1

Introduction

1.1 Plant-Wide System

There is a class of systems which are composed of many interacted subsystems' industrial fields. Especially with the development of the advanced technology and the increase in the requirement of products, many new distributed processes have appeared, the processes of producing products have become more and more complex, and the scales of industrial processes have become more and more large. The automation structure for this kind of systems has changed from the traditional centralized automation system to a decentralized and centralized automation system, and then to a distributed automation system.

Correspondingly, the control algorithm and control structure for this kind of system change from centralized control and decentralized control to the distributed control system. The distributed control refers to a control system where each subsystem is controlled by an individual controller, and these controllers communicate with other subsystem-based controllers and are coordinated according to the exchanged information for obtaining good global performance or some special common goals. So far, the distributed control, especially the DMPC, has been studied and are still being studied by many scientists, and many theories and algorithms have been developed. We think it is the right time to introduce the distributed control to more students and engineers.

To make it more clear which kind of system is suitable for distributed control, we give some examples as follows.

1. **Wind power generation farm**
   In a wind turbine power generation farm, as shown in Figure 1.1, wind turbines are spatially distributed. The output wind flow rate of each wind turbine decreases with increasing generated power. It affects the input wind flow rate of the downstream wind turbines, and then their dynamics. In this way, these wind turbines interact with each other. For the automation system, each wind turbine is controlled by an individual controller. And these controllers are connected by a network (fieldbus) and are able to communicate with each other by the network.

Distributed Model Predictive Control for Plant-Wide Systems, First Edition. Shaoyuan Li and Yi Zheng.

Figure 1.1 The wind farm

2. **Multizone building temperature regulation system**
   Multizone building temperature regulation systems are a class of typical spatially distributed systems, as shown in Figure 1.2, which are composed of many physically interacted subsystems (rooms or zones) labeled as $\mathcal{S}_1, \mathcal{S}_2, \ldots, \mathcal{S}_m$, respectively. The thermal influences between rooms of the same building occur through internal walls (the internal walls' isolation is weak) and/or door openings. A thermal meter and a heater (or air conditioner) are installed in each zone, which is used to measure and adjust the temperature of the multizone building.
3. **Distributed power network**
   Power networks are large networks consisting of a large number of components. The dynamics of the power network as a whole are the result of interactions between the individual components. The generators produce power that is injected into the network on the one side, while the loads consume power from the network on the other. If we consider each power plant, load, and station as a subsystem, it is a typical distributed system, whose subsystems interacted with each other and controlled separately.

In addition, since the number of players involved in the generation and distribution of power has increased significantly, in the near future, the number of source nodes of the power distribution network will increase even further as large-scale industrial suppliers and small-scale individual household will also start to feed electricity into the network. As a consequence, the structure of the power distribution network will change into a much more decentralized system with many generating sources and distribution agencies (Figure 1.3).

