6); however, the maximum protection against uncertainties occurs in (Γ_r =1, Γ_b =1) as expected. The maximum protection point provides a solution ensuring deterministic guarantees that constraints will be satisfied as data changes. The contour plot in Figure 3.8 shows the PoR versus the robustness factors. We note that PoR has the minimum (maximum) value equal to 2.14% (3.98%) at point Γ_r =0.2, Γ_b =0.6

($\mathit{\Gamma}_r$ =1, $\mathit{\Gamma}_b$ =1) where the scheduling cost has its minimum (maximum) value equal to 1.2194 € (1.2427 €). Hence, our system will suffer from a 3.65% increase in the scheduling cost with actual data if we stick to the nominal optimal solution without taking uncertainty into account. However, this value decreases to 2.12% with our proposed robust strategy at point $\mathit{\Gamma}_r$ =0.2, $\mathit{\Gamma}_b$ =0.6. Summing up, the simulation results show that the method allows the decision maker to make a trade-off between PoR and constraints' violation by adjusting the values of robustness factors regarding uncertain variables.

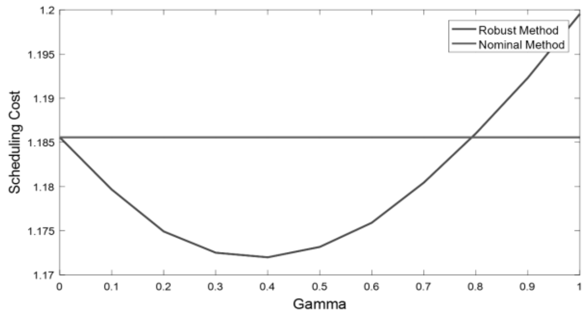


Figure 3. 6. Scheduling cost as a function of equal robustness factors (i.e., $\mathit{\Gamma}_r = \mathit{\Gamma}_b$).

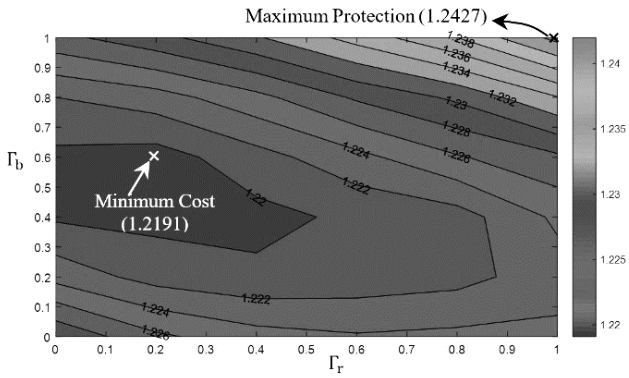


Figure 3. 7. Contour plot of the scheduling cost as a function of robustness factors.

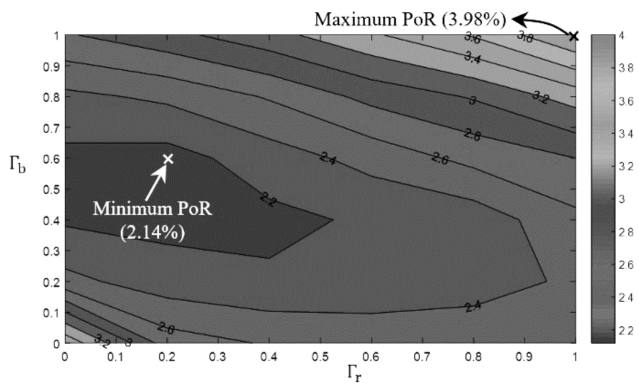


Figure 3. 8. Contour plot of the price of robustness as a function of robustness factors.

3.2.7. Conclusions

We present a robust optimization framework for day-ahead energy scheduling of a grid-connected residential user incorporating RES and ESS units. We also deal with the level of conservatism of the robust control algorithm by defining two independent robustness factors for uncertain data. Our approach flexibly allows the system operator to establish a trade-off between user's costs and level of conservatism. Simulation results show that the method allows the decision maker to make a satisfactory trade-off between constraint violation and PoR by selecting appropriate values for the robustness factors. Future work includes the following aspects:1) improving the uncertainty modeling of parameters by the definition of different uncertainty sets; 2) considering a quadratic pricing function for the energy bought from the grid which yields more realistic results and converts the problem into a non-linear optimization problem; 3) extending the proposed approach to a robust Model Predictive Control based strategy to achieve an online robust energy scheduling under forecast uncertainty.

From the findings and contribution of the research in this chapter, the following paper has been presented:

- S.M. Hosseini, R. Carli, M. Dotoli, "Robust Day-ahead Energy Scheduling of a Smart Residential User under Uncertainty," *IEEE European Control Conference (ECC)*, Naples, Italy, June 25-28, 2019.

3.3. An Online Approach for Energy Management of Residential Microgrids by Model Predictive Control (MPC)

3.3.1. Introduction

In this subsection, we propose an online strategy based on Model Predictive Control (MPC) for the energy scheduling of a grid-connected smart residential user equipped with deferrable and non-deferrable electrical appliances, a RES, and an ESS. The core of the proposed control scheme relies on an iterative finite horizon online optimization, implementing a quadratic cost function to minimize the electricity bill of the user's load demand and to limit the peak-to-average ratio (PAR) of the energy consumption profile whilst considering operational constraints. At each time step, the optimization problem is solved providing the cost-optimal energy consumption profile for the user's deferrable loads and the optimal charging/discharging profile for the ESS, taking into account forecast uncertainties by using the most updated predicted values of the local RES generation and the non-deferrable loads consumption. The performance and effectiveness of the proposed framework are evaluated for a case study where the dynamics of the considered residential energy system is simulated under uncertainties both in the forecast of the RES generation and the non-deferrable loads energy consumption. In particular, the proposed method is compared with an offline scheduling method presented in [338].

3.3.2. Aims and Objectives

The proposed control scheme relies on an iterative finite horizon on-line optimization, implementing a quadratic cost function to minimize the electricity bill of the user's load demand and to limit the peak-to-average ratio (PAR) of the energy consumption profile whilst considering operational constraints. At each time step, the optimization problem is solved providing the cost-optimal energy consumption profile for the user's deferrable loads and the optimal charging/discharging profile for the ESS, taking into account forecast uncertainties by using the most updated predicted values of local RES generation and non-deferrable loads consumption.

3.3.3. Related Works and Contributions

Energy scheduling systems can be designed to optimize the operating plan of users in real time or over a future (typically the next day, i.e., day- ahead). Independently from the planning time scale, these approaches allow full exploitation of the potential of both local energy generation and storage to reduce the energy consumption costs, while limiting the peak-to-average ratio of the energy profiles and complying with customers' needs. The reader is referred to surveys [339] and [340] for further details about the key features of different approaches. Among the more recent contributions on day-ahead energy scheduling, The strategy of day-ahead energy scheduling methods mainly relies on the offline scheduling of users' energy consumption in which the optimization problem is solved once for the whole period of the prediction horizon. As a result, the assessment of the forecast uncertainties in the problem parameters is not possible. In fact, despite the apparent dynamical nature of the local electrical energy generation and demand in a smart MG and the obvious forecast uncertainty, these issues have not been addressed in any of the cited literature contributions.

Despite RESs are useful in residential MGs since they provide environmentally friendly and low-cost energy, their associated challenges on the stability of SGs are significant, due to the inherent uncertain and random nature of RESs. The accuracy of energy forecast of RESs is still an issue under discussion in literature. For instance, [341] reports that the mean absolute error (MAE) of wind energy generation for short-term hourly forecast, in which the prediction horizon is larger than 6 hours and less than 2 days, ranges between 13% to 21%. Thus, in order to maintain the stability of smart MGs, a real-time control regarding forecast uncertainty is necessary [342]. On the other hand, the profile of energy demanded by the non-deferrable appliances can be obviously consider as another uncertain parameter since it may change from the estimated profile based on changing user's preferences [343].

MPC is known as one of the most promising methods for dealing with forecast uncertainties in the real time control of dynamical systems. As regards the previously published contributions on the application of MPC to the real time scheduling of residential MGs, in [343] and [344] the optimal scheduling of deferrable appliances and distributed energy resources in smart residential MGs is studied by using single-time and multi-time scale stochastic MPC approaches, respectively. These two papers take the inherent dynamical feature of RESs into consideration. Nevertheless, uncertainty of non-deferrable appliances profile is disregarded in both contributions. Further, both the electrical and thermal energies management for multiple residential MG is addressed by an MPC approach in [345]. It models an individually-owned PV source and ESS for each MG and a shared combined heat and power (CHP) unit for all MGs. User preference and comfort are also included in the design, but the dynamical analysis of the RES and the load profile have been neglected. In [346], a real-time optimization algorithm for residential load management in a MG considering uncertainties in the future load and user's energy consumption needs is proposed. Although [346] addresses the uncertainty of estimated base loads using a receding horizon approach, it neither takes into account the effects of RESs and ESSs -two important components of MGs- nor the uncertainty of RESs.

Moreover, we remark that most of the previous studies adopt a linear function to model the energy bought from the network. Instead, in order to achieve a more realistic result, the actual cost function should be considered as non-linear, for instance in a quadratic form [338],[347].

Summing up, to the best of the authors' knowledge, the real-time energy scheduling of a MG with the possibility of concurrent occurrence of uncertainties in the estimated load demand and RES unit and considering a non-linear objective function is still an unsolved problem in residential energy management. In this work, a new energy scheduling approach for residential applications is developed in a retail electricity market considering uncertainties in the estimation of load demand and RES production. Note that the majority of the previous related works assume an accurate and perfect profile for load demand estimation, weather forecast and storage device strategy, which does not correspond to reality. In our MPC-based method, instead, the concept of receding horizon control makes is possible to compute corrective actions with regard to any disturbance in the parameters estimation. Also, we consider a quadratic pricing function for the energy bought from the grid, which yields more realistic results than the recalled approaches. The main goals of our research are the full use of the RES in variable weather conditions, the optimal planning of the usage of electrical devices and determining an optimal strategy of storage charging/discharging, whilst minimizing the cost of energy acquired from the grid and limiting the PAR in the aggregate load demand.

3.3.4. System Model

In this section we describe the architecture of a residential MG comprising a stand-alone user connected to the distribution network and equipped with deferrable and non-deferrable loads, a local RES and an ESS unit. For the ease of implementation, we assume that the user possesses one deferrable and one non-deferrable load only. However, note that the presented optimization algorithm can be straightforwardly expanded to scenarios with multiple users and loads. A Home Energy Management System (HEMS) is employed to control the demand response of the end-user and provide an opportunity for interaction between smart appliances, RES, ESS and distribution network autonomously. Figure 3.9 depicts the generic architecture of the system.

The detailed models of the system components with the energy scheduling optimization problem are presented in the sequel. An intelligent energy scheduler (IES) as a subsystem of HEMS is in charge of energy distribution of the user for all time slots according to Fig. 11. This unit is capable to optimally manage the user's energy demand of the deferrable load by receiving electrical energy from the distribution network, transferring energy with the storage device, and harvesting the renewable energy from the RES source. The control outputs are the energy profile of the deferrable load and the charging/discharging strategy of the ESS. The MPC scheme allows selecting these variables optimally upon the prediction horizon iteratively considering the dynamics of forecast profiles of the RES and user's estimated energy demands.

3.3.4.1. Basics on Model Predictive Control

Nowadays, MPC is known as an established technique for dealing with different complex control problems under uncertainty. In this section, MPC is used to solve an online energy scheduling problem that provides the optimal decisions about the turn on/off intervals of deferrable loads and the optimal periods for charging/discharging of the ESS, whilst minimizing the total cost of energy bought from the distribution network in the given receding horizon. At time t the cost minimizing control strategy is computed for a relatively short future time horizon $\mathcal{H}(t) = [t+1, t+H]$. The value of the forward-looking objective function is repetitively minimized at subsequent time slots $t+1, t+2, \ldots \in \mathcal{T}$, and every time the variables of the first time step only (i.e., $t+1$) are implemented as the optimal decision variables in accordance with the receding horizon concept.

In particular, the formulation process of the proposed MPC-based energy management can be decomposed into three steps as follows:

Step 1. This step consists in modeling subsystems that are not affected by uncertainty (i.e., the ESS and deferrable loads) through the definition of discrete-time difference equations corresponding constraints.

Step 2. This step consists in the definition of the objective function: the electricity cost for energy acquired by the distribution network in the given finite receding horizon considering a time-varying cost coefficient for each time slot (here, a dual-rate tariff) and a mixed integer quadratic cost function.

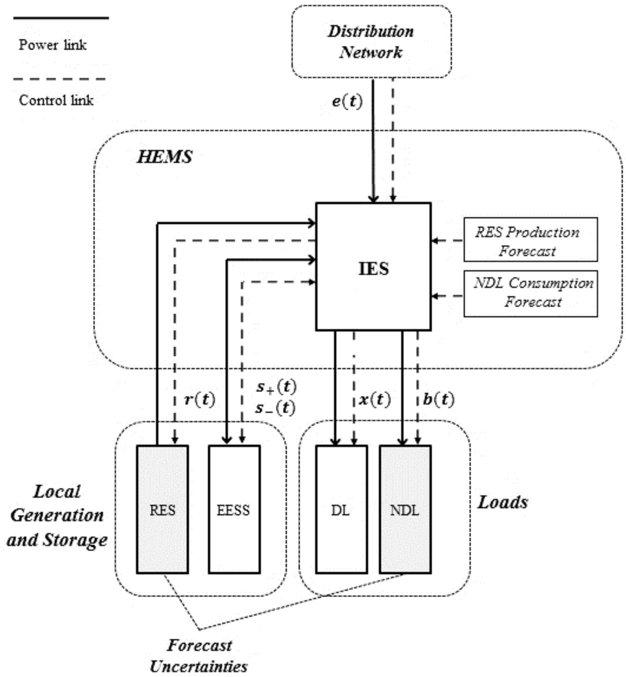


Figure 3. 9. Architecture of residential energy system components, energy flows and connection with distribution network.

Step 3. This step consists in modeling subsystems that are affected by uncertainty (i.e., the RES and non-deferrable loads). In particular, the non-deferrable load consumption profile and the RES production profile are assumed to be discrete-time Gaussian stochastic processes.

3.3.4.2. Deferrable Load

Deferrable loads (DLs) are electrical equipment whose operations can be controlled and programmed in advance. Indeed, in some appliances such as washing machines, ovens and hairdryers, the time of operation is flexible, so that their starting time can be delayed and shifted to other time-slots based on user options within a specific deadline (e.g., at the end of every day). This feature offers an opportunity for IESs to optimally manage in advance the energy activities in a residential energy system and take advantage of time-varying prices. The energy consumption profile of the deferrable load in the receding horizon is denoted for each $t \in \mathcal{T}$ by a vector of H decision variables: $\boldsymbol{x}(t) = [x(t+1), \dots, x(t+h), \dots, x(t+H)]$, where the scalar $x(t+h) \epsilon \mathbb{R}^+$ denotes the amount of energy needed by the deferrable load at time $t+h$. The deferrable load decision variables for each time $t \epsilon \mathcal{T}$ is subject to the following constraints:

$$x_{min} \leq x(t+h) \leq x_{max}, \tau \in \mathcal{T} \qquad (19)$$

$$\sum_{\tau=t_j^1}^{t_j^2} x(\tau) = E_j, j \in \mathcal{J}. \qquad (20)$$

Constraint (19) means that the operation of the deferrable load requires a minimum x_{min} and a maximum x_{max} energy level. Equation (20) means that the deferrable load requires that the cumulative consumption in the jth interval $[t_j^1, t_j^2]$ reaches a given threshold E_j to complete the needed task. We assume that the $J = |\mathcal{J}|$ intervals are defined by the user such that they do not overlap with each other (i.e., $t_j^1 \geq t_{j-1}^2$, $j \in \mathcal{J} \backslash \{1\}$) and are not larger than the receding horizon length (i.e., $t_j^2 - t_{j-1}^1 \leq H, j \in \mathcal{J}$). Note that (20) corresponds to $J = |\mathcal{J}|$ constraints. For instance, $\mathcal{J}$ could represent the set of J consecutive days, and E_j the daily energy amount required by the deferrable load in the jth day. Focusing on the receding horizon related to time t, constraints (19)-(20) can be rewritten as follows:

$$x_{min} \leq x(t+h) \leq x_{max}, \qquad h \in \mathcal{H} \qquad (21)$$

$$\sum_{h=\max\{t_k^1 - t, 0\}}^{\min\{t_k^2 - t, H\}} x(t+h) = X_k(t), k \in \mathcal{K}(t), \ (22)$$

where $X_k(t)$ is the residual threshold related to the kh interval:

$$X_k(t) = \begin{cases} E_k \text{ if } t < t_k^1 \\ E_k - \sum_{\tau=t_k^1}^{t} x(\tau) \text{ otherwise} \end{cases}, k \in \mathcal{K}(t). \qquad (23)$$

Note that we consider the subset $\mathcal{K}(t) \subseteq \mathcal{J}$ of constraints that affects the given receding horizon $[t+1, t+H]$. Hence, in (22) we assume that $t_k^2 > t \wedge \left|t_1^2 - t\right| < H$.

3.3.4.3. Non-deferrable Load

Non-deferrable loads (NDLs) are electrical equipment whose standard operation time cannot be changed. We represent the non-deferrable load consumption profile in the receding horizon for each $t \epsilon \mathcal{T}$ by a vector of H input parameters $\boldsymbol{b}(t) = \big(b(t+1), \dots, b(t+h), \dots, b(t+H)\big)^T$. This vector is assumed to be computed by a forecast sub-module of the HEMS (see Fig. 1), using a prediction algorithm based on historical data.

3.3.4.4. Renewable Energy Source

We represent the RES production profile in the receding horizon for each $t \epsilon \mathcal{T}$ as a vector of H input parameters $\boldsymbol{r}(t) = \big(r(t+1), \dots, r(t+h), \dots, r(t+H)\big)^T$. This vector is assumed to be updated at each $t \epsilon \mathcal{T}$ by a forecast sub-module of the HEMS (see Fig. 1), using a prediction algorithm based on weather data.

3.3.4.5. Energy Storage System

The ESS unit receives and stores energy from the distribution network and/or the RES, and releases energy to supply the loads. Two vectors of H decision variables $\boldsymbol{s}_+(t) = \big(s_+(t+1), \dots, s_+(t+h), \dots, s_+(t+H)\big)^T$ and $\boldsymbol{s}_-(t) = \big(s_-(t+1), \dots, s_-(t+h), \dots, s_-(t+H)\big)^T$ respectively model the device charge and discharge energy profiles in the receding horizon for each $t \in \mathcal{T}$. The rate of charging (discharging) of the stored energy has to be bounded by a maximum charging (discharging) rate q^+ (q^-):

$$\begin{aligned} 0 \leq s_+(t+h) \leq q^+, h \in \mathcal{H} \\ 0 \leq s_-(t+h) \leq q^-, h \in \mathcal{H}. \end{aligned} \quad (24)$$

The dynamics of the ESS for $h \epsilon \mathcal{H} \triangleq \{1, \dots, h, \dots, H\}$ and $t \epsilon \mathcal{T}$ can be expressed as a first order discrete time model:

$$\begin{aligned} s(t+h) = s(t+h-1) + \eta_+ s_+(t+h) + \\ \frac{1}{\eta_-} s_-(t+h), \forall h \in \mathcal{H}, \end{aligned} \quad (25)$$

where $s(t+h)$ denotes the charge level of the storage device and η_+ and η_- are the charging and discharging efficiencies, both in the [0,1] range. We assume that the storage energy degradation and leakage effects are negligible.

Moreover, the charge level is upper bounded by the maximum storage capacity q_{tot} and is imposed to be non-negative:

$$\begin{aligned} -s(t) \leq \sum_{j=1}^{h} \left(\eta_+ s_+(t+h) + \frac{1}{\eta_-} s_-(t+h) \right) \\ \leq q_{tot} - s(t), h \in \mathcal{H} \end{aligned} \quad (26)$$

where $s(t)$ denotes the charge at the beginning of the receding horizon.

3.3.4.6. Grid Energy Flow

The total energy that the user needs to buy from the grid in the h-th time slot can be simply calculated by scalar aggregation of deferrable and non-deferrable energy demands and energy for charging the ESS minus the energy produced and injected by RES (in the presence of solar irradiance) and ESS (during energy discharging) to the MG. This relation can be stated as follows:

$$e(t+h) = x(t+h) + b(t+h) - r(t+h) \\ + s_{+}(t+h) - s_{-}(t+h), \forall h \in \mathcal{H}. \quad (27)$$

For all the discrete time instances within the simulation period, the exchanged energy per slots is constrained by contract and has to be non-negative:

$$0 \leq e(t+h) \leq E_{max}, h \in \mathcal{H}, \quad (28)$$

where E_{max} is the maximum allowable energy consumption per time slot.

The cost of energy transferred within the network over the receding horizon for $t \in \mathcal{T}$ can be represented as follows:

$$C\big(\boldsymbol{x}(t), \boldsymbol{s}_{+}(t), \boldsymbol{s}_{-}(t)\big) = \sum_{h=1}^{H} k(t+h) . \big(e(t+h)\big)^{2} \quad (29)$$

where $k(t+h)$ is the known cost coefficients at the time slot t. For the sake of realizing a realistic result, we consider the cost function as a non-linear quadratic.

3.3.5. Problem Formulation

This section presents the mathematical formulation of the proposed receding horizon scheme. A quadratic programming problem is formulated as a finite horizon open-loop optimization problem for the optimal energy management under operational constraints and system dynamics

3.3.5.1. Online Optimization Problem

Having modeled all the energy flows and costs in the considered time window, we now define the control strategy that permits the user to compute the optimal energy scheduling of deferrable loads and the optimal operations of the ESS.

$$\min_{\boldsymbol{x}, \boldsymbol{s}_{+}, \boldsymbol{s}_{-}} \sum_{h=1}^{\mathrm{H}} k(t+h)\big(x(t+h) + b(t+h) - \\ r(t+h) + s_{+}(t+h) - s_{-}(t+h)\big)^{2} \quad (30)$$

s.t. (21), (22), (24), (25).

Problem (30) is a quadratic optimization problem that consists in determining the $3H$ decision variables in $\boldsymbol{x}$, $\boldsymbol{s}_+$, $\boldsymbol{s}_-$ that minimize the objective function in (30) and meet the recalled $6H$ bounding constraints, $2H$ inequality constraints, and $K(t)$ equality constraints.

3.3.5.2. MPC Algorithm

The total cost payable by the user at each time slot is minimized iteratively. According to the MPC strategy, this function is updated and recomputed at each time slot until the simulation end time. The MPC law is described by Algorithm 3.1. At each time instant, the IES unit receives the updated forecast vectors of the NDL consumption (i.e., $\boldsymbol{b}(t)$) and RES production (i.e., $\boldsymbol{r}(t)$) (line 3). Then, the values of the residual threshold related to the kh interval are updated by (24) using the given inputs of E_k and $s(0)$ (line 4). Hence, the online optimization problem (29) is executed (line 5).

Algorithm 3.1 – MPC algorithm

Inputs: $\boldsymbol{b}(t)$, $\boldsymbol{r}(t)$, $\{E_k\}$, $s(0)$
Procedure:
1 Set $t \leftarrow 0$
2 **iterate**
3 Get forecast data $\boldsymbol{b}(t)$ and $\boldsymbol{r}(t)$
4 Update user constraints parameters through (23)
5 Solve the optimization problem (11)
6 Apply only $x(t+1)$, $s_+(t+1)$, and $s_-(t+1)$
7 Set $t \leftarrow t+1$
Outputs: $x(t+1)$, $s_+(t+1)$, and $s_-(t+1)$

The optimal decision variables of the first time step are extracted from the optimization results and implemented as the control outputs in accordance with the receding horizon concept (line 6). This process is repeated with updated inputs as time goes on (line 2 and 7). We assume that (29) is always feasible through all the MPC algorithm iterations.

3.3.6. Simulation Results and Comparison

This section assesses the performance of the proposed MPC algorithm implemented in the Matlab environment using the Optimization toolbox. Simulations refer to a sampling time of 1 hour, a period of analysis equal to two days (i.e., $\mathcal{T} = [0,48]$), and a receding horizon of 24 hours (i.e., $\mathcal{H} = [\mathrm{t}+1, \mathrm{t}+24]$). The obtained results are reported in the sequel and are analyzed and compared with the previously published offline method (here, “offline” means that the scheduling problem is solved only once fahead of the whole simulation period). In particular, four different cases are analyzed: the proposed MPC-based method with/without uncertainties (case 1 and 3) and the offline method in with/without uncertainties (case 2 and 4).

3.3.6.1. Scenario Setup and Uncertainty Modeling

Simulations are carried out on a smart home with the following electrical components: non-deferrable loads, one deferrable load, one ESS and one photovoltaic panel. Table 3.2 reports the parameters related to the deferrable load and ESS as well as the dual-rate cost coefficients for the energy bought from the distribution network.

As mentioned before, for the RES production and non-deferrable load consumption we consider forecast profiles affected by uncertainties. Different methods can be found in the literature for modeling uncertainties associated with MGs.

Table 3. 2. Simulation Parameters

Quantity	Symbol	Value
Maximum deferrable load consumption per slots (kWh)	x_{max}	3
Minimum deferrable load consumption per slots (kWh)	x_{min}	0
Cumulative deferrable load consumption threshold for 1st day (kWh)	E_1	25
Cumulative deferrable load consumption for 2nd day (kWh)	E_2	32
1st interval for cumulative consumption of deferrable load (hour)	$[t_1^1, t_1^2]$	[1, 24]
2nd interval for cumulative consumption of deferrable load (hour)	$[t_2^1, t_2^2]$	[25, 48]
Maximum charging rate of ESS per slot (kWh)	q^+	1
Minimum charging rate of ESS per slot (kWh)	q^-	1
Maximum storage capacity (kWh)	q_{tot}	30
Charging and ischarging efficiencies	η_+, η_-	1
Initial storage charge level (kWh)	$s(0)$	0
Peak hours (from 8am to 7 pm) payment coefficient (€/kWh^2)	-	0.070
Off-Peak hours payment coefficient (€/kWh^2)	-	0.045

A widespread method for uncertainty modeling is Gaussian normal distribution. Studying the effect of the type of uncertainty distribution function is beyond the scope of this work. Thus, we adopt discrete Gaussian distributed random variables for modeling uncertainties in both the RES and NDL profiles.

Figure 3.10 reports the actual renewable energy profile produced by the RES (red bars) and the actual non-deferrable load energy profile consumed by the user (green bar).

At each iteration, the forecast is simulated by adding to the actual profile a normally distributed random sequence with zero mean and a standard deviation equal to 0.2 [kWh] for both the RES production and NDL consumption.

3.3.6.2. Scenario Setup and Uncertainty Modeling

Simulations of energy scheduling in presence of uncertainties are repeated over 1,000 experiments. the first row of Table 3.3 reports the mean values of energy cost and PAR over all the experiments. Referring to a specific realization of the forecast estimation, the scheduling results are shown in Figure 3.11. In particular, Figures 3.11a and 3.11b illustrate the results of Algorithm 3.1 in terms of schedule of deferrable loads (i.e., $x(t)$) and storage charging/discharging profiles (i.e., $s_+(t)$, $s_-(t)$). Moreover, Figure 3.11c reports the scheduled energy exchanges with the grid. Primarily, it is evident that the scheduling arranges the deferrable appliances operation during low peak time slots to minimize cost. Furthermore, it is apparent that the scheduling makes sure that the user exploits the energy from the renewable source and leverages the storage device. Hence, when the required aggregate load is larger than

Table 3. 3. Energy Cost and PAR Comparison

Case	Method	Uncertainties	Energy Cost (€/kWh^2)	PAR
1	Proposed MPC-based scheduling	Yes	8.1848*	1.6169*
2	Offline scheduling [338]	Yes	9.2187*	1.7223*
3	Proposed MPC-based scheduling	No	7.7436	1.3466
4	Offline scheduling [338]	No	7.7436	1.3466

* mean value over 1,000 experiments

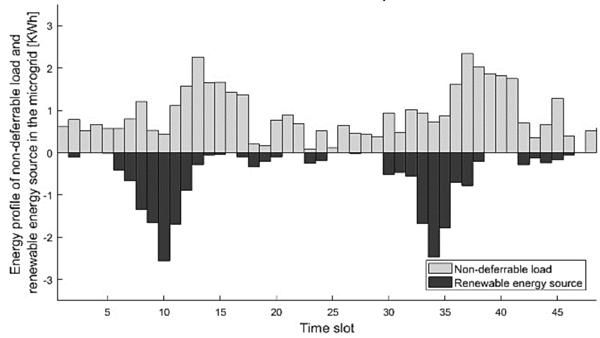
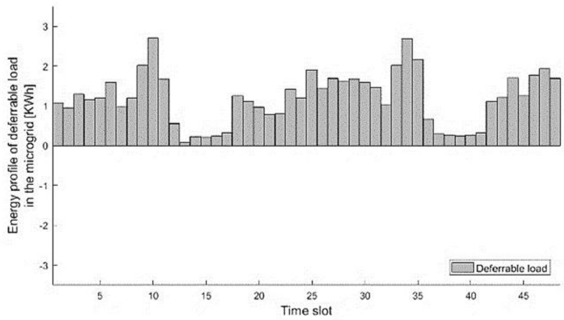
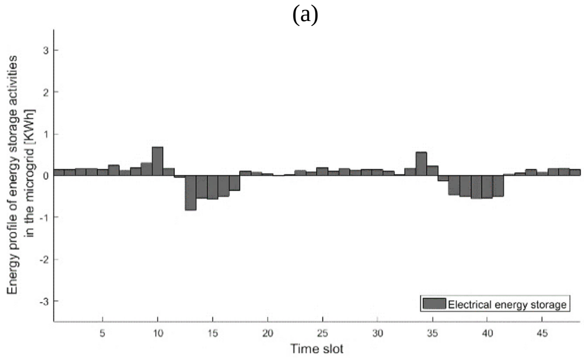


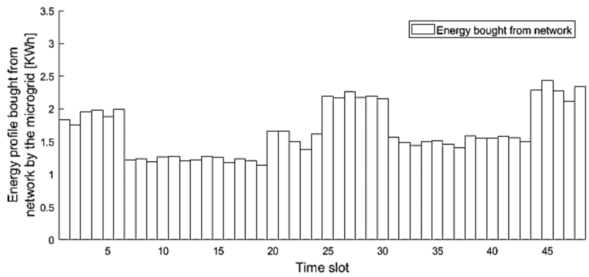
Figure 3. 10. Actual profile of RES production and NDL consumption.



(a)



(b)



(b)

Figure 3. 11. Optimal scheduling of energy activities under uncertainties in forecast profiles of RES and NDL by the proposed MPC-based method (case 1).

the available renewable energy, the difference is supplied by discharging the battery. If the storage charge is not sufficient, the remaining needed energy is imported from the grid. On the other hand, if the available renewable energy is greater than the demand, the scheduling uses the surplus to charge the battery.

3.3.6.3. Results Discussion and Comparison

A comparison between the considered four cases including offline and proposed MPC-based methods with/without uncertainties is provided in Table 3.2. Indeed, understanding the effect of the uncertainties on cost and PAR of energy scheduling in offline and online MPC methods is critical for optimal user's consumption management. Referring to a specific realization of the forecast estimation, Figure 3.13 reports the scheduled energy exchanges with the grid computed by the offline method. It is evident that results in Figure 3.13 present higher peaks than results in Figure 3.12. Not surprisingly, by our online approach an effective tracking on the uncertain states can be accomplished by updating all data in each time slots. Moreover, as can be seen in Table 3.2 (first and second rows), the mean values of energy cost and PAR in the presented method (case 1) are lower than those achieved by the offline method (case 2). These results demonstrate the effectiveness of the MPC-based approach compared to the offline scheduling scheme. The optimal energy scheduling is achieved not only by shifting the operation time of user's deferrable appliance to the non-peak intervals, but also by selecting the best strategies for charging/discharging the ESS decided on the basis of an equilibrium between the estimated renewable energy over the forecast horizon and energy's tariffs at different time slots.

Finally, results related to case 3 and 4 (third and fourth rows of Table 3.2) show that in case of no uncertainty (i.e., the forecast of RES production and NDL consumption does not change over time), the proposed MPC algorithm and the offline scheduling method achieve the same results, as expected: Figure 3.14 reports the scheduled energy exchanges with the grid in case of no uncertainty, showing that a flatter profile is achieved with respect to the presence of uncertainties.

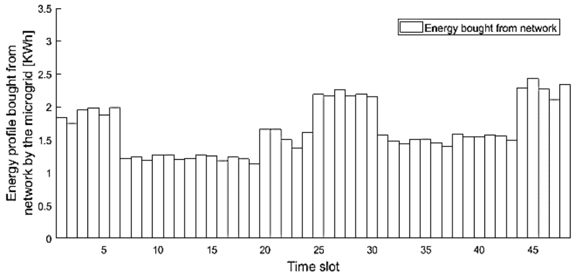


Figure 3. 12. Optimal scheduling of energy activities under uncertainties in forecast profiles of RES and NDL by the proposed MPC-based method (case 1).

