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Introduction

Modern power grids rely on hierarchical control architectures to achieve stable, secure, and economic operation, which involves various kinds of advanced measurement, communication, and control techniques [1, 2]. Under the pressures of global climate change and energy shortage, power systems have been undergoing fundamental changes. The past decade has witnessed the leaping penetration of renewable energy resources and distributed generations, the proliferation of electric vehicles, and the active participation of customers, all of which are devoted to recreating a more reliable, flexible, sustainable, and affordable power grid.

On the generation side, fossil fuels are gradually giving place to environment-friendly renewable generations. By the end of 2020, the total installed capacity of global renewable energies reached 2802.004 GW, including 1332.885 GW of hydropower, 732.41 GW of wind energy, and 716.152 GW of solar energy [3]. The rapid growth of renewable energy shows signs of speeding up in the near future. On the consumption side, many new forms of loads have emerged and started participating in system operation with unprecedented enthusiasm. These include, just to name a few, electric vehicles, active participation of load demand [4, 5], energy storages [6, 7], and microgrids [8].

Despite the tremendous environmental and economical benefits, the ongoing changing trends on both generation and consumption sides are gravely challenging the traditional power system control technologies. Renewable energies such as photovoltaics (PVs) and wind power generations (WTGs) are intrinsically uncertain [9], leading to volatile operating conditions. Besides, most PVs and WTGs are integrated via power electronic devices with low/zero inertia and may operate in various control modes. The load-side diversity and participation also complicate the system control problem, which requires a careful design of the interaction protocol to achieve the smart grid vision.

We have to thoroughly and carefully address all these issues to facilitate the grand ambition of the ongoing system revolution. This extremely challenging task calls for advanced future power system control technologies to handle volatile

Merging Optimization and Control in Power Systems: Physical and Cyber Restrictions in Distributed Frequency Control and Beyond, First Edition. Feng Liu, Zhaojian Wang, Changhong Zhao, and Peng Yang.

operating conditions and massive controllable participants. Unfortunately, the existing power system control paradigm that features a centralized hierarchical structure may fail to achieve this goal. Here, we envision a new paradigm that reshapes the hierarchy and merges optimization with control, which may provide a new opportunity to tackle the task. This chapter will first introduce the traditional control methods in power systems and then introduce some state-of-the-art methods.

1.1 Traditional Hierarchical Control Structure

The functional operation of a power system depends on its control systems. As one of the largest and most complicated man-made systems, the modern power system must keep the frequency strictly synchronized and the voltages around their nominal values among thousands of generators and loads spanning over continents and interconnected through tens of thousands of miles of electric wires and cables. Therefore, an appropriate control architecture appears to be highly crucial to a reliable and efficient operation of power systems, if not the most. As a matter of fact, during the past one hundred years, power system control has evolved to be a layered/hierarchical structure encompassing diverse time scales and control objectives, ranging from millisecond to years. Figure 1.1 illustrates the time scales of power system controls with different control objectives. Generally, a slow time-scale layer is more concerned with the economy of operation during a long-time period, while a fast time-scale layer focuses on stability and security during a short-time dynamic process.

The time-scale decomposition and the hierarchical control structure in traditional power systems greatly simplify the control synthesis problem. For example, in most cases, detailed fast time-scale dynamics can be neglected in slow time-scale control problems and vice versa. Such decomposition works well when the time scales of the two layers are significantly different. Even if the difference is less noticeable, e.g. between seconds and minutes, it is still acceptable. Nonetheless, the recent transition of our power system shows that it might be more suitable to combine layers in different time scales, say, merging slow optimization and fast control. This idea sets the first motivation for us to write the book.

In the rest of this section, we shortly introduce the hierarchies of traditional frequency and voltage controls.

1.1.1 Hierarchical Frequency Control

In an alternating current (AC) power system, frequency reflects the active power balance across the overall system. The frequency goes down when generation is

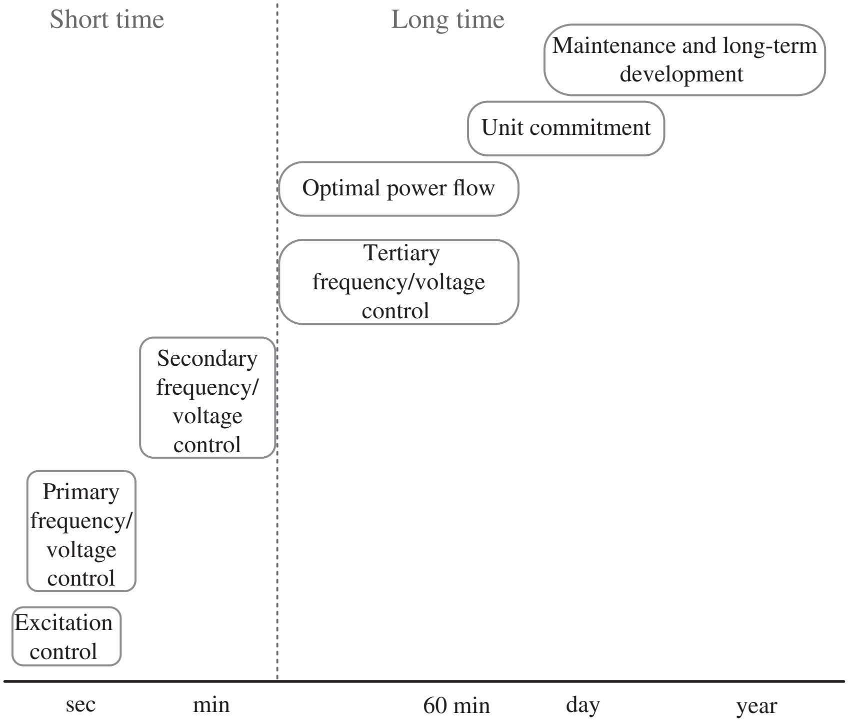

Figure 1.1 Time-scale decomposition of controls in a traditional power system.

less than load and vice versa. Therefore, a power system must adopt frequency control to maintain its frequency within a small neighborhood of the nominal value, such as 50 or 60 Hz.