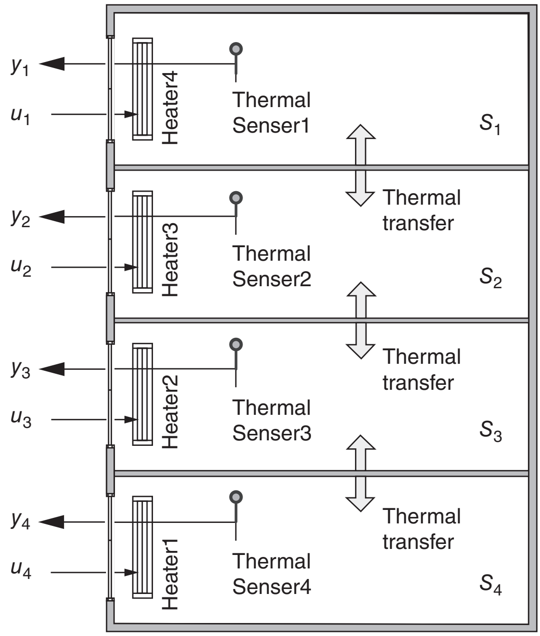

Figure 1.2 The multizone building temperature regulation system

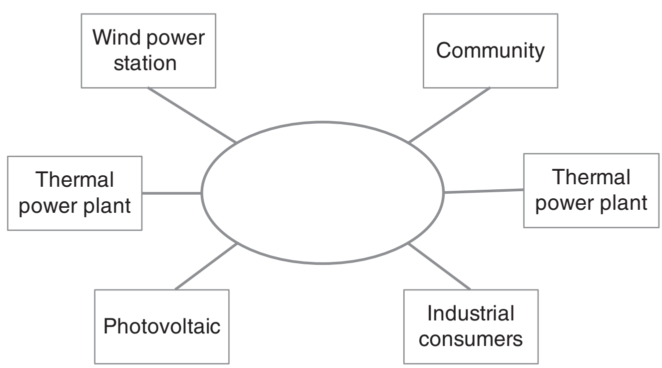

Figure 1.3 Distributed power generation power network

1.2 Control System Structure of the Plant-Wide System

The control structure is a very general concept. It includes how to schedule the controllers, and the inputs/outputs of each controller. The control system structure of the plant-wide system is shown in Figure 1.4, which is a hierarchical structure. The top layer, denoted as layer 4, is a steady economic optimization layer which is used to optimize the key process parameters, e.g., the product quantity, product quality, feeding material quality, etc. Layer 3 is a real-time optimization layer which dynamically optimizes the set-point of the multivariable layers.

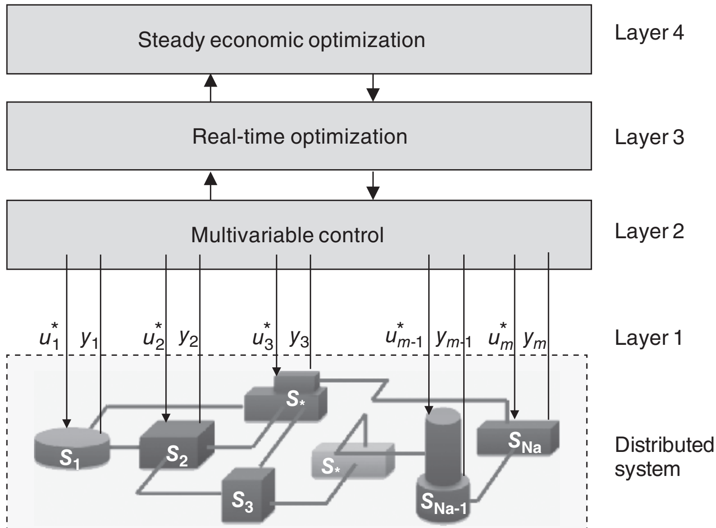

Figure 1.4 Hierarchical control system for the plant-wide system

This layer considers the dynamic economic performance and efficiency. The slow time variation of the process condition is taken into account in this layer. Below this layer is a multivariable layer which coordinates the interaction between each control loop and gives a set-point for the field control loop. The lowest layer, a field control loop layer, which is not drawn in this figure, is used to regulate the process variable, e.g., the temperature, flow rate, or pressure. In some cases, the multivariable takes some work of the field control loop layer when the control problem is complicated. In this structure, with an increase in the layer level, the information to communicate is deduced, and the computing interval is increased.

Here, we consider the multivariable control layer. For a plant-wide system, there are many inputs and outputs. With the development of a network, communication technology, and field-bus product, as well as intelligent meters, the control theory for a multivariable system is developed correspondingly. Many advanced control methods appear in the literature works, and the control structure in a multivariable layer changes from the centralized control to the decentralized control, to the distributed control. In addition, recently, the distributed structures for the real-time dynamic optimization layer and steady-state optimization layer have also appeared in the literature works. The real-time optimization layer and multivariable control loop are combined together in some cases. This is out of the scope of discussion in this book. In the following, three types of control structures, centralized control structure, decentralized control structure, and distributed control structure, in a multivariable control layer are specified to show the advantage of the distributed control framework.