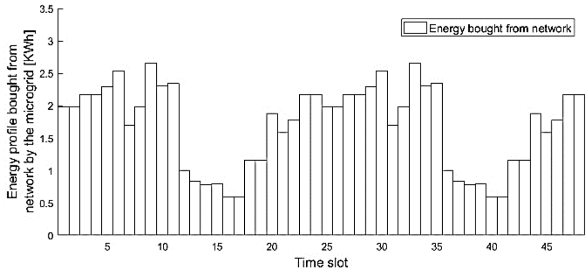


Figure 3. 13. Scheduled energy exchanges with the grid by the offline method in [338] (case 2).

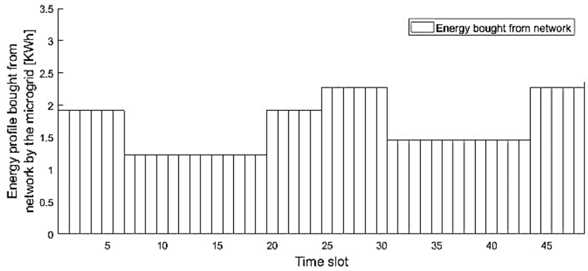


Figure 3. 14. Scheduled energy exchanges with the grid by the proposed MPC-based method (case 3) and by the offline method (case 4).

3.3.7. Conclusions

In this section, we propose an MPC-based energy scheduling method for a grid-connected smart residential user equipped with deferrable and non-deferrable loads, a RES, and an ESS under dynamics of deferrable load and RES profiles. Aiming at a realistic result, we employ a quadratic function for supply-demand cost. The optimal planning of deferrable load consumption and the ESS charging/discharging strategies are computed solving an online optimization problem at each time slot over a receding horizon. The method is applied to a simulated case study. A comparison is made between the MPC-based and an existing offline scheduling method, enlightening the performance and effectiveness of the proposed framework to tackle uncertainties in the forecast data efficiently. The proposed scheme shows the capability to reduce the total user's energy cost, lower the PAR level, and ensure the sustainability of the energy scheduling under uncertain conditions.

From the findings and contribution of the research in this chapter, the following paper has been presented:

- S.M. Hosseini, R. Carli, M. Dotoli, "Model Predictive Control for Real-Time Residential Energy Scheduling under Uncertainties," *IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Miazaki, Japan, October 7-10, 2018

3.4. An Online Approach for Energy Management of Residential Microgrids by Robust Model Predictive Control (RMPC)

3.4.1. Introduction

In order to address the concerns of data uncertainty in residential energy scheduling, in this subsection we present an online DSM framework based on RMPC for residential SGs. The considered system incorporates a grid-connected residential SG including multiple smart homes equipped with controllable loads (CLs) with programmable and interruptible operation, and critical non-controllable loads (NCLs) with inflexible and fixed power curve. A shared ESS unit is also implemented to increase the flexibility of the energy scheduling. The work aims at minimizing the users' energy payment and limiting the peak-to-average ratio (PAR) of the SG's energy consumption while taking into account all device/comfort/contractual constraints of the system as well as the feasibility constraints on cumulative energy transferred between all users and the power grid under load demand uncertainty. We present a RMPC-based optimization method to solve the residential energy scheduling problem taking a quadratic cost function. The proposed approach provides an online optimal scheduling of the CLs for all users and the charging/discharging activities of the shared ESS at each time slot. Firstly, the energy price and all corresponding constraints of the system are modeled. Then, a min-max robust problem is established regarding an interval-based uncertainty set. Then, some mathematical transformations are adopted to convert the min-max problem to an equivalent quadratically constrained linear programming problem (QCLPP). Finally, we implement an MPC approach to solve the resulting equivalent QCLPP iteratively over a finite-horizon time window based on the receding horizon concept. The robustness of the proposed online approach against the level of conservativeness of the solution is investigated.

3.4.2. Related Works and Contributions

The literature reports several online methods for residential energy scheduling under forecast uncertainty. References [348] and [349] introduce an RMPC-based framework for the optimal scheduling of a residential MG for addressing forecast uncertainties, minimizing the total energy cost and reducing the conservativeness of the solution. The most of existing real-time studies as well as the MPC-based approach presented in subsection 3.3 assume a non-realistic linear cost function for the energy bought from the grid and do not address the effect of uncertainty in the feasibility of energy transferred between users and the power grid. Moreover, the impact of methods on PAR has not been investigated. Also, the approaches presented in [348] and [349] are only focused on isolated residential MGs. Hence, further research is still required to address the issue of data uncertainty in grid-connected smart homes. In this subsection we present a new RMPC-based optimization framework for residential energy scheduling. The main contributions of this work are summarized as follows:

1) An online energy scheduling framework based on RMPC is introduced to state and solve the household energy scheduling problem with a shared ESS under quadratic cost function.

2) Forecast load uncertainty in both the objective function and corresponding contractual constraints is tackled. The problem includes uncertain terms in both the left-hand side (LHS) and the right-hand side (RHS) of the inequality constraints.

3) All technical constraints and a contractual obligation imposed by the power grid, limiting the total energy consumption per time slot to a maximum are formulated.

4) The conservativeness of the proposed scheme and its flexibility for applying to different applications are analyzed.

5) A detailed simulated case study on a sample SG with load uncertainty is presented. A comprehensive comparison of our proposed online method with an offline robust scheduling method is provided to validate the effectiveness of the proposed approach in making a trade-off between the expected energy payment and the constraints' violation rate.

3.4.3. Aims and Objectives

In this subsection we present an online demand side management framework based on robust model predictive control (RMPC) for residential SGs. We aim at minimizing the users' energy payment and limiting the peak-to-average ratio (PAR) of the energy consumption while taking into account all device/comfort/contractual constraints, specifically the feasibility constraints on energy transferred between users and the power grid in presence of load demand uncertainty. We consider a quadratic cost function for the energy bought from the electric grid.

3.4.4. System Model

The architecture of the system under study is shown in Figure 3.15. A residential area of N smart users, each comprising both CL and NCL is considered. These loads are monitored in an online manner by a smart meter including an *energy consumption controller* (ECC). The ECC unit monitors and controls the energy consumption of users to enable the collaboration between the power grid and each user. A digital communication infrastructure, e.g., a *local area network* (LAN) is implemented to connect all ECC units to the power grid. Home energy management system (HEMS) units are in charge of energy distribution of each user for all time slots. Each HEMS should optimally manage the users' energy demand of the CL and NCL by receiving electrical energy from the power grid and transferring energy with the ESS. The control outputs are the energy profile of the CLs and the charging/discharging strategy of the ESS. Let $\mathcal{N} \triangleq \{1, \dots, n, \dots, N\}$ denote the set of users. At time $t \in \mathcal{T}$ ($|\mathcal{T}| = T$), we consider a time window $\mathcal{H}(t) \triangleq \{t+1, \dots, t+h, \dots, t+H\}$ including H discrete time slots with equal length. The value of the forward-looking objective function related to the time horizon is repetitively optimized at subsequent time slot $t \in \mathcal{T}$, but only the decision variable values of the first-time step is applied according to receding horizon concept. In the following, vectors are marked by bold letters.

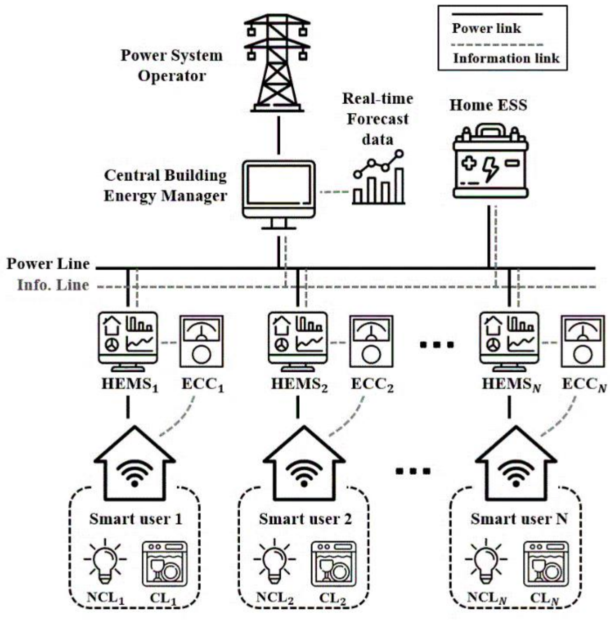


Figure 3. 15. The architecture of the smart system.

3.4.4.1. Model of Subsystem Components

We refer to the energy consumption profile of the user's CL by vector $\boldsymbol{x}_n(t) \triangleq [x_n(t+1), \dots, x_n(t+h), \dots, x_n(t+H)]$ for each user $n \in \mathcal{N}$ with H decision variables, where the energy demand profile of the CL at time slot $t+h$ for user n is stated by the scalar $x_n(t+h) \in \mathbb{R}^+$. The users' CLs are limited by a bounding operating power. We introduce parameter vectors $\overline{\boldsymbol{x}}_n(t) \triangleq [\overline{x}_n(t+1), \dots, \overline{x}_n(t+h), \dots, \overline{x}_n(t+H)]$ and $\underline{\boldsymbol{x}}_n(t) \triangleq [\underline{x}_n(t+1), \dots, \underline{x}_n(t+h), \dots, \underline{x}_n(t+H)]$ to denote the bounding power range for each user n, respectively.

$$\underline{\boldsymbol{x}}_n(t) \le \boldsymbol{x}_n(t) \le \overline{\boldsymbol{x}}_n(t) \quad \forall n \in \mathcal{N} \tag{31}$$

Moreover, a constraint on the cumulative energy should be considered for each user to fulfill the total energy requirement and completing the task at the end of given time windows:

$$\sum_{\tau=t_{n,j}^1}^{t_{n,j}^2} x_n(\tau) = \bar{E}_{n,j} \quad \forall n \in \mathcal{N}, \forall j \in \mathcal{J}. \tag{32}$$

Equation (32) corresponds to $J = |\mathcal{J}|$ constraints meaning that the cumulative consumption of the CL for each user in the jth interval $[t_{n,j}^1, t_{n,j}^2]$ needs to reach a specific threshold $\bar{E}_{n,j}$. The set $\mathcal{J}$ of intervals are supposed to be defined by users (e.g., theuy could represent successive days). The intervals are not overlapped with each other (i.e., $t_{n,j}^1 \ge t_{n,j-1}^2$, $j \in \mathcal{J}\backslash\{1\}$) and are not larger than the time horizon (i.e., $t_{n,j}^2 - t_{n,j-1}^1 \le H, j \in \mathcal{J}$). This constraint can be rewritten as:

$$\sum_{h=\max\{t_{n,k}^1-t,0\}}^{\min\{t_{n,k}^2-t,H\}} x_n(t+h) = X_{n,k}(t), k \in \mathcal{K}(t). \tag{33}$$

where $X_{n,k}(t)$ is the threshold power for each user at time step t, defined as follows:

$$X_{n,k}(t) = \begin{cases} \bar{E}_{n,k} & t < t_{n,k}^1 \\ \bar{E}_{n,k} - \sum_{\tau=t_{n,k}^1}^{t} x_n(\tau) & \text{otherwise} \end{cases} \tag{34}$$
$$, k \in \mathcal{K}(t).$$

where the subset $\mathcal{K}(t) \subseteq \mathcal{J}$ of constraints is assumed to affect the time horizon $[t+1, t+H]$. Thus, we assume that $t_k^2 > t \wedge |t_1^2 - t| < H$.

We also introduce the parameter vector $\boldsymbol{b}_n(t) \triangleq [b_n(t+1), \dots, b_n(t+h), \dots, b_n(t+H)]$ for each user n to denote the forecasted NCLs' profile. We assume that this vector is computed based on historical data by a forecast sub-module (see Fig. 1). Note that all the users' CL profiles are collected in a column vector $\boldsymbol{x} = [\boldsymbol{x}_1; \dots; \boldsymbol{x}_N]$ whose length is NH.

The shared household ESS unit, mainly batteries such as lead-acid and Li-ion, provides flexibility to users in the scheduling energy consumption. The shared ESS should optimally store energy from the grid and release it to supply the load demand. To model the charging/discharging activities of the ESS during the time windows ahead of time, we introduce two vectors $\boldsymbol{s}^+(t) \triangleq [s^+(t+1), \dots, s^+(t+h), \dots, s^+(t+H)]$ and $\boldsymbol{s}^-(t) \triangleq [s^-(t+1), \dots, s^-(t+h), \dots, s^-(t+H)]$, each with H decision variables, where $s^+(t+h)/s^-(t+h)$

is the energy stored/released in/from the ESS at any time slot $t+h$. Also, we define two parameters η_+ and η_- as the charging and discharging efficiencies of the ESS, respectively, fulfilling the ranges $0 < \eta_+ \leq 1$ and $\eta_- \geq 1$. Obviously, the rate of charging (discharging) of the stored energy has to be bounded by a maximum charging (discharging) rate:

$$0 \leq s^+(t+h) \leq \overline{S}^+, \quad \forall h \in \mathcal{H} \tag{35}$$

$$0 \leq s^-(t+h) \leq \underline{S}^-, \quad \forall h \in \mathcal{H} \tag{36}$$

where $\overline{S}^+$ and $\underline{S}^-$ are the maximum charging and discharging levels. The ESS energy inventory balance for $h \in \mathcal{H}$ is presented as a first-order discrete time model as follows:

$$z(t+h) = z(t+h-1) + \eta_+ s^+(t+h) - s^-(t+h)/\eta_-, \quad \forall h \in \mathcal{H} \tag{37}$$

where $z(t+h)$ is the charge rate of the ESS at time slot $t+h$. The battery degradation and leakage effects are assumed to be negligible. Moreover, we consider a constraint to assume that the charge level at the beginning of the time window $z(0)$ and at the last time slot of simulation $z(T)$ are equal:

$$z(0) = z(T) = \sum_{t=0}^{T} \eta_+ s^+(t) + \sum_{t=0}^{T} s^-(t)/\eta_- \tag{38}$$

Finally, a constraint is considered to enforce that the maximum charge/discharge level is bounded by the maximum storage's capacity $\overline{Q}$ and to impose it is non-negative, as follows:

$$-z(t-1) \leq \eta_+ s^+(t) + s^-(t)/\eta_- \leq \overline{Q} - z(t), \quad \forall t \in \mathcal{T}. \tag{39}$$

3.4.4.2. Power Balance and Energy Pricing Models

In each time slot, the total amount of energy required for supplying the users' energy demand can be simply calculated by scalar aggregation of CLs and NCLs consumptions as well as the amount of energy which is accumulated or released by the ESS. The energy profile of expected power consumption (*EPC*) in the time horizon is a vector is denoted by $\boldsymbol{EPC}(t) \triangleq [EPC(t+1), \ldots, EPC(t+h), \ldots, EPC(t+H)]$ which must meet the following equilibrium condition:

$$EPC(t+h) = \sum_{n=1}^{N} x_n(t+h) + \sum_{n=1}^{N} b_n(t+h) + s^+(t+h) - s^-(t+h), \ \forall h \in \mathcal{H}. \tag{40}$$

A contractual constraint forced by the power grid is applied, limiting the users' energy consumption to a maximum level at each time slot. We define the vector $\overline{\boldsymbol{EPC}}(t) \triangleq \left[\overline{EPC}(t+1), \ldots, \overline{EPC}(t+h), \ldots, \overline{EPC}(t+H)\right]$, defined by the energy provider, as the maximum permissible exchanged energy with the power grid. The total energy bought from the power grid is assumed to be non-negative. Thus, the constraints on the exchanged energy can be defined as:

$$\boldsymbol{EPC}(t) \leq \overline{\boldsymbol{EPC}}(t) \quad \forall h \in \mathcal{H}. \tag{41}$$

Substituting (40) in (41) yields:

$$\sum_{n=1}^{N} x_n(t+h) + \sum_{n=1}^{N} b_n(t+h) + s^{+}(t+h) - s^{-}(t+h) \leq \overline{EPC}(t+h), \forall h \in \mathcal{H}, \forall t \in \mathcal{T}. \tag{42}$$

The required energy of CLs and NCLs as well as the charging energy of the ESS can be bought from the power grid. We take a time-varying electricity pricing based on peak and off-peak times with known cost coefficients $\boldsymbol{c}(t) \triangleq [c(t+1), \ldots, c(t+h), \ldots, c(t+H)]$, provided by the power system operator to end users. Here, the power generation cost is assumed to be a quadratic function of the energy consumption. For the sake of realizing a realistic result, we model the cost function $\mathcal{C}$ as a quadratic function of the total exchanged energy with the power grid. Therefore, the cost function (CF) of energy purchased from the grid over the receding horizon for $t \in \mathcal{T}$ can be represented as follows:

$$CF\left(\boldsymbol{x}(t), \boldsymbol{s}^{+}(t), \boldsymbol{s}^{-}(t)\right) = CF\left(\boldsymbol{EPC}(t)\right) = \sum_{h=1}^{H} c(t+h)\left(\overline{EPC}(t+h)\right)^{2} \tag{43}$$

Hence, the cost function $\mathcal{C}$ is increasing with respect to the total exchanged energy and strictly convex.

3.4.5. Problem Formulation and Algorithm Development

In this subsection, we develop our control framework for optimal energy scheduling of residential SGs. At the first step, we define the data uncertainty set of the users' behavior, then formulate the robust scheduling problem aimed at determining the cost-optimal energy scheduling of the users' CLs and the ESS charging/discharging strategies. To obtain a tractable problem, the strong duality theorem is employed. Finally, at the second step, MPC is adopted to solve the problem at each time slot iteratively until the end of simulation.

3.4.5.1. Uncertainty Set

In order to model uncertainty set, we use cardinality constrained uncertainty. We define the budget of uncertainty Γ, taking values in $[0,\ H]$, which is the number of time slots protected against uncertainties. The problem solution is guaranteed to be feasible if no more than Γ of the parameters are subject to uncertainty. By changing the value of Γ, we can adjust the conservatism of the method against disturbance in parameters. We assume a symmetric distribution, i.e. $[\underline{\boldsymbol{b}}_n(t), \overline{\boldsymbol{b}}_n(t)] \triangleq [\boldsymbol{b}_n(t) - \widehat{\boldsymbol{b}}_n(t), \boldsymbol{b}_n(t) + \widehat{\boldsymbol{b}}_n(t)]$, in which $\overline{\boldsymbol{b}}_n(t) \triangleq [\overline{b}_n(t+1), \dots, \overline{b}_n(t+h), \dots, \overline{b}_n(t+H)]$ and $\underline{\boldsymbol{b}}_n(t) \triangleq [\underline{b}_n(t+1), \dots, \underline{b}_n(t+h), \dots, \underline{b}_n(t+H)]$ are the vectors of semi-amplitude of maximum/minimum variations (computed by historical data). Detailed forecast algorithms will not be discussed here since they are beyond the scope of this work.

3.4.5.2. Robust Formulation of the Scheduling Problem

The robust formulation of the energy scheduling problem with a quadratic objective function and linear equality and inequality constraints is presented in this section. The objective is to formulate an optimization problem aiming at minimizing the users' payment and optimizing the ESS charging/discharging activities. The problem remains feasible for any realization of the uncertainty in load demand within the defined uncertainty set. The optimization problem at instant t is stated as:

$$\min_{\boldsymbol{x}(t),\, \boldsymbol{s}^+(t),\, \boldsymbol{s}^-(t)} CF\big(\boldsymbol{x}(t), \boldsymbol{s}^+(t), \boldsymbol{s}^-(t)\big) + CF_{pr}(\boldsymbol{x}(t), \boldsymbol{s}^+(t), \boldsymbol{s}^-(t), \Gamma) \tag{44}$$

s.t. (31),(33)-(39), and

$$\sum_{n=1}^{N}\big(x_n(t+h) + b_n(t+h)\big) + s^+(t+h) - s^-(t+h) + EPC_{pr}(\boldsymbol{x}(t), \boldsymbol{s}^+(t), \boldsymbol{s}^-(t), \Gamma) \leq \overline{EPC}(t+h), \forall h \in \mathcal{H} \tag{45}$$

where $CF_{pr}(\boldsymbol{x}(t), \boldsymbol{s}^+(t), \boldsymbol{s}^-(t), \Gamma)$ is the protection function of the objective, and $\overline{EPC}(\boldsymbol{x}(t), \boldsymbol{s}^+(t), \boldsymbol{s}^-(t), \Gamma)$ $(\forall h \in \mathcal{H})$ is the protection function of the contractual constraints at each time t. The protection functions include all sub-terms containing maximum variation of the uncertain parameter (i.e. $\hat{b}_n(h), \forall h \in \mathcal{H}$). As can be seen, in our problem uncertainty affects both the objective function and contractual constraints. To assume that the objective function is not subject to uncertainty, and data uncertainty only affects the elements in the matrix of constraints, following [337] without loss of generality we can transform (44) as:

$$\min_{K(t), \boldsymbol{x}(t),\, \boldsymbol{s}^+(t),\, \boldsymbol{s}^-(t)} K(t) \tag{46}$$

s.t. (31),(33)-(39), (45) and

$$CF\big(\boldsymbol{x}(t), \boldsymbol{s}^+(t), \boldsymbol{s}^-(t)\big) + CF_{pr}(\boldsymbol{x}(t), \boldsymbol{s}^+(t), \boldsymbol{s}^-(t), \Gamma) - K(t) \leq 0 \tag{47}$$

where $K(t)$ is a scalar auxiliary variable. The corresponding protection functions are defined as follows:

$$CF_{pr}(\boldsymbol{x}(t), \boldsymbol{s}^{+}(t), \boldsymbol{s}^{-}(t), \Gamma) =$$
$$\max_{\mathcal{F}_1(t)\cup\{m_1(t)\}}\Big(\sum_{h\in\mathcal{F}_1(t)} 2c(t+h)$$
$$\sum_{n=1}^{N} \hat{b}_n(t+h) \sum_{n=1}^{N} |x_n(t+h)|$$
$$+(\Gamma - \lfloor\Gamma\rfloor) 2c\big(t+m_1(t)\big)$$
$$\sum_{n=1}^{N} \hat{b}_n\big(t+m_1(t)\big) \sum_{n=1}^{N} \big|x_n\big(t+m_1(t)\big)\big| \Big) +$$
$$\max_{\mathcal{F}_2(t)\cup\{m_2(t)\}}\Big(\sum_{h\in\mathcal{F}_2(t)} 2c(t+h) \sum_{n=1}^{N} \hat{b}_n(t+h)\, |s^{+}(t+$$
$$h)|$$
$$+(\Gamma - \lfloor\Gamma\rfloor) 2c\big(t+m_2(t)\big)$$
$$\sum_{n=1}^{N} \hat{b}_n\big(t+m_2(t)\big) \big|s^{+}\big(t+m_2(t)\big)\big| \Big) +$$
$$\max_{\mathcal{F}_3(t)\cup\{m_3(t)\}}\Big(\sum_{h\in\mathcal{F}_3(t)} 2c(t+h) \sum_{n=1}^{N} \hat{b}_n(t+h)\, |s^{-}(t+$$
$$h)|$$
$$+(\Gamma - \lfloor\Gamma\rfloor) 2c\big(t+m_3(t)\big)$$
$$\sum_{n=1}^{N} \hat{b}_n\big(t+m_3(t)\big) \big|s^{-}\big(t+m_3(t)\big)\big| \Big) +$$
$$\max_{y,\mathcal{F}_4(t)\cup\{m_4(t)\}}\Big(\sum_{h\in\mathcal{F}_4(t)} c(t+h)\Big(\sum_{n=1}^{N} \hat{b}_n(t+h)\Big)^2 y$$
$$+(\Gamma - \lfloor\Gamma\rfloor) c\big(t+m_4(t)\big)\Big(\sum_{n=1}^{N} \hat{b}_n\big(t+m_4(t)\big)\Big)^2 y \Big) \quad (48)$$
$$\text{s.t. } \mathcal{F}_k(t) \subseteq \mathcal{H}, |\mathcal{F}_k(t)| = \lfloor\Gamma\rfloor, m_k(t) \in \mathcal{H}\backslash\mathcal{F}_k(t), \quad \forall k \in \{1,2,3,4\}, \quad (49)$$
$$y \triangleq 1. \quad (50)$$

Note that in our problem uncertainty not only affects the LHS of inequality constraints, but also their RHS. In (47), three first maximization terms are related to the uncertainty associated with the decision variables. The last maximization term is related to the uncertainty in the RHS. Our aim is to protect each term against all cases that up to $\lfloor\Gamma\rfloor$ of uncertain parameters (i.e. $\sum_{n=1}^{N} \hat{b}_n(t+h), h \in \mathcal{F}_k(t)$) are allowed to vary, and one uncertain parameter (i.e. $\sum_{n=1}^{N} \hat{b}_n\big(m_3(t)\big)$) changes by coefficient $(\Gamma - \lfloor\Gamma\rfloor)$. We adopt auxiliary variable y and a constraint $y \triangleq 1$ to address the uncertainty in the RHS. Moreover, the protection function of the H contractual constraints for each time slot can be expressed as:

$$EPC_{pr}(\boldsymbol{x}(t), \boldsymbol{s}^{+}(t), \boldsymbol{s}^{-}(t), \Gamma) = \max_{y, \mathcal{F}_c(t) \cup \{m_c(t)\}} \Big(\sum_{n \in \boldsymbol{\mathcal{F}}_c(t)} \hat{b}_n(t+h)\, y + (\Gamma - \lfloor \Gamma \rfloor) \hat{b}_{m_c}(t+h) y \Big) \tag{51}$$

s.t. (50) and

$$\mathcal{F}_c(t) \subseteq \mathcal{N}, |\mathcal{F}_c(t)| = \lfloor \Gamma \rfloor, m_c(t) \in \mathcal{N} \backslash \mathcal{F}_c(t), \forall h \in \mathcal{H}. \tag{52}$$

Since the robust formulation of scheduling problem includes strong nonlinearities and cardinality calculations, we take advantage of the strong duality theorem by defining new auxiliary variables to transform it to linear equivalent from [337]. Hence, the constraint (47) can be rewritten as:

$$-K(t) + CF\big(\boldsymbol{x}(t), \boldsymbol{s}^{+}(t), \boldsymbol{s}^{-}(t)\big) + \big(z_1(t) + z_2(t) + z_3(t) + z_4(t)\big)\Gamma + \sum_{h \in \mathcal{H}} q_1(t+h) + \sum_{h \in \mathcal{H}} q_2(t+h) + \sum_{h \in \mathcal{H}} q_3(t+h) + q_4(t) \le 0 \tag{53}$$

$$\sum_{h=1}^{H} z_k(t) \le \Gamma \tag{54}$$

$$0 \le z_k(t) \le 1, \quad \forall k \in \{1,2,3,4\} \tag{55}$$

$$\begin{gathered} z_1(t) + q_1(t+h) \ge \\ 2c(t+h)\big(\textstyle\sum_{n=1}^{N} \hat{b}_n(t+h)\big)\ell_1(t+h), \\ -\ell_1(t+h) \le \textstyle\sum_{n=1}^{N} x_n(t+h) \le \ell_1(t+h) \quad \forall h \in \mathcal{H}, \end{gathered} \tag{56}$$

$$\begin{gathered} z_2(t) + q_2(t+h) \ge \\ 2c(t+h)\big(\textstyle\sum_{n=1}^{N} \hat{b}_n(t+h)\big)\ell_2(t+h), \\ -\ell_2(t+h) \le \textstyle\sum_{n=1}^{N} x_n(t+h) \le \ell_2(t+h) \ \forall h \in \mathcal{H}, \end{gathered} \tag{57}$$

$$\begin{gathered} z_3(t) + q_3(t+h) \ge \\ 2c(t+h)\big(\textstyle\sum_{n=1}^{N} \hat{b}_n(t+h)\big)\ell_3(t+h), \\ -\ell_3(t+h) \le \textstyle\sum_{n=1}^{N} x_n(t+h) \le \ell_3(t+h) \ \forall h \in \mathcal{H}, \end{gathered} \tag{58}$$

$$\begin{gathered} z_4(t) + q_4(t) \ge \\ \textstyle\sum_{j \in \mathcal{J}} c(t+h)\left(\sum_{n=1}^{N} \hat{b}_n(t+h)\right)^2 \ell_4(t) \\ -\ell_4(t) \le y \le \ell_4(t), \end{gathered} \tag{59}$$

$$\begin{gathered} q_m(t+h) \ge 0 \forall m(t) \in \{1,2,3\}, \forall h \in \mathcal{H}, \\ \ell_m(t+h) \ge 0 \forall m(t) \in \{1,2,3\}, \forall h \in \mathcal{H}, \\ q_4(t), \ell_4(t) \ge 0, \end{gathered} \tag{60}$$

where $z_k(t)$ and $q_k(t)$ ($\forall k \in \{1,2,3,4\}$), y, $q_m(t+h)$, $\ell_m(t+h)$ ($\forall m(t) \in \{1,2,3\}, \forall h \in \mathcal{H}$), $q_4(t)$ and $\ell_4(t)$ are auxiliary variables for the dual problem. The dual of the contractual constraints (45) can be formed in the same fashion as follows:

$$EPC(t+h) + z_c(t)\Gamma + \sum_{h \in \mathcal{H}} q_c(t+h) \le \tag{61}$$

$$\begin{gathered}\overline{EPC}(t+h), \quad \forall h \in \mathcal{H}, \\ z_c(t) + q_c(t+h) \geq \\ \left(\sum_{n=1}^{N} \hat{b}_n(t+h)\right)\ell_c(t+h), \ \forall h \in \mathcal{H}, \\ -\ell_c(t+h) \leq y \leq \ell_c(t+h), \ \forall h \in \mathcal{H}, \\ z_c(t), q_c(t+h), \ell_c(t+h) \geq 0, \forall h \in \mathcal{H}.\end{gathered} \tag{62}$$

where $q_c(t)$ and $\ell_c(t)$ are auxiliary variables for the dual problem. Our robust scheduling problem is a quadratically constrained linear programming problem (QCLP) with $((N+10)+9)$ decision variables, $(N+2)$ equality constraints, one quadratic and $(11H+29$ linear inequality constraints as well as $\big((N+8)H+8\big)$ bounding constraints at each iteration:

$$\begin{gathered}\min_{\substack{K(t),\boldsymbol{x}(t),\boldsymbol{s}^{+}(t),\boldsymbol{s}^{-}(t),y,\\ z_1(t),z_2(t),z_3(t),z_4(t),z_c(t),\\ \boldsymbol{q}_1(t),\boldsymbol{q}_2(t),\boldsymbol{q}_3(t),\boldsymbol{q}_4(t),q_c(t)\\ \boldsymbol{\ell}_1(t),\boldsymbol{\ell}_2(t),\boldsymbol{\ell}_3(t),\boldsymbol{\ell}_4(t),\ell_c(t)}} \quad K(t) \\ \text{s.t. (31)-(39), (53)-(62)}\end{gathered} \tag{63}$$

3.4.5.3. MPC Implementation

Here, at the second step of the control framework, the MPC strategy is applied to solve the robust optimization problem of (63) iteratively over a finite-horizon time window based on receding horizon concept. The objective function and constraints are updated and recomputed at each time slot until the simulation end time. At each time step, the control unit receives the updated forecast data of the NCL and create related uncertainty sets. The actual value of residual energy threshold is updated. Based on updated data, the online optimization problem (63) is executed. Then, the optimal decision variables (ie., $\boldsymbol{x}(t), \boldsymbol{s}^{+}(t), \boldsymbol{s}^{-}(t)$) of the first time step are extracted and applied as the control outputs. This process is repeatedly carried out ahead of time until the end time of simulation. The proposed online control algorithm is shown in Figure 3.16.

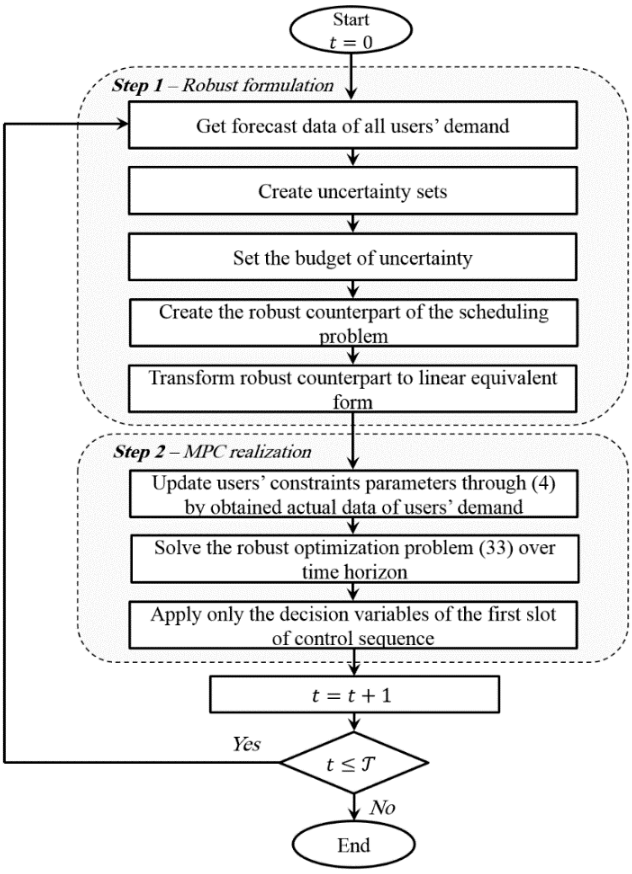


Figure 3. 16. The proposed RMPC-based algorithm.