In traditional power systems, most electric power is supplied by large-capacity synchronous generators. The huge rotating inertia of generators can serve as a buffer of kinetic energy to mitigate moderate power imbalance, limiting frequency changes instantaneously. For example, a sudden load demand increase will be naturally supported by extracting the kinetic energy from synchronous generators. Consequently, the frequency will drop. However, the kinetic energy stored in the inertia is quite limited, which is inadequate to cope with large or long-term frequency deviation. Therefore, intentional frequency control becomes a must to maintain system frequency more effectively and flexibly.

In accord with the control hierarchy mentioned above, frequency control includes three layers with respect to three different time scales, i.e. the primary control with a typical time scale in tens of seconds, the secondary control in several minutes, and the tertiary control in several minutes to tens of minutes, as shown in Figure 1.2. The first two layers act in a fast time scale that involves

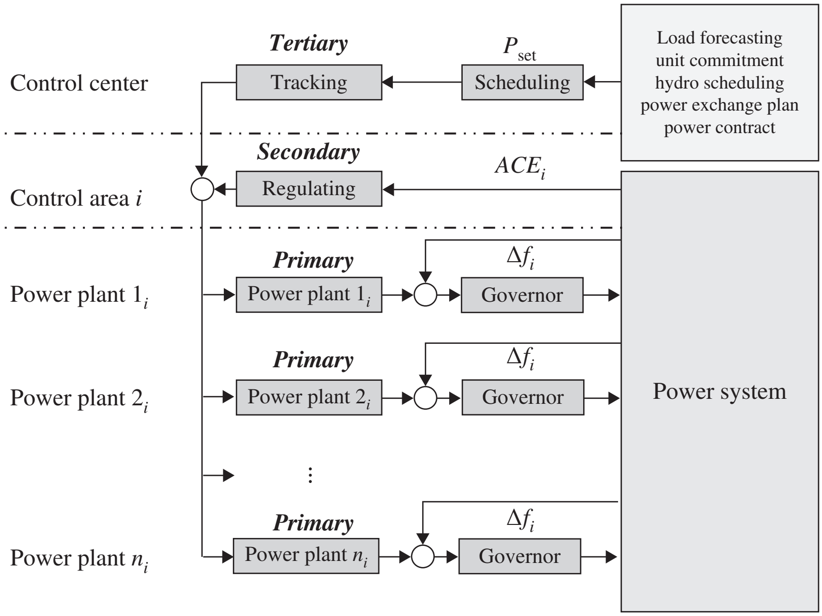

Figure 1.2 Diagram of hierarchical frequency control.

physical dynamics such as excitation control and governor control, while the last layer in a slow time scale involves operational or market dynamics such as economic dispatch (ED) and electricity market clearing. It is obvious from Figure 1.2 that the hierarchy of frequency control heavily relies on a control center.

1.1.1.1 Primary Frequency Control

Primary frequency control is designed to limit frequency deviation within an acceptable range. It is usually fulfilled via automatic governor regulation of generators. Denote by P_i^g the mechanical power of generator i and Δf_i the frequency deviation from the nominal value at bus i. Let the power compensation ΔP_i^g be $\Delta P_i^g = -k_i^p \Delta f$ with $k_i^p > 0$, and send it to change the valve opening of the prime mover, such that the system frequency regains a state of operating equilibrium.

Obviously, the primary frequency control is indeed a proportional feedback control, or droop control. It responds fairly fast to frequency deviation since only local frequency measurement is required. However, it may not restore system frequency to the nominal value due to the proportional control strategy.

In practice, not all generators in the system need to be equipped with a governor control. Those generators, however, usually are competent to provide fast power support. Hence one can still categorize them into primary frequency control when needed.

1.1.1.2 Secondary Frequency Control

Secondary frequency control is designed to eliminate frequency deviation. It is usually fulfilled via automatic generation control (AGC). In a multi-area power system, the area control error (ACE) is a linear combination of the deviations of system frequency and the tie-line powers delivered to or received from its neighboring areas [10]. For the ith area, the ACE is defined as

$$\text{ACE}_i = K_i^s \Delta f_i + \sum_{j \in \mathcal{N}_i} \Delta P_{ij}$$

where $K_i^s > 0$ is a constant that stands for the responsibility of this area in response to the frequency deviation, which is referred to as area frequency response coefficient (AFRC). ΔP_{ij} is the power deviation of the tie-line connecting areas i and j. As a matter of fact, when the ACEs of all control areas converge to zero, the system frequency restores to the nominal value. Therefore, traditional AGC uses ACEs as the feedback signals to compute the control command that reflects the total required power compensation in the area. The obtained control command is then distributed to individual generators in proportion to their participation factors.

