Distributed Control, Optimization, Coordination of Smart Microgrids

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CHAPTER 1

Introduction

Microgrids are power distribution systems typically classified by Direct Current (DC) and Alternating Current (AC) networks and are interconnected clusters of Distributed Generation Units (DGUs), loads and energy storage devices. Due to the technological developments and politics for environmental protection, renewable generation sources and new loads such as Electric Vehicles (EVs) are largely implemented in power systems. Renewable generation sources generally reduce the cost of electricity generation and provide clean energy for customers. However, renewable generation sources are uncontrollable and should be managed as the uncertainty of generation side in addition to the uncertainty of load side. Power networks traditionally tackled the uncertainty of loads via adjusting the controllable generations. However, thanks to the increased share of renewable generations and large scale introduction of new loads such as EVs, new control strategies are required to address the uncertainties of power networks. The integration of smart sensors and meters, advanced two-way communication technologies, distributed control strategies, and IT-infrastructures can be utilized to promote the control strategies to address the uncertainties of power networks.

The chapter is organized as follows. The background and problem statement are presented in Section 1.1. In Section 1.2, the literature is reviewed. In Section 1.3, the contributions and thesis outline are presented. In Section 1.4, the relations between the chapters are presented. The list of publications and notations are presented in Sections 1.5 and 1.6, respectively.

1.1 Background and Problem Statement

Microgrid networks are typically classified by DC and AC networks, which are interconnected clusters of Distributed Generation Units (DGUs), loads and energy storage devices. Power networks can be modeled by dynamical systems affected by external disturbances such as loads and uncontrolled generations.

In DC power networks, in order to guarantee a proper and safe functioning of the overall network and the appliances connected to it, the main goal is voltage stabilization (see for instance [1–10]). Moreover, as different DGUs may generally have different generation (or storage) capacities, an additional goal is to (fairly) share the total demand of the network among its DGUs (see for instance [11–15]). This goal is usually called power or current sharing and its achievement does not generally permit to regulate the voltage at each node towards the corresponding pre-specified reference value. Consequently, different forms of voltage regulation have been proposed in the literature, where for instance the average value of the voltages of the whole microgrid is controlled towards a desired setpoint (see for instance [12–14]). Moreover, it is well known that electric loads are in practice *time-varying* and, due to the random and unpredictable diversity of usage patterns, it is more realistic to consider unknown *time-varying* loads described for instance by dynamical systems or *stochastic* processes. Therefore, the first problem is achieving (average) voltage regulation (and current sharing) in DC power networks with *time-varying* or *stochastic* loads and renewable sources.

In AC power networks, the supply-demand mismatch induces frequency deviations from the nominal value, eventually leading to fatal stability disruptions [16,17]. Therefore, reducing this deviation is of vital importance for the overall network resilience and reliability, attracting a considerable amount of research activities on the design and analysis of the so-called Load Frequency Control (LFC), also known as Automatic Generation Control (AGC), where a suitable control scheme continuously changes the generation setpoints to compensate supply-demand mismatches, regulating the frequency to the corresponding nominal value (see for instance [16,17] and the references therein). Moreover, besides ensuring the stability of the overall power infrastructure, in order to solve the so-called economic dispatch problem [18], modern control schemes aim also at reducing the operational costs associated to the LFC. In the literature (see for instance [18–21] and the references therein), this control objective is referred to as *Optimal* LFC (OLFC). Nowadays, renewable energy sources and *new* loads such as EVs are an integral part of the power infrastructure. As a consequence, unavoidable uncertainties are sharply increasing and may put a strain on the system stability. For this reason, the resilience and reliability of the power grid may benefit from the design and analysis of control strategies that theoretically guarantee the system stability in presence of *time-varying* loads and renewable sources. Thus, the second problem is achieving LFC and OLFC in AC power networks with the *time-varying* loads and renewable sources.