3.4.5.4. Sensitivity Analysis of Budget of Uncertainty in the RMPC Algorithm

The budget of uncertainty (Γ) can be adjusted in the robust scheduling problem of (63) to give the different robustness levels. Accordingly, the conservatism of the solution against uncertainty can be controlled. In the case that $\Gamma = 0$, the values of the protection functions $CF_{pr}(\boldsymbol{x}(t), \boldsymbol{s}^{+}(t), \boldsymbol{s}^{-}(t), \Gamma)$ and $EPC_{pr}(\boldsymbol{x}(t), \boldsymbol{s}^{+}(t), \boldsymbol{s}^{-}(t), \Gamma)$ ($\forall h \in \mathcal{H}$) are equal to zero, which means that the uncertainty is not considered and the optimization problem is solved based on nominal forecasted values (here we call it nominal scheduling). In this case, the results present minimum payment for users, but the obtained solution is over-optimistic. On the other hand, when $\Gamma = |H|$ which denotes the maximum protection level, the uncertainty in parameters is fully addressed, but the obtained solution is in the most conservative case. For obtaining a medium protection level, the decision maker can flexibly change $\Gamma \in [0, |H|]$ to adjust a trade-off between user's payment and constraint violation rate.

3.4.6. Case Study

To evaluate the performance of the proposed method, a simulated case study is conducted. The grid-connected system of Figure 3.15 consists of three residential smart users ($N = 3$), each equipped with a CL and an NCL. However, the model can be simply applied to scenarios with multiple loads for each user. A shared ESS unit is implemented for all users. The problem is solved by CPLEX 12.8 in MATLAB R2017a on a PC with an Intel Core i7-7500 (4 CPUs), 2.70 GHz and 12 GB RAM memory. The length of each time slot is assumed to be one hour ($h = 1$) and the prediction horizon is 24 hours ($\mathcal{H} = [t+1, t+24]$). Also, the simulation is assumed to perform the scheduling for one day ($\mathcal{T} = 24$). For the energy bought from the power grid, we consider the dual-rate cost coefficients. The features of the supply side, demand side components and the ESS unit are listed in Table 3.4. To model NCL's uncertainties, we assume discrete Gaussian distributed random variables in each iteration. Figure 3.17 shows the actual aggregated NCL profile for all the users.

We intend to analyze the effects of our proposed RMPC-based method on the total energy cost, feasibility constraints violation rate, and PAR. To obtain some insight on the robustness of the method, we provide the simulation results of the energy scheduling for three different values of the budget of uncertainty.

Table 3. 4. Simulation Parameters

Quantity	Symbol	Value	Unit
Total CL threshold (user 1)	$\overline{\mathrm{E}}_1(t)$	20	kWh
Total CL threshold (user 2)	$\overline{\mathrm{E}}_2(t)$	16	kWh
Total CL threshold (user 3)	$\overline{\mathrm{E}}_3(t)$	20	kWh
CL range per slot	$[\underline{x}_n, \overline{x}_n]$	[0,6]	kWh
EPC range per slot	$EPC(t+h)$	[0,8.3]	kWh
Budget of uncertainty range	Γ	[0,24]	-
Simulation time	$\mathcal{T}$	24	hours
Peak demand slots	c_p	$\{[9,11] \cup [16,21]$	hours
Off-Peak demand slots	c_{op}	$\begin{Bmatrix}[1,8] \cup [12,15], \\ \cup [22,24]\end{Bmatrix}$	hours
Rate of peak demand slots $(\forall h \in c_p)$	$c(t+h)$	0. 1875	¢ /kWh
Rate of off-peak demand slots $(\forall h \in c_{op})$	$c(t+h)$	0.0937	¢ /kWh
Initial charge of ESS	$z(0)$	0	kWh
Maximum charging/discharging energy per slot	$\overline{S}^+/\underline{S}^-$	2	kWh
Maximum capacity of ESS	$\overline{Q}$	45	kWh
Charging/discharging efficiencies	η_+/η_-	0.95	-

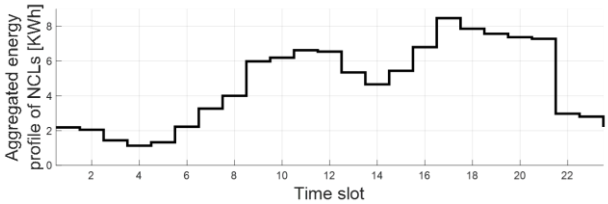


Figure 3. 17. Actual aggregated NCL profile for all the users.

Figure 3.18 demonstrates the aggregated energy profiles of CLs and the charging/discharging activities of the shared ESS unit for $\Gamma = 0$ (nominal scheduling without protection), $\Gamma = 12$ (medium protection level) and $\Gamma = H = 24$ (full-protection level). As can be observed, the energy scheduling shifts the CLs' operation time to the time slots with lower cost coefficients.

The shared ESS unit takes part in the minimization of the total energy cost by optimal charging and discharging activities during the time horizon. When $\Gamma = 0$, the total cost is obviously minimum (1.6475 €/day). However, this case assumes a perfect forecast data and optimistically ignores the effect of data uncertainty on results. It can cause too much change in the obtained results from the optimal target and a high violation rate in contractual constraints in presence of parameters' uncertainty. Conversely, by choosing $\Gamma = 24$, the maximum protection (the worst-case mode) is achieved. However, the total cost is maximum (1.6810€/day) which is 2.03% more than the nominal scheduling case. By varying this parameter within the possible range ($\Gamma \in [0,24]$), the robustness level can be controlled.

Here, we adopt the middle value in the range, $\Gamma = 12$, to avoid conservative solutions and high constraint violation rate. In this case, the total cost is 1.6653 €/day which is 0.93% lower than the full-protection mode. Moreover, the results in Figure 3.18 depict that a lower PAR is obtained by increasing the budget of uncertainty. We further present and compare the results achieved for different realizations of uncertain variables to evaluate the performance of the RMPC-based method in real conditions. With this aim, Monte Carlo (MC) simulations are implemented to create 10000 scenarios for the uncertainty associated with NCLs. At each MC iteration, we add a normal distributed random sequence with zero mean and standard deviation of 0.2 [kWh] to the nominal forecast values of NCLs to generate the actual profile.

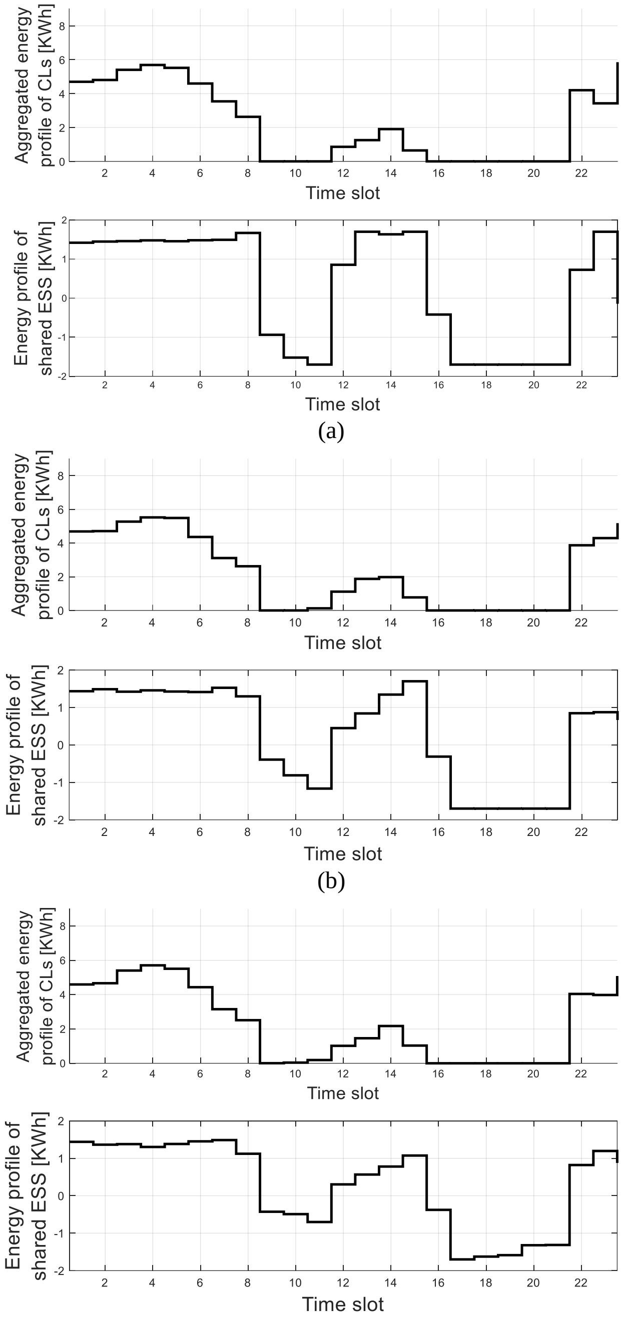


Figure 3. 18. Aggregated energy profiles of CLs versus energy profiles of shared ESS: (a) nominal scheduling ($\Gamma = 0$); (b) medium protection level ($\Gamma = 12$); (c) full protection level ($\Gamma = 24$).

To investigate the conservatism of the method, we present the results for the average profile of the MC simulations for all iterations. The average profiles of total energy bought from the power grid versus maximum EPC for nominal scheduling, medium-protection level and full-protection level are presented in Figures 3.19a to 3.19c respectively. The results show that, under certain scenarios, the total energy profile in the nominal scheduling ($\Gamma = 0$) violates the contractual constraints in some time slots, which is undesirable (Figure 3.19a). By adopting medium-level protection $\Gamma = 12$, instead, the constraints are satisfied with very high probability (Figure 3.19b). The constraints can be completely met with taking the worst-case mode $\Gamma = 24$, confirming the full-protection against uncertainty (Figure 3.19c).

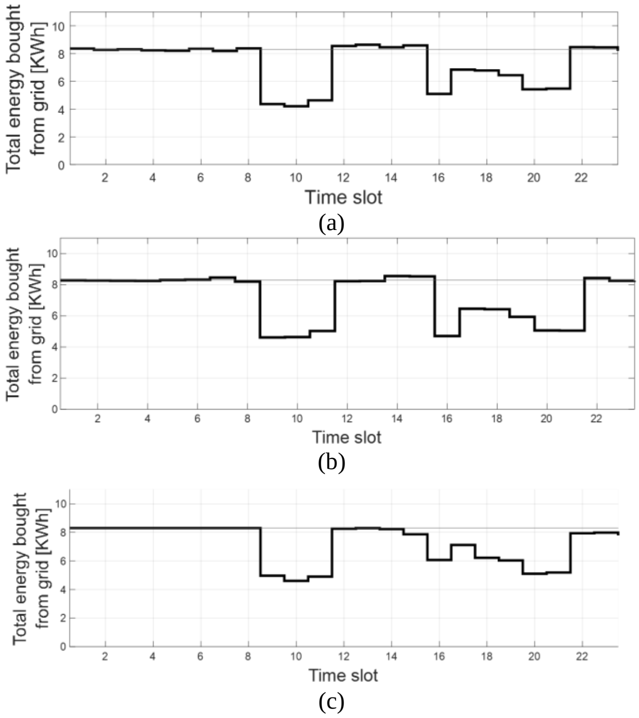
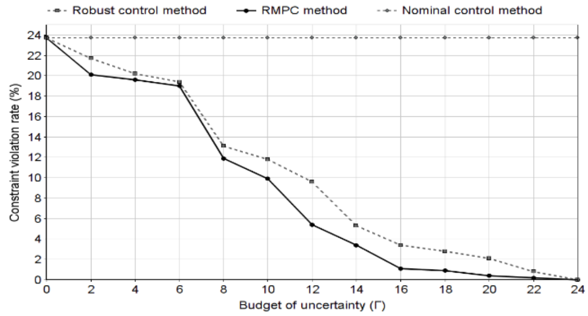
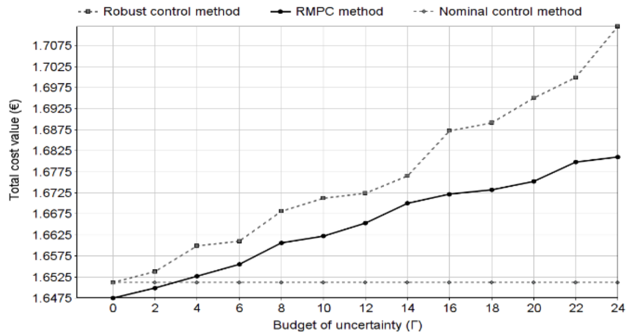


Figure 3. 19. Average profiles of total energy bought from the grid versus maximum EPC (blue fixed line): (a) nominal scheduling ($\Gamma = 0$); (b) medium protection level ($\Gamma = 12$); (c) full-protection level ($\Gamma = 24$).

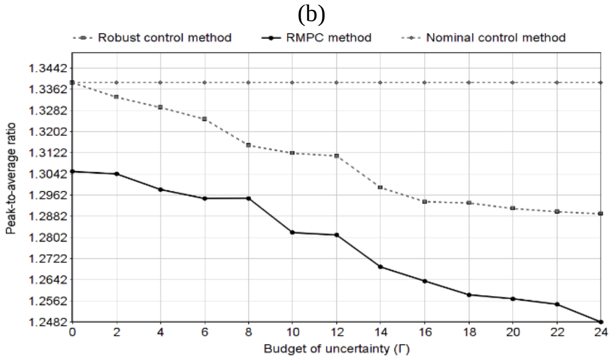
Finally, Figure 3.20 provides a comparison between the proposed online RMPC-based method, the offline robust control method which simulates the problem once at the beginning of the simulation for the whole day, as well as the nominal control method which ignores the effect of uncertainty. The figure shows the trend of constraints violation rate, the total cost values and the PAR values by varying the budget of uncertainty from 0 to 24. In particular, based on Figure 3.20a, it can be observed that the number of violations in our proposed RMPC-based approach is always lower than in offline robust control approach, confirming the RMPC-based scheduling is more robust. Moreover, according to Figure 3.20b, the RMPC provides a better tracking on the NCLs' uncertainty than the offline robust control, leading a less conservative solution. The comparison of the three methods based on the PAR demonstrates that the RMPC-based method provides a lower PAR over all values of the budget of uncertainty. Summing up, the simulation results validate the effectiveness of the proposed method, enabling the decision maker to make a trade-off between the total payable cost by users and constraints violation rate by changing the value of the budget of uncertainty.



(a)



(b)



(c)

Figure 3. 20. Comparison between proposed RMPC-based method, robust control and nominal control methods: (a) constraint violation rate; (b) total cost value; (c) peak-to-average ratio (PAR) versus budget of uncertainty

3.4.7. Conclusions

A RMPC-based DSM framework for residential SGs with multiple users and a shared ESS is proposed in this section. The objective is to minimize the total energy cost and the PAR of the energy consumption, as well as to satisfy the constraints violation rate of the total energy purchased from the grid at each time slot when taking the forecast uncertainty of load demands into account. A QCLPP programming is established to optimally schedule CLs and the energy activities of the shared ESS unit in an online fashion. We then apply the proposed scheme to a sample simulated system to validate the effectiveness of our method in comparison to the offline robust scheduling and the nominal scheduling. The robustness of the proposed online approach against the level of conservatism of the solution is also investigated. The focus of future work is on expanding the system model to involve other subsystems such as non-interruptible loads, distributed generators, and renewable energy sources. Moreover, in the future we apply the approach to distributed multi-agent architecture of large-scale residential SGs.

From the findings and contribution of the research in this chapter, the following paper has been presented:

- S.M. Hosseini, R. Carli, M. Dotoli, "A Residential Demand-Side Management Strategy under Nonlinear Pricing Based on Robust Model Predictive Control," *IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Bari, Italy, October 6-9, 2019.

3.5. A Novel Robust Approach for Comprehensive Energy Management of Large-scale Residential Microgrids with RESs, PEVs and Heat Pumps

3.5.1. Introduction

In this subsection we present a comprehensive robust framework for day-ahead energy scheduling of large-scale interconnected smart homes with both individual and shared RESs and ESSs, as well as various electrical components under uncertainties on RES generation and users' behavior. In our framework, we assume that each user incorporates NCLs, an energy-based CL, a comfort-based CL such as a heat pump (HP), an individually-owned RES, and a PEV with vehicle-to-home (V2H) and home-to-vehicle (H2V) operating modes [350]. Moreover, all users share an ESS, and a number of PVSs and DWTs as well. The propose approach is motivated by the emerging need for intelligent demand-side management (DSM) approaches in smart MGs in presence of both power generation and demand uncertainties. The proposed robust energy scheduling strategy allows the decision maker (i.e., the energy manager of the MG) to make a satisfactory trade-off between the users' payment and constraints' violation rate considering the energy cost saving, the system technical limitations and the users' comfort by adjusting the values of the budget of uncertainty. The proposed framework is generic and flexible as it can be applied to different structures of MGs considering various types of uncertainties in energy generation or demand.

3.5.2. Aims and Objectives

Our main objective is minimizing the total energy payment for the MG while satisfying the related constraints in presence of forecast uncertainty in RES generation and users' demand. We aim at obtaining a robust solution, including the optimal scheduling of the CLs for each user and the charging/discharging strategies of the shared ESS and individual PEVs at each time slot. Hence, we present a tractable robust optimization scheme to solve the energy scheduling problem with a quadratic cost function, which realistically models the cost of energy bought from the grid. Also, the MG is able to sell the energy back to the grid by a linear cost function. All the related device/comfort/contractual constraints, including specifically a contractual obligation imposed by the power grid restricting the users' exchanged energy over time slots, are modeled. First, a deterministic model of the scheduling problem is formulated. Hence, a min-max robust counterpart considering uncertain parameters is established regarding the cardinality-constrained uncertainty set. We finally apply some mathematical transformations to solve the equivalent problem effectively. We also investigate the effect of the proposed approach on the peak-to-average ratio (PAR) of the total exchanged energy. We deal with the robustness of the proposed approach against the level of conservativeness of the solution.

3.5.3. Related Works and Contributions

Utility companies mainly use generators burning fossil fuels to provide energy in a reliable way. Accordingly, in numerous research works the power generation cost is assumed to be a quadratic function of the energy consumption [351]-[356]. For instance, [347] and [352] propose incentive-based energy scheduling mechanisms for smart homes considering tractable quadratic cost functions. A distributed bi-level residential energy management is presented in [353] by formulating a multi-objective constrained non-linear problem to optimize electricity cost, discomfort, and appliance interruptions. In the context of energy scheduling under uncertainty, one of the widely used strategies for DSM is known as stochastic optimization based on statistical data [357]-[361]. In this context, for example, Kim *et al.* [357] present a stochastic dynamic programming for energy scheduling based on statistical knowledge about future prices to find decision thresholds for both noninterruptible and interruptible loads. In [358], a stochastic optimization framework for energy management of a smart home is proposed coping with the uncertainty associated with RES generation and PEV's plug-state as a Markov decision process. A probability distribution model combining household power consumption, PEV home-charging and RES generation is developed by Munkhammara *et al.*

[359] through a convolution approach to merge three separate existing probability distribution models. In [361], an energy scheduling scheme for the optimal energy management of a MG utilizing the probabilistic forecasts of wind power and users' energy demand is presented. First, they formulate the energy scheduling problem as a stochastic model predictive control problem, and then convert it to a standard convex quadratic programming using machine-learning techniques.

Although stochastic DSM methods show effective performance facing uncertainty in resources availability or demand, they suffer from some serious limitations: for example, large presence of uncertain data which need to be modeled, dependency between some uncertain parameters, insufficient historical data for new houses, and high computational effort due to significant number of scenarios impose additional difficulty and cost to such models [350], [362]. Hence, dealing with the mentioned issues of stochastic-based approaches, robust optimization was proposed as an alternative promising solution [362]-[369]. A comparison between robust optimization and stochastic optimization approaches for energy scheduling of residential appliances under uncertainties in real-time electricity prices is provided in [362]. The authors prove that robust optimization has a significantly better computational performance. Moreover, modeling uncertainty through robust optimization using data intervals is simpler than modeling uncertainty by stochastic optimization, which requires random variables with detailed statistical information [362]. Among the research efforts towards energy scheduling utilizing robust optimization, [363] discusses the robust optimal scheduling of a residential SG incorporating an ESS under uncertainty in energy price. The authors assume that the uncertain energy prices are randomly distributed with a known probability distribution around the predicted values. In [370][364], a robust optimization approach is proposed considering the uncertain output variation of RESs. A two-stage complementary framework is adopted to plan the collaborative scheduling of the ESS with an incentive-based demand response program called Direct Load Control (DLC) which directly shuts down the remote CLs to maintain the power balance in a MG. A multi-objective robust scheduling model is established in [365], where both supply and demand sides are affected by uncertainty. The aim is to obtain the lowest operating cost and the highest renewable energy utilization rate. The uncertain problem is transformed into a deterministic problem and a genetic algorithm is used to solve the deterministic problem. Wang *et al.* [366] develop a robust optimization approach with adjustable robustness level for household load scheduling considering power uncertainty of household photovoltaic system. The authors formulate the day-ahead load scheduling problem as a min-max uncertain problem considering interval-based uncertain parameters, and then transform it into the robust counterpart. However, they adopt a linear cost function for the energy exchanged with the grid, and they do not address the uncertainty associated with users' behavior. Paul and Padhy [367] adopt robust conditional value at risk optimization as a linear risk measure approach to protect the day-ahead residential energy scheduling against uncertainties associated with RES generation and energy price volatility. In [368], the robust optimal energy scheduling of a SG affected by uncertainty is investigated. The authors establish a mixed-integer linear programming (MILP) formulation to minimize the overall energy cost. However, the focus of this work is on the uncertainty associated with price signals, and on analyzing the effect of price uncertainty on the operation of the SG's components, which is different than our focus that is on uncertainty related to users' behavior and RES energy generation. In a related work, Paridari *et al.* [369] deal with the robust energy scheduling of smart home appliances comprising the ESS unit, taking the uncertain behavior of users into account. Although it deals with uncertainty in load demand, such a work focuses on uncertainty associated with CLs as decision variables, that is different than our focus on uncertainty involved with NCLs. The authors map the load uncertainty to the cost function coefficients and formulate the problem as a MILP. In addition, the uncertainty associated with RES energy generation is not considered in that work. Moreover, unlike our work, all the aforementioned studies [362] to [369] adopt a linear cost function for energy bought from the power grid, and do not take the effect of uncertainty in the feasibility of energy exchange between users and power grid into account. Additionally, the effects of the energy scheduling method on the PAR of the total energy demand are not quantified in the mentioned works.

Regarding other robust optimization methods addressing uncertainty in parameters, we can refer to two-stage robust methods, including affine adjustable robust counterpart approaches [370], [371]. There can be found different types of multi-stage robust optimization methods in the literature, mainly solved by two classes of algorithms, namely Benders and column-and-constraint generation algorithms. The former approach is based on applying decomposition techniques to transform the original two-stage problem into a single-stage problem, and then utilizing the Benders algorithm to solve the reformulated problem [370]. On the contrary, the latter approach is based on the column-and-constraint generation, which leads to critical uncertain scenarios, requiring recourse decision variables and second-stage constraints to solve the reformulated problem [372].

However, as our energy scheduling problem has a quadratic objective function with several binary variables, applying these two-stage robust approaches, where the optimization problem is set as a min-max-min problem which is needed to be dualized by adding extra bilinear terms in the objective function, can result in an extremely large-scale mixed-integer quadratic programming (MIQP) model, which is more computationally expensive and more complicated than our proposed single-stage robust technique. Therefore, the scheduling is most likely to be intractable with the increase of the problem size for large-scale MG where the number of components (in particular, energy storage systems or plug-in electric vehicles) in the MG increases [370], [373]. Another robust method to address uncertainty in optimization problems is based on the affine adjustable robust counterpart assuming affine functions of uncertain parameters for resource decisions [374], [336]. However, in contrast with our case, such a class of robust approaches is generally unable to handle problems with integer resource decisions [370], [373], [375]. Moreover, this method typically needs full knowledge about the past data on the uncertain demand to derive a decision by inserting them in a linear decision rule, which is mostly unavailable [337]. The advantage of our robust optimization framework is that it is more general and applicable to a wide spectrum of demand-side management problems. In addition, the final problem is tractable and can be easily implemented by using commercial optimization tools. We better highlight these advantages of our method in the case study section.

Hence, although some studies have made positive attempts for optimizing the energy scheduling of residential MGs in presence of forecast uncertainties, due to their respective limitations, further research is still required to cope with the challenge of RES energy generation and users' behavior uncertainty in residential load scheduling. Summing up, the specific contributions of this work lie in the following aspects.

1) We present a comprehensive model and a systematic robust methodology to state and solve the optimal energy scheduling problem of a grid-connected residential MG with several users incorporating individually owned RESs, NCLs, energy-based and comfort-based CLs, and PEVs. Moreover, the smart users share a given number of RESs and an ESS under a dynamic quadratic pricing. However, the MG is also able to sell its extra energy back to the grid by a dynamic linear pricing. We take the forecast uncertainty caused by the RESs energy profiles, as well as the users' energy demand, into account.

2) We establish a quadratic min-max robust problem under the cardinality-constrained uncertainty set inspired by the method proposed by Bertsimas and Sim [337] and convert it to a MIQP model to solve the equivalent robust counterpart of the scheduling problem. Forecast uncertainty in both the objective function and corresponding contractual constraints is addressed. The problem includes uncertain terms both in the objective function and in the left-hand side (LHS) and the right-hand side (RHS) of the inequality constraints. To the best of the authors' knowledge, no robust quadratic programming approach for the energy scheduling of the residential MG has ever been proposed to tackle the uncertainties associated with RES energy generation and users' energy demand under quadratic pricing.

3) Our proposed framework is generic and flexible as it can be applied to different structures of MGs considering various types of uncertainties in energy generation or demand.

4) We deal with the conservativeness of the proposed scheme for different scenarios and quantify the effects of the budget of uncertainty on the cost saving, the PAR and constraints' violation rate. Our robust approach enables the decision maker (i.e., the energy manager of the

MG) to make a trade-off between the users' payment and constraints' violation rate by adjusting the values of the budget of uncertainty.

We validate the effectiveness of the proposed approach on a sample residential MG with several users under forecast uncertainty. We also provide a comprehensive comparison between our proposed robust energy scheduling and energy scheduling with an exact forecast profile without protection against data uncertainty. To better show the advancement of our approach with respect to the related literature, we also compare the results of our proposed approach with a related robust method, confirming the performance of the proposed framework.

3.5.4. System Model

In this section, we present a mathematical model of the day-ahead energy scheduling problem for the users' appliances and PEVs, the individual and shared resources (i.e., the RESs and the ESS), as well as the demand-supply balance and constraints.

The features of the considered MG are defined according to residential MG architectures commonly used in the most recent studies. For instance, based on the well-known definitions and system structures provided in [376]-[379], a residential MG can be considered as a locally controlled system to promote the integration of distributed generation sources, energy storage systems, interconnected users with household loads, plug-in electric vehicles along with smart meters and home energy consumption controllers, in which households' energy demands can be supplied by local generations while their extra required/surplus energy can be bought/sold from/to the power grid. The architecture of the considered system is shown in Figure 3.21. We assume that each user owns a smart meter comprising an energy consumption controller (ECC). The ECC is in charge of controlling the user's energy consumption and enforcing the collaboration in the MG. The activities of all the smart users are controlled by the energy management system (EMS) that is also in charge of acquiring pricing signals from the power grid and managing the operations of shared resources. A digital communication infrastructure (e.g., a local area network (LAN)) is implemented to connect all the MG components to the energy management system [376]. For the ease of implementation, we assume that each user comprises one RES, one NCL, one CL, one Heat Pump (HP), and one PEV only, but the model can be straightforwardly expanded to scenarios with several loads and PEVs for each user. Let $\mathcal{N} \triangleq \{1, \dots, n, \dots, N\}$ denotes the set of users. We consider a time window $\mathcal{H} \triangleq \{1, \dots, h, \dots, H\}$ including H discrete time slots with equal length Δh. In the following, vectors are denoted by bold letters. The MG model is detailed in the sequel.

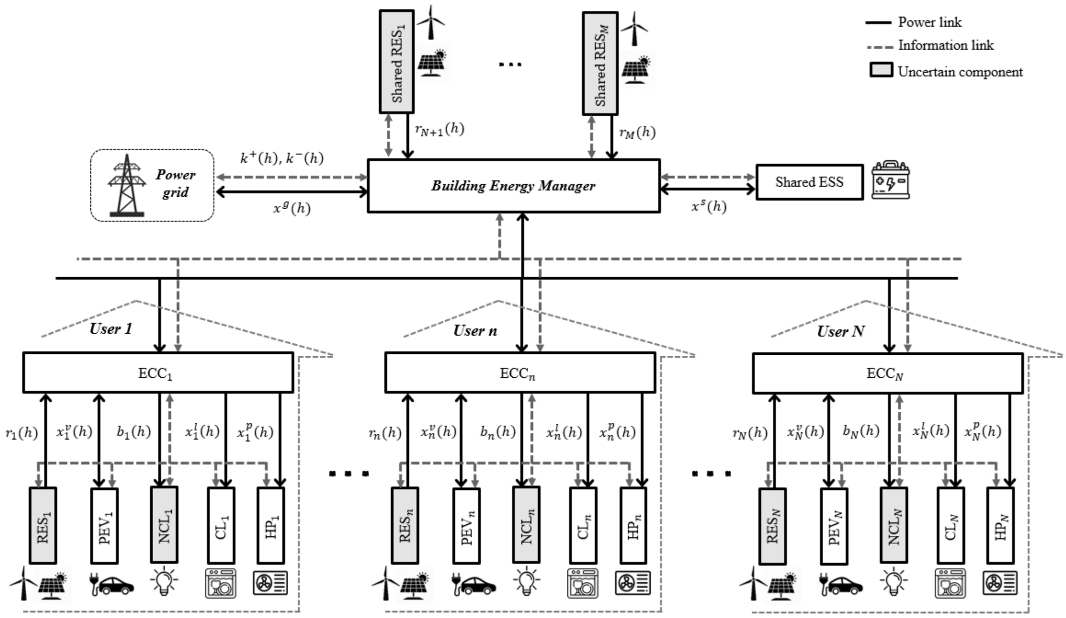


Figure 3. 21. Scheme of energy flows and connections between distribution network, users' energy system components, and shared devices.

3.5.4.1. Renewable Energy Sources

We assume that the MG incorporates a number M of RESs, (e.g., photovoltaic systems or domestic wind turbines) denoted as $\mathcal{M} \triangleq \{1, \dots, m, \dots, M\}$ including both the RESs that are shared and those that are individually owned by users ($M > N$). We define M column vectors of H input parameters $\boldsymbol{r}_m \triangleq [r_m(1); \dots; r_m(h); \dots; r_m(H)]$ ($m \in \mathcal{M}$) collecting the energy profiles produced by the RESs. These vectors are assumed to be calculated by a forecast sub-module of the EMS using a prediction algorithm based on weather data [380].

3.5.4.2. Users' Energy Loads

First of all, we assume that users are equipped with NCLs, which are inflexible loads, whose operation time cannot be shifted and whose profile cannot be modulated (i.e., with fixed power profile). We introduce N column vectors of H input parameters $\boldsymbol{b}_n \triangleq [b_n(1); \dots; b_n(h); \dots; b_n(H)]$ ($n \in \mathcal{N}$) to denote the users' NCL profiles. We assume that these vectors are computed by forecast sub-modules of the ECCs using a prediction algorithm [381]. We show in subsection 3.5.6.2 that, in order to solve the scheduling problem, our approach only requires knowledge of the lower and upper bounds of the NCLs profiles as well as RESs production curves, which are typically available based on historical data.

Second, we assume that users are also equipped with CLs, which are loads with flexible and programmable operations. Such controllable loads can be operated on a favorable schedule.

CLs can be commonly categorized into two different classes [382]: 1) energy-based CLs: these appliances are characterized by a prescribed energy requirement (e.g., pumps of waters supply networks, PEVs), i.e., a certain amount of energy has to be consumed over a set of time slots delimited by a minimum starting-time slot and a maximum ending-time slot; 2) comfort-based CLs: these devices consume energy to control a physical variable influencing the user's comfort (e.g., heating, ventilation and air conditioning (HVAC) systems, refrigerators). Without loss of generality, we assume that for each user one CL for each class is identified.