1.2.1 Centralized Control

As shown in Figure 1.5, the centralized multivariable controller gets all the information of the plant-wide system, and then calculates the control law of all the inputs together, and sends the

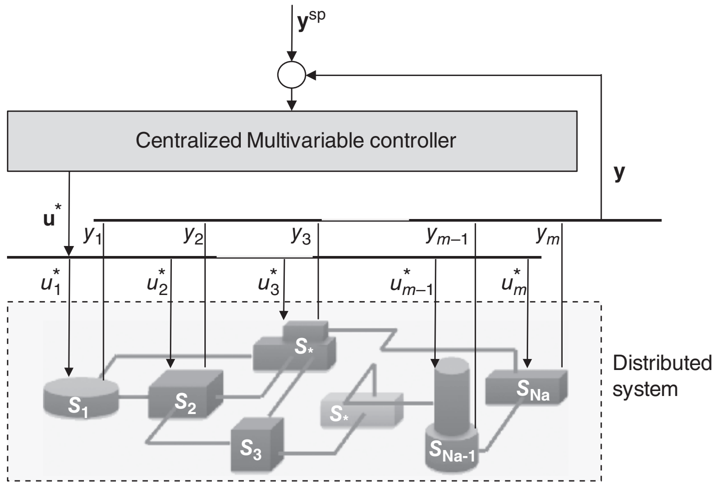

Figure 1.5 Centralized control

control signals to the actuators via the network. The control structure could achieve the best dynamic performance of the overall closed-loop system. However, since there are hundreds (or thousands) of input and output variables in a large-scale plant-wide system, the computational burden is unavoidably high if all control variables are solved together by a centralized controller during a controller period. In addition, since the information of the whole system is necessary when using centralized control, it requires that the network communication must be robust as the communication load is unavoidably high. Furthermore, under this control structure, if one of the subsystems does not work due to some fault, or we proceed with regular maintenance, the multivariable controller must be stopped, and the control of the whole system is interrupted. Thus, this control structure is not sufficiently flexible. Finally, it can be seen that if any part of the controller, actuators, sensors, networks, or control computer has a fault, the multivariable algorithm will lose its effectiveness, which means a low capability of error tolerance, which will not be expected by either the controller engineer or the owner of factories.

1.2.2 Decentralized Control and Hierarchical Coordinated Decentralized Control

Considering the less flexibility, the worse error tolerance, the large computational burden, and the heavy network communication load of centralized control, people decompose the centralized controller into many relevant small-scaled controllers, as shown in Figure 1.6. These controllers work with each other independently even when the corresponding controlled subsystems couple with each other. These classes of multivariable controllers have the advantages of simple structure, less computational burden, better error tolerance, good flexibility, and easy designing and implementation. Since the computation for obtaining the control law of the entire system is distributed to many small-scaled controllers, the computation burden of each controller is dramatically decreased. In addition, if several subsystems or controllers do not

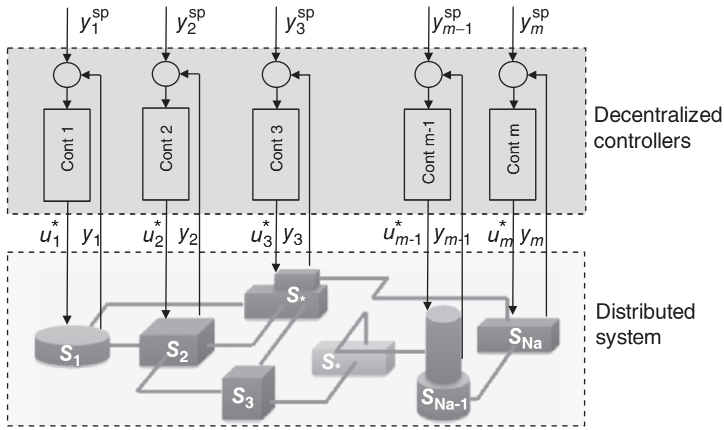

Figure 1.6 Decentralized control

work due to some fault, the other controllers are still able to work, which means good error tolerance. Furthermore, if there are some new subsystems required to be appended to or deleted from the existing plant-wide system, it needs to do nothing with the existing controllers, which means good structure flexibility.