AGC typically adopts a proportional–integral (PI) control to drive ACEs to zero. However, as a power system always works in a time-varying environment, the ACEs do not converge to zero but rather fluctuate around zero. So does the system frequency.

1.1.1.3 Tertiary Frequency Control

Although the secondary frequency control can eliminate the frequency deviation, it is not responsible for achieving an optimal power generation allocation. Instead, this task is fulfilled by the tertiary frequency control that aims to minimize the operation cost of the system (e.g. generation cost or network loss) by reallocating the power production among generators. Thus, it is also called ED, usually performed every 5–15 min. This problem can be mathematically formulated as a constrained optimization problem, where the constraints include power balance, generation limits, line flow limits, etc. Traditionally, the ED problem is solved to generate the control commands in the control center, and then the control commands are sent to the dispatchable generators as the set points. In a deregulated power system, or power market, the ED problem is replaced by a market clearing problem. Pricing issues and strategic behaviors of participants need to be carefully considered as well.

1.1.2 Hierarchical Voltage Control

While frequency is determined by the active power balance of the overall system, voltage is more closely relevant to local reactive power supply. When the reactive power supply is inadequate, the voltage will be lower than the nominal value,

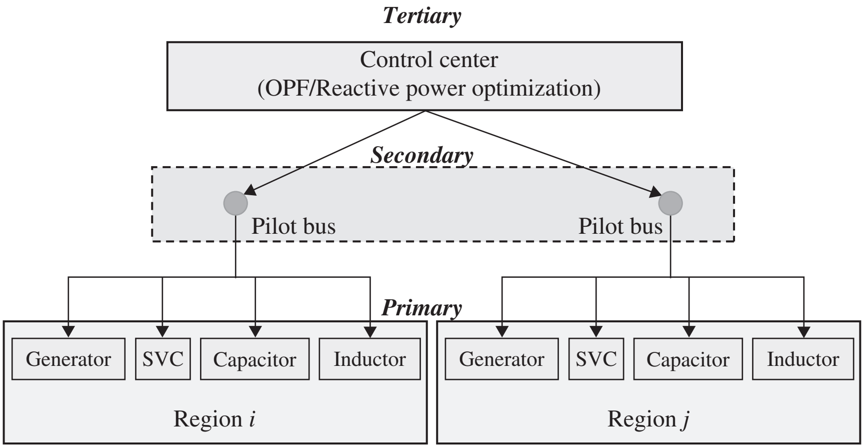

Figure 1.3 Diagram of hierarchical voltage control.

and vice versa. Therefore, voltage control is usually realized by regulating reactive power generation or consumption of generators, transformers, reactive power compensators, loads, etc. Usually, the load-based voltage regulation is adopted in an emergency only. Except for reactive power sources/loads, flexible AC transmission systems based on power electronics provide an additional option to voltage control by changing the equivalent line impedance.

Unlike frequency, voltage is more like a local indicator for reactive power adequacy than a system-wide indicator for active power balance. In addition, since reactive power is not suitable for long-distance transmission (for avoiding unexpected transmission loss and voltage instability), a voltage control problem is usually considered and implemented in local regions. For coordinating voltage controls in different regions to enhance system-wide performance, a hierarchical voltage structure emerges. Similar to frequency control, voltage control also has a central-dominant hierarchy that comprises three layers: the primary voltage control with a typical time scale in tens of seconds, the secondary voltage control in several minutes, and the tertiary voltage control in several minutes to tens of minutes. Figure 1.3 illustrates the diagram of hierarchical voltage control.

1.1.2.1 Primary Voltage Control

As the fastest control layer in the hierarchy, primary voltage control aims to stabilize the voltage rapidly when voltage deviation from the preset value exceeds a certain threshold. It is fulfilled by using local feedback control of various reactive power sources including synchronous generators, capacitors, series inductors, static Var compensator (SVC), static synchronous compensator (STATCOM), etc. For example, one can use automatic voltage regulator (AVR) to flexibly control the terminal voltage of generators (via the excitation system), often within a range of $\pm 5\% \sim \pm 10\%$ with respect to its rated value. In practice, PI controllers are extensively employed; otherwise, droop controllers or proportional controllers appear to be more helpful for a stable operation.

1.1.2.2 Secondary Voltage Control

As mentioned above, primary voltage control is built on fully local voltage deviation. Hence a controllable reactive power source or load in a subregion would provide little support to other subregions even if it has plenty of reactive power reserve. In this regard, secondary voltage control is developed. It is implemented in a control center of one region, within a time scale from tens of seconds to several minutes, or even longer up to the time constant of controlled devices. Secondary voltage control aims to coordinate the region-wide voltage control by utilizing the reference voltage of a pilot bus that represents the voltage situation or reactive adequacy in a local region. In operation, the reference voltage deviation of the pilot bus is sent to local primary voltage controllers, attached to the primary control signals, to coordinate all the controllable voltage/Var sources and loads within this region.

Except for reactive power sources and loads, onload tap changers can also be used to facilitate secondary voltage control by changing the taps of transformers. However, it should be aware that adjusting transformer taps only changes reactive power distribution rather than generating reactive power. Therefore, we only enable it when the reactive power is sufficient in the region. Otherwise, it may worsen the reactive power shortage, even resulting in disastrous voltage collapse.