As for the energy-based CLs, we introduce a column vector $\boldsymbol{x}_n^l \triangleq [x_n^l(1); \dots, x_n^l(h); \dots, x_n^l(H)]$ for each user $n \in \mathcal{N}$ with H decision variables referring to the consumption profile of the CL. We collect all the users' CL profiles in a column vector $\boldsymbol{x}^l \triangleq \left[\boldsymbol{x}_1^l; \dots; \boldsymbol{x}_N^l\right]$ whose length is NH. Due to operational requirements, users' loads are restricted by minimum and maximum operating levels. We use two column vectors of H input parameters $\bar{\boldsymbol{l}}_n \triangleq \left[\bar{l}_n(1); \dots, \bar{l}_n(h); \dots, \bar{l}_n(H)\right]$ and $\underline{\boldsymbol{l}}_n \triangleq \left[\underline{l}_n(1); \dots; \underline{l}_n(h); \dots; \underline{l}_n(H)\right]$ to indicate the maximum and minimum energy level for each user n, respectively. Furthermore, a constraint should be enforced for each user to make sure that the cumulative energy fulfills the total energy requirement, denoted as L_n ($n \in \mathcal{N}$), by the deadline to complete the task at the end of the time window:

$$\underline{\boldsymbol{l}}_n \leq \boldsymbol{x}_n^l \leq \bar{\boldsymbol{l}}_n, \qquad n \in \mathcal{N} \tag{64}$$

$$\textstyle\sum_{h=1}^{H} x_n^l(h) = L_n, \qquad n \in \mathcal{N}. \tag{65}$$

As for the comfort-based CLs, just to fix ideas, we refer to the HVAC heat pumps (HPs) serving the users' household indoor environment. The following discrete time model can be used to represent the nth user's indoor temperature [383]:

$$\begin{aligned} T_n(h) &= e^{-\Delta h/\tau_n}\, T_n(h-1) \\ &+ \left(1 - e^{-\Delta h/\tau_n}\right)\left(T^{ext}(h) + \pi_n x_n^p(h)\right), h \in \\ &\mathcal{H}, n \in \mathcal{N} \end{aligned} \tag{66}$$

where $T_n(h)$ and $T_{ext}(h)$ are the household indoor and outdoor temperatures at time slot h, respectively, τ_n is the time constant of the first order dynamics of the household indoor temperature, π_n is the total heating/cooling gain in the considered environment ($\pi_n > 0$ if the HVAC system is in heating mode and $\pi_n < 0$ if the HVAC system is in cooling mode), and $x_n^p(h)$ is the heat pump consumption at time slot h. Note that vector $\boldsymbol{T}^{ext}(t) \triangleq [T^{ext}(1); \dots; T^{ext}(h); \dots; T^{ext}(H)]$ collecting the outdoor temperature profiles in the time window $\mathcal{H}$ is an input parameter, computed using weather prediction data. Conversely, vector $\boldsymbol{T}_n \triangleq [T_n(1); \dots; T_n(h); \dots; T_n(H)]$ collecting for each user $n \in \mathcal{N}$ the household indoor temperature profile is a variable of the problem. Vector $\boldsymbol{T}_n$ has to be computed in accordance with the following constraint:

$$T_n^{min}(h) \le T_n(h) \le T_n^{max}(h), \quad h \in \mathcal{H}, n \in \mathcal{N} \quad (67)$$

where $\boldsymbol{T}_n^{min} \triangleq \left[T_n^{min}(1); \dots; T_n^{min}(h); \dots; T_n^{min}(H)\right]$ and $\boldsymbol{T}_n^{max} \triangleq [T_n^{max}(1); \dots; T_n^{max}(h); \dots; T_n^{max}(H)]$ denote the vectors of lower and upper bounding of the nth user's household indoor temperature, respectively. Range $[T_n^{min}(h), T_n^{max}(h)]$ ($h \in \mathcal{H}$) is a time-varying parameter that allows users to represent thermal comfort preferences within the occupancy period. Similarly, vector $\boldsymbol{x}_n^p \triangleq \left[x_n^p(1); \dots; x_n^p(h); \dots; x_n^p(H)\right]$ collecting for each user $n \in \mathcal{N}$ the heat pump consumption profile is a variable of the problem. Vector $\boldsymbol{x}_n^p$ has to be computed in accordance with the following constraint:

$$0 \le x_n^p(h) \le E_n, \quad h \in \mathcal{H}, n \in \mathcal{N} \quad (68)$$

where E_n is the maximum energy that the pump can consume in one time slot with duration Δh.

Third, we assume that users are also equipped with PEVs, which act as versatile active elements that are able to consume, store, and supply energy [384]. This means that the PEVs' battery charging is bidirectional, in accordance with the following modes of operation: H2V (home to vehicle, i.e., the charging of the PEV is a function of the total demand in the home, aiming at preventing overloads) and V2H (vehicle to home, i.e., the PEV is used to operate as an offline uninterruptible power supply) [384]. To model the charging/discharging activities of the PEV of user n within the time windows, we define a column vector $\boldsymbol{x}_n^v \triangleq [x_n^v(1); \dots; x_n^v(h); \dots; x_n^v(H)]$, with H decision variables, where $x_n^v(h)$ is the energy stored/released in/by the PEV of user n at time slot h. Due to the conversion losses of the PEV, we define ζ_n^+ and ζ_n^- as the charging and discharging efficiencies for the PEV of user n, respectively.

Since PEVs may not be connected to the grid throughout the whole time window for various reasons (e.g., driving on the road), we assume that the PEV of each user $n \in \mathcal{N}$ is connected to the power system within a given plugged-in interval $\left[k_n^s, k_n^f\right]$. This interval is defined by users at the beginning of the scheduling horizon, e.g. on a daily basis, according to their preferences and PEVs' availability. During this interval, the PEV is plugged to the MG, and thus can be either charged or discharged:

$$x_n^v(h) = 0, h \in \mathcal{H} \backslash \left[k_n^s, k_n^f\right], n \in \mathcal{N} \quad (69)$$

$$\underline{v}_n \le x_n^v(h) \le \overline{v}_n, h \in \left[k_n^s, k_n^f\right], \in \mathcal{N} \quad (70)$$

where we denote as $\overline{v}_n$ and $\underline{v}_n$ the maximum charging and discharging rates, respectively.

To avoid simultaneous charging and discharging of the PEV battery, the dynamics of the charge level of the PEV of user n can be written as a first order discrete time model as follows:

$$v_n(h) = \begin{cases} v_n(h-1) + \zeta_n^+ x_n^v(h) \text{if} x_n^v(h) \ge 0 \\ v_n(h-1) + x_n^v(h)/\zeta_n^- \text{ if} x_n^v(h) < 0' \end{cases} \quad (71)$$

$$h \in [k_n^s, k_n^f], n \in \mathcal{N}$$

where $v_n(h)$ and $v_n(k_n^s - 1) \triangleq v_n^0$ denote the charge level of the PEV of user n at time slot h and the initial battery charge level at the beginning of plugged-in interval, respectively. In this work, we assume that the battery degradation and leakage effects are negligible. Moreover, we assume that the charge level of the PEV of user n at the end of plugged-in interval (i.e., $v_n(k_n^f)$) has to be equal to a given desired level V_n:

$$V_n = v_n(k_n^f). \tag{72}$$

The charge level is bounded by the minimum and maximum battery capacity $\underline{V_n}$ and $\overline{V}_n$ as follows:

$$\underline{V_n} \le v_n(h) \le \overline{V}_n \ , h \in [k_n^s, k_n^f], n \in \mathcal{N}. \tag{73}$$

Through the use of logical and supporting variables, we now transform (71) into a linear form. First, we introduce a column vector of H logical variables $\boldsymbol{\delta}_n^v \triangleq [\delta_n^v(1); \dots; \delta_n^v(h); \dots; \delta_n^v(H)]$, where each component $\delta_n^v(h)$ takes value 0 or 1 if the PEV stores (i.e., $x_n^v(h) \ge 0$) or releases (i.e.,$x_n^v(h) < 0$) energy, respectively:

$$\delta_n^v(h) \in \{0,1\}, h \in \mathcal{H}, n \in \mathcal{N} \tag{74}$$

$$\boldsymbol{x}_n^v \ge \mathbf{0}_{H,1} \ \Leftrightarrow \boldsymbol{\delta}_n^v = \mathbf{0}_{H,1}, n \in \mathcal{N} \tag{75}$$

where we denote as $\mathbf{0}_{n,1}$ the n-dimensional column vector with all elements equal to zero. Second, we introduce a supporting vector $\boldsymbol{x}_n^{v\delta} \triangleq [x_n^{v\delta}(1); \dots; x_n^{v\delta}(h); \dots; x_n^{v\delta}(H)]$ defined as follows:

$$\boldsymbol{x}_n^{v\delta} = \boldsymbol{\delta}_n^v \circ \boldsymbol{x}_n^v, n \in \mathcal{N} \tag{76}$$

where the symbol $\circ$ denotes the entrywise product. Note that logical equations (75)-(76) can be replaced with:

$$\boldsymbol{x}_n^v \le \overline{v}_n(\mathbf{1}_{H,1} - \boldsymbol{\delta}_n^v), n \in \mathcal{N} \tag{77}$$

$$\boldsymbol{x}_n^v \ge \underline{v_n}\boldsymbol{\delta}_n^v, n \in \mathcal{N} \tag{78}$$

$$\boldsymbol{x}_n^{v\delta} \le \boldsymbol{x}_n^v - \underline{v_n}(\mathbf{1}_{H,1} - \boldsymbol{\delta}_n^v), n \in \mathcal{N} \tag{79}$$

$$\boldsymbol{x}_n^{v\delta} \ge \boldsymbol{x}_n^v - \overline{v}_n(\mathbf{1}_{H,1} - \boldsymbol{\delta}_n^v), n \in \mathcal{N} \tag{80}$$

$$\boldsymbol{x}_n^{v\delta} \le \overline{v}_n\boldsymbol{\delta}^v \ , n \in \mathcal{N} \tag{81}$$

$$\boldsymbol{x}_n^{v\delta} \ge \underline{v_n}\boldsymbol{\delta}_n^v, n \in \mathcal{N} \tag{82}$$

where we denote as $\mathbf{1}_{n,1}$ the n-dimensional column vector with all elements equal to one.

Using the above defined supporting vectors $\boldsymbol{\delta}_n^v$ and $\boldsymbol{x}_n^v$, is thus transformed into a linear form:

$$v_n(h) = v_n(h-1) + \zeta_n^+\left(x_n^v(h) - x_n^{v\delta}(h)\right) + x_n^{v\delta}(h)/\zeta_n^-, \tag{83}$$

$$h \in [k_n^s, k_n^f], n \in \mathcal{N}.$$

Finally, we collect all the users' PEV decision variables vectors in column vectors$\boldsymbol{x}^v \triangleq [\boldsymbol{x}_1^v; \dots; \boldsymbol{x}_N^v]$, $\boldsymbol{x}^{v\delta} \triangleq [\boldsymbol{x}_1^{v\delta}; \dots; \boldsymbol{x}_N^{v\delta}]$, and $\boldsymbol{\delta}^{\mathrm{v}} \triangleq [\boldsymbol{\delta}_1^{\mathrm{v}}; \dots; \boldsymbol{\delta}_{\mathrm{N}}^{\mathrm{v}}]$, whose lengths are NH.

3.5.4.3. Shared Energy Storage System

The shared ESS unit provides flexibility to users in the scheduling energy consumption. Household energy storage devices are mainly batteries such as lead-acid and Li-ion. Here the shared ESS is modeled. The shared ESS should optimally store energy from the grid ahead of time and consume it during peak hours when the grid load demand is high. To model the charging/discharging activities of the ESS within the time windows, we define a column vector $\boldsymbol{x}^s \triangleq [x^s(1); \dots; x^s(h); \dots; x^s(H)]$, with H decision variables, where $x^s(h)/x^s(h)$ is the energy stored/released in/by the battery at time slot h. Due to the conversion losses of the ESS, we define η^+ and η^- as the charging and discharging efficiencies, respectively.

Similar to the PEVs' model, the dynamics of the charge level of the ESS for $h \in \mathcal{H}$ can be written as a first order discrete time model as follows:

$$s(h) = \begin{cases} s(h-1) + \eta^+ x^s(h) \text{if} x^s(h) \geq 0 \\ s(h-1) + x^s(h)/\eta^- \text{ if} x^s(h) < 0 \end{cases}, \quad (84)$$
$$h \in \mathcal{H}$$

where $s(h)$ and $s(0) \triangleq s^0$ denote the charge level of the ESS at time slot h and at the beginning of time horizon, respectively. In this work, we assume that the battery degradation and leakage effects are negligible. Moreover, we assume that the charge level at the last time slot $s(H)$ and at the beginning of the time window s^0 are equal since the final energy level is also the initial condition for the next time window of the scheduling:

$$s^0 = s(H). \quad (85)$$

The maximum charge level is bounded by the minimum and maximum battery capacity $\underline{S}$ and $\overline{S}$ as follows:

$$\underline{S} \leq s(h) \leq \overline{S}, h \in \mathcal{H}. \quad (86)$$

Similar to the PEVs' model, through the use of logical and supporting variables, we now transform (84) into a linear form. Firstly, we introduce a column vector of H logical variables $\boldsymbol{\delta}^s \triangleq [\delta^s(1); \dots; \delta^s(h); \dots; \delta^s(H)]$, where each component $\delta^s(h)$ takes value 0 or 1 if the ESS stores (i.e., $x^s(h) \geq 0$) or releases (i.e.,$x^s(h) < 0$) energy, respectively:

$$\delta^s(h) \in \{0,1\}, h \in \mathcal{H} \quad (87)$$

$$\boldsymbol{x}^s \geq \mathbf{0}_{H,1} \Leftrightarrow \boldsymbol{\delta}^s = \mathbf{0}_{H,1} \quad (88)$$

Secondly, we introduce a supporting vector $\boldsymbol{x}^{s\delta} \triangleq \left[x^{s\delta}(1); \dots; x^{s\delta}(h); \dots; x^{s\delta}(H)\right]$ defined as follows:

$$\boldsymbol{x}^{s\delta} = \boldsymbol{\delta}^{s} \circ \boldsymbol{x}^{s}, n \in \mathcal{N}. \tag{89}$$

Note that logical equations (88)- (89) can be replaced with:

$$\boldsymbol{x}^{s} \leq \overline{s}\left(\mathbf{1}_{H,1} - \boldsymbol{\delta}^{s}\right) \tag{90}$$

$$\boldsymbol{x}^{s} \geq \underline{s}\boldsymbol{\delta}^{s} \tag{91}$$

$$\boldsymbol{x}^{s\delta} \leq \boldsymbol{x}^{s} - \underline{s}\left(\mathbf{1}_{H,1} - \boldsymbol{\delta}^{s}\right) \tag{92}$$

$$\boldsymbol{x}^{s\delta} \geq \boldsymbol{x}^{s} - \overline{s}\left(\mathbf{1}_{H,1} - \boldsymbol{\delta}^{s}\right) \tag{93}$$

$$\boldsymbol{x}^{s\delta} \leq \overline{s}\boldsymbol{\delta}^{s} \tag{94}$$

$$\boldsymbol{x}^{s\delta} \geq \underline{s}\boldsymbol{\delta}^{s} \tag{95}$$

where $\overline{s}$ and $\underline{s}$ are the maximum charging and discharging rates.

Using the above defined supporting vectors $\boldsymbol{\delta}^{s}$ and $\boldsymbol{x}^{s\delta}$, (84) is thus transformed into a linear form:

$$\begin{gathered} s(h) = s(h-1) + \eta^{+}\left(x^{s}(h) - x^{s\delta}(h)\right) + \\ x^{s\delta}(h)/\eta^{-}, \\ h \in \mathcal{H}. \end{gathered} \tag{96}$$

3.5.4.4. Demand-Supply Balance

To satisfy the power balance in the system, a demand-supply balance constraint should be fulfilled at each time slot h. We introduce $\boldsymbol{x}^{g} \triangleq [x^{g}(1), \dots, x^{g}(h), \dots, x^{g}(H)]$ as a column vector of H decision variables modeling the energy profile exchanged between users and the power grid within the time window. The following balance equation must be thus satisfied:

$$\begin{gathered} \sum_{n=1}^{N}(\boldsymbol{x}_{n}^{l} + \boldsymbol{x}_{n}^{v} + \boldsymbol{x}_{n}^{p} + \boldsymbol{b}_{n} - \boldsymbol{r}_{n}) + \boldsymbol{x}^{s} - \\ \sum_{m=N+1}^{M}\boldsymbol{r}_{m} = \boldsymbol{x}^{g}. \end{gathered} \tag{97}$$

Finally, for the sake of keeping notations lightened, we rename the $P \triangleq N + M$ vectors of optimization input parameters with $\boldsymbol{d}_{p} \in \mathbb{R}^{H}$ ($p \in \mathcal{P} \triangleq \{1, \dots, P\}$), as follows:

$$\boldsymbol{d}_{p} = \begin{cases} \boldsymbol{b}_{p} \text{ if } p \in [1, N] \\ -\boldsymbol{r}_{p-N} \text{ if } p \in [N+1, N+M] \end{cases}, p \in \mathcal{P}. \tag{98}$$

In addition, we introduce a column vector $\boldsymbol{x}^{a} \triangleq [x^{a}(1); \dots; x^{a}(h); \dots; x^{a}(H)]$ of H supporting variables:

$$\boldsymbol{x}^{a} = \sum_{n=1}^{N}(\boldsymbol{x}_{n}^{l} + \boldsymbol{x}_{n}^{v} + \boldsymbol{x}_{n}^{p}) + \boldsymbol{x}^{s} \tag{99}$$

Hence, the energy balance equation can be compactly rewritten as follows:

$$\boldsymbol{x}^{a} + \sum_{p=1}^{P}\boldsymbol{d}_{p} = \boldsymbol{x}^{g}. \tag{100}$$

3.5.4.5. Power Grid Energy Pricing and Constraints

A contractual obligation is enforced by the energy provider as an additional constraint, restricting the residual MG energy that could be bought/sold from/to the power grid to a maximum level at each time slot. We denote the maximum purchasable and salable energy profile imposed by the energy provider as a column vector $\overline{\boldsymbol{g}} \triangleq [\overline{g}(1);\dots;\overline{g}(h);\dots;\overline{g}(H)]$ and $\underline{\boldsymbol{g}} \triangleq \left[\underline{g}(1);\dots;\underline{g}(h);\dots;\underline{g}(H)\right]$, respectively. Thus, the values of the exchanged energy per time slot $x^g(h)$ ($h \in \mathcal{H}$) must be subject to the following constraints:

$$\underline{g}(h) \le x^g(h) \le \overline{g}(h), h \in \mathcal{H}. \tag{101}$$

Furthermore, we assume that the residential MG cannot simultaneously buy and sell energy from an imbalance in the energy prices of energy bought/sold from/to the power grid. We consider two different sets of pricing functions for the energy bought/sold from/to the grid. In particular, we assume that the pricing function for the energy bought from the main grid is a quadratic function. On the other hand, we assume that the pricing function for the energy sold to the main grid is linear. Consequently, the cost function incurred by the MG at the hth time slot is defined as follows:

$$C_h\big(x^g(h)\big) = \begin{cases} k^+(h)\big(x^g(h)\big)^2 \text{if} x^g(h) \ge 0 \\ k^-(h)x^g(h) \text{ if } x^g(h) < 0 \end{cases}, h \in \mathcal{H} \tag{102}$$

where $\boldsymbol{k}^+ \triangleq [k^+(1);\dots;k^+(h);\dots;k^+(H)]$ and $\boldsymbol{k}^- \triangleq [k^-(1);\dots;k^-(h);\dots;k^-(H)]$ are column vectors collecting the known time-varying cost coefficients of buying/selling energy from/to the power grid, respectively.

Through the use of logical and supporting variables, we now transform (102) into a quadratic form. First, we introduce a column vector of H logical variables $\boldsymbol{\delta}^g \triangleq [\delta^g(1);\dots;\delta^g(h);\dots;\delta^g(H)]$, where each component $\delta^g(h)$ takes value 0 or 1 if the MG has an amount of energy to buy (i.e., $x^g(h) \ge 0$) or to sell (i.e., $x^g(h) < 0$), respectively:

$$\delta^g(h) \in \{0,1\}, h \in \mathcal{H} \tag{103}$$

$$\boldsymbol{x}^g \ge \mathbf{0}_{H,1} \Leftrightarrow \boldsymbol{\delta}^g = \mathbf{0}_{H,1}. \tag{104}$$

Second, we introduce a supporting vector $\boldsymbol{x}^{g\delta} \triangleq \left[x^{g\delta}(1);\dots;x^{g\delta}(h);\dots;x^{g\delta}(H)\right]$ defined as follows:

$$\boldsymbol{x}^{g\delta} = \boldsymbol{\delta}^g \circ \boldsymbol{x}^g. \tag{105}$$

Note that, following [387], logical equations (104)-(105) can be replaced with:

$$\boldsymbol{x}^g \le \overline{\boldsymbol{g}} \circ \left(\mathbf{1}_{H,1} - \boldsymbol{\delta}^g\right) \tag{106}$$

$$\boldsymbol{x}^{g} \geq \underline{\boldsymbol{g}} \circ \boldsymbol{\delta}^{g} \tag{107}$$

$$\boldsymbol{x}^{g\delta} \leq \boldsymbol{x}^{g} - \underline{\boldsymbol{g}} \circ \left(\mathbf{1}_{H,1} - \boldsymbol{\delta}^{g}\right) \tag{108}$$

$$\boldsymbol{x}^{g\delta} \geq \boldsymbol{x}^{g} - \overline{\boldsymbol{g}} \circ \left(\mathbf{1}_{H,1} - \boldsymbol{\delta}^{g}\right) \tag{109}$$

$$\boldsymbol{x}^{g\delta} \leq \overline{\boldsymbol{g}} \circ \boldsymbol{\delta}^{g} \tag{110}$$

$$\boldsymbol{x}^{g\delta} \geq \underline{\boldsymbol{g}} \circ \boldsymbol{\delta}^{g}. \tag{111}$$

Furthermore, using the above defined supporting vector $\boldsymbol{x}^{g\delta}$, the non-linear formulation of the energy cost at the hth time slot in (102) is thus transformed into a quadratic form:

$$\begin{gathered} C_h\left(x^{g}(h), x^{g\delta}(h)\right) = k^{+}(h)\left(x^{g}(h)\right)^{2} \\ -k^{+}(h)\left(x^{g\delta}(h)\right)^{2} + k^{-}(h)x^{g\delta}(h),\ h \in \mathcal{H}. \end{gathered} \tag{112}$$

The cost incurred by the residential MG to exchange the energy profile $\boldsymbol{x}^{g}$ with the power grid over the whole time window is the summation of costs over all the time slots, which is compactly written based on (112) as:

$$\begin{gathered} C\left(\boldsymbol{x}^{g}, \boldsymbol{x}^{g\delta}\right) = \sum_{h=1}^{H} C_h\left(x^{g}(h), x^{g\delta}(h)\right) = \\ (\boldsymbol{x}^{g})^{T}\boldsymbol{K}^{+}\boldsymbol{x}^{g} - \left(\boldsymbol{x}^{g\delta}\right)^{T}\boldsymbol{K}^{+}\boldsymbol{x}^{g\delta} + (\boldsymbol{k}^{-})^{T}\boldsymbol{x}^{g\delta} \end{gathered} \tag{113}$$

where $\boldsymbol{K}^{+} = diag(\boldsymbol{k}^{+})$. Finally, replacing (100) in (113), we get that the cost incurred by the residential MG over the whole-time window is equivalent to:

$$\begin{gathered} C\left(\boldsymbol{x}^{g\delta}, \boldsymbol{x}^{a}\right) = \left(\boldsymbol{x}^{a} + \sum_{p=1}^{P} \boldsymbol{d}_p\right)^{T}\boldsymbol{K}^{+}\left(\boldsymbol{x}^{a} + \right. \\ \left. \sum_{p=1}^{P} \boldsymbol{d}_p\right) \\ -\left(\boldsymbol{x}^{g\delta}\right)^{T}\boldsymbol{K}^{+}\boldsymbol{x}^{g\delta} + (\boldsymbol{k}^{-})^{T}\boldsymbol{x}^{g\delta}. \end{gathered} \tag{114}$$

3.5.5. Deterministic Formulation of the Scheduling Problem

In the preliminary deterministic model, uncertainty is disregarded, and the scheduling problem is solved based on nominal forecasted values. We first formulate the problem aiming at determining the cost-optimal energy scheduling of the users' CLs, HPs, and PEVs, ESS charging/discharging profile, and buying/selling strategies:

$$\min_{\substack{\boldsymbol{x}^{l},\boldsymbol{x}^{p},\boldsymbol{x}^{v},\boldsymbol{x}^{v\delta},\boldsymbol{x}^{s},\boldsymbol{x}^{s\delta},\boldsymbol{x}^{g},\boldsymbol{x}^{g\delta}, \\ \boldsymbol{x}^{a},\boldsymbol{\delta}^{v},\boldsymbol{\delta}^{s},\boldsymbol{\delta}^{g}}} C\left(\boldsymbol{x}^{g\delta}, \boldsymbol{x}^{a}\right) \tag{115}$$

s.t. (64)-(70), (72)-(74), (77)-(83), (85)-(87),

(90)-(96), (99)-(101), (103), (106)-(108).

Problem (115) is called *nominal scheduling*. It is convenient rewriting (115) into a reduced form omitting superfluous terms as follows. First, we note that the objective function (114) contains terms not depending on decision variables, which can be thus neglected. To this aim we transform (114) as follows:

$$\begin{aligned} C\left(\boldsymbol{x}^{g\delta}, \boldsymbol{x}^{a}\right) = {\boldsymbol{x}^{a}}^{T}\boldsymbol{K}^{+}\boldsymbol{x}^{a} + \\ 2\left(\sum_{p=1}^{P}\boldsymbol{d}_{p}\right)^{T}\boldsymbol{K}^{+}\boldsymbol{x}^{a} - \\ \left(\boldsymbol{x}^{g\delta}\right)^{T}\boldsymbol{K}^{+}\boldsymbol{x}^{g\delta} + (\boldsymbol{k}^{-})^{T}\boldsymbol{x}^{g\delta} + \\ \left(\sum_{p=1}^{P}\boldsymbol{d}_{p}\right)^{T}\boldsymbol{K}^{+}\left(\sum_{p=1}^{P}\boldsymbol{d}_{p}\right) \\ = c\left(\boldsymbol{x}^{g\delta}, \boldsymbol{x}^{a}\right) + \left(\sum_{p=1}^{P}\boldsymbol{d}_{p}\right)^{T}\boldsymbol{K}^{+}\left(\sum_{p=1}^{P}\boldsymbol{d}_{p}\right) \end{aligned} \tag{116}$$

where in the last member of (116) we incorporate all the terms depending only on decision variables in $c\left(\boldsymbol{x}^{g\delta}, \boldsymbol{x}^{a}\right) \triangleq {\boldsymbol{x}^{a}}^{T}\boldsymbol{K}^{+}\boldsymbol{x}^{a} + 2\left(\sum_{p=1}^{P}\boldsymbol{d}_{p}\right)^{T}\boldsymbol{K}^{+}\boldsymbol{x}^{a} - \left(\boldsymbol{x}^{g\delta}\right)^{T}\boldsymbol{K}^{+}\boldsymbol{x}^{g\delta} + (\boldsymbol{k}^{-})^{T}\boldsymbol{x}^{g\delta}$ and we leave out all the terms depending on optimization input parameters.

Second, we note that equality constraints (100) can be removed. Indeed, replacing (100) in (101) and (106)-(111), variables vector $\boldsymbol{x}^{g}$ can be omitted.

Summing up, the deterministic energy scheduling problem is reformulated as follows:

$$\min_{\substack{\boldsymbol{x}^{l},\boldsymbol{x}^{p},\boldsymbol{x}^{v},\boldsymbol{x}^{v\delta},\boldsymbol{x}^{s},\boldsymbol{x}^{s\delta},\boldsymbol{x}^{g\delta}, \\ \boldsymbol{x}^{a},\boldsymbol{\delta}^{v},\boldsymbol{\delta}^{s},\boldsymbol{\delta}^{g}}} c\left(\boldsymbol{x}^{g\delta}, \boldsymbol{x}^{a}\right) \tag{117}$$

s.t. (64)-(70), (72)-(74), (77)-(83), (85)-(87), (90)-(96), (99)-(101), (103), (106)-(108), and

$$\boldsymbol{x}^{a} + \sum_{p=1}^{P}\boldsymbol{d}_{p} \le \overline{\boldsymbol{g}} \tag{118}$$

$$\boldsymbol{x}^{a} + \sum_{p=1}^{P}\boldsymbol{d}_{p} \ge \underline{\boldsymbol{g}} \tag{119}$$

$$\boldsymbol{x}^{a} + \overline{\boldsymbol{g}} \circ \boldsymbol{\delta}^{g} + \sum_{p=1}^{P}\boldsymbol{d}_{p} \le \overline{\boldsymbol{g}} \tag{120}$$

$$\boldsymbol{x}^{a} - \underline{\boldsymbol{g}} \circ \boldsymbol{\delta}^{g} + \sum_{p=1}^{P}\boldsymbol{d}_{p} \ge \boldsymbol{0}_{H,1} \tag{121}$$

$$\boldsymbol{x}^{a} - \boldsymbol{x}^{g\delta} + \underline{\boldsymbol{g}} \circ \boldsymbol{\delta}^{g} + \sum_{p=1}^{P}\boldsymbol{d}_{p} \ge \underline{\boldsymbol{g}} \tag{122}$$

$$\boldsymbol{x}^{a} - \boldsymbol{x}^{g\delta} + \overline{\boldsymbol{g}} \circ \boldsymbol{\delta}^{g} + \sum_{p=1}^{P}\boldsymbol{d}_{p} \le \overline{\boldsymbol{g}} \tag{123}$$

Note that in the argument of (117) we disregard all the constant terms of the energy cost (116) depending on optimization input parameters, and we replace (101) and (106)- (109) with (118)- (119) and (120)- (123), respectively.

3.5.6. Robust Formulation of the Scheduling Problem

The previously defined deterministic scheduling problem unrealistically assumes perfect knowledge of users' energy demand and RES generation (i.e., $\boldsymbol{d}_p,\ p \in \mathcal{P}$). However, the variation in the forecast profile of the NCLs' consumption and RESs generation may cause too much deviation from the optimum in the obtained results, leading to an ineffective scheduling. Here, in order to tackle the users' behavior uncertainty, we firstly define the uncertainty set, then reformulate the problem into its robust counterpart.

3.5.6.1. Data Uncertainty Set of Users' Behavior

Denoting the column vector of parameters related to the pth source of uncertainty (i.e., the NCL consumption profile of each user $n \in \mathcal{N}$ or the produced energy profile of each individual and shared RES $m \in \mathcal{M}$) as $\widetilde{\boldsymbol{d}}_p \triangleq [\tilde{d}_p(1); \ldots; \tilde{d}_p(h); \ldots; \tilde{d}_p(H)]$, we assume a symmetric distribution for all the uncertain parameters $\tilde{d}_p(h)$ $(h \in \mathcal{H}, p \in \mathcal{P})$:

$$\boldsymbol{d}_p - \widehat{\boldsymbol{d}}_p \leq \widetilde{\boldsymbol{d}}_p \leq \boldsymbol{d}_p + \widehat{\boldsymbol{d}}_p, p \in \mathcal{P} \qquad (124)$$

where $\boldsymbol{d}_p$ is the previously defined vector of nominal values and $\widehat{\boldsymbol{d}}_p \triangleq [\hat{d}_p(1), \ldots, \hat{d}_p(h), \ldots, \hat{d}_p(H)]$ $(p \in \mathcal{P})$ is the vector collecting the semi-amplitude of maximum variations related to the profile of the pth source of uncertainty. We get that:

$$\widehat{\boldsymbol{d}}_p = \begin{cases} \widehat{\boldsymbol{b}}_p \text{ if } p \in [1, N] \\ \hat{\boldsymbol{r}}_{p-N} \text{ if } p \in [N+1, P] \end{cases}, p \in \mathcal{P} \qquad (125)$$

where $\widehat{\boldsymbol{b}}_n$ and $\hat{\boldsymbol{r}}_m$ is the vector of semi-amplitudes related to the energy profile of the nth user's NCL and the mth RES, respectively. We assume that these semi-amplitudes are available based on historical data. Detailed forecast algorithms will not be discussed here since they are beyond the scope of this work.

Rather than protecting the MG against the worst-case deviation of all the parameters, we adopt the cardinality-constrained uncertainty method in [337] that allows to decide the level of conservativeness and is able to withstand parameters' uncertainty without excessively affecting the objective function and constraints. We define a non-negative parameter Γ_0 (not necessarily integer) as the budget of uncertainty. This is a robustness factor that denotes the number of parameters (i.e., $d_p(h), n \in \mathcal{P}, h \in \mathcal{H}$) protected against disturbances, taking values in [0, PH]. The problem solution is guaranteed to be feasible if no more than $\lfloor \Gamma_0 \rfloor$ of the parameters $\tilde{d}_p(h)$ are subject to uncertainty, and one $\tilde{d}_p(h)$ changes no more than $(\lfloor \Gamma_0 \rfloor - \Gamma_0)\hat{d}_p(h)$. Note that $\lfloor\cdot\rfloor$ denotes the ceiling operator: given the real number a, $\lfloor a\rfloor$ is the greatest integer less than or equal to a.

3.5.6.2. Robust Counterpart of the Scheduling Problem

The robust counterpart of the scheduling problem is aimed at achieving a problem formulation that is feasible for any realization of the uncertainty within the defined uncertainty set. Here, uncertainty affects both the objective function in (117) and the inequality constraints in (118)-(123) of the energy scheduling formulated in the previous section. Moreover, we remark that uncertainty not only affects the LHS of inequality constraints, but also their RHS.