However, since there is no communication and coordination among decentralized controllers, the controller performance is destroyed if the coupling among subsystems is strong enough. In order to avoid the degradation of the performance of the global system, one method is to enlarge the scale of each local controller, where several strong coupled subsystems are controlled by one local controller. By using this strategy, the performance of the global system could be guaranteed, but the computational burden of each local controller is increased, and the flexibility of overall system is deduced. This strategy bypasses and does not solve the problem of how to improve the global performance when strong interactions exist among the subsystems each of which is controlled by a separated controller.

Unfortunately, in most cases, strong couplings exist in the plant-wide system. Thus, people add a coordinator to coordinate each subsystem-based controller for improving the global performance of the entire plant-wide system, as shown in Figure 1.7, and is called hierarchical coordinating decentralized control. Through different coordinating algorithms, the global performance of the entire system could be significantly improved if strong interactions exist. However, all local controllers should communicate with the coordinator as the global information is necessary for the coordinator. The centralized structure appeared in the coordinator.

1.2.3 Distributed Control

Recently, with the development of computer technologies, fieldbus, network communicating technologies, and smart meter in process industries, which allows the control technologies and methodologies to utilize their potentials for improving control, the distributed control structure has appeared gradually instead of the centralized and decentralized structure for the plant-wide system. As shown in Figure 1.8, the global system is divided into many interacted subsystems, and each subsystem is controlled by a separate controller; these peer controllers communicate