Microgrids are power distribution systems which include controllable loads and Distributed Energy Resources (DERs). Controllable loads can work with or without the main grid and DERs are integrated with Distributed Generations (DG) includes PhotoVoltaics (PV), Wind Turbines (WT), and Distributed Storage (DS) [22]. An Energy Management Strategy (EMS) is required in microgrids to control the power flows among different buses (nodes). An EMS should provide the operational goals of the microgrid such as the minimization of costs and supplying the demanded loads. Typically, a nonlinear optimization problem is used to model the microgrid energy management where usually it is assumed that we have a perfect prediction of the loads and renewable sources. Thus, commonly an offline optimization approach is utilized to address the energy management problem. However, the uncertainties of the loads, renewable sources, and market do not let us have a perfect prediction of them [23]. Moreover, *new* loads such as EVs insert more uncertainties to the microgrids. Hence, the third problem is achieving a distributed optimal EMS in smart microgrids with *stochastic* loads and underlying distribution network constraints.

Moreover, microgrids are energy systems typically composed of a Transmission System Operator (TSO), Distribution System Operators (DSOs), and buildings [24]. In the power networks, DSOs have the task of active distribution systems management with high penetration renewable generations [25]. However, DSOs may miss scheduling data or even be bypassed by TSOs. Therefore, the DSO requires a control method to operate as the system operator. Thanks to the uncertainties of the power network such as loads or renewable sources, the frequency may deviate from its nominal values; therefore, a control strategy is required for the regulation of frequency [26]. The frequency regulation is traditionally obtained via the control of generated power [27] while the building decisions are not considered. In order to take advantage of building units, it is required to separate the building dynamics from the microgrid dynamics. Then, it is possible to present a control strategy achieving the frequency control and minimizing the costs of different units in the power network [28]. However, the large scale introduction of EVs and penetration of renewable energy sources challenge the stability of power networks controlled by the current control strategies. The smart charging of EVs can potentially provide flexibility to address the stability challenges in the power network where EVs' batteries operate as the energy storage devices for the power network [29,30]. More precisely, in smart charging of EVs when the demanded load is lower than the generated power, the EVs charge their batteries (Grid-to-Vehicle or G2V mode) and when the demanded load is higher than the generated power, the EVs discharge their batteries to the power network (Vehicle-to-Grid or V2G mode). In smart charging, an aggregator coordinates the charging and discharging schedule of EVs to satisfy the utility of EVs and provide ancillary services [24, 29]. However, the social behavior of EV drivers, *i.e.*, the extent to which EV drivers are willing to use smart charging, is a vital factor the smart charging which should be taken into account. Specifically, we need to study whether EV drivers are willing to have their batteries used as energy storage devices and which factors influence their willingness. Thus, the fourth problem is achieving an optimal control strategy in smart microgrids with considering the social behavior of EV drivers to use smart charging.

1.2 Literature Review

In this section, we firstly present a literature review for control of smart microgrids composed of DC and AC power networks. Then, we bring a literature review for optimal energy management in smart microgrids consisting optimal microgrid energy management and optimality and social behavior of EV drivers.

1.2.1 Control of smart microgrids

Smart microgrid networks are typically classified by DC and AC networks, which are interconnected clusters of Distributed Generation Units (DGUs), loads and energy storage devices. In this subsection, we present literature reviews for control of DC and AC networks.

DC networks

The recent wide spread of renewable energy sources, electronic appliances and batteries (including for instance EVs) motivates the design and operation of DC networks, which are generally more efficient and reliable than AC networks, attracting growing research interest [3].

In [1], a nonlinear passivity-based control (PBC) scheme for power converters with constant loads is proposed, where the Brayton–Moser theory is used to tune the control parameters. A robust decentralized voltage control scheme is presented in [5] for islanded DC microgrids, where the current loads are assumed to be measurable. A nonlinear adaptive control scheme is designed in [7] to increase the stability margin of DC power neworks with unknown constant power loads. An input-to-state stability (ISS)-like Lyapunov function is obtained and used for control design in [8], ensuring voltage stability in DC microgrids with known constant loads. A robust and decentralized passivity-based control technique for solving the voltage regulation problem in DC networks including boost converters with unknown constant impedance (Z), current (I), and power (P) loads is proposed in [9]. In [10], the authors study the conditions under which voltage PI controllers (locally) passivate the generation units and the constant ZIP loads. A passivity-based control technique is proposed in [31] to achieve (global) voltage regulation in DC networks with unknown constant ZIP loads. In [32], a systematic and constructive design based on the port-Hamiltonian framework is proposed. However, all these works provide stability guarantees only in presence of constant load components, while loads are in practice *time-varying*.