Getting inspiration from the cardinality-constrained approach in [337], the robust counterpart of the deterministic scheduling formulation (117)-(123) is given by the following non-linear optimization problem:

$$\min_{\substack{x^l,x^p,x^v,x^{v\delta},x^s,x^{s\delta},x^{g\delta},\\ x^a,\delta^v,\delta^s,\delta^g}} c\left(\boldsymbol{x}^{g\delta},\boldsymbol{x}^a\right)+\beta(\boldsymbol{x}^a,\Gamma_0) \tag{126}$$

s.t. (64)-(70), (72)-(74), (77)-(83), (85)-(87),

(90)-(96), (99)-(101), (103), (106)-(108), and

$$x^a(h)+\sum_{p\in\mathcal{P}} d_p(h)+\gamma_h(\Gamma_0)\le\overline{g}(h),\ h\in\mathcal{H} \tag{127}$$

$$x^a(h)+\sum_{p\in\mathcal{P}} d_p(h)-\gamma_h(\Gamma_0)\ge\overline{g}(h),\ h\in\mathcal{H} \tag{128}$$

$$x^a(h)+\overline{g}(h)\delta^g(h)+\sum_{p=1}^{P} d_p(h)+\gamma_h(\Gamma_0)\le\overline{g}(h),\quad h\in\mathcal{H} \tag{129}$$

$$x^a(h)-\underline{g}(h)\delta^g(h)+\sum_{p=1}^{P} d_p(h)-\gamma_h(\Gamma_0)\ge 0,\quad h\in\mathcal{H} \tag{130}$$

$$x^a(h)-x^{g\delta}(h)+\underline{g}(h)\delta^g(h)+\sum_{p=1}^{P} d_p(h)-\gamma_h(\Gamma_0)\ge\underline{g}(h),\quad h\in\mathcal{H} \tag{131}$$

$$x^a(h)-x^{g\delta}(h)+\overline{g}(h)\delta^g(h)+\sum_{p=1}^{P} d_p(h)+\gamma_h(\Gamma_0)\le\overline{g}(h),\quad h\in\mathcal{H} \tag{132}$$

where $\beta(\boldsymbol{x}^a,\Gamma_0)$ is the protection function of the objective function, and $\gamma_h(\Gamma_0)$ $(h\in\mathcal{H})$ are the protection functions of the inequality constraints. For a given solution of (126)-(132), the above introduced $(H+1)$ protection functions are defined as follows:

$$\beta(\boldsymbol{x}^{a*}, \Gamma_0) = \max_{\substack{\mathcal{Q}_1 \cup \{q_1\},\ldots,\\ \mathcal{Q}_H \cup \{q_H\},\\ \Gamma_1,\ldots,\Gamma_H}} 2 \sum_{h\in\mathcal{H}} \Big(k^+(h) |x^{a*}(h)| \sum_{p\in\mathcal{Q}_h} \hat{d}_p(h) +$$

$$+(\Gamma_h - \lfloor \Gamma_h \rfloor) k^+(h) |x^{a*}(h)| \hat{d}_{q_h}(h) \Big) \qquad (133)$$

$$\boldsymbol{\gamma}(\Gamma_0) \triangleq \begin{bmatrix} \gamma_1(\Gamma_0) \\ \vdots \\ \gamma_H(\Gamma_0) \end{bmatrix} =$$

$$\max_{\substack{\mathcal{Q}_1 \cup \{q_1\},\\ \ldots,\\ \mathcal{Q}_H \cup \{q_H\},\\ \Gamma_1,\ldots,\Gamma_H}} \begin{bmatrix} \sum_{p\in\mathcal{Q}_1} \hat{d}_p(1) + (\Gamma_1 - \lfloor \Gamma_1 \rfloor) \hat{d}_{q_1}(1) \\ \vdots \\ \sum_{p\in\mathcal{Q}_H} \hat{d}_p(H) + (\Gamma_H - \lfloor \Gamma_H \rfloor) \hat{d}_{q_H}(H) \end{bmatrix} \qquad (134)$$

$$\text{s.t. } \mathcal{Q}_h \subseteq \mathcal{P}, |\mathcal{Q}_h| = \lfloor \Gamma_h \rfloor, q_h \in \mathcal{P} \backslash \mathcal{Q}_h, h \in \mathcal{H} \qquad (135)$$

$$0 \le \Gamma_h \le P, h \in \mathcal{H}, \sum_{h\in\mathcal{H}} \Gamma_h = \Gamma_0. \qquad (136)$$

where we introduce H supporting variables $\Gamma_1, \ldots, \Gamma_h, \ldots, \Gamma_H$ to quantify the portions (not necessarily integer) of the total uncertainty budget Γ_0 over all the time slots (see Figure 3.22). In (133)-(136) we also introduce H subsets $\mathcal{Q}_1, \ldots, \mathcal{Q}_h, \ldots, \mathcal{Q}_H$ and H indices $q_1, \ldots, q_h, \ldots, q_H$ to deal with uncertainty. In particular, $\mathcal{Q}_h \subseteq \mathcal{P}$ (with $h \in \mathcal{H}$) is the subset of uncertainty sources p defined by (125), whose value in time slot h gets the maximum variation (i.e., $d_p(h) + \hat{d}_p(h)$). At most $\lfloor \Gamma_h \rfloor$ uncertainty sources are assumed to belong to this subset. Further, in case Γ_h is not integer, an uncertainty source q_h is selected at each time slot h, whose value is affected by a variation lower than the maximum deviation (i.e., the value is between $d_{q_h}(h)$ and $d_{q_h}(h) + \hat{d}_{q_h}(h)$). For a given time slot h, all the remaining uncertainty sources p not belonging to $\mathcal{Q}_h$ and different from q_h get the nominal values (i.e., $d_p(h)$). As a result, in (126)-(132) robustness is taken into account considering the maximum variation for each uncertainty parameters over the whole time horizon, given the allocation $\Gamma_1, \ldots, \Gamma_h, \ldots, \Gamma_H$ of the total uncertainty budget Γ_0 over all the time slots.

Further details on the above-defined robust counterpart (126)-(132) and the differences with the approach proposed in [337] are provided in Appendix A.

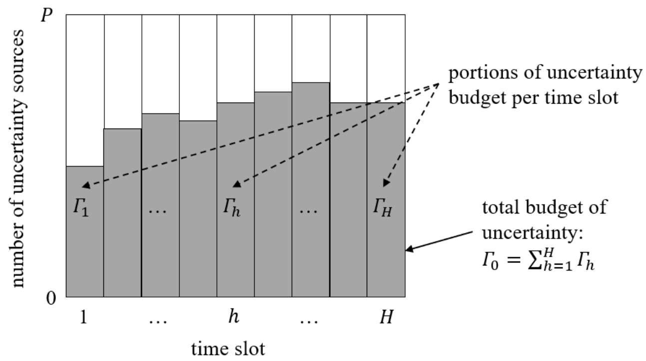


Figure 3. 22. Illustration of the allocation of the total uncertainty budget over time slots.

3.5.6.3. Reformulation of the Robust Counterpart

Observing (126) to (132), it can be found that the robust counterpart of the scheduling problem includes strong non-linearities and cardinality calculations due to the inner maximization defined by (133)-(136) and placed in (126)-(132). Thus, it is still difficult to solve the problem in its current min-max form. This can be resolved by transforming the robust counterpart into an easier form. By introducing further supporting variables $\boldsymbol{y}$,Λ, λ, Θ_{ph}, $\boldsymbol{\theta}_{ph}$ (with $p \in \mathcal{P}, h \in \mathcal{H}$) and taking advantage of the strong duality theorem [388], we transform (126)-(132) into an equivalent MIQP formulation as follows:

$$\min_{\substack{\boldsymbol{x}^l,\boldsymbol{x}^p,\boldsymbol{x}^v,\boldsymbol{x}^{v\delta},\boldsymbol{x}^s,\boldsymbol{x}^{s\delta},\boldsymbol{x}^{g\delta},\\ \boldsymbol{x}^a,\boldsymbol{\delta}^v,\boldsymbol{\delta}^s,\boldsymbol{\delta}^g,\\ \boldsymbol{y},\Lambda,\boldsymbol{\lambda},\\ \Theta_{11},\dots,\Theta_{1H},\dots,\Theta_{P1},\dots,\Theta_{PH},\\ \boldsymbol{\theta}_{11},\dots,\boldsymbol{\theta}_{1H},\dots,\boldsymbol{\theta}_{P1},\dots,\boldsymbol{\theta}_{PH}}} c(\boldsymbol{x}^{gu},\boldsymbol{x}^a) + \Gamma_0\Lambda + \sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\Theta_{ph} \tag{137}$$

s.t. (64)-(70), (72)-(74), (77)-(83), (85)-(87),
(90)-(96), (99)-(101), (103), (106)-(108), and

$$\boldsymbol{x}^a + \sum_{p=1}^{P}\boldsymbol{d}_p + \Gamma_0\boldsymbol{\lambda} + \sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\boldsymbol{\theta}_{ph} \le \overline{\boldsymbol{g}} \tag{138}$$

$$\boldsymbol{x}^a + \sum_{p=1}^{P}\boldsymbol{d}_p - \Gamma_0\boldsymbol{\lambda} - \sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\boldsymbol{\theta}_{ph} \ge \underline{\boldsymbol{g}} \tag{139}$$

$$\boldsymbol{x}^a + \overline{\boldsymbol{g}} \circ \boldsymbol{\delta}^g + \sum_{p=1}^{P}\boldsymbol{d}_p + \Gamma_0\boldsymbol{\lambda} + \sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\boldsymbol{\theta}_{ph} \le \overline{\boldsymbol{g}} \tag{140}$$

$$\boldsymbol{x}^a - \underline{\boldsymbol{g}} \circ \boldsymbol{\delta}^g + \sum_{p=1}^{P}\boldsymbol{d}_p - \Gamma_0\boldsymbol{\lambda} - \sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\boldsymbol{\theta}_{ph} \ge \boldsymbol{0}_{H,1} \tag{141}$$

$$\boldsymbol{x}^a - \boldsymbol{x}^{g\delta} + \underline{\boldsymbol{g}} \circ \boldsymbol{\delta}^g + \sum_{p=1}^{P}\boldsymbol{d}_p - \Gamma_0\boldsymbol{\lambda} - \sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\boldsymbol{\theta}_{ph} \ge \underline{\boldsymbol{g}} \tag{142}$$

$$\boldsymbol{x}^a - \boldsymbol{x}^{g\delta} + \overline{\boldsymbol{g}} \circ \boldsymbol{\delta}^g + \sum_{p=1}^{P} \boldsymbol{d}_p + \Gamma_0 \boldsymbol{\lambda} + \sum_{p\in\mathcal{P}} \sum_{h\in\mathcal{H}} \boldsymbol{\theta}_{ph} \leq \overline{\boldsymbol{g}} \tag{143}$$

$$w_0 \Lambda + \boldsymbol{w}^T \boldsymbol{\lambda} \geq 0 \tag{144}$$

$$w_0 \Theta_{ph} + \boldsymbol{w}^T \boldsymbol{\theta}_{ph} \geq 0, p \in \mathcal{P}, h \in \mathcal{H} \tag{145}$$

$$w_0\left(\Lambda + \Theta_{ph}\right) + \boldsymbol{w}^T\left(\boldsymbol{\lambda} + \boldsymbol{\theta}_{ph}\right) \geq w_0 2k^+(h)\hat{d}_p(h)y(h) + \boldsymbol{w}^T \widehat{\boldsymbol{d}}_p,$$

$$p \in \mathcal{P}, h \in \mathcal{H} \tag{146}$$

$$-\boldsymbol{y} \leq \boldsymbol{x}^a \leq \boldsymbol{y}. \tag{147}$$

where w_0 is the non-negative weight associated to the protection function of the objective and $\boldsymbol{w} \triangleq [w_1; \dots; w_H]$ is a column vector collecting the non-negative weights associated to the protection function of the inequality constraints.

A detailed description of the introduced supporting variables and a comprehensive proof of the robust counterpart reformulation are provided in Appendix B.

We finally remark that (137)-(147) is a MIQP problem that consists in determining the $(H(P(H+1)+4N+6)+1)$ real and$H(N+2)$ binary decision variables, which minimize the objective function in (137) and meet the $12HN$ bounding constraints (64), (68), and (70), the $(3HN+2N+2H+1)$ equality constraints (65)-(66), (69), (72), (83), (85), (96), and (99), the $2H(5N+16)$ inequality constraints (67), (77)-(82), (86), (90)-(95), (101), (110)-(111), and (140)-(147), and the $H(N+2)$ integrality constraints (74), (87), and (103).

3.5.6.4. The Robust Control Solution Based on Budget of Uncertainty

Solving the transformed robust counterpart (137)-(147), the energy scheduling can be obtained with different robustness levels. Indeed, the robustness of the energy scheduling varies with the total budget of uncertainty (Γ_0). Here, the role of Γ_0 is to adjust the robustness of the proposed scheduling method against the level of conservativeness of the solution. Accordingly, the conservativeness of the solution can be controlled. Note that for $\Gamma_0 = 0$, $\beta(\boldsymbol{x}^a, \Gamma_0) = 0$ and $\gamma_h(\Gamma_0) = 0$ ($h \in \mathcal{H}$), the constraints are equivalent to those of the deterministic problem. In this case, the total cost is minimum, but the results are too optimistic. Likewise, for $\Gamma_0 = PH$, the uncertainty is fully addressed during the operation, but the solution is obtained in the most conservative case (i.e., the worst case over all the possible realization of uncertain parameters). Thus, by varying $\Gamma_0 \in [0, PH]$, a flexibility is provided for the decision maker to adjust the robustness of the method against the level of conservativeness and a trade-off between users' energy payment and constraint violation rate is found. In the subsequent case study, we show that even in the case of higher number of changes than Γ_0, the robust solution is feasible with very high probability. The conservativeness of the solution and the maximum probability of constraint violation under the given uncertainty bounds can be controlled by adjusting the value of the budget of uncertainty [337].

3.5.7. Simulation Results and Analysis

In this section, we provide a day-ahead energy scheduling on a weekday for a residential MG to evaluate the performance of the proposed robust framework. We investigate the effects of the proposed method on: 1) the users' energy payment, 2) the constraint violation rate, and 3) the PAR in exchanged energy. Note that the PAR in exchanged energy can be defined as in [347]:

$$PAR = \max_{h \in \mathcal{H}} |x^g(h)| \Big/ \frac{1}{H} \sum_{h=1}^{H} x^g(h). \qquad (148)$$

The problem is solved by CPLEX 12.8 in MATLAB R2017a on a desktop PC with an Intel i7-7500U core processor with 2.70 GHz (4 CPUs) and 12 GB RAM memory.

3.5.7.1. Parameters and Settings

The sample power system (see Figure 3.21) has $N = 10$ smart users subscribing to the EMS. For simplicity, we assume that each user consists of a CL, a NCL, and a PEV, while all users share an ESS, a PVS and a DWT. We consider the time window for simulation of one day from 0:00 to 23:59. Each time slot is set equal to one hour, meaning that the decision is made by solving the optimization problem for the next $H = 24$ hours. As mentioned, we assume that, in the cost function, the term corresponding to the electricity bought from the power grid is quadratic, while the related term to the electricity sold back to the power grid is linear. The price signals for bought and sold electrical energy throughout the day are taken from [347], [389][390]. Accordingly, the daily cost coefficients for the energy bought from the power grid during peak-demand time slots (i.e., [9:00 to 11:00] and [16:00 to 21:00]) and off-peak-demand time slots (i.e., [0:00 to 8:00], [12:00 to 15:00] and [22:00 to 24:00]) are set to 0.1875 $₵/\mathrm{kWh}^2$ and 0.0937 $₵/\mathrm{kWh}^2$ respectively. Also, the cost coefficients for energy sold to the power grid for peak-demand and off-peak-demand time slots are considered as 0.1188 $₵/\mathrm{kWh}$ and 0.0594 $₵/\mathrm{kWh}$ respectively. Figure 3.23 shows both the buying and selling cost coefficient profiles. We assume that the maximum permissible energy transferred with the power grid (both for buying and selling) for all time slots is 60 kWh. The energy required by the energy-based CLs ranges from 0 to 3.5 kWh. We assume that the cumulative daily energy demand for each user's

CL is 30 kWh. To model the users' NCLs, we use the actual profiles of average hourly electricity consumption for a sample of homes in Italy taken from [391]. The aggregated forecast energy demand profile of NCLs over all users (i.e., $\sum_{n=1}^{N} \boldsymbol{b}_n$) and the corresponding uncertainty range (that is 10% of the forecast value for each time slot) is presented in Figure 3.24. We consider a shared ESS unit with maximum storage capacity 120 kWh, and with the maximum charging/discharging rate of 25 kWh. We assume that both charging and discharging efficiencies are 0.9, initial charge level is zero, and battery degradation and leakage effects are negligible. The hybrid forecast energy generation profile of the shared PVS and DWT, taken from [392], with corresponding uncertainty range (that is 10% of the forecast value for each time slot), is represented in Figure 3.25. It is to be noted that, as the energy generation profiles of the RESs depend on weather conditions, we assume that the hybrid forecast energy generation profile of individual RESs for each user is obtained scaling by 10% the shared PVS and DWT profile (i. e., Figure 3.25) and considering a 10% uncertainty range for each time slot. For each PEV, we assume that the initial battery charge level and the desired final state of charge are 1 and 5 kWh, respectively. Also, we assume that the PEV leaves home at 8:00 and returns at 18:00. That is, the PEV is plugged-in during time slots [0:00, 08:00] ∪ [18:00, 24:00] and can participate in the energy scheduling (e.g., release its remaining stored energy to the system after arrival). We adopt discrete Gaussian distributed random variables to model the uncertainties of NCLs and RESs. We also assume that users are equipped with identical HVAC systems (i.e., HPs) and the desired indoor temperature setpoint ranges in [18, 21] °C. Moreover, we consider active setpoints during time slots [06:00, 8:00] ∪ [17:00, 24:00], that is when occupants are present. We set a desired temperature at 19°C upon the nominal arrival time of occupants (i. e., 18:00), and the HP can start running earlier (e. g., 17:00) to raise the temperature to the desired value. We take the profile of daily outdoor temperature for a typical winter day in Italy from [391], and we set the value of model parameters as $\tau_n = 3600$ s, $\pi_n = 15\ {}^{W\,s}/_{m}$ and $E_n = 2.5$ kWh.

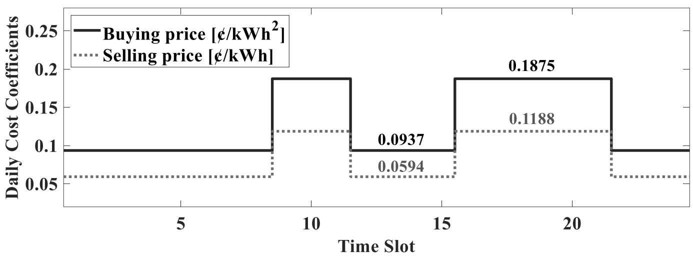


Figure 3. 23. Daily cost coefficients for the energy bought/sold from/to the power grid during peak-demand and off-peak-demand time slots..

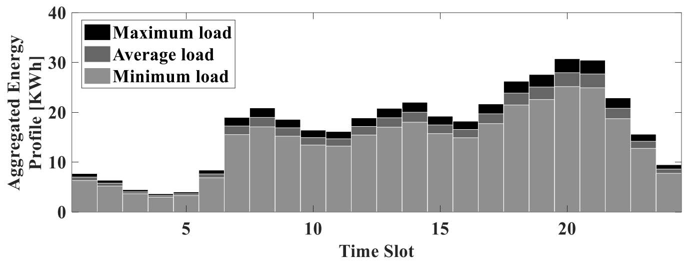


Figure 3. 24. Aggregated forecast energy demand profile of NCLs with corresponding uncertainty ranges.

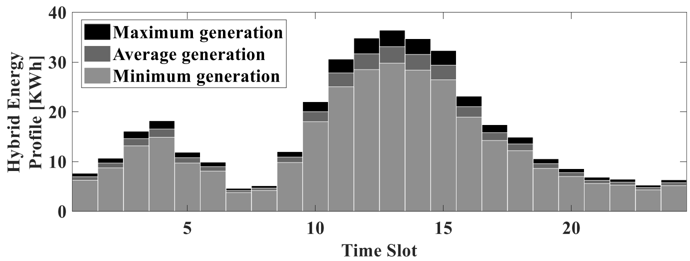


Figure 3. 25. Hybrid forecast energy generation profiles of shared PVS and DWT with corresponding uncertainty ranges.

3.5.7.2. Results

We simulate the energy scheduling of the sample MG by applying the method for three cases of analysis. First, the simulation results are reported and compared in three cases.

Case 1: the nominal model with perfect forecast data ignoring uncertainty (i.e., when $\Gamma = 0$). Therefore, no protection terms are considered against data uncertainty (i.e. $\beta(\boldsymbol{x}^a, \Gamma_0) = 0$ and $\gamma_h(\Gamma_0) = 0, h \in \mathcal{H}$).

Case 2: the robust model considering full protection against data uncertainty (i.e., the worst-case realization) by adopting the maximum budget of uncertainty ($\Gamma_0 = PH = 528$), implying the most conservative solution.

Case 3: the robust model considering uncertainty with $\Gamma_0 = \Gamma_0^*$, where $\Gamma_0^* \in$ (0, PH) corresponds to a potential choice for the budget of uncertainty when the robustness of the solution rarely changes for $\Gamma_0 > \Gamma_0^*$. This value can be obtained after sensitivity analyses over different budgets of uncertainty (we set $\Gamma_0^* = 104$), meaning that increasing the protection level by choosing $\Gamma_0 > \Gamma_0^*$ does not provide a significant improvement in the robustness of the solution against uncertainty, due to the change in constraint violation for $\Gamma_0 \in [104{,}528]$).

The results of the energy scheduling for the three cases are presented in Figures 3.26-3.29. In Figure 3.26, the scheduled aggregated energy profiles of the energy-based CLs over users (i.e., $\sum_{n=1}^{N} \boldsymbol{x}_n^l$) are reported. Figure 3.27 represents the charging/discharging activities of the shared ESS (i.e., $\boldsymbol{x}^s$). Figure 3.28 shows the optimal aggregated charging/discharging activities of PEVs (i.e., $\sum_{n=1}^{N} \boldsymbol{x}_n^v$). In Figure 3.29, the scheduled aggregated energy profiles of the HPs over users (i.e., $\sum_{n=1}^{N} \boldsymbol{x}_n^p$) are reported. First, the results show that the scheduling arranges the operation time of the CLs to the off-peak time slots for minimizing the energy payment. Second, the ability of optimally storing the energy in the off-peak time slots and releasing it during the peak hour periods by the ESS and PEVs effectively contributes to the minimization of the total energy payment. Furthermore, the scheduling tries to exploit the energy harvested from the RESs first for supplying the users' energy demand or charging the ESS and PEVs, and secondarily for transferring surplus energy to the power grid. For this specific scenario, the users' daily energy payments and the PAR values for *cases 1*, *2*, and *3* are respectively 27.81€, 29.98€, and 28.62€ and 2.277, 2.325, and 2.297. Although the solution of *case 1* leads to the minimum daily users' energy payment (7.25% lower than *case 2*, and 2.84% lower than *case 3*) and the lowest PAR (6.61% lower than *case 2*, and 3.11% lower than *case 3*), the result is the most optimistic case since it ignores the effects of the data uncertainty. Therefore, in real conditions, any disturbance in the forecast profiles of the load demands or the RESs energy generation may cause an excessive increase in the obtained value of the objective function. Also, the contractual constraints can be easily violated over the time window in presence of any disturbances because of the lack of any protection term in (101) against data uncertainty.

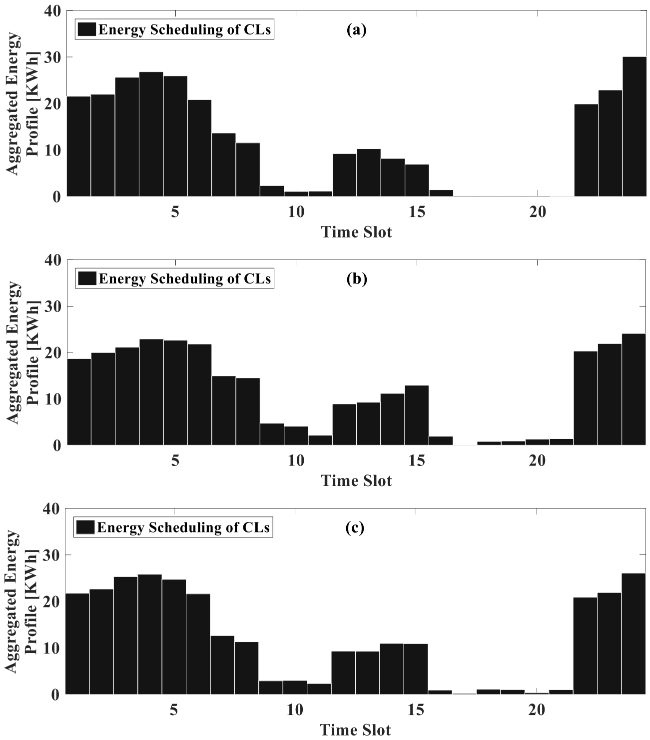


Figure 3. 26. Aggregated energy profiles of the energy-based CLs for: (a) *case 1*, (b) *case 2*, and (c) *case 3*.

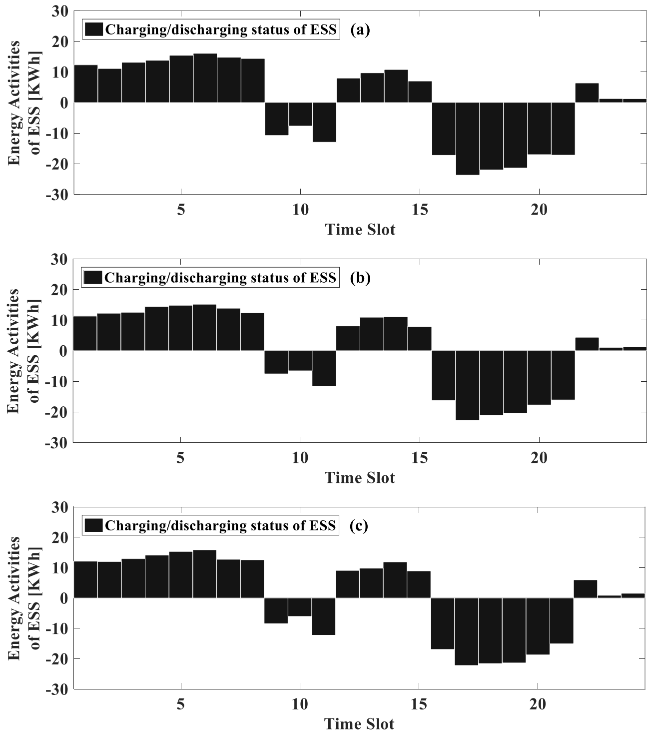


Figure 3. 27. Charging/discharging strategies of shared ESS for: (a) *case 1*, (b) *case 2*, and (c) *case 3*.

On the other hand, the solution of *case 2* provides full immunity against the worst-case realization. Here, the worst-case occurs when the energy demand uncertainty takes its upper bound, while the RESs generation uncertainty stands on its lower band during all time slots. This case guarantees that the solution is immunized against all possible uncertain data, leading to zero constraint violation rate. However, this immunity is obtained at the expenses of an unnecessarily too conservative solution, causing the highest users' daily energy payment (i.e., 29.98€) and highest PAR (i.e., 2.613). In order to prevent such a too conservative solution, *case 3* provides a compromise where there is a respective decrease of 4.53% and 1.21% in the users' daily energy payment and the PAR compared to those in the *case 2*. Meanwhile, the solution obtained by *case 3* is robust against data uncertainty with very high probability (i.e., more than 99%) that is discussed in the next subsection. In general, by adjusting the budget of uncertainty in the possible range ($\Gamma_0 \in [0, 528]$), the level of conservativeness of the solution can be controlled and a trade-off between the users' energy payment and the constraint violation rate can be established based on the decision maker's preferences. In the next subsection, we also argue that when the forecast data are subject to uncertainty, the robust model provides a good performance in flattening the profile of the total exchanged energy with the power grid, leading to a lower PAR. For a further validation of the results, the method should be also analyzed in real conditions, i.e., evaluating the results achieved for different realizations of uncertain variables, as provided in the next subsection.

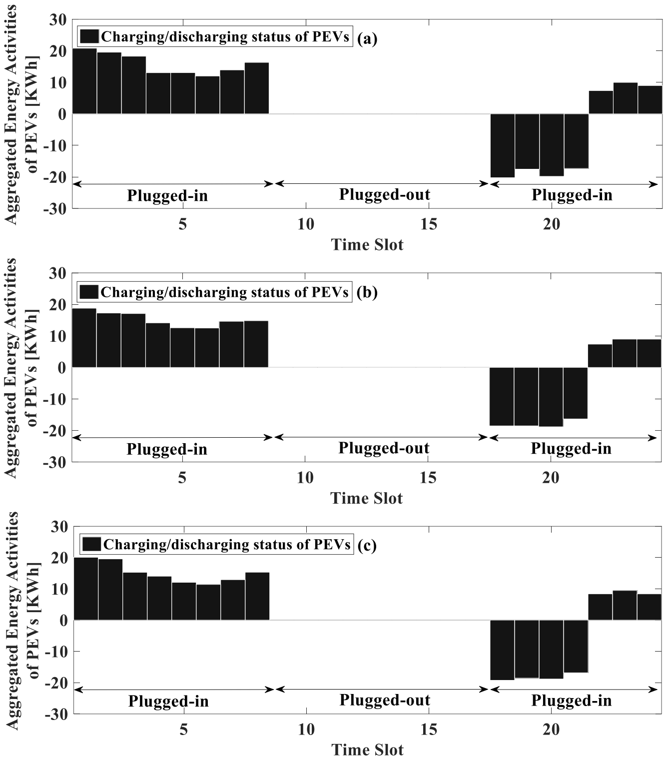


Figure 3. 28. Aggregated charging/discharging strategies of PEVs for: (a) *case 1*, (b) *case 2*, and (c) *case 3*.

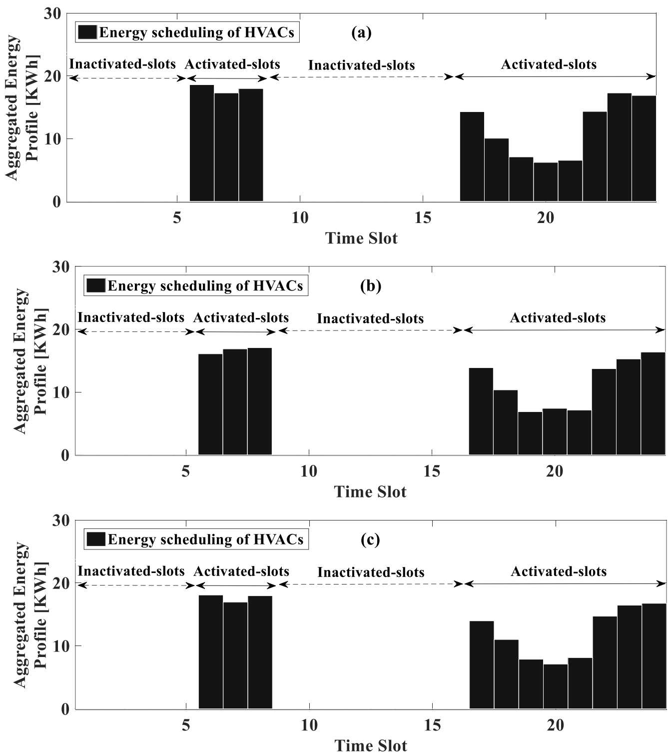


Figure 3. 29. Aggregated energy profiles of the HPs for: (a) *case 1*, (b) *case 2*, and (c) *case 3*.

3.5.7.3. Discussions

To show the impact of data uncertainty on the problem and demonstrate the effectiveness of the proposed robust approach against it, Monte Carlo (MC) simulations are used to generate 10,000 scenarios for the users' demand and the RESs generation uncertainties. We then present a sensitivity analysis of the protection level with respect to the daily energy payment, the constraint violation rate, and the PAR through comparing the solutions generated by different budgets of uncertainty. The actual profile of the NCLs at each MC iteration is obtained by adding a normally distributed random sequence with zero mean and standard deviation equal to 0.2 kWh to the nominal forecast values. In order to obtain some insights on the effect of changing the budget of uncertainty on the users' energy payment, constraint violation rate and the PAR, and ultimately to show the robustness of the approach, we present the energy scheduling results for the average profile of the MC simulations for all iterations. The profiles of the average energy exchanged with the power grid over all MC iterations compared to the maximum permissible energy bought/sold from/to the power grid per time slot (i.e., $\overline{g}(h)/\underline{g}(h)$), indicated with the dashed line, for *case 1*, *case 2*, and *case 3* are illustrated in Figures 3.30a, 3.30b and 3.30c, respectively. It can be found that, under the considered scenarios, the energy exchanged between users and the power grid violates constraint (101) in more than 34.83% of time slots in *case 1 (the nominal model)*, which is undesirable (Figure 3.31a). Conversely, in *case 2* (*robust model* - worst-case mode), these constraints are fully satisfied, confirming that full protection is established (Figure 3.31b). In *case 3* (*the robust model* with $\Gamma_0 = \Gamma_0^* = 104$), the average exchanged energy profile (Figure 3.31c) shows that even by adopting a budget of uncertainty less than 20% of the maximum protection level, the constraint (101) over time window is met with very high probability (more than 99%). Table 3.5 reports the comparison of the average MC simulation results achieved by the three cases of simulation in terms of the daily total cost, the probability of constraint violation, the PAR, and the so-called *price of robustness* (PoR) defined as the percentage of relative difference between the costs achieved by a robust solution and a nominal solution [337]. We calculate the PoR as:

$$PoR = 100\frac{\sum_{h=1}^{H} C_h\left(x^{g,rob}(h)\right)-\sum_{h=1}^{H} C_h(x^{g,nom}(h))}{\sum_{h=1}^{H} C_h(x^{g,nom}(h))} \quad (149)$$

where $x^{g,nom}(h)$ and $x^{g,rob}(h)$ ($h \in \mathcal{H}$) are the optimal values of the energy that the MG exchanges with the power grid in accordance with the nominal and the robust scheduling, respectively. Although in *case 1* a better respective saving of 3.61% and 1.88% in the value of average daily users' energy payment can be achieved compared to those in *case 2* and *case 3*, the constraint violation rate is drastically higher than those in two other cases (i.e., 35.02% and 34.10% higher than the values in the *case 2* and *case 3* respectively). On the other hand, the daily users' energy payment in *case 3* is 1.76% lower than its value in *case 2*. Moreover, the PAR in the total energy exchanged in *case 3* is

1.19% lower than its value in *case 2*. Moreover, the PAR in the total energy exchanged in *case 3* is 1.66% lower than the PAR in *case 2*. Therefore, we can conclude that by selecting $\Gamma_0 = \Gamma_0^*$, we avoid a significant penalty for the objective function value to protect the solution against constraint violation. Hence, the results confirm the importance of suitably selecting the budget of uncertainty for a trade-off between cost and robustness. In addition, the fourth column of Table 3.5 reports the average computational runtime in the three scenarios: the computation time for all the simulations is less than 1.5 seconds.