1.1.2.3 Tertiary Voltage Control

Reactive power distribution has a remarkable influence on the power loss of power transmission. In this regard, tertiary voltage control is responsible for optimizing the reactive power distribution across the overall power grid. This target is achieved by changing the reference voltages of pilot buses in each control region. In this sense, tertiary voltage control can also be regarded as a particular type of optimal power flow (OPF) problem, where only reactive power is optimized. Therefore its time scale follows the pace of ED or slower, varying from several minutes to several hours.

1.2 Transitions and Challenges

The central-dominant hierarchical control architecture has effectively supported the operation of traditional power systems for decades. As power systems evolve into a new era, a critical question arises: Can the traditional control paradigm still apply? The key features in future power systems that may hinder the classical control paradigm include the following:

- **Massive entities**: A huge amount of dynamic devices are integrated into the power system from different voltage levels, including WTGs, PVs, electric vehicles, and energy storage, to name a few. The number of controllable and uncontrollable devices increases by orders of magnitudes, calling for a more scalable control scheme with an effective coordination.
- **Heterogeneous dynamics**: Due to the increasing diversity of control modes and physical natures of electrical devices, the dynamics in future power systems are extensively heterogeneous. It brings intricate interaction patterns and significantly complicates system-level analysis and control design, calling for a more compatible control scheme.
- **Uncertain and fast-changing environments**: The high penetration of renewable energy resources and complex loads significantly increases the uncertainties in power systems. In addition, distributed energies usually belong to individual owners, which could be switched on or off frequently. The increasing uncertainty leads to volatile operating conditions, which requires much faster control responses to retain power balance and economical operation in fast-changing environments, calling for a more adaptive and robust control scheme.

In light of these transitions, the classical center-dominant hierarchical control paradigm may fail to meet what the future power systems demand, and reshaping it to fit the future becomes a must. Ideally, we envision that the future paradigm should be scalable to the massive amounts of devices, compatible with ever-increasing heterogeneity, efficient in fast-changing operation environments, flexible to diverse operation modes, and robust against unexpected perturbations and even failures. Toward this ambition, fruitful progress has been made to combine advanced control and optimization theories with power system engineering. Two of the most promising topics among them are (i) relieving the dependence on central coordinators and (ii) reshaping the original control hierarchy. The former advocates a distributed control paradigm that endows the power system with higher scalability, compatibility, and robustness. The latter suggests merging the slow time-scale optimization and fast time-scale control to achieve stronger adaptability and faster response. The following two sections will briefly introduce the state of the art of these two innovative topics.

1.3 Removing Central Coordinators: Distributed Coordination

In terms of the way of coordinating, three approaches may be involved: centralized control, decentralized control, and distributed control.

Centralized control features a control center that collects information of all agents, performs a central computation to get control commands, and sends them back to each agent (Figure 1.4a). The control center can solve a complex centralized optimization problem to increase the economic efficiency of the whole system. However, the system may break down if the control center fails, which is the notorious single-point-of-failure issue. In addition, privacy becomes a big problem because the control center requires information from all agents. Another problem is that this approach is not scalable as it heavily relies on detailed information of all agents in the system. Moreover, collecting the information is time-consuming in large systems, which remarkably slows down the response.

Decentralized control needs no control center and adopts purely local control strategies to compute control commands, i.e. no communication between agents (Figure 1.4b). Thus, decentralized control usually has a rapid response, which has been widely adopted, particularly in the primary control. However, agents adopting decentralized control may conflict with each other since there is a lack of coordination.

The distributed control also needs no control center but requires communication among agents such that each agent can compute control commands locally[1] (Figure 1.4c). Roughly speaking, the complexity of distributed control is between those of centralized and decentralized ones. Similar to decentralized control, the structure of distributed control is also simple and easy to apply. However, distributed control can enable coordination among agents to facilitate global objectives as the agents can exchange information. Compared with centralized control, distributed control has several potential advantages. First, each agent only needs to share limited information with a subset of the other agents, i.e. its neighbors on the communication graph. This feature consequently improves cybersecurity, better protects privacy, and reduces the expense of communication networks. Second, distributed control avoids the single-point-of-failure issue and hence is more robust. Third, distributed control may be computationally superior to the centralized rival by decomposing a large-scale global problem into a set of small-scale local problems. Finally, distributed control can adapt to volatile operation conditions, such as fast variation of renewable generations and topology changes.

Since the distributed control structure inherits advantages both from the centralized and decentralized ones, it has been widely recognized as a promising solution to the aforementioned challenges and has inspired plenty of achievements in this field. Interestingly, it has many overlaps with another topic, distributed optimization, in both problem formulations and algorithms. The two closely related topics, sometimes, may lead to confusion. In this regard, this book adopts the following terminology. When considering distributed control, we design a controller and implement it to physical systems in a distributed manner, and hence the controller's dynamics directly couple with the physical dynamics. On the other hand,