In all these works the load components are assumed to be constant. However, it is well known that electric loads are in practice *time-varying* and, due to the random and unpredictable diversity of usage patterns, it is more realistic to consider unknown *time-varying* loads described for instance by dynamical systems or *stochastic* processes (see for instance [33–35]). A cascade control system for the energy management of DC microgrids with I loads is presented in [36], where the proposed control scheme includes an adaptive estimation of the quasi-*stochastic* load current profiles. In [37], a droop control scheme is designed for DC microgrids with *stochastic* Z loads. Moreover, in some papers, the *Stochastic* Differential Equations (SDEs) have been used for modeling the loads and other uncertainties in power system networks (see for instance [38–40]). In [38], the random load characteristic is considered to develop a *stochastic* model for voltage stability analysis. A *stochastic* power system model based on *stochastic* differential equations is presented in [39] to consider the uncertain factors such as load levels and system faults. In [40], a systematic and general approach to model power systems as continuous *stochastic* differential-algebraic equations is proposed and it justifies the need for *stochastic* models in power system analysis. Additionally, [35,41] for AC networks and [42,43] for DC networks consider *time-varying* loads. More precisely, [42] presents a design methodology based on Hamiltonian surface shaping and power flow control for a hierarchical control scheme that regulates renewable energy sources and energy storage in DC microgrids. A control scheme for two interconnected Boost DC-to-DC power converters feeding a *time-varying* current demand is proposed in [43]. However, the two latter works do not provide any stability or convergence guarantee.

AC networks

Traditionally, an AC power network is subdivided in the so-called *control areas*, each of which represents an electric power system or combination of electric power systems to which a common LFC scheme is applied [44, 45]. The LFC problem is usually addressed at each control area by primary and secondary control schemes. More precisely, the primary control layer preserves the stability of the power system acting faster than the secondary control layer, which typically provides the generation setpoints to each control area [18]. Then, in order to obtain OLFC, a tertiary control layer can be used to reduce the generation costs in slow timescales. To tackle the same problem in fast timescales, distributed control schemes are usually adopted, where the control areas cooperate with each other [46]. For the latter case, there exist generally two types of control approaches: consensus-based protocols or primal-dual algorithms. By using the first approach, all the control areas that exchange information through a communication network achieve the same marginal cost, solving the OLFC problem typically in absence of constraints [41, 47–56]. The second approach performs OLFC by solving an optimization problem that may potentially include constraints for instance on the generated or exchanged power [19, 20, 57–67]. In the following, we briefly discuss some of the relevant works in the literature on the design and analysis of control schemes achieving LFC and OLFC.

In [68–71], different control schemes for solving the LFC problem in presence of constant loads are proposed. More precisely, in [68] and [69], distributed PI droop controllers are designed, while stability conditions for droop controllers are investigated in [70], where the well-known port-Hamiltonian framework is used. Based on the sliding mode control methodology, a decentralised control scheme is proposed in [71], where besides frequency regulation, the power flows among different areas are maintained at their scheduled values. In [18, 21, 46, 49, 57, 72–75], different control schemes for solving the OLFC problem in presence of constant loads are proposed. More precisely, a distributed passivity-based control scheme is proposed in [18], where the voltages are assumed to be constant. A distributed sliding mode control strategy is proposed in [21], where, although the robustness property of sliding mode is able to face *time-varying* loads, the stability of the desired equilibrium point is established under the assumption of constant loads only. A hierarchical control scheme is proposed in [46], while decentralized integral control and distributed averaging-based integral control schemes are proposed in [49]. In [57], the convergence is proved under the assumptions of convex cost functions and known power flows, while a gradient-based approach is proposed in [72]. A linearized power flow model is adopted in [73], while a primal-dual approach is proposed in [74], where an aggregator collects the frequency measurements from all the control areas in order to compute and broadcast the generation setpoints to each control area. A real-time bidding mechanism is developed in [75].