Summing up, the simulation results show that the method allows the decision maker to make a trade-off between constraint violation rate and PoR by adjusting the values of the budget of uncertainty. The robust energy scheduling not only reduces the users' energy bills and the PAR by encouraging users to shift high-load CLs to the off-peak time slots, but also guarantees the solution to satisfy constraints with very high probability in the presence of the demand and the RESs generation uncertainties. The simulation also shows that the proposed robust approach is computationally tractable, with a reasonable computational running time. We remark that the proposed framework is generic and flexible as it can be applied to different structures of MGs (for example, with multiple CLs, NCLs, PEVs and non-interruptible loads) considering various types of uncertainties in distributed energy generation (e.g., a large number of shared distributed generation resources, which can be included in set $\mathcal{M}$) or demand, appearing in the LHS or RHS of the constraints of the robust counterpart.

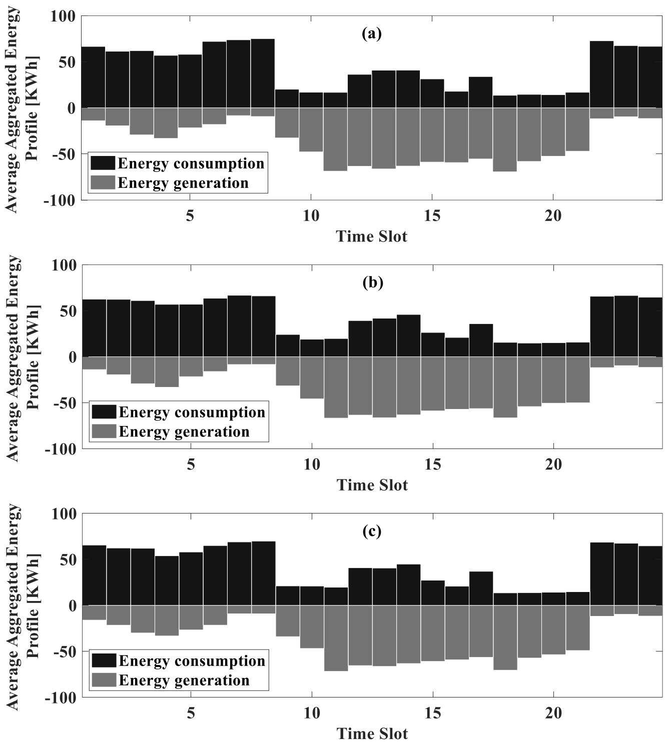


Figure 3. 30. Average aggregated energy consumed by the MG (i.e., NCLs' and CLs' demands, HPs' demand, ESS's charging and PEVs' charging and average energy generated by the MG (i.e., shared and individual RESs' generation, ESS's discharging and PEVs' discharging for: (a) *case 1*, (b) *case 2*, and (c) *case 3*.

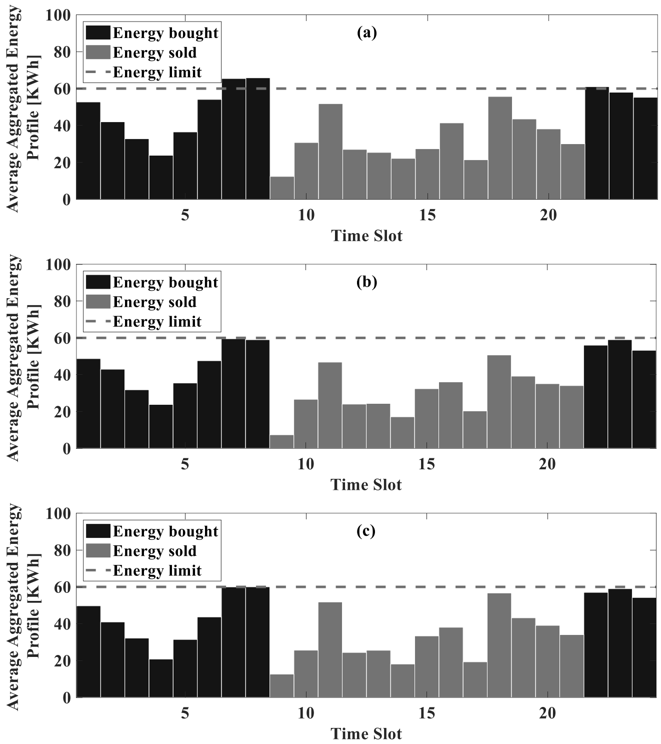


Figure 3. 31. Average total energy bought/sold from/to the grid versus maximum permissible energy exchanged with the grid for: (a) *case 1,* (b) *case 2,* and (c) *case 3.*

3.5.7.4. Comparison with a Related Approach

For the sake of assessment and to better show the advancement of our approach with respect to the related literature, we compare the results of our approach with a well-known existing robust technique. Specifically, we use as reference approach the box-uncertainty-set method, where uncertain parameters are assumed to take their values from different intervals independently (we refer to [335], [393] for more details about the box-uncertainty-set method). We present a sensitivity analysis of the MC simulation results with respect to different budgets of uncertainty for both methods in terms of total energy payment, level of conservativeness, and the PAR of the energy profile, all reported in Figures 3.32a-3.32c. As can be observed from the results, despite the constraint violation rate within the primary time slots for our approach is slightly higher than the box-uncertainty-set method, our method provides a less conservative solution which always exhibits lower daily energy payments and PARs than the box-uncertainty-set method.

Table 3. 5. Comparison of Average MC Simulation* Results

	Daily Users' Payment (€/day)	Constraint violation rate (%)	PAR (%)	PoR (%)	Computa-tional runtime (s)
Case 1	29.11	35.02	2.339	0	1.16
Case 2	30.20	0.00	2.380	3.74	1.48
Case 3	29.67	0.92	2.352	1.92	1.25

* Simulation over 10,000 iterations

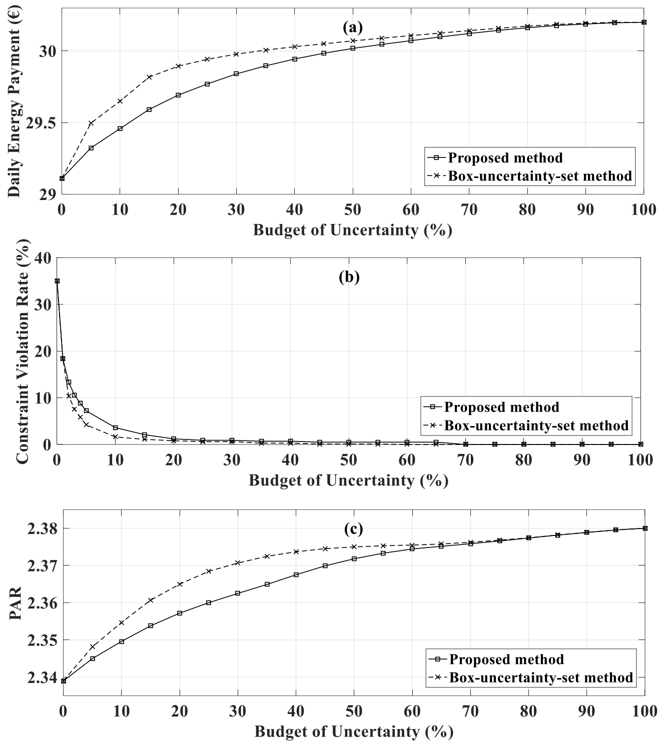


Figure 3. 32. Sensitivity analysis of the daily energy payment (a), the constraint violation rate (b), and the PAR (c) with respect to different budgets of uncertainty for the proposed method and the robust optimization approach based on box- uncertainty set.

These results confirm the effectiveness of our approach, enabling the decision maker to make a good trade-off between the total energy payment by users, the level of conservativeness and the PAR by changing the value of the budget of uncertainty.

3.5.8. Conclusions

This section proposes a novel adjustable robust energy scheduling framework for residential MGs comprising energy-based and comfort-based CLs, individual PEVs and RESs, shared ESS and RESs under quadratic/linear dynamic pricing. We focus on uncertainties associated with RES generation and users' energy demand. A MIQP problem is formulated to find the optimal scheduling of CLs as well as charging/discharging strategies of the ESS and PEVs. The simulation results highlight the robustness of the proposed energy scheduling in the uncertain context. A trade-off can be made by the decision maker to resolve the conflict between energy payment minimization and the contractual constraint satisfaction, which is advantageous for both the residential MG and the power grid. The future research paths include extending the system model by integrating additional subsystems such as non-interruptible loads, or other types of uncertainty sources such as uncertain real-time pricing and PEV plug-in/out times. Moreover, towards the deployment of large-scale SGs, the proposed robust scheduling problem can be expanded and resolved in a distributed multi-agent fashion. Future work may also incorporate the robust method with a receding horizon mechanism for online energy scheduling.

From the findings and contribution of the research in this chapter, the following paper has been presented:

- S. M. Hosseini, R. Carli and M. Dotoli, "Robust Optimal Energy Management of a Residential Microgrid Under Uncertainties on Demand and Renewable Power Generation," in *IEEE Transactions on Automation Science and Engineering*, 2020. doi: 10.1109/TASE.2020.2986269

4. Robust Distributed/Decentralized Approaches for Coordinated Charge Control of Electric Vehicles in Smart Grids

4.1. Introduction

Although the centralized optimization techniques generally show a high ability for finding best possible solutions, and are usually easy to implement, they suffer from poor privacy protection of users as well as computational and communication complexities and failures. Therefore, most recent studies are alternatively oriented toward distributed or decentralized techniques, where optimization tasks are distributed through different incorporated subsystems based on distributed information structures. In this section, we deal with the problem of optimal charging of large-scale PEV fleets in SGs aiming at the minimization of the aggregated charging cost and battery degradation, while satisfying the PEVs' individual load requirements and the overall grid congestion limits in a fully distributed fashion.

4.2. A Distributed Approach for Charge Control of Electric Vehicle Fleets Considering Grid Congestion and Battery Degradation

4.2.1. Introduction

According to the International Energy Agency's (IEA) statistical reports, in 2012 the transportation sector accounted for 63.7% of the world's petroleum consumption and 7135 million tons of carbon dioxide emissions [394]. Responding to these concerns, Plug-in Electric Vehicles (PEVs) are being promoted as a vital technology for sustainable city logistics to reduce fossil fuel consumption and greenhouse gas emissions [395]. At the same time, the broad deployment of PEVs may also pose new technical challenges to the power grid, endangering the reliability, security, and efficiency of the energy system [396]. In particular, the large-scale penetration of PEVs in national/regional stocks can impose a large additional burden on the power grid [397]. Indeed, uncoordinated random PEVs' charging may bring to a variety of challenges to the power quality and reliability of power grids, requiring additional power generation capacity and threatening the smooth operation of the distribution network [398]. As a consequence, developing intelligent coordinated optimal charging strategies for large-scale PEV fleets has recently become a challenging research topic [399]. Thanks to the advances of Information and Communication Technology (ICT) [400], [401], the implementation of such optimal control approaches is becoming more immediate and affordable in the field of demand side management [402].

4.2.2. Aims and Objectives

In this subsection, we present a novel fully distributed control strategy for the optimal charging of large-scale PEV fleets aiming at the minimization of the aggregated charging cost and battery degradation, while satisfying the PEVs' individual load requirements and the overall grid congestion limits. The proposed resolution algorithm requires a minimal shared information between PEVs that communicate only with their neighbors without relying on a central aggregator, thus guaranteeing the PEV users' privacy.

4.2.3. Related Works and Contributions

Over the past years, a wide spectrum of works has explored the intelligent coordination of PEV fleets' charging. The first literature contributions address the optimal PEVs' charging problem based on a centralized control scheme, where a central operator is responsible for collecting all the information from the individual PEVs and for centrally computing their optimal charging profiles. Such a scheme is able to find the best possible solution and is generally easy to implement; however, it suffers from poor privacy protection of PEV users and from computational and communication concerns in large-scale PEV fleets, which are unavoidable, due to the high volume of individual PEVs' data [403]. Hence, when the number of PEVs increases, a distributed strategy is much more efficient, since the optimization tasks are distributed through many agents. Even more importantly, PEV users' privacy is satisfactorily preserved, since only the minimal personal information needs to be locally broadcasted to the PEV's neighbors. Consequently, recent studies are oriented towards distributed PEVs' charging scheduling. For instance, References [404],[405] propose a distributed PEVs' charging strategy to smooth the daily grid load profile concerning communication and computational overhead as well as PEV users' privacy. In addition, a distributed waterfilling algorithm subject to individual constraints and coupled waterlevels is developed by Reference [406] and implemented on PEVs' fleets for optimal charging. However, none of the aforementioned distributed strategies considers capacity constraints related to the overall grid or single components' congestion constraints, such as the power distribution lines and feeders' capacity limits. To tackle this critical issue, grid capacity constraints are being incorporated in recent PEVs scheduling methods to realistically model the reliability and efficiency of the system [407] Only few works address the PEVs' charge scheduling problem under grid congestion management relying on a distributed control architecture. For instance, the authors in Reference [408] introduce a Lagrangian partial decomposition technique for the distributed scheduling of PEVs considering the transmission grid congestion. In References [409],[410], a distributed control strategy for PEVs' charge scheduling is proposed enforcing capacity constraints on the distribution network. However, unlike our approach, the cited work [408] adopts a linear, and hence not fully realistic, cost function for the energy purchased from the power grid. Moreover, none of the cited studies [408],[409],[410] involve the issue of PEVs' battery degradation in the charge scheduling problem, despite battery degradation is also a stringent requirement for real systems. Therefore, although both these studies have made positive efforts towards finding the optimal charging of PEVs in a distributed setting, due to their respective limitations, more research is still needed to provide a realistic and fully distributed framework for solving the scheduling problem of large-scale PEVs fleets in a comprehensive way.

Responding to the need for efficient control strategies for the optimal charging of a fleet of PEVs that may also deal with the associated scalability and feasibility issues, we present a new charge scheduling framework with the specific contributions as follows: 1) we address the optimal charging of PEV fleets tackling both the power capacity limits related to the distribution network and the impact of charging strategies on battery degradation, in order to preserve the reliability and efficiency of both the power grid and the individual PEVs; 2) we establish a novel fully distributed control strategy for the optimal charging of large-scale PEVs' fleets, in order to coordinate PEVs and eliminate the need for a central coordinator, reducing the computational complexity and guaranteeing the PEV users' privacy. Our objective is obtaining a global optimum solution which minimizes the aggregated charging cost and battery degradation based on the PEVs' individual satisfactions and requirements. Considering a realistic quadratic cost function for the energy purchased from the power grid, and a quadratic PEVs battery degradation model as well, we formulate the optimization problem as a convex quadratic programming (QP) problem, where all the PEVs' decision variables are coupled both via the objective function and some grid resource sharing constraints. Hence, we adopt the distributed control algorithm for waterfilling of Networked Control Systems (NCSs) with coupling constraints proposed in Reference [410] to solve our iterative distributed strategy effectively. We validate the proposed approach on numerical experiments with a large number of PEVs and show the ability of the method in finding a global optimum solution with a favorable computational efficiency.

4.2.4. System Model

We consider a fleet $\mathcal{N}$ of N PEVs, connected via the so-called G2V (Grid-to-Vehicle) mode of operation to a common distribution grid characterized by a given limited capacity. For the sake of simplicity, we assume that the PEV charging addresses the active power dispatch only, as commonly supposed by most works in the related literature [399]. We are interested in determining the optimal charging schedule for the whole fleet over a given time horizon H, composed by H equally spaced time intervals with length Δ each. The following parameters are used to model the system under analysis:

$\mathcal{H}$	scheduling horizon ($\mathcal{H} = \{1, \dots, h, \dots, H\}$)
h	index denoting the generic time slot in the scheduling horizon ($h \in \mathcal{H}$)
H	number of time slots in the scheduling horizon ($H = \|\mathcal{H}\|$)
Δ	fixed length of time slot
$\mathcal{N}$	fleet of PEVs ($\mathcal{N} = \{1, \dots, n, \dots, N\}$)
n, m	indices denoting the PEVs in the fleet ($n, m \in \mathcal{N}$)
N	number of PEVs in the fleet ($N = \|\mathcal{N}\|$)
K	diagonal matrix whose main diagonal contains the cost coefficients: $k = [k(1); \dots; k(h); \dots; k(H)] \in \mathbb{R}^H$
d	profile of inflexible demand (not including PEVs' load): $d = [d(1); \dots; d(h); \dots; d(H)] \in \mathbb{R}^H$
σ	trade-off parameter taking care of PEVs' battery degradation
b	profile of distribution grid capacity per slot: $b = [b(1); \dots; b(h); \dots; b(H)] \in \mathbb{R}^H$
χ_n	set of constraints for PEV n ($n \in \mathcal{N}$): $\chi_n \subset \mathbb{R}^H$.

Finally, the decision variables of the PEV fleet charging problem are the following:

x_n	vector of decision variables representing the charging profile of PEV n ($n \in \mathcal{N}$) over the time horizon: $x_n = [x_n(1), \dots, x_n(h), \dots, x_n(H)] \in \mathbb{R}^H$

4.2.5. Optimization Model

The proposed mathematical model of the PEV fleet charging problem is defined as a QP:

$$\min_{x_1,\dots,x_n,\dots,x_N} (d + \sum_{n\in\mathcal{N}} x_n)^T K(d + \sum_{n\in\mathcal{N}} x_n) + \sigma \sum_{n\in\mathcal{N}} \|x_n\|^2 \quad (150)$$

$$\text{s.t.} \quad x_n \in \chi_n, n \in \mathcal{N} \quad (151)$$

$$\sum_{n\in\mathcal{N}} x_n \leq b. \quad (152)$$

The above decision model relies on decision variables $\boldsymbol{x}_1, \dots, \boldsymbol{x}_n, \dots, \boldsymbol{x}_N$ representing the charging profile of the PEVs over the time horizon. The objective in (150) is minimizing the total charging cost, which is the summation of the costs of energy bought from the grid by the PEVs' fleet over the whole-time horizon and the costs due to the batteries' degradation. On the one hand, for the first cost term in (150), we consider a dynamic quadratic pricing, where the cost of electricity depends on the overall demand (namely, the aggregate PEVs' demand $\sum_{n=1}^{N} x_n$ in addition to the inflexible demand (d) in accordance with time-dependent cost coefficients in k. On the other hand, for the second cost term in (150), we assume that the batteries' degradation is highly correlated to the integral of power transferred through the battery [407]. Moreover, in the above decision model two classes of constraints are addressed. The first one addresses charging constraints characterizing each PEV, as indicated in (151). For instance, sets χ_n $(n \in \mathcal{N})$ could represent both some bounding on the charging rate and the achievement of a required state of charge at the end of the time horizon. Without loss of generality, we assume that χ_n $(n \in \mathcal{N})$ are compact and convex sets. The second class of constraints concerns the power grid capacity resources shared by PEVs. As indicated by the vector inequality (152), we consider that the overall capacity (represented by the time-varying parameters in b) has not to be violated over the time horizon. We finally remark that, since there is a multiple coupled objective function in (150), and since (152) are multiple coupled constraints, the optimization problem (150)-(152) is coupled from both the objective function and constraint perspectives.

4.2.6. The Proposed Distributed Algorithm

4.2.6.1. Communication Network Modeling

We assume that all the PEVs are connected to a communication network, modeled as an undirected and connected graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$: vertices $n \in \mathcal{N}$ represent the PEVs, while edges $(n, m) \in \mathcal{E}$ model the available communication links.

The following parameters are used to model the communication network:

P weights matrix: $P \in [0,1]^{N \times N}$. P_{mn} (i.e., the element (m, n) of the matrix P) is used by PEV n to weight information received from PEV m. Note that $P_{mn} = 0$ means that no communication between n and m occurs, whilst $P_{nn} = 0$ denotes the self-weight of PEV n.

As typically done in the related literature [405], we finally assume that P is a double stochastic matrix (i.e., the sum of all the elements in each row and columns is equal to one).

4.2.6.2. Algorithm Description

Taking the optimization theory for NCSs into account, problem (150)-(152) can be solved in a fully distributed setting using the distributed waterfilling approach [406]. In the related literature, the waterfilling principle was originally used to determine the optimal transmission power between sub-channels in accordance with noise levels aiming at the maximization of data rate in a communication link. Subsequently, the waterfilling concept inspired effective and efficient mechanisms for several types of engineering problems, including distributed optimization [406]. In particular, leveraging on distributed waterfilling, solving (150)-(152) in a fully distributed setting corresponds to solving a multiple-waterlevel multi-constrained waterfilling problem [410]. Indeed, PEVs act as waterfilling sub-systems aiming at determining their own waterlevels, which are all coupled together by the overall objective function and the constraints on the shared resources. Interacting with neighbors only, each PEV computes its own waterlevel taking into consideration the waterlevels of all other PEVs, while avoiding the violation of the coupling constraint and contributing to achieve the minimum of global cost.

Problem (150)-(152) is solved by the distributed mechanism reported in Algorithm 4.1, which properly adapts the distributed control algorithm for waterfilling of NCSs with coupling constraints proposed in Reference [410]. Specifically, Algorithm 4.1 is composed by an iterative procedure that is synchronously executed by all the PEVs and composed by alternating communication and update steps, making use of the following parameters:

τ number of communication steps per iteration ($\tau \in \mathbb{N}$)

ρ positive parameter of the distributed waterfilling algorithm proposed in Reference [410].

Algorithm 4.1 – The proposed distributed algorithm based on multi-user waterfilling with coupling constraints[1]

initialize: $x_n^{(0)}$ and $l_n^{(0)}$

$t \leftarrow 0$

repeat

1. update the PEVs' charging profile average based on τ consensus communication steps:

$$\omega_n^{(t)} = \sum_{m \in \mathcal{N}} (P^\tau)_{mn} x_m^{(t)} \tag{153}$$

2. update the ground-level:

$$\beta_n^{(t+1)} = (K + (\rho + \sigma) I_H))^{-1} \big(d + N\omega_n^{(t+1)} - x_n^{(t)} + l_n^{(t)}\big) - \rho (K + (\rho + \sigma) I_H))^{-1} x_n^{(t)} \tag{154}$$

3. update the charging profile:

$$x_n^{(t+1)} = \mathrm{Proj}_{\mathcal{X}_n}\big(-\beta_n^{(t+1)}\big) \tag{155}$$

4. update the Lagrange multipliers' vector estimate based on τ consensus communication steps:

$$v_n^{(t+1)} = \textstyle\sum_{m \in \mathcal{N}} (P^\tau)_{nm} l_n^{(t)} \tag{156}$$

5. update the Lagrange multipliers' vector:

$$r_n^{(t+1)} = \frac{1}{1+\rho} \big(v_n^{(t+1)} + N\omega_n^{(t+1)} - b\big) - \frac{\rho}{1+\rho} l_n^{(t)} \tag{157}$$

6. project the Lagrange multipliers' vector onto the non-negative orthant:

$$l_n^{(t+1)} = \mathrm{Proj}_{\mathbb{R}_+^H}\big(r_n^{(t+1)}\big) \tag{158}$$

$t \leftarrow t + 1$

until convergence is reached

return: $x_n^{(t)}$

[1]We denote the projection of σ onto $\mathcal{Y}$ as $\mathrm{Proj}_{\mathcal{Y}}(\sigma)$, i.e.: $\mathrm{Proj}_{\mathcal{Y}}(\sigma) = \underset{y \in \mathcal{Y}}{\mathrm{argmin}} \parallel y - \sigma \parallel^2$

For details on the algorithm steps, the reader is referred to Reference [410]. However, we remark that the setting addressed in Reference [410] is restricted to a specific quadratic objective function, which accounts only for a coupled quadratic form (i.e., $\sigma = 0$) whose corresponding matrix is the H-dimensional identity matrix (i.e., $K = I_H$). Differently from Reference [410], Algorithm 4.1 addresses the linearly constrained distributed optimization problem in the case of a more general quadratic objective function (i.e., the sum of a coupled quadratic form whose corresponding matrix is K and a separable quadratic form whose corresponding matrix is σI_H). For this reason, differently from the approach proposed in Reference [410], matrices K and σI_H appear in the computation ground-level defined by step 2 of Algorithm 4.1. We finally remark that, under the considered assumptions, and choosing the value of algorithm parameters in accordance with conditions provided in Reference [410] (i.e., $\rho > N - 1$), the iterations of Algorithm 4.1 converge and the corresponding results coincide with the optimal solution obtained solving (150)-(152) in a centralized fashion [410].

4.2.6.3. Numerical Experiments

In this section we show the performance of the proposed control algorithm through numerical examples. We consider a scenario with $N = 100 \div 10000$ non-homogenous PEVs, each characterized by individual values of model parameters. In particular, the individual constraints set of PEV n (with $n \in \mathcal{N}$) is modeled by $\mathcal{X}_n = x_n \in \mathbb{R}^H | \sum_{h\in\mathcal{H}} x_n(h)\Delta = X_n, x_n^{lb} \leq x_n \leq x_n^{ub}$, where X_n (uniformly distributed in the range (5,15) [kWh]), $x_n^{lb}(h)$ (set to 0 [kW] over the whole horizon $\mathcal{H}$), and $x_n^{ub}(h)$ (set to 3.3 [kW] in the time window when PEVs are plugged-in, which is randomly extracted from $\mathcal{H}$) respectively denote the overall required cumulative energy charge, the minimum and maximum charging rate. The known cost coefficients over the time horizon are: $k(h) = 0.01$ [€/kW^2], $h \in \mathcal{H}$. The base load consumption curve d of the distribution network is inferred from Reference [398] (see dotted line in Figure 4.1). Furthermore, we scale this curve such that the penetration of the PEVs is constant, i.e., we impose that the ratio $\left(\max_h d(h)\right)/N$ is constant as the size of the PEVs changes. As for the capacity of the distribution network, we scale the right-hand side of the coupling constraint according to the size of PEVs: $b(h) = 11.13N$ [kW], $h \in \mathcal{H}$. Simulations are carried out for a 1-day scheduling horizon with $H = 24$ time slots of one hour each (i.e., $\Delta = 1$ [hour]). The proposed algorithm is implemented and tested in the Matlab environment with initialization vectors for the PEVs set to zero and ρ parameter chosen in order to satisfy the convergence conditions. Results converge to the exact minimum values that may be obtained solving the scheduling problem (150)-(152) in a centralized fashion via a quadratic programming solver (corresponding to $24N$ variables, $48N$ bounding, N equality, and 24 inequality constraints).

In Figure 4.1 we report the results obtained by Algorithm 4.1 when $N = 100$. We consider two different cases of analysis in the formulation of problem (150)-(152). Figure 4.1 reports in solid line the aggregated charging profile of the PEVs without considering the battery degradation cost (i.e., setting to zero the second term in (150) by imposing $\sigma = 0$). Note that in this case a perfect valley-filling load profile could not be feasible, since we account for the overall capacity of the power grid distribution lines devoted to PEVs (i.e., constraint in (152)). In addition, Figure 4.1 reports in dashed line the obtained results considering the battery degradation (i.e., $\sigma = 10$). We note that in the latter case the presence of two terms in the objective function lead to spreading the aggregated charging profile on the time horizon more than in the former case, where the valley filling effect is more pronounced. On the one hand, as σ increases, the penalization for the battery degradation takes over and the results loose optimality in terms of aggregated energy cost. On the other hand, this shows that the resulting control algorithm allows capturing individual cost functions for the PEVs as a function of battery state of charge.

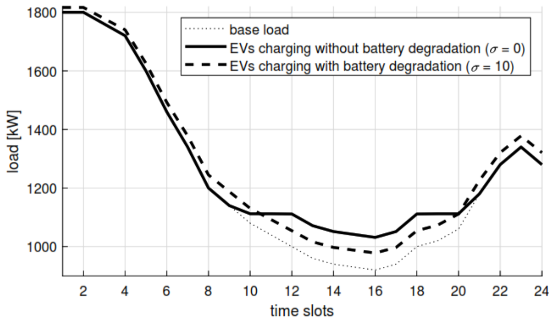


Figure 4. 1. Charging scheduling of Algorithm 3 for a fleet of N = 100 PEVs.

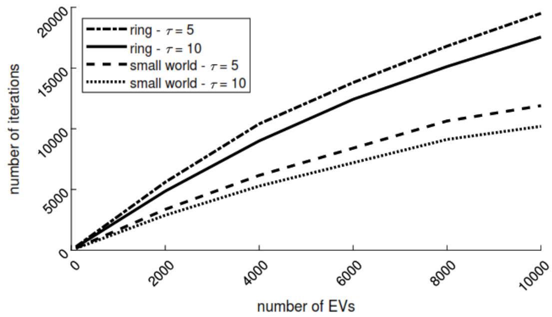


Figure 4. 2. Number of iterations of Algorithm 3 as function of number of PEVs.

Finally, we provide a numerical analysis of the algorithm complexity. In particular, Figure 4.2 shows the number of iterations versus the number of PEVs for two different classical topologies (undirected ring and small world) and two values for the number of communications per iteration ($\tau = 5, \tau = 10$). In all the analyzed cases, the weights' matrix P is determined by the Metropolis-Hastings method [410]. From Figure 4.2 it is apparent that the number of iterations typically increases with the number of PEVs in all cases; however, the corresponding growing rate gradually slows down, confirming the approach scalability. As a final remark, from Figure 4.2 we note that the higher the communication density the lower the number of iterations that is needed.

4.2.7. Conclusions

This subsection proposes a novel distributed control strategy for the optimal charging of large-scale PEV fleets considering the constraints on the power grid, charging locations and individual PEVs. The proposed algorithm allows minimizing both the aggregated energy charging and battery degradation cost based on the PEVs' individual requirements while satisfying the overall grid congestion limits. Numerical experiments on a simulated case study show the effectiveness of the proposed approach in finding a global optimum solution while respecting both the power grid and PEVs' fleet congestion limits with a favorable computational efficiency. Future research will address extending our distributed framework to include the reactive power dispatch in the optimal PEVs charging scheduling, modelling non-idealities of communication network and uncertainties that affect the estimation of optimization model parameters, and investigating the adoption of alternative fully distributed approaches such as gossip based algorithms.

From the findings and contribution of the research in this chapter, the following paper has been presented:

- S. M. Hosseini, R. Carli, G. Cavone, M. Dotoli, "Distributed Control of Electric Vehicle Fleets Considering Grid Congestion and Battery Degradation," in *Internet Technology Letters*, vol. 3, no. 3, pp. 1-6, 2020. doi: 10.1002/itl2.161.

4.3. A Robust Decentralized Approach for Charge Control of Electric Vehicle Fleets under Uncertainty on Inelastic Demand and Energy Pricing Considering Grid Congestion and Battery Degradation

4.3.1. Introduction

Despite the increasing development of PEVs, some barriers still need to be solved for their efficient widespread usage. One of the major challenges concerns the optimal PEVs' charging strategy in a proper PEVs' charging infrastructure [411]. On the one hand, incorporating massive PEVs fleet into power grids needs coordinated charging strategies to prevent high electricity costs for charging and huge-peak power demand causing system instability. Indeed, uncoordinated random PEVs charging brings a variety of challenges to the power quality and reliability of power grids, threatening the smooth operation of the distribution network. On the other hand, unpredictable users' load demand and the uncertain electricity price in day-ahead electricity markets can impose serious challenges to the design of near-optimal PEVs charge scheduling by moving the obtained solutions away from optimal points.

Coping with these challenges of the largescale adoption of PEVs fleets in the power system, this subsection presents a robust decentralized framework for day-ahead charge control of PEVs fleets under uncertainty on the dynamic electricity price and the inelastic loads demand. The main objective of this work is minimizing both the overall charging energy payment and the aggregated battery degradation cost of PEVs while preserving the robustness of the solution against perturbations in the uncertain parameters. Moreover, we take into account the power congestion limits of the overall capacity of the distribution network and the PEVs' individual needs such as charge level requirements and battery degradation cost. The proposed approach relies on the so-called uncertainty set-based robust optimization, where uncertain parameters are assumed to take their values from different domain sets independently [336]. To solve the defined problem, we first establish a related deterministic model of the PEVs charge scheduling problem. Hence, we convert the deterministic model into a min-max robust counterpart regarding the uncertainty set inspired by the approach proposed in [337]. Finally, we apply some mathematical transformations on the robust counterpart to obtain an equivalent quadratic programming (QP) problem where all the PEVs' decisions are coupled via the grid resource-sharing constraints and the robust counterpart supporting constraints. We adopt an extended Jacobi-Proximal Alternating Direction Method of Multipliers (ADMM) algorithm [412] to solve effectively the resulting optimization problem in a decentralized fashion. We finally remark that, whereas many decentralized mechanisms have been developed for the coordinated PEVs charge scheduling, little or no attention has been devoted to extend such methods in a robust optimization perspective. Therefore, differently from the related literature, we consider a novel tractable robust decentralized framework that improves the performance with respect to classical deterministic decentralized approaches in presence of disturbances, while effectively dealing with the conservativeness of the obtained solutions.