1 The topology of a physical system is not necessarily identical to its communication graph.

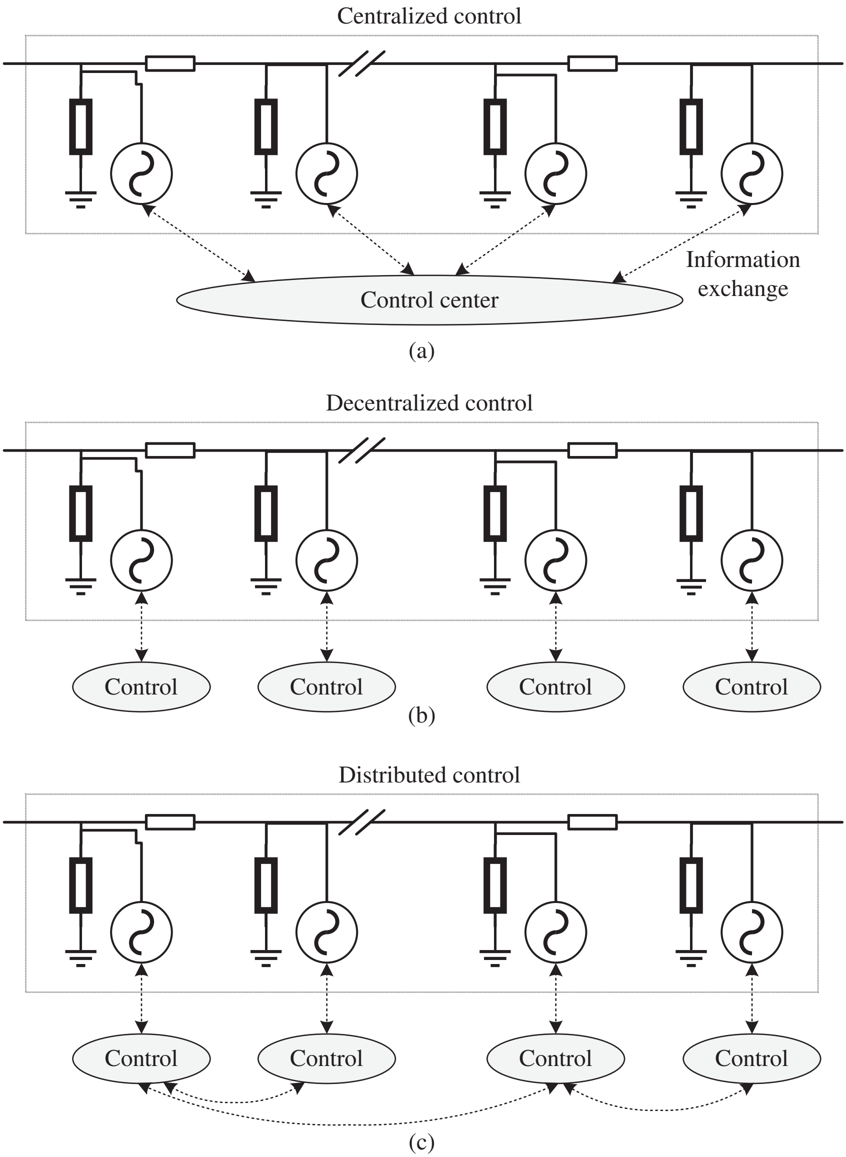

Figure 1.4 Diagram of centralized (a), decentralized (b), and distributed (c) control.

when considering distributed optimization, we construct a distributed algorithm to solve optimization problems subject to some snapshots of the physical systems while the solving process does not directly couple with the physical dynamics. In this sense, the primary and secondary frequency/voltage regulations are categorized as a control problem, while the tertiary frequency/voltage control, i.e. ED, is categorized as an optimization problem. However, we use distributed optimal control when both optimization and control are taken into account.

1.3.1 Distributed Control

Distributed control considers a group of dynamic agents as follows:

$$\dot{x}_i = f_i(x_i, x_k, u_i), \quad k \in \mathcal{N}_i \tag{1.1a}$$

$$y_i = g_i(x_i) \tag{1.1b}$$

where $x_i \in \mathbb{R}^{n_i}$ is the state variable of agent i, $y_i \in \mathbb{R}^{m_i}$ is the output, and $\mathcal{N}_i$ is the set of the neighbors of dynamic agent i on the physical network. Agent i can exchange information with its neighbors on the communication network, denoted by $\mathcal{N}_i^c$. Note that generally $\mathcal{N}_i^c \neq \mathcal{N}_i$.

We expect to design the following distributed controller that depends on the local output:

$$\dot{u}_i = h_i(y_i, y_j), \quad j \in \mathcal{N}_i^c \tag{1.2}$$

One of the most extensively used approaches is to adopt the consensus-based distributed control [11], which takes the following form:

$$\dot{u}_i(t) = \sum_{j \in \mathcal{N}_i^c} a_{ij} \left(y_j(t) - y_i(t) \right) \tag{1.3}$$

where a_{ij} is the weight between buses i and j. According to the consensus algorithm, $y_i(t) = y_j(t)$ holds for all i, j in the steady state. In this sense, the output y_j essentially serves as a global variable to coordinate all agents in the system. Individual agents estimate the variable locally and approach the consensus through iterative computation and information exchange. Therefore, by appropriately choosing the output y_j, various kinds of distributed controllers can be devised.

Specifically, in power systems, the global coordination variable could be generation ratio and marginal cost. The former one is the ratio between actual generation and the maximal capacity, which implies that all generators supply the load fairly up to their maximal capability [12–17]. References [12, 13] apply a consensus algorithm to the active power control of PVs for achieving a unified utilization ratio. This method can also apply in reactive power control [14–16] and harmonic control [17]. The latter implies that all generators share the same marginal cost and hence reach the economical optimum [18, 19]. Reference [18] shows that individual distributed generators in a microgrid can maintain identical marginal costs by using a consensus-based distributed controller while restoring the nominal frequency. This idea is further extended to direct current (DC) microgrids in [19].