Nowadays, renewable energy sources and *new* loads such as EVs are an integral part of the power infrastructure. As a consequence, unavoidable uncertainties are sharply increasing and may put a strain on the system stability. For this reason, the resilience and reliability of the power grid may benefit from the design and analysis of control strategies that theoretically guarantee the system stability in presence of *time-varying* or *stochastic* loads and renewable sources. Although the present control strategies with constant uncontrolled power injections (*i.e.*, the difference between the power generated by the renewable energy sources and the one absorbed by the loads) are efficient to deal with LFC problem, they cannot operate properly in practice with *time-varying* or *stochastic* renewables and loads and more advanced methods are required [76]. However, most of the recent papers consider constant loads for OLFC problem [18, 21, 46, 49, 57, 68–70, 72–75]. In most of the recent papers (see for instance [18, 21, 71, 74, 75]), the loads are assumed to be constant but it is well known that the loads are *time-varying* in practice and it is more realistic to model the loads as dynamic systems. To do this, an internal model approach is proposed in [41], where the loads behaviour is described as the output of a dynamical exosystem, as it is customary in output regulation theory [77, 78] which takes into account the *time-varying* load and voltage dynamics. However, in [41] the turbine governor dynamics are neglected, while it is generally important in terms of tracking performance to describe the generation side in a satisfactory level of detail. Moreover, the exosystem model adopted in [41] to describe the load dynamics is linear, assumed to be incrementally passive, generally does not allow to achieve OLFC and depends on some predefined constant matrices.

1.2.2 Optimal energy management in smart microgrids

In this subsection, we present literature reviews for optimal microgrid energy management and optimality and social behavior of EV drivers.

Optimal microgrid energy management

In [79–82], online algorithms for real-time energy management systems are proposed to address the uncertainties of loads and renewable generation sources. These papers propose the algorithms which do not need a prior statistical knowledge of the loads. However, in real-time approach, we have many communicational challenges especially in the case of having numerous variable loads. Moreover, we may not be able to measure all of the loads in microgrids and it is too expensive to install smart meters for all of the loads. Therefore, there are not enough infrastructures for implementation of the online EMS in many microgrids. In [83], a Security Constrained Unit Commitment (SCUC) algorithm adopting the battery storages to make the wind farms dispatchable is proposed. In latter method, for each wind generation unit, a battery storage is considered such that they are connected to one bus. The variations of the wind farms are controlled via programming the charge and discharge of the batteries. However, the latter method does not provide a distributed algorithm and does not consider the underlying power flow constraints. In [84], a SCUC method for ac-dc grids is presented which applies the Conditional Value-at-Risk (CVaR) to carry out the issue of the renewable and load fluctuations. The latter algorithm employs l_1-norm approximation to relax the nonconvex optimization problem. This relaxation makes the optimization problem nonexact and the optimal value of relaxed problem may not be the same as the nonconvex one. A two-stage robust SCUC algorithm is introduced in [85] to tackle the problem of wind power uncertainty and the Column and Constraint Generation (C&CG) method is utilized to address a large number of second-stage constraints in SCUC. Nonetheless, the convergence speed can be slow thanks to a large number of vertices; thus, the latter algorithm has high computational cost. A fully parallel stochastic SCUC method is introduced in [86] as a nonconvex optimization problem and addressed by decomposing the problem into three solution modules through the Auxiliary Problem Principle (APP). These three modules are solved in a parallel manner. Although the latter paper has proposed a fully parallel SCUC algorithm, there is no convergence proof for such nonconvex Mixed Integer Programming (MIP) problem.