4.3.2. Aims and Objectives

Whereas many decentralized mechanisms have been developed for the coordinated electric vehicles (EVs) charge scheduling, little or no attention has been devoted to extend such methods in a robust optimization framework. Therefore, this subsection proposes a novel robust decentralized charging strategy for large-scale PEV fleets. The system incorporates multiple PEVs as well as inelastic loads connected to the power grid under power flow limits. We aim at minimizing both the overall charging energy payment and the aggregated battery degradation cost of PEVs while preserving the robustness of the solution against uncertainties in the price of the electricity purchased from the power grid and the demand of inelastic loads. The proposed approach relies on the so-called uncertainty setbased robust optimization. The resulting charge scheduling problem is formulated as a tractable quadratic programming problem where all the PEVs' decisions are coupled via the grid resource-sharing constraints and the robust counterpart supporting constraints. We adopt an extended Jacobi-Proximal Alternating Direction Method of Multipliers algorithm to effectively solve the formulated scheduling problem in a decentralized fashion, thus allowing the method applicability to large scale fleets. Simulations of a realistic case study show that the proposed approach not only reduces the costs of the PEV fleet, but also maintains the robustness of the solution against perturbations in different uncertain parameters, which is beneficial for both PEVs' users and the power grid.

4.3.3. Related Works and Contributions

Recent studies on coordinated smart charging of PEVs mainly try to fill the valley of off-peak demand hours [413], smooth out the peaks of the aggregated demand curve [414], and minimize the cost of PEVs charging (or maximize the environmental benefits) [415]. The majority of existing literature addresses the PEVs charge scheduling problem based on a centralized control scheme, where a central operator makes decisions on the optimal charging strategies of all PEVs, and purchases the total required energy from the power grid [416]-[418]. Despite a satisfactory performance in finding optimal scheduling solutions, centralized charging schemes may result in load peaks in individual PEVs, they generally suffer from poor privacy protection, and can pose computational and communication concerns in large-scale PEV fleets, due to the high volume of individual PEVs' data [419]. Therefore, decentralized strategies for PEVs charge control have gained attention due to their high potential for real-world applications. Indeed, decentralized control schemes allow each PEV to individually minimize its own charging costs independently, by solving a decomposed optimization sub-problem through local information. For example, in [420], the authors propose a decentralized PEV charging control framework to flatten the energy demand profile during peak-hour intervals by adopting a shrunken-primal-dual subgradient algorithm, which can be used either at the charging points or implemented by a central coordinator for parallel computing. In addition, the authors in [421] present a partial augmented Lagrangian method for the decentralized coordination of PEV charging, considering capacity limits for each feeder. Decentralized approaches to PEVs scheduling considering congestion management based on the well-known alternating direction method of multipliers (ADMM) are developed in [422] and [423]. However, despite the fact that the unpredictable users' load demand and the electricity markets may impose serious challenges to the design of near-optimal PEVs charge scheduling, none of the aforementioned decentralized approaches give attention to this issue. As a matter of fact, assuming a deterministic strategy for PEVs scheduling can result in a non-optimal or even infeasible solution [424]. Regarding the few studies contributing to decentralized PEVs' scheduling taking data uncertainty into account, the authors in [424] propose a two-stage dynamic stochastic optimization scheme addressing uncertainties on electricity price, users' load demand and renewable energy generation. A stochastic model predictive control-based approach dealing with the electricity price uncertainty is also presented in [425]. However, these stochastic-based approaches generally suffer from some limitations, such as the large presence of uncertain data requiring to be modeled, dependency between some uncertain parameters, insufficient historical data in real situations, and high computational burden due to a significant number of scenarios.

Therefore, despite the fact that these current researches have made positive endeavors towards the optimal PEVs scheduling, further research is still needed to effectively solve large-scale PEVs charge control problems in a coordinated manner in the presence of uncertainties imposed by some supply- or demandside parameters' data. Hence, the main contributions of this work are: *1)* We present a novel mathematical model and an iterative coordinated framework, without relying on a central decision-maker, using an extended Jacobi-Proximal ADMM algorithm [412] to minimize the aggregated charging cost of large-scale PEV fleets under both PEVs' individual requirements and grid power flow limits. *2)* We account for the data uncertainties associated with the dynamic electricity price and the inelastic load demand by formulating a robust counterpart of the charge scheduling problem using an uncertainty setbased method inspired by [337]. *3)* We define suitable robustness factors to mitigate the conservativeness of the proposed approach and we investigate the effects of such robustness factors on the robustness of the solution against variations of the uncertain parameters within the given uncertainty sets.

We demonstrate the benefits of our proposed approach by a realistic case study with a large number of PEVs. The results show that the proposed approach not only limits the aggregate PEVs energy payment, but also maintains the robustness of the solution against perturbations in different uncertain parameters, which is beneficial for both PEVs' end-users and the power grid.

4.3.4. System Model

The system architecture is shown in Figure 4.3. The control framework comprises two main parts: *1)* a set of *agents* which simultaneously solve local optimization sub-problems aimed at determining the PEVs optimal charging strategies and making robustness decisions, and 2) the *coordinator* who is responsible for initializing agents parameters, gathering updated data from all agents, and broadcasting back the updated coordination data. We consider a time horizon $\mathcal{H} = 1, \ldots, h, \ldots, H$, containing H time slots with equal duration Δh. The components of the system are modeled in the following subsections.

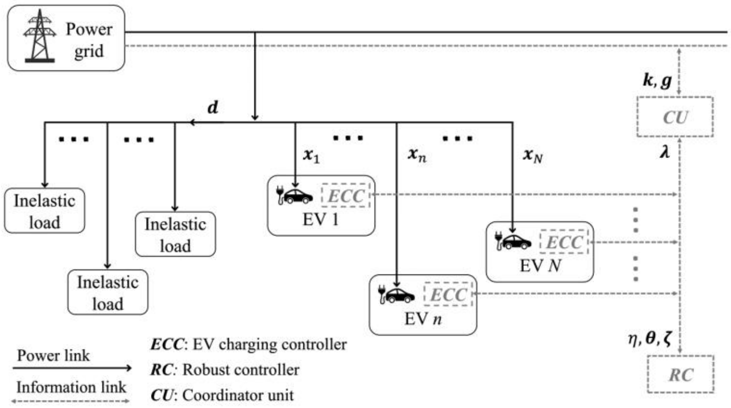


Figure 4. 3. Scheme of the proposed system architecture.

4.3.4.1. Electric Vehicles

We assume to have a fleet of PEVs $\mathcal{N} = 1, \dots, n, \dots, N$ in the system under the grid-to-vehicle operating mode. The charging profile of the PEV n is represented by a column vector $\mathbf{x}_n = [x_n(1), \dots, x_n(H)]^\top$, collecting the non-negative power charging rates over the time horizon. Denoting as $l_n^{lb} = [l_n^{lb}(1), \dots, l_n^{lb}(H)]^\top$ and $l_n^{ub} = [l_n^{ub}(1), \dots, l_n^{ub}(H)]^\top$ the minimum and maximum power charge rates required by the PEV n, respectively, the charging profile $\mathbf{x}_n$ has to be upper and lower bounded as follows:

$$\mathbf{l}_n^{lb} \leq \mathbf{x}_n \leq \mathbf{l}_n^{ub}, \quad n \in \mathcal{N}. \tag{159}$$

Note that $l_n^{lb}(h) = l_n^{ub}(h) = 0$ for all the time slots $h \in \mathcal{H}$ in which the PEV n is not plugged-in to the feeder. Furthermore, each PEV n has to be recharged by a certain amount of energy l_n at the end of the time window:

$$\Delta\text{h}\ \mathbf{1}_{H,1}^\top\, \mathbf{x}_n = l_n, \quad n \in \mathcal{N} \tag{160}$$

where $\mathbf{1}_{H,1}$ denotes the H-dimensional column vector with all ones. For the sake of compactness, for each PEV we introduce the set of feasible strategies as follows:

$$\mathcal{X}_n = \{\mathbf{x}_n \in \mathbb{R}^H | (1) - (2) \text{ hold}\}, \quad n \in \mathcal{N}. \tag{161}$$

Finally, we suppose that PEVs suffer from degradation in terms of capacity decreasing and resistance increase. Consequently, for each PEV we adopt a degradation cost function as follows [422]:

$$c_n^d(\mathbf{x}) = \phi_n \parallel \mathbf{x}_n \parallel^2 \tag{162}$$

where ϕ_n is the known degradation coefficient of the PEV n.

4.3.4.2. Grid Constraints and Energy Pricing

We assume a linear time-varying cost function for the energy bought from the power grid. Denoting as $\mathbf{k} = [k(1), \dots, k(H)]^\top$ the cost coefficients over the time horizon, the cost incurred by the charging of the PEV n is:

$$c_n^e(\mathbf{x}_n) = \sum_{h \in \mathcal{H}} k(h) \Delta \mathrm{h}\, x_n(h) = \Delta \mathrm{h}\, \mathbf{k}^\top \mathbf{x}_n \qquad (163)$$

Furthermore, we assume a limited capacity for power transferred with the power grid as follows:

$$\mathbf{d} + \sum_{n \in \mathcal{N}} \mathbf{x}_n \leq \mathbf{g}. \qquad (164)$$

where the H-dimensional column vectors $\mathbf{d} = [d(1), \dots, d(H)]^\top$ and $\mathbf{g} = [g(1), \dots, g(H)]^\top$ represent the profiles of the day-ahead inelastic load demand and of the maximum power that can be adsorbed from the distribution grid, respectively.

4.3.5. Problem Formulation

4.3.5.1. Deterministic Energy Scheduling Problem

The deterministic PEVs charge scheduling problem is formulated based on nominal forecasted values of inelastic load demand and energy pricing:

$$\min_{\mathbf{x}_1 \in \chi_1, \dots, \mathbf{x}_N \in \chi_N} c(\mathbf{x}_1, \dots, \mathbf{x}_N) \qquad (165)$$

$$\text{s.t. (164).}$$

In (165) the objective function $c(\mathrm{x}_1, \dots, \mathrm{x}_N) = \sum_{n \in \mathcal{N}} c_n^d(\mathrm{x}_n) + c_n^e(\mathrm{x}_n)$ aims at minimizing both the total charged energy cost and battery degradation cost for the whole fleet of PEVs. The optimization problem (165) is labeled *deterministic* or *nominal* energy scheduling problem.

4.3.5.2. Data Uncertainty Set Definition

The previously defined deterministic scheduling problem unrealistically assumes perfect knowledge of inelastic load demand and energy pricing (i.e., of vectors **d** and **k**). However, the variation in the forecast of these profiles may cause a large deviation from the optimum in the obtained results, leading to inefficient scheduling. Following the so-called set-based uncertainty model [336], we define a computationally tractable method to tackle uncertainty in the scheduling strategy, which consists in finding the solutions that are feasible for any realization of uncertainty in a given set. Indeed, the set-based uncertainty approach is an effective methodology to obtain robust solutions to uncertain optimization problems [336]. To this aim, we firstly define the uncertainty set. We assume that the sources of uncertainties affecting the inelastic load demand and energy pricing are unknown but the corresponding maximum/minimum values are available. We denote the vectors of the uncertain parameters for the inelastic load profile as $\tilde{\mathbf{d}} = \left[\tilde{d}(1), \dots, \tilde{d}(H)\right]^\top$, and for cost coefficient profile as $\tilde{\mathbf{k}} = \left[\tilde{k}(1), \dots, \tilde{k}(H)\right]^\top$, assuming symmetric distributions as follows:

$$\mathbf{d} - \hat{\mathbf{d}} \leq \tilde{\mathbf{d}} \leq \mathbf{d} + \hat{\mathbf{d}} \qquad (166)$$

$$\mathbf{k} - \hat{\mathbf{k}} \leq \tilde{\mathbf{k}} \leq \mathbf{k} + \hat{\mathbf{k}} \qquad (167)$$

where $\hat{\mathbf{d}} = \left[\hat{d}(1), \dots, \hat{d}(H)\right]^\top$ and $\hat{\mathbf{k}} = \left[\hat{k}(1), \dots, \hat{k}(H)\right]^\top$ are the vectors collecting the semi-amplitude of maximum variations of the inelastic load demand and the cost coefficients, respectively.

Rather than protecting the schedule against the worst-case deviation of all the parameters, we adopt the cardinality-constrained uncertainty method [337] that allows decision maker to decide the level of conservativeness and is able to withstand parameters' uncertainty without excessively affecting the objective function and constraints. We introduce the so-called robustness factors (also known as budgets of uncertainty) γ_k and γ_d related to energy pricing and inelastic load demand, respectively. As for γ_k, this is a robustness factor that denotes the number of parameters (i.e., $k(h)$, $h \in \mathcal{H}$) protected against disturbances, taking values in $[0, H]$. The problem solution is guaranteed to be feasible if no more than $\lfloor \gamma_k \rfloor$ of the parameters $\tilde{k}(h)$ are subject to uncertainty, and one $\tilde{k}(h)$ changes no more than $(\gamma_k - \lfloor \gamma_k \rfloor)\hat{k}(h)$. Note that $\lfloor \cdot \rfloor$ denotes the ceiling operator: given the real number a, $\lfloor a \rfloor$ is the greatest integer lower than or equal to a. As for γ_d, this parameters takes values in $[0, H]$ with an analogous meaning as in the γ_k case.

4.3.5.3. Robust Energy Scheduling Problem

The objective function (165) and the constraint (164) are affected by the uncertainty on inelastic load profile and cost coefficients. Replacing **k** and **d** with $\tilde{\mathbf{k}}$ and $\tilde{\mathbf{d}}$ in (163) and (164), and allowing $\tilde{\mathbf{k}}$ and $\tilde{\mathbf{d}}$ to take values in the sets defined in (166)-(167), (165) turns into a robust optimization problem. Getting inspiration from the cardinality-constrained approach proposed in [337], we can straightforwardly provide the *robust counterpart* of the optimization problem (165), which aims at achieving a solution that is feasible for any realization of the uncertainty within the a given uncertainty set.

By defining the budget of uncertainty γ_k and the corresponding protection function $\beta(\mathbf{x}_1, \dots, \mathbf{x}_N, \gamma_k)$ for the objective function term (163), as well as the budget of uncertainty γ_d and the corresponding protection functions $\boldsymbol{\delta}(\gamma_d) = [\delta_1(\gamma_d), \dots, \delta_H(\gamma_d)]^\top$ for the capacity constraints (164), the robust counterpart of the deterministic scheduling formulation (165) is given by the following non-linear optimization problem:

$$\min_{\mathbf{x}_1 \in \chi_1, \dots, \mathbf{x}_N \in \chi_N} c(\mathbf{x}_1, \dots, \mathbf{x}_N) + \beta(\mathbf{x}_1, \dots, \mathbf{x}_N, \gamma_k) \quad (168)$$

$$\text{s.t. } \mathbf{d} + \textstyle\sum_{n \in \mathcal{N}} \mathbf{x}_n + \boldsymbol{\delta}(\gamma_d) \leq \mathbf{g}.$$

where

$$\beta(\mathbf{x}_1, \dots, \mathbf{x}_N, \gamma_k) = \quad (169)$$

$$\max_{\substack{\{\mathcal{Q} \cup \{q\} | \mathcal{Q} \subseteq \mathcal{H}, \\ |\mathcal{Q}| = \lfloor \Gamma_0 \rfloor, q \in \mathcal{H} \setminus \mathcal{Q}\}}} \left(\sum_{h \in \mathcal{Q}} \hat{k}(h) \left| \sum_{n \in \mathcal{N}} x_n(h) \right| + (\gamma_k - \lfloor \gamma_k \rfloor) \hat{k}(q) \left| \sum_{n \in \mathcal{N}} x_n(q) \right| \right)$$

$$\boldsymbol{\delta}(\gamma_d) = \begin{bmatrix} \delta_1(\gamma_d) \\ \vdots \\ \delta_H(\gamma_d) \end{bmatrix} = \max_{u(1), \dots, u(H)} \begin{bmatrix} u(1)\hat{d}(1) \\ \vdots \\ u(H)\hat{d}(H) \end{bmatrix} \quad (170)$$

$$\text{s.t. } \quad 0 \leq u(h) \leq 1, \quad h \in \mathcal{H} \quad (171)$$

$$\sum_{h \in \mathcal{H}} u(h) \leq \gamma_d \quad (172)$$

Note that in (169) where we introduce the subset $\mathcal{Q}$ and the index q to deal with uncertainty. In particular, $\mathcal{Q}$ is the subset of time slot indices, whose corresponding cost coefficients get the maximum deviation from the nominal values. At most $\lfloor \gamma_k \rfloor$ indices are assumed to belong to this subset. Further, in case γ_k is not integer, we select a time slot index q, whose corresponding cost coefficient is affected by a variation lower than the maximum deviation (i.e., the value is between $k(q)$ and $k(q) + \hat{k}(q)$). All the remaining cost coefficient get the nominal values (i.e., $k(h)$ for h not belonging to $\mathcal{Q}$ and different from q). Similarly, in (170)-(172), we introduce the H decision variables $u(1), \dots, u(H)$ to quantify the portions (not necessarily integer) of the total uncertainty budget γ_d allocated over all the time slots.

Observing (168), it can be found that the robust counterpart of the scheduling problem includes strong non-linearities and cardinality calculations due to the inner maximization defined by (169) and (170)-(172). Thus, it is still difficult to solve the problem in its current min-max form. Getting inspiration from [337], this issue can be resolved by transforming the robust counterpart into an easier form. By introducing the supporting variables η, $\boldsymbol{\theta} = [\theta(1), \dots, \theta(H)]^\top$, and $\boldsymbol{\zeta} = [\zeta(1), \dots, \zeta(H)]^\top$, it could be demonstrated that the robust counterpart (168) is equivalent to the following QP formulation:

$$\min_{\substack{\mathbf{x}_1\in\mathcal{X}_1,\ldots,\mathbf{x}_N\in\mathcal{X}_N,\\ \eta\in\mathbb{R}_+,\boldsymbol{\theta}\in\mathbb{R}_+^H,\boldsymbol{\zeta}\in\mathcal{Z}}} \left(\sum_{n\in\mathcal{N}} (\phi_n \mathbf{x}_n^\top \mathbf{x}_n + \Delta\mathrm{h}\, \mathbf{k}^\top \mathbf{x}_n) + \gamma_k \eta + \mathbf{1}_{H,1}^\top \boldsymbol{\theta}\right) \tag{173}$$

$$\text{s.t.} \quad \textstyle\sum_{n\in\mathcal{N}} x_n + \hat{d} \circ \zeta \le g - d \tag{174}$$

$$\hat{k} \circ \sum_{n\in\mathcal{N}} x_n - \eta 1_{H,1} - \theta \le 0_{H,1} \tag{175}$$

where the symbol $\circ$ denotes the entrywise product and $\mathcal{Z}$ is a constraint set defined as follows:

$$\mathcal{Z} = \left\{\boldsymbol{\zeta} \in \mathbb{R}^H \middle| \mathbf{0}_{H,1} \le \boldsymbol{\zeta} \le \mathbf{1}_{H,1}, \mathbf{1}_{H,1}^\top \boldsymbol{\zeta} \ge \gamma_d\right\}. \tag{176}$$

We finally remark that the robust counterpart (173)-(175) has $NH + H^2 + 1$ real variables and N equality, $2H + 1$ inequality, and $2HN + 3H + 1$ bounding constraints, in contrast with the NH variables and N equality, H inequality, and $2HN$ bounding constraints necessary for the nominal scheduling (165).

4.3.6. The Decentralized Robust Resolution Approach

In this section we propose an iterative resolution process that leads all the PEVs to achieve an agreement on the optimal set of robust charging strategies, without relying on a central decision-maker, i.e., to compute in a decentralized fashion the global optimal solution of (173)-(175). The proposed approach is based on a decentralized duality-based mechanism. To this aim, we introduce $N + 2$ decision units (see Figure 4.3): N PEV charging controller (ECC) agents solving as many independent local optimization sub-problems, the robustness controller (RC) agent that is in charge of calculating supporting variables of the robust counterpart, and the coordinator unit (CU) that collects the strategies from agents to calculate the Lagrange multipliers that are sent back to the agents. Note that the functions of the RC agent and the CU could be merged into one unit, so that the total number of units can be reduced to $N + 1$. For the sake of clarity, in the sequel we consider the roles of the coordinator and RC agent separated.

4.3.6.1. Reformulation of the Robust Counterpart

Although the objective function in (173) is separable, problem (173)-(175) cannot be easily decomposed since the decision variables are coupled in the global constraints (174)-(175). Hence, for convenience, we preliminarily convert (173)-(175) as follows:

$$\min_{\substack{\mathbf{x_1}\in\mathcal{X}_1,\dots,\mathbf{x_N}\in\mathcal{X}_\mathcal{N}\\ ,\mathbf{x_{N+1}}\in\mathcal{X}_{\mathcal{N}+1}}} \left(\sum_{i\in\mathcal{N}} \mathbf{x}_i^\top Q_i\mathbf{x}_i + \sum_{i\in\mathcal{N}\cup\{N+1\}} \mathbf{f}_i^\top\mathbf{x}_i\right) \tag{177}$$

$$\text{s.t.} \quad \textstyle\sum_{i\in\mathcal{N}\cup\{N+1\}} A_i\mathbf{x}_i = \mathbf{b} \tag{178}$$

where ECCs (i.e., agents $i \in \mathcal{N}$) and the RC (i.e., agent $i = N + 1$) determine their own decision variables blocks, having access to their objective function parameters, local constraint sets, and local and global parameters of coupling constraints (178), where:

$$\mathbf{x}_{N+1} = (\eta, \boldsymbol{\theta}^\top, \boldsymbol{\zeta}^\top, \boldsymbol{\sigma}^\top)^\top \tag{179}$$

$$\mathcal{X}_{\mathcal{N}+1} = \mathbb{R}_+ \times \mathbb{R}_+^H \times \mathcal{Z} \times \mathbb{R}_+^{2H} \tag{180}$$

$$Q_i = \phi_i I_H, \quad i \in \mathcal{N} \tag{181}$$

$$f_i = \Delta\mathrm{h}\, k, \quad i \in \mathcal{N} \tag{182}$$

$$f_{N+1} = \left(\gamma_k, 1_{1,H}, 0_{1,H}, 0_{1,2H}\right)^\top \tag{183}$$

$$A_i = \begin{pmatrix} I_H \\ \mathrm{diag}(\hat{k}) \end{pmatrix}, \quad i \in \mathcal{N} \tag{184}$$

$$A_{N+1} = \begin{pmatrix} 0_{1,H} & 0_{H,H} & \mathrm{diag}(\hat{d}) & \\ -1_{1,H} & -I_H & 0_{H,H} & I_{2H} \end{pmatrix} \tag{185}$$

$$b = \begin{pmatrix} g - d \\ 0_{H,1} \end{pmatrix} \tag{186}$$

We highlight that, introducing the vectors of non-negative slack variables $\boldsymbol{\sigma} \in \mathbb{R}_+^{2H}$ in the decision variable vector $\mathbf{x}_{N+1}$ defined in (179), the resulting optimization problem (177)-(178) is a quadratic programming problem subject to a linear equality coupling constraint. As a consequence, an ADMM approach can be adopted to solve the problem by dual decomposition.

4.3.6.2. The Proposed Decentralized Algorithm

We propose Algorithm 4.2 as the decentralized iterative resolution process to solve (177)-(178). Algorithm 4.2 relies on a modified version of the Jacobi-Proximal ADMM defined in [412]. In particular, the proposed algorithm is based on iterating the following three steps:

$$x_i^{(t+1)} = \underset{\mathbf{x}_i\in\boldsymbol{\mathcal{X}}_i}{\operatorname{argmin}} \left(x_i^\top Q_i x_i + f_i^\top x_i + \tfrac{\rho_i}{2} \left\| x_i - x_i^{(t)} \right\|^2 + \right.$$

$$\frac{\alpha}{2}\left\|A_i x_i + \sum_{j\in\{\mathcal{N}\setminus\{i\}\}\cup\{N+1\}} A_j x_j^{(t)} - b + \frac{\lambda^{(t)}}{\alpha}\right\|^2\Bigg), i \in \mathcal{N} \tag{187}$$

$$x_{N+1}^{(t+1)} = \underset{\mathbf{x}_{N+1}\in\boldsymbol{\mathcal{X}}_{N+1}}{\operatorname{argmin}} \Big(f_{N+1}^{\top} x_{N+1} +$$

$$\frac{\alpha}{2}\left\|A_{N+1} x_{N+1} + \sum_{i\in\{\mathcal{N}} A_i x_i^{(t+1)} - b + \frac{\lambda^{(t)}}{\alpha}\right\|^2\Bigg) \tag{188}$$

$$\lambda^{(t+1)} = \lambda^{(t)} + \alpha\left(\sum_{i\in\mathcal{N}\cup\{N+1\}} A_i x_i^{(t+1)} - b\right). \tag{189}$$

In the initialization phase of Algorithm 4.2 (lines 1-3), the Coordinator initializes the Lagrange multipliers vector $\boldsymbol{\lambda}^{(0)}$ related to the coupling constraint (178), whilst each ECC agent $i \in \mathcal{N}$ initializes its own strategy $\mathbf{x}_i^{(0)}$. The proposed algorithm works iteratively (line 4). Finally, the Coordinator terminates the iterative process when an adequate termination criterion is reached (line 16).

Remark 1: While all the ECCs (i.e., agents $i \in \mathcal{N}$) update their own strategies in a Jacobi fashion (i.e., in parallel), the RC (agent $i = N + 1$) updates its strategy in a Gauss-Seidel fashion (i.e., sequentially). Indeed, in (188) the RC incorporates the results of the preceding update done by ECCs in (187).

Remark 2: Following [412], it could be demonstrated that Algorithm 4.2 asymptotically converges to the global optimum of (177)-(178) if the following conditions related to the algorithm parameters are satisfied:

$$\rho_i \geq \alpha(N-1)\|A_i\|^2, \quad i \in \mathcal{N}. \tag{190}$$

4.3.7. Numerical Experiments

In this section, we apply the proposed robust framework to the day-ahead charge scheduling for a fleet of PEVs serving the residential MG end-users related to the scenario presented in [426].

The proposed algorithm is implemented in MATLAB R2019a on a desktop PC with i7-7500U core 2.70 GHz processor and 16 GB RAM memory. Initialization vectors are set to zero-values, whilst parameter α is assigned a unitary value and ρ_i ($i \in \mathcal{N}$) is equal to the right-hand side of (177).

Algorithm 4.2 – Decentralized Convergence to the Robust Optimal Charging Schedule

Parameters: α (CU, ECC $i \in \mathcal{N}$, and RC), ρ_i (ECC $i \in \mathcal{N}$)
Inputs: Q_i, f_i, $\mathcal{X}_i$, A_i (ECC $i \in \mathcal{N}$), f_{N+1}, $\mathcal{X}_{N+1}$, A_{N+1} (RC), b (CU, ECC $i \in \mathcal{N}$, and RC)

CU initializes $\boldsymbol{\lambda}^{(0)}$
each ECC $i \in \mathcal{N}$ initializes $\mathbf{x}_i^{(0)}$
set $t \leftarrow 0$
repeat
  CU broadcasts $\boldsymbol{\lambda}^{(t)}$ to ECCs and RC
  for each ECC $i \in \mathcal{N}$ **do**
    ECC i updates its own charging strategy by (187)
  end for
  CU gathers $A_i\mathbf{x}_i^{(t+1)}$ ($i \in \mathcal{N}$) from ECCs
  CU sends $\sum_{i\in\mathcal{N}} A_i\mathbf{x}_i^{(t+1)}$ to RC
  RC updates the robustness strategy by (188)
  CU gathers $A_{N+1}\mathbf{x}_{N+1}^{(t+1)}$ from RC
  CU updates the Lagrange multipliers vector by (189)
  Set $t \leftarrow t+1$
  until an adequate termination criterion is reached
Outputs: $\mathbf{x}_1^{(t)}, \dots, \mathbf{x}_N^{(t)}$

4.3.7.1. Parameters and Setting

We consider a time window for simulations of one weekday from 0:00 to 23:59. Each time slot is set equal to 60 minutes (i.e., $\Delta h = 1$ hour), meaning that the charging schedule is achieved by solving the optimization problem for the next $H = 24$ hours. The energy pricing over the scheduling window is based on the locational marginal price by ISO-NE (New England Independent System Operator) [427]. The nominal profile of electricity pricing (i.e., $\mathbf{k}$) is shown in Figure 4.4 through the solid line, whilst the corresponding uncertainty range (i.e., $\mathbf{k} - \hat{\mathbf{k}}$, $\mathbf{k} + \hat{\mathbf{k}}$) - determined as 15% of the nominal value for each time slot - is shown in Figure 4.4 by the dotted-lines.

We consider $N = 100$ homogenous PEVs: for all of them the charging rate ranges from 0 to 3.3 kW. The time window when the PEV $n \in \mathcal{N}$ is plugged-in (i.e., the time slot $h \in \mathcal{H}$ such that $l_n^{ub}(h) \geq 0$) and the energy amount required to achieve the desired charge level (i.e., l_n) are both randomly extracted in accordance with the PEVs data probability distribution considered in [428]. For all PEVs the degradation coefficient is $\sigma_n = 10\ cents/k\mathrm{W}^2$.

We assume that all PEVs are connected to node-25 of the single phase distribution network considered in [426]. Figure 4.5 shows as solid-line bars the nominal profile of the inelastic demand inferred by [426], which includes the overall electrical energy consumption of the residential users (i.e., $\mathbf{d}$). The corresponding uncertainty range (i.e., $\mathbf{d} - \hat{\mathbf{d}}$, $\mathbf{d} + \hat{\mathbf{d}}$) of the inelastic demand (that is shown in Figure 4.5 by dotted-lines) is determined as 15% of the nominal value for each time slot. In addition, Figure 4.5 shows as dashed line the profile of the maximum permissible power flow imposed by the distribution network to the PEVs feeders [426].

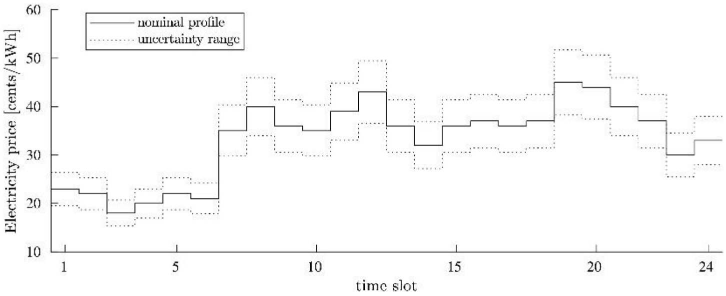


Figure 4. 4. Profile of electricity price with corresponding uncertainty ranges.

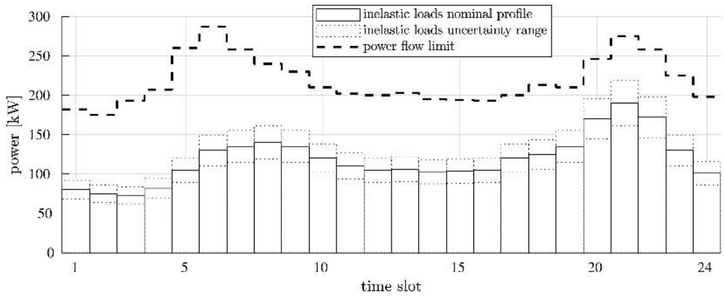


Figure 4. 5. Profile of inelastic demand with corresponding uncertainty ranges.

4.3.7.2. Results and Discussion

First, we determine the results obtained by Algorithm 1 in the following three cases.

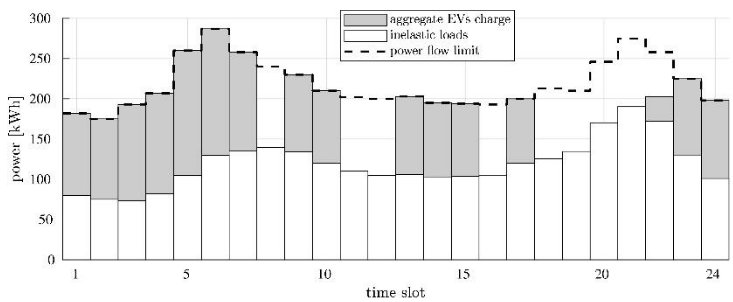
• *Case 1*: the deterministic optimization model (i.e., when $\gamma_k = \gamma_d = 0$). Therefore, no protection terms are considered against data uncertainty (i.e., $\beta(\mathbf{x}_1, \dots, \mathbf{x}_N, \gamma_k) = 0$ and $\boldsymbol{\delta}(\gamma_d) = \mathbf{0}_{H,1}$).

• *Case 2*: the robust optimization model considering full protection against data uncertainty (i.e., the worst-case realization) by adopting the maximum budgets of uncertainty ($\gamma_k = \gamma_d = H$), implying the most conservative solution.