Consensus-based distributed control has a simple structure, which can achieve a *fair* or *economical* operation. The fairness is realized by maintaining equal generation ratios, while the economy is realized by holding an equal marginal generation cost. On the other side, this simple structure conversely restricts the applicability of consensus-based distributed control when considering complicated optimization objectives or constraints such as line flow limits, which are very common in power systems. In such circumstances, we need more sophisticated designs, which will be discussed in detail in the remaining chapters of this book.

1.3.2 Distributed Optimization

Distributed optimization considers a group of agents that cooperatively solve the following separable (convex) optimization problem with constraints:

$$\min_{x_i,\ i=1,\dots,N} \quad \sum_{i=1}^{N} C_i\left(x_i\right) \tag{1.4a}$$

$$s.t. \quad \sum_{i=1}^{N} f_i(x_i) \leq 0, \tag{1.4b}$$

$$x_i \in X_i,\ i = 1, 2, \dots, N \tag{1.4c}$$

where $C_i\left(x_i\right), f_i\left(x_i\right)$ are convex functions and X_i is a convex set.

In distributed optimization, each agent carries out local computation on a subproblem and exchanges information with neighbors. Convergent computation gives an optimal solution to the original optimization problem. Some commonly used distributed optimization algorithms include consensus-based algorithms, dual decomposition, alternating direction method of multipliers (ADMM), and gradient-based algorithms, to name a few. An introduction to these algorithms can be found in Appendix A. Here, we briefly introduce the applications of the most popular consensus-based algorithms and ADMM in power systems.

Consensus-based algorithms are especially relevant in ED problems, where marginal costs or prices of generators serve as the global coordination variables for consensus [21–24]. In [22], an average consensus method is presented to solve the ED problem in a distributed fashion, where two stopping criteria are derived based on sign consensus. Reference [21] extends the consensus method to solve the ED problem with transmission losses. In [23] an incremental cost-consensus algorithm is suggested with a convergence proof. In addition, literature [24] shows that a consensus-based algorithm can track the optimal solution to the active power ED problem with generation capacity constraints. However, as mentioned in the previous part, this appears to be restrictive in dealing with complicated constraints.

Compared with consensus-based algorithms, ADMM has been more extensively employed to deal with complicated constraints, such as OPF problems. In terms of power flow models, the appliances of ADMM roughly fall into four categories: (i) AC OPF problems [25–27], (ii) DC OPF problems [28–30], (iii) distribution flow with the second-order cone relaxation [31–33], and (iv) linearized distribution flow [34–36]. Reference [25] proposes an asynchronous ADMM algorithm of the AC OPF problem to cope with the communication delay by extending the synchronous ADMM algorithm [26, 27]. In [28], a fully distributed accelerated ADMM algorithm is presented, where a consensus-based push-sum method is derived to improve the convergence. In [29], a consensus-based ADMM approach is employed to solve DC OPF problems. Reference [30] utilizes machine learning to predict the optimal dual variable under different realizations of system loads, remarkably accelerating the convergence of ADMM. The distribution flow (DistFlow) model is considered in references [31–36]. To cope with the nonconvexity of the DistFlow model, references [31–33] apply a second-cone relaxation while references [34–36] choose to linearize the DistFlow model by ignoring the line loss.

Note that ADMM algorithms are usually concerned with optimization problems only by assuming the dynamics of physical power systems are fast enough and negligible. One consequence is that the algorithms are not applicable in a fast-changing environment. Otherwise, the influence of physical power system dynamics will turn to be non-ignorable, making the assumption invalid.

1.4 Merging Optimization and Control

As analyzed above, distributed control and optimization have their own advantages and deficiencies and are applied in different layers. So a natural question is whether they could be combined to address both optimization and control issues in complicated environments. This question inspires the idea of merging primary and secondary controls in a fast time scale with ED or OPF in a slow time scale [10, 37, 38]. This leads to a cross-layer design approach of distributed optimal control that bridges the gap between optimization and control in different time scales. As a result, we expect the merged distributed optimal control could achieve optimality automatically and rapidly while guaranteeing system stability, even under complicated operational constraints and changing environments.

Generally, this idea has two sides: *optimization-guided control* and *feedback-based optimization*. On the one side, we intend to design a feedback controller for power systems, which could drive the system states to the optimal solution of an optimization problem in the steady state, such as ED. At the same time, the system should be asymptotically stable. On the other side, we hope to solve optimization problems by making use of feedback control. In this case, some state variables are obtained by measuring instead of solving complicated system equations, such as power flow equations. In this section, we explain them, respectively.

1.4.1 Optimization-Guided Control

The main idea of optimization-guided control is to design a (dynamic) feedback controller for power systems, which drives the system to the optimal solution to an optimization problem, such as ED or OPF. The framework is illustrated in Figure 1.5.

In this framework, the lower layer is the fast-time-scale dynamics of a power system with control inputs. We formulate it into a general control system:

$$\begin{cases} \dot{x} &= g_d\left(x, u'_d\right) \\ y_d &= h_d(x) \end{cases} \tag{1.5}$$

where x is the vector of state variables, u'_d is the vector of control inputs, and y_d is the vector of system outputs.