It is well known that electric loads are in practice *stochastic* thanks to the random and unpredictable diversity of usage patterns. However, most of the recent papers do not consider exact stochastic models for the loads (see for instance [22, 23, 79]) and do not consider the underlying power flow constraints with a distributed structure (see for instance [83–86]). Furthermore, in the stochastic EMS, it is crucial how to simulate the randomness. It is a custom to assume that the randomness has a certain distribution and apply Monte Carlo approach to produce simulation data. However, the stochastic loads have time-series scenarios with self-correlation in time. Hence, the simulation data should be generated based on the transformation process of the randomness over time [87].

Optimality and social behavior of EVs

A centralized model predictive control (MPC) is proposed in [24] to optimize control variables over a common time horizon, considering the potential role of individual buildings in frequency control of the power system, by introducing electrical energy storage units. In [88, 89], V2G-based strategies stabilizing a power grid with large-scale Renewable Energy Sources (RESs) are introduced. A decision-making strategy considering the State of Charge (SoC) of the EVs, time of day, electricity price and EV charging requirements is introduced in [90]. In [91], a method that takes advantage of V2G is proposed to evaluate the resulting changes in generation dispatch and emissions. The advantages of the smart charging are studied in [92], where the degradation rate of EVs' batteries is considered. In [93], the effects of combined driving and V2G option on the lifetime performance of EVs' batteries are investigated. In [94], the benefits and challenges of V2G technology are reviewed and the optimization techniques obtaining different V2G objectives with multiple constraints are summarized. Bidirectional AC-DC and DC-DC converters are proposed in [95] to transfer electrical power via V2G and G2V modes of EVs where a Proportional Integral (PI) controller is deployed for the (dis)charging current and voltage control of EVs. In [96], a qualitative review of policies for integrating EVs in the grid is reviewed and three policy strategies composed of cost-reflective pricing, intelligent technology and integrated infrastructure planning are proposed to address the environmental and economic issues in power networks. In [97], the most popular variants of V2G option for EVs are reviewed and their viability are investigated. In [98], the implementation impacts, requirements, benefits, challenges and strategies of V2G and G2V technologies of EVs for distributed systems are studied. The impacts of operating costs and market rules in power networks are investigated in [99] via developing a centralized V2G system. In [100], an optimal pricing mechanism based on the consumers' demand and social welfare is proposed for the V2G technology. A method deploying the V2G option of EVs for frequency regulation on a daily basis and peak reduction on days with high electricity demand is proposed in [101].

Having the battery of your EV used as an energy storage device means that when energy demand is high, electricity can be used from the battery instead of the grid. That way, peak energy demand can be reduced. To meet peak energy demand often peak power load plants are used, that emit more CO2 emissions than base load power plants [102–104]. Therefore, reducing peak demand can reduce CO2 emissions and contribute to reducing environmental problems. But having the battery of your EV used as an energy storage device may degrade the quality of the battery. If the quality of the battery of the EV degrades, the charge level of the EV may reduce which in turn reduces the range of the EV. With a lower range, the distance a fully charged EV can drive is lower. The range of the EV is an important factor influencing the adoption of an EV. Indeed, range anxiety (*i.e.*, the extent to which people are uncertain about the charge levels of their EVs) is a barrier to EV adoption [105]. Furthermore, a study using a discrete choice experiment suggests that range anxiety is an important determinant of the willingness to use V2G [106]. Specifically, the stronger one's range anxiety, the less willing one is to use V2G. After all, if drivers are afraid that the range of their EV may not be sufficient, they are less likely to have energy from their battery used which will decrease their EV range. However, this study hardly included EV drivers. The question remains whether range anxiety also reduces the willingness to smart charge among EV drivers. We hypothesize that the stronger one's range anxiety, the less willing one is to have his EV battery used as an energy storage device.