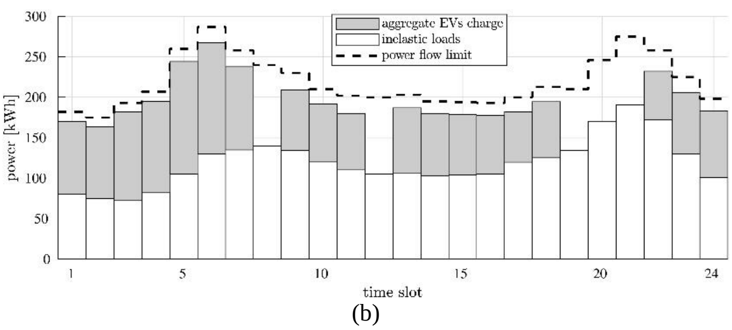
• *Case 3*: the robust optimization model considering uncertainty with $\gamma_k = \gamma_k^*$ and $\gamma_d = \gamma_d^*$, where $\gamma_k^* \in (0, H]$ and $\gamma_d^* \in (0, H]$ correspond to a potential choice for the budget of uncertainty when the robustness of the solution rarely changes for $\gamma_k \geq \gamma_k^*$ and $\gamma_d \geq \gamma_d^*$. This value can be obtained after sensitivity analyses over different budgets of uncertainty (we set $\gamma_k^* = 5$ and $\gamma_d^* = 17$), meaning that increasing the protection level by choosing $\gamma_k > \gamma_k^*$ and $\gamma_d > \gamma_d^*$ does not provide a significant improvement in the robustness of the solution against uncertainty.

We investigate the effects of the proposed method in the three cases by two well-known indices: *1)* the price of robustness (PoR) and *2)* the constraint violation rate (CVR) [336]. The PoR is defined as the percentage of relative difference between the cost achieved by a robust solution and a nominal solution. The CVR measures the percentage number of times a given solution does not satisfy the inequality constraints in (163) in reference to several realizations of the uncertainty parameters in a Monte Carlo (MC) simulation with 10000 runs.

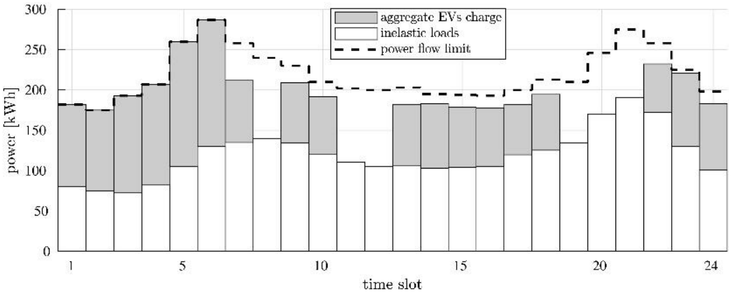
The results of the energy scheduling for the three cases are presented in Figure 4.6. The PEVs' energy payments for cases 1, 2, and 3 are respectively 466.00$, 484.51$, and 469.50$. Although - as expected - the solution of case 1 leads to the minimum PEVs' energy payment, the result is the most optimistic case, since it ignores the effects of the data uncertainty. Therefore, in real conditions, any disturbance in the forecast profiles of the load demands or energy pricing may cause an excessive increase in the obtained value of the objective function. Also, the grid constraints can be easily violated over the time window in presence of any disturbances because of the lack of any protection term in (163) against data uncertainty (in fact, CVR = 31.24%). On the other hand, the solution of case 2 provides full immunity against the worst-case realization. Here, the worst-case occurs when the energy demand and energy pricing uncertainties take their upper bounds during all time slots. This case guarantees that the solution is immunized against all possible uncertain data, leading to CVR = 0. However, this immunity is obtained at the expenses of an unnecessarily too conservative solution, causing the highest PoR (equal to 3.97%). In order to prevent such a too conservative solution, case 3 provides a compromise where there is a respective decrease in the PEVs' cost compared to case 2 as well as in the PoR (equal to 0.75%). Meanwhile, the solution obtained by case 3 is robust against data uncertainty (CVR = 14.68%). In general, by adjusting the budgets of uncertainty in the possible range, the level of conservativeness of the solution can be controlled and a trade-off between the PoR and the CVR may be obtained.



(a)



(b)

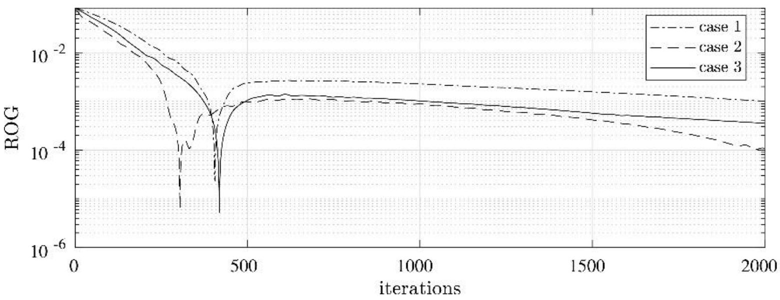


(c)

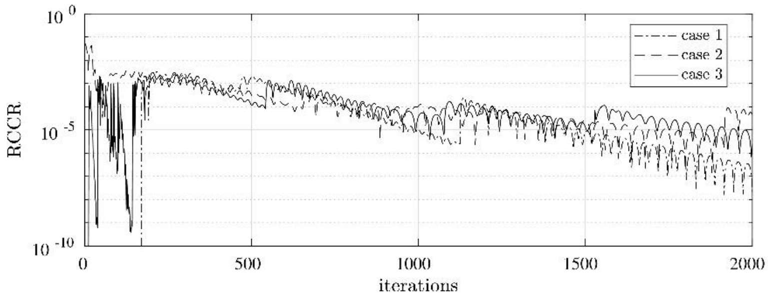
Figure 4. 6. Aggregated PEVs charging schedule - (a) case 1; (b) case 2; (c) case 3.

Moreover, for each case of analysis, in Figure 4.7 we report *1)* the relative optimality gap (ROG) and *2)* the relative coupling constraint residual (RCCR) as a function of iterations. The ROG is defined as the relative difference between the objective cost achieved by the algorithm solution at a given iteration and the optimal cost c^* computed by a centralized solver: $\left|c\left(\mathbf{x}_1^{(t)}, \dots, \mathbf{x}_N^{(t)}\right) - c^*\right| / c^*$ The RCCR measures the relative deviation observed in the equality coupling constraint by the algorithm solution at a given iteration: $\left\|\sum_{i\in\mathcal{N}\cup N+1} A_i\mathbf{x}_i^{(t)} - \mathbf{b}\right\| / \| \mathbf{b} \|$ As it can be seen from Figure 4.7, Algorithm 4.2 achieves optimality and feasibility in all cases, while the value of the robustness factors does not affect the algorithm convergence speed. We finally remark that in all the simulations runs the results obtained by the proposed decentralized algorithm converge to the exact optimal values of (173)-(175), which may be achieved in a centralized fashion via a linear programming solver, confirming the approach optimality.

Second, we present a sensitivity analysis of the 10000 runs MC simulation results with respect to different budgets of uncertainty $\gamma_k \in [0, H]$ and $\gamma_d \in [0, H]$ in terms of average PoR and CVR, all reported in Figure 4.8. As can be observed from the results, both the PoR and CVR present a non-linear trend. On the one hand, for any fixed value of γ_k, as the value of γ_d increases, the PoR monotonically gets worse, whilst the CVR monotonically gets better. On the other hand, for a fixed high value of γ_d, both the PoR and CVR are quite constant with respect to changes in γ_k; conversely, for a fixed low value of γ_d, the variations of the PoR and CVR have a convex and concave profile presenting a local maximum and minimum, respectively.

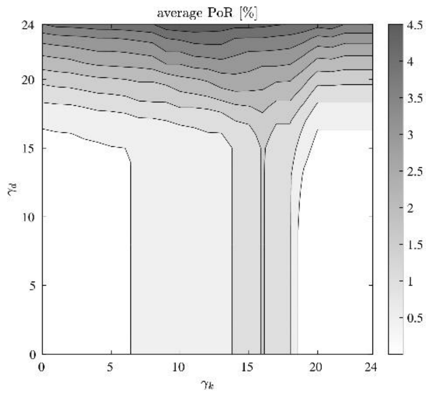


(a)

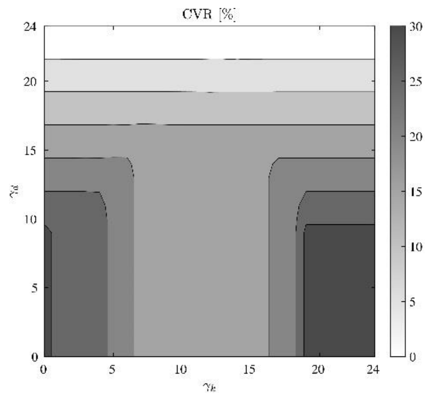


(b)

Figure 4. 7. Evolution of the ROG (a) and RCCR (b) across iterations.



(a)



(b)

Figure 4. 8. Sensitivity analysis of the average PoR (a) and CVR (b) with respect to different budgets of uncertainty

In addition, the PoR and the CVR present a mutually dual behavior, confirming that they are two competing indices: the PoR is higher where the CVR is higher, and viceversa.

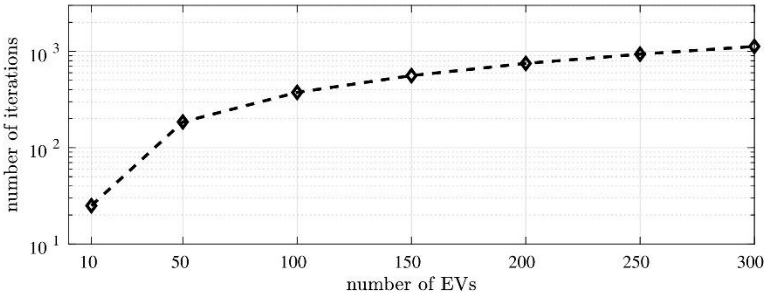


Figure 4. 9. Number of iterations required by Algorithm 4.2 to achieve $ROG < 10^{-3} \wedge RCCR < 10^{-3}$ for different number of PEVs (average results over MC simulations).

This result confirms the effectiveness of our approach, enabling the chance of a good trade-off between the total energy payment and the level of conservativeness by changing the value of the budget of uncertainty.

Finally, we provide a numerical analysis of the algorithm complexity when the number of PEVs vary in the range $N = 10 \div 300$. To this aim, we scale both the inelastic load demand curve **d** and the power flow limit curve **g** in Fig. 3, such that the penetration of the PEVs is constant, i.e., we impose that the ratios $\left(\max_h d(h)\right)/N$ and $\left(\max_h g(h)\right)/N$ are constant while changing N. Referring to $\gamma_k = 5$ and $\gamma_d = 17$, Figure 4.9 shows that the number of iterations required by the proposed algorithm to make both the relative optimality gap and the relative coupling constraint residual lower than a given threshold over different size of PEVs. From Figure 4.9 we note that the number of iterations increases linearly with the number of PEVs, confirming the approach scalability.

4.3.8. Conclusions

In this subsection, we propose a novel robust control algorithm for optimally controlling the battery charging of electric vehicles under grid resource sharing constraints in a decentralized fashion. On the one hand, the proposed approach fills a gap in the existing literature, where there is a lack of investigations on decentralized robust approaches aimed at efficiently increasing the penetration of PEVs while preserving the power grid congestion limits. On the other hand, the application to numerical experiments based on real case studies highlights the robustness of the proposed energy scheduling in the uncertain context. A trade-off can be made relying on a decentralized framework to resolve the conflict between energy payment minimization and contractual constraint satisfaction, which is advantageous for both the electric vehicle users and the power grid operator. Future research will address: demonstrating the optimality and convergence properties of the proposed approach, assessing the scalability of the algorithm in larger-scale scenarios, extending the system model by integrating additional objective functions and constraints, and modeling other types of uncertainty sources that may affect decision parameters.

From the findings and contribution of the research in this chapter, the following paper has been presented:

- S. M. Hosseini, R. Carli, A. Parisio and M. Dotoli, "Robust Decentralized Charge Control of Electric Vehicles under Uncertainty on Inelastic Demand and Energy Pricing," *IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Toronto, Canada, Oct 11-14, 2020.

5. Conclusions and Future Work

In this thesis several approaches were proposed to address the optimal DSM of smart electrical energy systems (e.g., smart residential MGs and smart PEVs fleets) in the presence of disturbances in forecast data. The proposed approaches represented improvements with respect to the state of the art in the exploitation of optimization techniques to solve problems arising in energy management and control of SGs.

The first part of thesis focused on centralized techniques for the DSM of residential MGs under uncertainty in forecast data. We presented several day-ahead and online energy scheduling for residential MGs. Several elements of novelty and original contributions of this part may be highlighted as:

- The optimization technique presented in subchapter 3.2 is the first to the best of the author's knowledge to provide a robust DSM under bounded uncertainty sets dealing with intermittency in both RESs and loads in residential smart users including ESS units. The proposed approach developed a robust optimization framework for the day-ahead scheduling of residential smart user under uncertainties of forecast data. Unlike stochastic scenario-based techniques, the proposed method took advantage from a robust optimization scheme including minimum information on the sources of uncertainty - namely only the deterministic range of the uncertain variables and the resistance against any disturbance in the uncertainty set - and characterized by a lower computational burden than stochastic optimization that normally utilizes time consuming Monte Carlo sampling.
- The optimization technique presented in subchapter 3.3 is the first to the best of the author's knowledge to provide an online energy scheduling of a residential MG with the possibility of concurrent occurrence of uncertainties in the estimated load demand and RES unit while considering a non-linear objective function. The proposed method is a new energy scheduling approach for residential applications in a retail electricity market regarding uncertainties in the estimation of load demand and RES generation. In our MPC-based method, the concept of receding horizon control made is possible to compute corrective actions with regard to any disturbance in the parameter's estimation. Also, we considered a quadratic pricing function for the energy bought

from the grid, which yields more realistic results than the recalled approaches. The proposed approach provided a full exploitation of the RES in variable weather conditions, the optimal planning of the usage of electrical devices and determining an optimal strategy of storage charging/discharging, whilst minimizing the cost of energy acquired from the grid and limiting the PAR in the aggregate load demand.

- The optimization technique presented in subchapter 3.4 is the first to the best of the author's knowledge to provide an online energy scheduling framework based on RMPC to state and solve the energy scheduling problem of a residential MG with a shared ESS under quadratic cost function. The proposed approach tackled the forecast load uncertainty in both the objective function and corresponding contractual constraints. The problem included uncertain terms in both the left-hand side and the right-hand side of the inequality constraints. All technical constraints and a contractual obligation imposed by the electric grid, limiting the total energy consumption per time slot to a maximum level were formulated. Moreover, the conservativeness of the proposed scheme and its flexibility for applying to different applications were analyzed and discussed.
- Finally, the optimization technique presented in subchapter 3.5 is the first to the best of the author's knowledge to provide a comprehensive model and a systematic robust methodology to state and solve a more generic energy scheduling problem of a grid-connected residential MG with several users incorporating individually owned RESs, NCLs, energy-based and comfort-based CLs, and PEVs. Moreover, the smart users shared a given number of RESs and an ESS under a dynamic quadratic pricing. However, the MG was also able to sell its extra energy back to the grid by a dynamic linear pricing. We took the forecast uncertainty caused by the RESs energy profiles, as well as the users' energy demand, into account. To the best of the authors' knowledge, no robust quadratic programming approach for the energy scheduling of the residential MG has ever been proposed to tackle the uncertainties associated with RES generation and users' energy demand under quadratic pricing. The proposed framework is generic and flexible as it can be applied to different structures of MGs considering various types of uncertainties in energy generation or demand. Moreover, we dealt with the conservativeness of the proposed scheme for different scenarios and quantify the effects of the budget of uncertainty on the cost saving, the PAR and constraints' violation rate. The proposed robust approach enables the decision maker (i.e., the energy manager of the MG) to make a trade-off between the users' payment and constraints' violation rate by adjusting the values of the budget of uncertainty.

- The future research paths of this first set of approaches presented in the thesis include extending the system model by integrating additional subsystems such as non-interruptible loads, or other types of uncertainty sources such as uncertain real-time pricing and PEV plug-in/out times.

The second part of thesis focused on distributed techniques to deal with the problem of optimal charging of large-scale PEV fleets aiming at the minimization of the aggregated charging cost and battery degradation, while satisfying the PEVs' individual load requirements and the overall grid congestion limits. The elements of novelty and original contributions of this part consist in:

- The optimization technique presented in subchapter 4.2 is the first to the best of the author's knowledge to address the optimal charging of PEV fleets considering both the power capacity limits related to the distribution network and the impact of charging strategies on battery degradation, in order to preserve the reliability and efficiency of both the power grid and the individual PEVs. Moreover, we established a novel fully distributed control strategy for the optimal charging of large-scale PEVs' fleets, in order to coordinate PEVs and eliminate the need for a central coordinator, reducing the computational complexity and guaranteeing the PEV users' privacy. The proposed method aimed at obtaining a global optimum solution which minimized the aggregated charging cost and battery degradation based on the PEVs' individual satisfactions and requirements. The proposed approach considered a quadratic cost function for the energy purchased from the power grid, and a quadratic PEVs battery degradation model as well, and formulated the optimization problem as a convex quadratic programming problem, where all the PEVs' decision variables were coupled both via the objective function and some grid resource sharing constraints.
- The optimization technique presented in subchapter 4.3 is the first to the best of the author's knowledge to provide a novel mathematical model and an iterative coordinated framework, without relying on a central decision-maker, using an extended Jacobi-Proximal ADMM algorithm to minimize the aggregated charging cost of large-scale PEV fleets under both PEVs' individual requirements and grid power flow limits. We accounted for the data uncertainties associated with the dynamic electricity price and the inelastic load demand by formulating a robust counterpart of the charge scheduling problem using an uncertainty setbased method. Moreover, we defined suitable robustness factors to mitigate the conservativeness of the proposed approach, and we investigated the effects of such robustness factors on the robustness of the solution against variations of the uncertain parameters within the given uncertainty sets.

- Future research of this second set of approaches presented in the thesis will include demonstrating the optimality and convergence properties of the proposed approach, assessing the scalability of the algorithm in larger-scale scenarios, extending the system model by integrating additional objective functions and constraints, and modeling other types of uncertainty sources that may affect decision parameters.

Appendix A

In this appendix, we provide the mathematical steps employed in defining (126)-(132) as the robust counterpart of the scheduling problem (117)-(123).

Preliminarily, for the ease of implementation, following [337], we transform (117)-(123) into an equivalent form where the objective function is not subject to uncertainty, and data uncertainty only affects the elements in the LHS of constraints. In particular, we get an equivalent problem with linear objective function and both quadratic and linear constraints as follows:

$$\min_{\substack{\boldsymbol{x}^l,\boldsymbol{x}^p,\boldsymbol{x}^v,\boldsymbol{x}^{v\delta},\boldsymbol{x}^s,\boldsymbol{x}^{s\delta},\boldsymbol{x}^{g\delta},\\ \boldsymbol{x}^a,\boldsymbol{\delta}^v,\boldsymbol{\delta}^s,\boldsymbol{\delta}^g,\alpha,\boldsymbol{x}^b}} \alpha \tag{191}$$

s.t. (64)-(70), (72)-(74), (77)-(83), (85)-(87),

(90)-(96), (99)-(101), (103), (106)-(108),

and

$$\boldsymbol{x}^b = \mathbf{1}_{P,1} \tag{192}$$

$$c\left(\boldsymbol{x}^{g\delta},\boldsymbol{x}^a\right) - \alpha \leq 0 \tag{193}$$

$$\boldsymbol{x}^a + \textstyle\sum_{p=1}^{P} \boldsymbol{d}_p \circ \boldsymbol{x}_p^b \leq \overline{\boldsymbol{g}} \tag{194}$$

$$\boldsymbol{x}^a + \textstyle\sum_{p=1}^{P} \boldsymbol{d}_p \circ \boldsymbol{x}_p^b \geq \underline{\boldsymbol{g}} \tag{195}$$

$$\boldsymbol{x}^a + \overline{\boldsymbol{g}} \circ \boldsymbol{\delta}^g + \textstyle\sum_{p=1}^{P} \boldsymbol{d}_p \circ \boldsymbol{x}_p^b \leq \overline{\boldsymbol{g}} \tag{196}$$

$$\boldsymbol{x}^a - \underline{\boldsymbol{g}} \circ \boldsymbol{\delta}^g + \textstyle\sum_{p=1}^{P} \boldsymbol{d}_p \circ \boldsymbol{x}_p^b \geq \mathbf{0}_{H,1} \tag{197}$$

$$\boldsymbol{x}^a - \boldsymbol{x}^{g\delta} + \underline{\boldsymbol{g}} \circ \boldsymbol{\delta}^g + \textstyle\sum_{p=1}^{P} \boldsymbol{d}_p \circ \boldsymbol{x}_p^b \geq \underline{\boldsymbol{g}} \tag{198}$$

$$\boldsymbol{x}^a - \boldsymbol{x}^{g\delta} + \overline{\boldsymbol{g}} \circ \boldsymbol{\delta}^g + \textstyle\sum_{p=1}^{P} \boldsymbol{d}_p \circ \boldsymbol{x}_p^b \leq \overline{\boldsymbol{g}}. \tag{199}$$

Note that in (191) and (193) we introduce the scalar auxiliary variable α to move the uncertain parameters from objective function to inequality constraints. Similarly, we introduce vector $\boldsymbol{x}^b \triangleq \left[\boldsymbol{x}_1^b; \dots; \boldsymbol{x}_p^b; \dots; \boldsymbol{x}_P^b\right]$ collecting P column vectors of H auxiliary variables $\boldsymbol{x}_p^b \triangleq \left[x_p^b(1); \dots; x_p^b(h); \dots; x_p^b(H)\right]$ $(p \in \mathcal{P})$ to preserve uncertain parameters in the LHS of constraints.

Assuming that optimization input parameters take the values defined by (125), we first replace the nominal value of the PH parameters $d_p(h)$ $(h \in \mathcal{H}, p \in \mathcal{P})$ with its deviated value $\tilde{d}_p(h)$ in all the minority (193), (194), (196), (198) and majority inequalities (195), (197), (199). Then, getting inspiration from the cardinality-constrained approach proposed in [337], for a fixed $\Gamma_0 \in [0, PH]$, we impose that only a subset of these parameters vary to adversely affect the solution. Finally, for each of the above mentioned constraints, the final mathematical expression is resorted as a summation of two main terms, one related to the deterministic function, and the second called protection function, with all sub-terms including the variation of the uncertain parameter (i.e., $\hat{d}_p(h), h \in \mathcal{H}, p \in \mathcal{P}$).

Summing up, the corresponding robust counterpart of the deterministic formulation (191)-(199) is given by the following non-linear optimization problem:

$$\min_{\substack{x^l,x^p,x^v,x^{v\delta},x^s,x^{s\delta},x^{g\delta},\\ x^a,\delta^v,\delta^s,\delta^g,\alpha,x^b}} \alpha \tag{200}$$

s.t. (64)-(70), (72)-(74), (77)-(83), (85)-(87),

(90)-(96), (99)-(101), (103), (106)-(108), and

$$c\left(\boldsymbol{x}^{g\delta}, \boldsymbol{x}^a\right) - \alpha + \beta(\boldsymbol{x}^a, \Gamma_0) \leq 0 \tag{201}$$

$$\sum_{p\in\mathcal{P}} d_p(h)\, x_p^b(h) + x^a(h) + \gamma_h(\boldsymbol{x}^b, \Gamma_0) \leq \overline{g}(h), h \in \mathcal{H} \tag{202}$$

$$\sum_{p\in\mathcal{P}} d_p(h)\, x_p^b(h) + x^a(h) - \gamma_h(\boldsymbol{x}^b, \Gamma_0) \geq \overline{g}(h),\ h \in \mathcal{H} \tag{203}$$

$$\begin{gathered} x^a(h) + \overline{g}(h)\delta^g(h) + \sum_{p=1}^{P} d_p(h) x_p^b(h) \\ +\gamma_h(\boldsymbol{x}^b, \Gamma_0) \leq \overline{g}(h),\ h \in \mathcal{H} \end{gathered} \tag{204}$$

$$\begin{gathered} x^a(h) - \underline{g}(h)\delta^g(h) + \sum_{p=1}^{P} d_p\,(h) x_p^b(h) \\ -\gamma_h(\boldsymbol{x}^b, \Gamma_0) \geq 0, h \in \mathcal{H} \end{gathered} \tag{205}$$

$$\begin{gathered} x^a(h) - x^{g\delta}(h) + \underline{g}(h)\delta^g(h) + \sum_{p=1}^{P} d_p\,(h) x_p^b(h) \\ -\gamma_h(\boldsymbol{x}^b, \Gamma_0) \geq \underline{g}(h), h \in \mathcal{H} \end{gathered} \tag{206}$$

$$\begin{gathered} x^a(h) - x^{g\delta}(h) + \overline{g}(h)\delta^g(h) + \sum_{p=1}^{P} d_p\,(h) x_p^b(h) \\ +\gamma_h(\boldsymbol{x}^b, \Gamma_0) \leq \overline{g}(h), h \in \mathcal{H} \end{gathered} \tag{207}$$

where the protection function of the objective $\beta(\boldsymbol{x}^a, \Gamma_0)$ is defined in (133) and the protection functions of the inequality constraints $\gamma_h\left(\boldsymbol{x}^b, \Gamma_0\right)$ is defined as $\gamma_h(\Gamma_0)$ $(h \in \mathcal{H})$ in (134) (here (192) is used for the sake of notation simplicity).

Finally, removing unnecessary variables α and $\boldsymbol{x}^b$, it is straightforward transforming (200)-(207) into (126)-(132).

We finally remark that, in this formulation, the approach proposed in [337] is slightly modified. First, in [337] the uncertainty is modeled constrain-wise (i.e., perturbations of uncertain parameters in different constraints are not linked to each other). This allows defining for each constraint an individual budget of uncertainty, which represents the deviation allowed to the uncertain parameters affecting the given constraint. Conversely, in (200)-(207) only one Γ_0 is introduced to denote the total budget of uncertainty for all the parameters. In effect, the PH uncertain parameters $d_p(h)$ $(h \in \mathcal{H}, p \in \mathcal{P})$ simultaneously affect all the constraints (193)-(199). Second, in [337] there are as many separated protection functions as the unlinked constraints. On the other hand, in the above-defined approach, the definition of protection function in (133)-(136) is coupled to ensure the maximum variation for the entire set of uncertainty sources over the whole time horizon.

Appendix B

In this appendix, we provide the mathematical steps employed in transforming the robust counterpart from the min-max formulation (126)-(132) to the MIQP form (137)-(147).

We preliminarily note that (133)-(136) define a multi-objective optimization problem that aims at determining the portions $\Gamma_1, \ldots, , \Gamma_h, \ldots, \Gamma_H$ of the uncertainty budget Γ_0 over all the time slots, which simultaneously maximize the values of the protection functions in the objective and constraints affected by uncertainty. This is formally expressed in the following lemma.

Lemma 1 (Protection functions as a solution of a multi-objective linear programming problem) - Protection functions $\beta(\boldsymbol{x}^a, \Gamma_0)$ and $\gamma_h(\Gamma_0)$ $(h \in \mathcal{H})$ defined in (133)-(136) equal to the optimal values of the objective functions in the following optimization problem:

$$\max_{\substack{\boldsymbol{u}_1,\ldots,\\ \boldsymbol{u}_H,\Gamma_1,\\ \ldots,\Gamma_H}} \begin{bmatrix} \sum_{h\in\mathcal{H}} 2k^+(h)|x^a(h)| \sum_{p\in\mathcal{P}} u_p(h)\hat{d}_p(h) \\ \sum_{p\in\mathcal{P}} u_p(1)\, \hat{d}_p(1) \\ \vdots \\ \sum_{p\in\mathcal{P}} u_p(H)\, \hat{d}_p(H) \end{bmatrix} \tag{208}$$

$$\text{s.t. } 0 \le u_p(h) \le 1, p \in \mathcal{P}, h \in \mathcal{H} \tag{209}$$

$$\sum_{p\in\mathcal{P}} u_p(h) \le \Gamma_h, h \in \mathcal{H} \tag{210}$$

$$0 \le \Gamma_h \le P, h \in \mathcal{H}, \sum_{h\in\mathcal{H}} \Gamma_h = \Gamma_0. \tag{211}$$

Proof: The optimal solution of (208)-(211) consists in the optimal allocation $\Gamma_1^*, \ldots, \Gamma_H^*$ (whose values are not necessarily integer) of the uncertainty budget Γ_0 among all the H slots in the time window $\mathcal{H}$ and, for each time slot $h \in \mathcal{H}$, the optimal assignment of supporting variables $u_1^*(h), \ldots, u_P^*(h)$ representing the levels of variation related to all the P uncertainty sources in $\mathcal{P}$. For each $h \in \mathcal{H}$, $\lfloor \Gamma_h^* \rfloor$ of these variables are equal to 1, one of these is equal to $\Gamma_h^* - \lfloor \Gamma_h^* \rfloor$, and the remaining ones are equal to zero. This is equivalent to the selection of subsets $\{\mathcal{Q}_h \cup \{q_h\} | \mathcal{Q}_h \subseteq \mathcal{P}, |\mathcal{Q}_h| = \lfloor \Gamma_h \rfloor, q_h \in \mathcal{P} \backslash \mathcal{Q}_h\}$ $(h \in \mathcal{H})$ with corresponding cost functions in the arguments of (133) and additional constraints $\sum_{h\in\mathcal{H}} \Gamma_h = \Gamma_0$ and $0 \le \Gamma_h \le P, h \in \mathcal{H}$.□

We finally state the cornerstone of our investigation.

Theorem 1 (Robust counterpart as a MIQP problem) – Robust counterpart (126)-(132) has the equivalent MIQP formulation (137)-(147).

Proof: Preliminarily, we consider the dual of (208)-(211) based on the duality theory for multi-objective optimization [388]:

$$\min_{\substack{\Lambda\in\mathbb{R},\boldsymbol{\lambda}\in\mathbb{R}^H,\\ \Theta_{11},\ldots,\Theta_{1H},\ldots,\\ \Theta_{P1},\ldots,\Theta_{PH}\in\mathbb{R},\\ \boldsymbol{\theta}_{11},\ldots,\boldsymbol{\theta}_{1H},\ldots,\\ \boldsymbol{\theta}_{P1},\ldots,\boldsymbol{\theta}_{PH}\in\mathbb{R}^H}} \begin{bmatrix} \Gamma_0\Lambda + \sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\Theta_{ph} \\ \Gamma_0\lambda(1) + \sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\theta_{ph}(1) \\ \vdots \\ \Gamma_0\lambda(H) + \sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\theta_{ph}(H) \end{bmatrix} \tag{212}$$

$$\text{s.t. } w_0\Lambda + \boldsymbol{w}^T\boldsymbol{\lambda} \geq 0 \tag{213}$$

$$w_0\Theta_{ph} + \boldsymbol{w}^T\boldsymbol{\theta}_{ph} \geq 0, p\in\mathcal{P}, h\in\mathcal{H} \tag{214}$$

$$\begin{aligned} & w_0\big(\Lambda + \Theta_{ph} - 2k^+(h)\hat{d}_p(h)|x^a(h)|\big) \\ & +\boldsymbol{w}^T\big(\boldsymbol{\lambda} + \boldsymbol{\theta}_{ph} - \widehat{\boldsymbol{d}}_p\big) \geq 0, p\in\mathcal{P}, h\in\mathcal{H}. \end{aligned} \tag{215}$$

where the previously defined parameters $w_0, w_1, \ldots, w_H$ correspond to the $(H+1)$ weights associated to the components in the mapping argument of (208). Note that in (212)-(215) we denote the $(H+1)$ dual variables of (210)-(211) (which can be compactly written as $\sum_{h\in\mathcal{H}}\sum_{p\in\mathcal{P}}u_p(h) \leq \Gamma_0$) as $\Lambda\in\mathbb{R}, \boldsymbol{\lambda}\in\mathbb{R}^H$ and the $(H+1)HP$ dual variables of (209) as $\Theta_{11},\ldots,\Theta_{PH}\in\mathbb{R}, \boldsymbol{\theta}_{11},\ldots,\boldsymbol{\theta}_{PH}\in\mathbb{R}^H$.

By theorem of strong duality for multi-objective optimization [388], optimal values of objective functions in (212)-(215) and (208)-(211) coincide. Using Lemma 1, the protection functions $\beta(\boldsymbol{x}^a,\Gamma_0)$ and $\gamma_h(\Gamma_0)$ $(h\in\mathcal{H})$ equal to the optimal values of the objective functions in (212)-(215).

Let us define a new supporting variables vector $\boldsymbol{y} \triangleq |\boldsymbol{x}^a|$ by introducing the inequality constraints defined in (147). Consequently, (215) can be rewritten as:

$$\begin{aligned} & w_0\left(\Lambda + \Theta_{ph} - \tfrac{1}{2}k^+(h)\hat{d}_p(h)y(h)\right) \\ & +\boldsymbol{w}^T\big(\boldsymbol{\lambda} + \boldsymbol{\theta}_{ph} - \widehat{\boldsymbol{d}}_p\big) \geq 0, p\in\mathcal{P}, h\in\mathcal{H}. \end{aligned} \tag{216}$$

Finally, replacing (212)-(214) and (216) into (126)-(132), we obtain that (126)-(132) is equivalent to MIQP problem (137)-(147).□

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