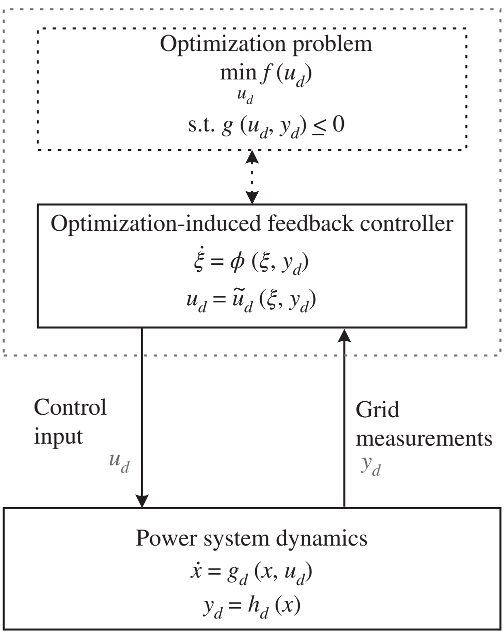

Figure 1.5 Conceptual diagram of optimization-guided feedback control.

The upper layer is the slow-time-scale ED or OPF process of the power system. We formulate it into a general constrained (convex) optimization problem with adjustable parameters:

$$\min_{u_d} \quad f\left(u_d\right) \tag{1.6a}$$

$$\text{s.t.} \quad g\left(u_d, y_d'\right) \leq 0 \tag{1.6b}$$

where u_d is the vector of decision variables and y_d' is the vector of adjustable parameters.

Our goal is to design a dynamic controller:

$$\begin{cases} \dot{\xi} &= \phi(\xi, y_d') \\ u_d &= \tilde{u}_d(\xi, y_d') \end{cases}, \tag{1.7}$$

such that the output of (1.7) at the steady state is equal to the optimal solution to (1.6). This equivalent relation can be established by noting that the solving process of optimization problem (1.6) essentially defines a dynamic process, e.g. the primal–dual gradient dynamics.

To merge the two layers above, we interconnect the controller (1.7) and the system (1.5) by letting $u_d = u_d'$ and $y_d = y_d'$,[2] as shown in Figure 1.5. Then we need to appropriately design the controller (1.7) such that the closed-loop power system guarantees the asymptotic stability with the equilibrium point identical to the solution to the optimization problem (1.6). This approach is closely related to the primal–dual gradient dynamics (or saddle-point dynamics) [39, 40] by noting that one can construct the controller (1.7) from the primal–dual gradient dynamics of the optimization problem (1.6). That is why this is called optimization-guided control.

The idea of optimization-guided control can date back to [41] that presents a methodology to regulate a nonlinear dynamical system to an optimal operation point, i.e. a solution to a given constrained convex optimization problem in terms of the steady-state operation. To this end, it constructs a dynamic extension of the Karush–Kuhn–Tucker (KKT) optimality conditions for the corresponding optimization problem. A similar method is applied in power systems [20], which exploits the pricing interpretation of the Lagrange multipliers to guarantee economically optimal operation at the steady state. This idea is further generalized as the notion of *reverse and forward engineering* methodology for designing optimal controllers, particularly in optimal frequency and voltage control of power systems [10, 37, 42, 43] Following and extending this idea, we will design frequency controllers considering various physical restrictions in this book.

2 Without confusion, we will not distinguish u_d/u_d' and y_d/y_d' in the rest of this chapter.

1.4.2 Feedback-Based Optimization

Feedback-based optimization provides an alternative way to merge optimization and control. One of the primary motivations for feedback-based optimization is to fast respond to power fluctuations due to time-varying loads and volatile renewable generations, since optimized strategies based on fixed operational conditions may not be applicable in this situation. Therefore, unlike optimization-guided control, feedback-based optimization is usually more concerned with the operational optimality than the stability of a power system. As a result, (quasi-) steady-state models of a power system other than its dynamical model are adopted.

The original idea of feedback-based optimization might come from straightforward intuition. A physical power system itself can be regarded as a *computer* that calculates and outputs exact information of power flow. Hence, one can accelerate the computation by directly measuring the state of the power system other than calculating it based on a mathematical model. From a control perspective, the use of measurements constitutes a feedback loop in optimization computing. That is why this approach is referred to as feedback-based optimization.

Figure 1.6 illustrates the conceptual framework of feedback-based optimization. In this framework, the lower level is the (quasi) steady-state power system described by the power flow equations:

$$0 = g_s\left(x, u_s\right)$$

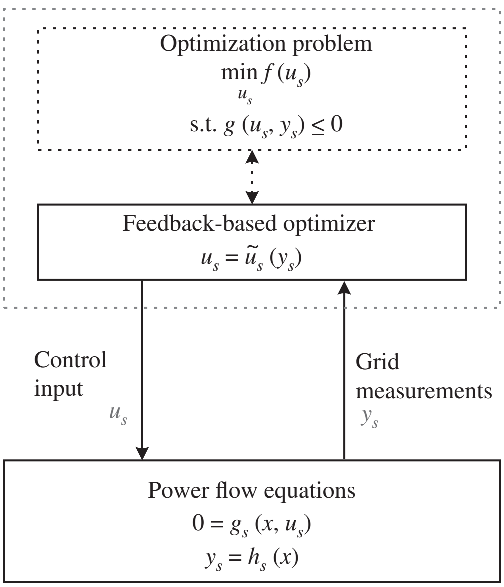

Figure 1.6 Conceptual diagram of feedback-based optimization.

where x is the system state, u_s is the controllable parameters such as generation set points, and y_s is the system outputs. The designer hopes to optimize the steady state x of the power system by adjusting u_s, rendering the following optimization problem:

$$\min_{u_s} \quad f\left(u_s\right) \tag{1.8a}$$

$$\text{s.t.} \quad g\left(u_s, y_s\right) \leq 0 \tag{1.8b}$$

In the above optimization problem, the power flow equations serve as part of the equality constraints. By measuring y_s from the physical power system, this constraint is eliminated. The optimal solution, u_s, to the problem (1.8) with respect to y_s is then sent to the physical power system to drive it to the desired working point.