As explained above, having the battery of your EV used as an energy storage device can contribute to reducing environmental problems. An important predictor of pro-environmental behavior is environmental self-identity. Environmental self-identity refers to the extent to which people see themselves as a pro-environmental person [107]. Researches have shown that environmental considerations influence whether people are willing to adopt EVs [108]. Furthermore, researches suggest that environmental considerations also influence the acceptance of smart charging [109]. However, it is unclear whether environmental self-identity is related to smart charging. We hypothesize that the stronger one's environmental self-identity, the more likely one is willing to have the battery of his EV used as an energy storage device.

1.3 Contributions and Thesis Outline

Nowadays, renewable energy sources and *new* loads such as EVs are an integral part of the power infrastructure. As a consequence, unavoidable uncertainties are sharply increasing and may put a strain on the system stability. For this reason, the resilience and reliability of the power grid may benefit from the design and analysis of control strategies that theoretically guarantee the system stability in presence of *time-varying* or *stochastic* loads and renewable sources. Although the present control strategies with constant loads are efficient to deal with different control objectives in power networks, they cannot operate properly in practice with *time-varying* or *stochastic* renewables and loads and more advanced methods are required [76]. In this thesis, we propose various control schemes to ensure stability and achieve voltage regulation in DC networks and LFC in AC networks including *time-varying* or *stochastic* loads. Indeed, we use output regulation methodology for control design when we model the loads as dynamical systems and we use Ito calculus framework when we model the loads by stochastic processes. Moreover, an EMS taking into account *stochastic* loads and system operational constraints in a microgrid is presented. Also, a MPC based control scheme considering the social behavior of the EV drivers via a corresponding real data set is proposed. We list the contributions of the thesis as follows:

- We model each component of the ZIP load in DC power networks as the sum of an unknown constant and the solution to a stochastic differential equation describing the load dynamics. Then, sufficient conditions for the stochastic passivity of the open-loop system are presented, facilitating the interconnection with passive control systems and the asymptotic stochastic stability of the power network controlled by the distributed control scheme proposed by [14] is proved.

- We formulate the voltage control problem in DC power networks including *time-varying* loads as a standard output regulation problem. Then, we consider *time-varying* impedance and current load components where each load component is described as the output of a nonlinear dynamical exosystem, as it is customary in output regulation theory [77,78]. Next, we propose a control scheme achieving voltage regulation and ensuring the stability of the overall network.

- We formulate the voltage control problem in DC power networks including *time-varying* and *uncertain* constant loads as a robust output regulation problem. Then, we consider superposition of *time-varying* and *uncertain* constant ZIP load components where each time-varying component of the load is described as the output of a dynamical exosystem, as it is customary in output regulation theory [77,78]. Next, we propose control schemes achieving voltage regulation and ensuring the local robust stability of the overall network including *time-varying* and *uncertain* constant ZIP loads. Then, we propose a control scheme achieving voltage regulation and ensuring the global robust stability of the overall network including *time-varying* and *uncertain* constant ZI loads.

- We formulate the LFC problem for nonlinear AC power networks including *time-varying* uncontrolled power injections (*i.e.*, the difference between the power generated by the renewable energy sources and the one absorbed by the loads) as a standard output regulation problem [77,78]. Then, the *time-varying* uncontrolled power injections are described as the outputs of nonlinear dynamical exosystems, as it is customary in output regulation theory [77,78]. Next, we propose a control scheme based on the classical output regulation theory for solving the conventional LFC problem in presence of *time-varying* uncontrolled power injections, ensuring the stability of the overall network. Then, we use an approximate output regulation method for solving an *approximate* OLFC problem in presence of *time-varying* uncontrolled power injections, ensuring the stability of the overall network.

- We formulate the EMS problem in microgrids as a nonconvex optimization problem taking into account the loads, power flows, and system operational constraints in a distribution network such that the costs of the DGs, DSs and energy purchased from the main grid are minimized and the customers' demanded loads are provided where the loads are considered stochastic generated by a time-homogeneous Markov chain. Next, we relax the nonconvex constraints to obtain a convex optimization problem according to the conditions provided in [110,111] for the exactness of this convexification. Then, to handle the customers' privacy, communication challenges, and high computational burdens of centralized optimization, we decompose the centralized optimiza-

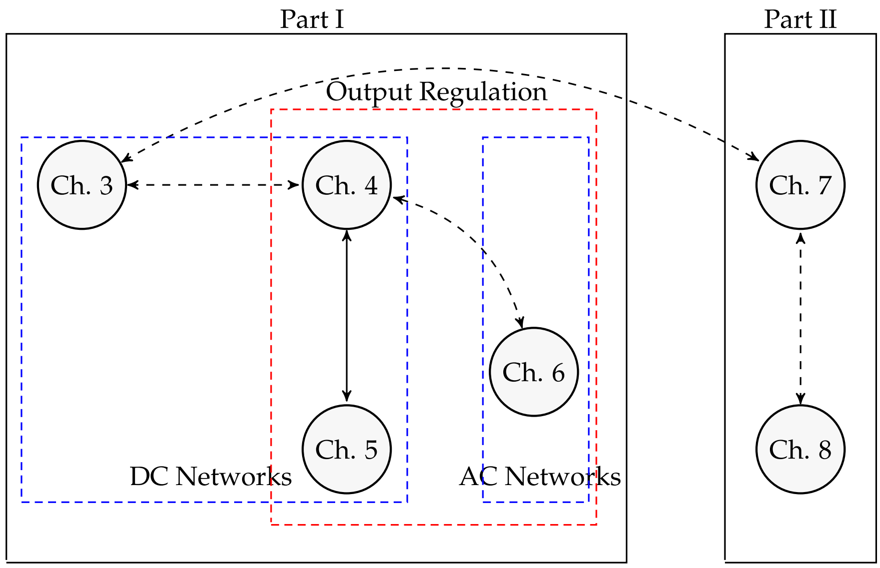

Figure 1.1: Graph of relations between chapters. Solid lines show strong relations and dashed lines represent weaker relations.

tion problem into a distributed problem via the Predictor Corrector Proximal Multiplier (PCPM) method proposed by [122].

- We exploit the dynamical Buildings-to-Grid (BtG) framework introduced by [24], integrating TSO, DSO networks, and buildings where EVs are considered instead of batteries. Then, we use a data set about EV drivers' social behavior to model the willingness of EV drivers for using smart charging via a probability variable. Finally, we propose a MPC strategy to achieve frequency regulation while minimizing the costs of power generations, buildings and EVs in the power network.

1.4 Relations Between Chapters

To summarize, Chapter 2 presents the preliminaries for the rest of this thesis. The voltage regulation in DC networks is the main topic of Chapters 3, 4 and 5, where the load components are described by SDEs in Chapter 3 and by *time-varying* exosystems in Chapters 4 and 5. The load frequency control in AC networks including *time-varying* loads is studied in Chapter 6. An energy management strategy in microgrids with stochastic loads and MPC based strategy considering the social behavior of EV drivers are presented in Chapters 7 and 8, respectively. Finally, the conclusions and future research are provided in Chapter 9. The relations between the chapters of this thesis are depicted in Figure 1.1.

1.5 List of Publications

Journal articles

[1] A. Silani and M. J. Yazdanpanah, "Distributed Optimal Microgrid Energy Management with Considering Stochastic Load," *IEEE Transactions on Sustainable Energy*, vol. 10, no. 2, pp. 729-737, 2019.

[2] A. Silani, M. Cucuzzella, J. M. A. Scherpen, and M. J. Yazdanpanah, "Output Regulation for Voltage Control in DC Networks with Time-Varying Loads," *IEEE Control Systems Letters*, vol. 5, no. 3, pp. 797-802, 2021.

[3] A. Silani, M. Cucuzzella, J. M. A. Scherpen, and M. J. Yazdanpanah, "Robust Output Regulation for Voltage Control in DC Networks with Time-Varying Loads," Submitted.

[4] A. Silani, M. Cucuzzella, J. M. A. Scherpen, and M. J. Yazdanpanah, "Output Regulation for Frequency Control with Time-varying Loads," Submitted.