The introduction of feedback in optimization has two salient advantages. First, it remarkably reduces the computational complexity by avoiding solving the high-dimensional nonlinear power flow equations. Second, it endows the optimization algorithms with the adaptability to time-varying working condition by feedback.

Similar to the optimization-guided control, the feedback-based optimization also involves the philosophy of forward and reverse engineering. However, the feedback-based optimization focuses on a slower time scale considering (quasi-)steady states, while the optimization-guided control needs to consider the dynamics of physical systems in a faster time scale. Nevertheless, in practical control system design, one sometimes needs to combine the two approaches to achieve satisfactory control performance.

1.5 Overview of the Book

This book includes four parts: (i) essential preliminaries of optimization and control theory and power system models (Chapter 2), (ii) optimization-guided controllers considering physical restrictions (Chapters 3–6), (iii) feedback-based optimization algorithms considering cyber restrictions (Chapters 7 and 8), and (iv) robustness and adaptability of the distributed control (Chapters 9–11). Related state-of-the-art technologies will be introduced and illustrated in detail with hands-on examples and real-world systems for the readers to learn about how to use them to address specific problems.

Part 1: Introduction and Preliminaries

After a general introduction in Chapter 1, Chapter 2 summarizes some essential preliminaries of distributed optimal controller design, including graph theory, convex analysis, operator theory, stability theory, power flow equations, and power system dynamics. It also provides a good reference to readers who are interested in related fields.

Part 2: Physical Restrictions

In this part, we design optimization-guided distributed frequency control of power systems considering physical restrictions.

Chapter 3 first introduces the notion of *reverse and forward engineering*. Furthermore, it presents a systematic method to design an optimization-guided feedback controller by taking the primary frequency regulation as an example. Particularly, we demonstrate how to bridge optimization and control by exploiting the structure of (partial) primal-dual dynamics.

Chapters 4 and 5 extend the methodology in Chapter 3 to incorporate operational constraints such as regulation capacity constraints and line flow limits into distributed optimal frequency control. Chapter 4 focuses on the per-node power balance, where the power mismatch is economically balanced within each area. A completely decentralized strategy is derived without communication. We address the input saturation issue by constructing a Lyapunov function using the projection technique, originally developed for variational inequality problems.

Chapter 5 focuses on the network power balance case, where power mismatch may be balanced by all generators and controllable loads across the overall system. We pay special attention to dealing with global inequality constraints imposed by line flow limits by employing the invariance principle for nonpathological Lyapunov functions.

Chapter 6 further considers nonsmooth objective functions, which widely exist in power systems. However, it is challenging to design distributed controllers in the presence of nonsmooth objective functions, as the traditional gradient descent approach does not apply. Here, we show how to leverage the Clark generalized gradient and differential inclusion to deal with such nonsmoothness issues.

Part 3: Cyber Restrictions

In this part, we design feedback-based optimization algorithms for both frequency and voltage control in power systems with cyber restrictions.

Chapter 7 investigates the distributed power control of microgrids with different kinds of asynchrony. We show how to fit different kinds of asynchrony into a unified framework and employ the operator splitting technique to prove the convergence. Specifically, frequency and voltage measurements are utilized as feedbacks to simplify the optimization algorithm.

Chapter 8 investigates the distributed optimal voltage control in distribution networks with different kinds of asynchrony. We combine the partial primal–dual gradient algorithm and the operator splitting techniques to handle complicated operational constraints and asynchrony. Moreover, we show how to utilize local measurements to facilitate the online implementation that is adjustable to time-varying environments.

Part 4: Robustness and Adaptability

This part further investigates the robustness and adaptability of the distributed optimal controllers.

Chapter 9 addresses the robustness of distributed frequency controller to unknown disturbances due to volatile renewable generations and loads. We show how to decompose the imbalanced power into subproblems in different time scales and resolve them by combining the primal–dual gradient, internal mode control, and L_2-gain theory.

Chapter 10 focuses on the adaptability of distributed optimal controller to partial control coverage, i.e. only a subset of generators is controllable. We show how to leverage incremental passivity conditions for both active and reactive power controls, which guarantee the closed-loop stability of the overall system even under large disturbances.

Chapter 11 addresses the adaptability of distributed optimal controllers to the heterogeneity of existing controls. We design a primal-dual gradient based controller of microgrids to unify different types of original controls. We show it is adaptable to the diversity of microgrids and plug-and-play operations.

This book also includes two appendices for the convenience of the readers. Appendix A provides a short review on typical distributed optimization algorithms, some of which are used in the previous chapters. Moreover, Appendix B presents the OPF theory of DC networks, which is omitted in Chapter 11 for clarity and simplicity.

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