[5] A. Silani, E. Van der Werff, M. Cucuzzella, K. C. Kosaraju, J. M. A. Scherpen, M. J. Yazdanpanah, and P. de Graaf, "Optimal Control and Social Behavior of EV drivers with Vehicle-to-Grid Option," In preparation.

Conference papers

[1] A. Silani, M. Cucuzzella, J. M. A. Scherpen, and M. J. Yazdanpanah, "Passivity Properties for Regulation of DC Networks with Stochastic Load Demand," *21st IFAC World Congress*, Berlin, Germany, 2020.

1.6 Notations

The set of complex numbers, real numbers and natural numbers are denoted by $\mathbb{C}$, $\mathbb{R}$, and $\mathbb{N}$, respectively. The set of positive (nonnegative) real numbers is denoted by $\mathbb{R}_{>0}$ ($\mathbb{R}_{\geq 0}$). Let $\mathbf{0}$ be the vector of all zeros or the null matrix of suitable dimension(s) and let $\mathbf{1}_n \in \mathbb{R}^n$ be the vector containing all ones. The i-th element of vector x is denoted by x_i. Given a vector $x \in \mathbb{R}^n$, $[x] \in \mathbb{R}^{n\times n}$ indicates the diagonal matrix whose diagonal entries are the components of x. Let $A \in \mathbb{R}^{n\times n}$ be a matrix. In case A is a positive definite (positive semi-definite) matrix, we write $A > \mathbf{0}$ ($A \geq \mathbf{0}$). Also, $\sigma(A)$ denotes the spectrum of matrix A. The $n \times n$ identity matrix is denoted by $\mathbb{I}_n$. The elements of a matrix whose values are not important are indicated by $*$. Let $x \in \mathbb{R}^n, y \in \mathbb{R}^m$ be vectors and $\tilde{x} \in \mathbb{R}^{1\times n}, \tilde{y} \in \mathbb{R}^{1\times m}$ be row vectors, then we define $\mathrm{col}(x, y) := (x^\top \; y^\top)^\top \in \mathbb{R}^{n+m}$ and $\mathrm{row}(\tilde{x}, \tilde{y}) := (\tilde{x} \;\; \tilde{y}) \in \mathbb{R}^{1\times(n+m)}$. Consider the vector $x \in \mathbb{R}^n$ and functions $g : \mathbb{R}^n \to \mathbb{R}^{n\times m}, h : \mathbb{R}^n \to \mathbb{R}^n$, then the Lie derivative of $h(x)$ along $g(x)$ is defined as $L_g h(x) := \frac{\partial h(x)}{\partial x} g(x)$, with $\frac{\partial h(x)}{\partial x} = \mathrm{col}\left(\frac{\partial h_1(x)}{\partial x}, \ldots, \frac{\partial h_n(x)}{\partial x}\right)$ and $\frac{\partial h_i(x)}{\partial x} = \left(\frac{\partial h_i(x)}{\partial x_1} \; \ldots \; \frac{\partial h_i(x)}{\partial x_n}\right)$, for $i = 1, \ldots, n$. The bold symbols denote the solutions to Partial Differential Equations (PDEs). Let V be an open neighborhood of the origin of $\mathbb{R}^q$. Then, a function $o_r^k : V \to \mathbb{R}^r$ is said to be zero up to the kth order if it is sufficiently smooth and vanishes at the origin together with all the partial derivatives of order less than or equal to k. Then, let $o^k(v)$ denote a function of v which is zero up to kth order regardless of the dimension of its range space (see [77, Definition 4.1]). A continuous function $\alpha : \mathbb{R}_{>0} \to \mathbb{R}_{>0}$ is said to be of class $\mathcal{K}$ if it is nondecreasing and $\alpha(0) = 0$ and it is said to be of class $\mathcal{K}_\infty$ if it also satisfies $\lim_{s\to\infty} \alpha(s) = \infty$. Let $A, B \in \mathbb{R}^{m\times n}$ be matrices, then the Hadamard (entrywise) product of A and B is defined as $(A \circ B)_{ij} := (A)_{ij}(B)_{ij}$.