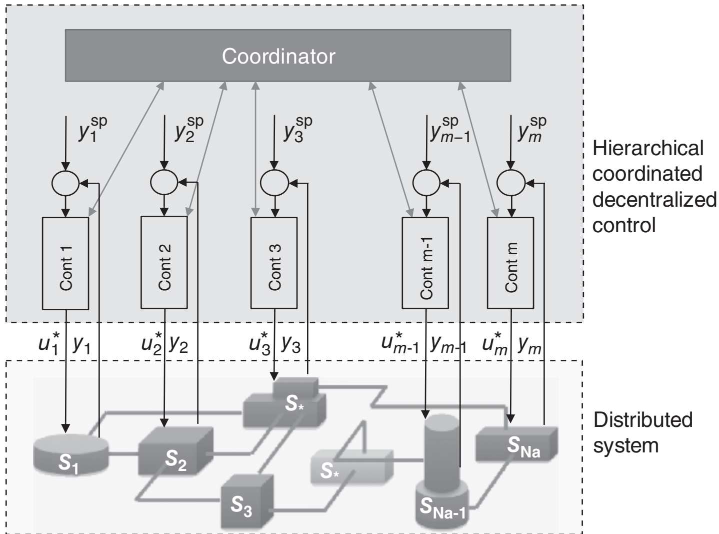

Figure 1.7 Hierarchical coordinated decentralized control

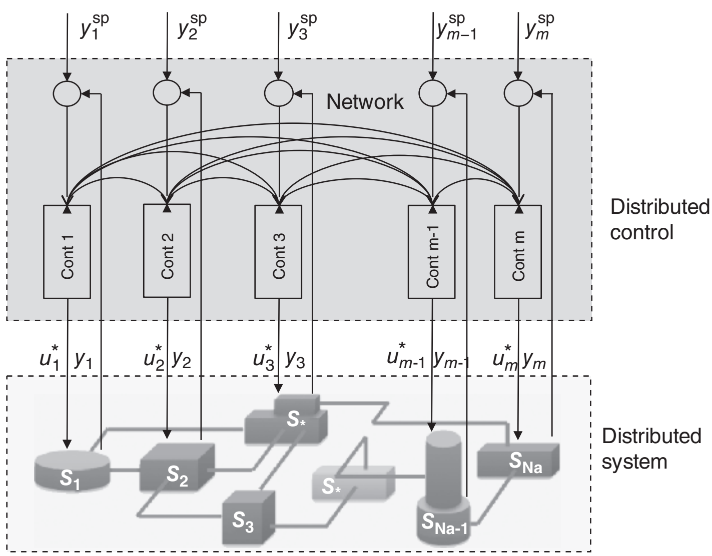

Figure 1.8 Distributed control

with each other through a network for achieving good global performance or a specifically common goal. This kind of control structure has the advantage of a decentralized control structure, e.g., high flexibility and good error tolerance, and the advantage of a centralized control structure, e.g., good global performance. In a distributed control structure, the most important problem is how to design coordinating strategies for different purposes.

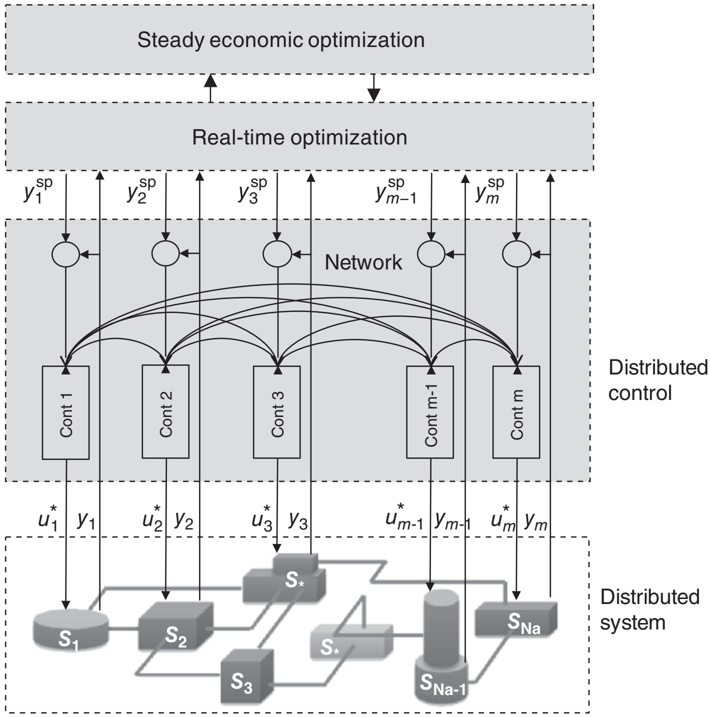

Figure 1.9 Distributed control in the hierarchical control system

Figure 1.9 shows the complete structure of an industrial control system structure with distributed control for the plant-wide system. The multivariable layer in Figure 1.4 is substituted by the distributed control which provides the set-points for the field control loops.

1.3 Predictive Control

1.3.1 What is Predictive Control

Model predictive control (MPC), also called receding horizon control, is one of the leading advanced control technologies employed in the process industries and can incorporate complex objectives as well as constraints in a unified framework. Using the current state, a control sequence is calculated to minimize a performance index while satisfying some specified constraints. Only the first element of the sequence is taken as controller output. At the next sampling time, the optimization is resolved with new measurements from the plant [1–3].

Predictive control was pioneered simultaneously by Richalet *et al.* [4] and Cutler and Ramaker [5]. The first implemented algorithms and successful applications were reported in the papers mentioned above. The use of finite impulse response models and finite step response models, which are easy to obtain for open loop stable processes, partly explains the wide acceptance especially in the hydrocarbon processing industries. Since the end of the seventies and early eighties, MPC has become the most widely applied multivariable control technique and many papers report that MPC has been applied successfully to various linear [3, 6, 7], nonlinear [8–11] systems in process industries and is becoming more widespread [3, 12, 13]. Some examples are a distillation column [6, 14], a fluidized bed catalytic cracker [15], a hydrocracker [16], a utility boiler [17], a chemical reactor [1], a transonic wind turbine [18], a pulp and paper plant [3], and a metallurgical process [12, 19–21]. Applications of MPC to faster systems were also reported, such as a mechatronic servo system [22], a power converter [23], and a robot arm [24]. This list is far from complete, but it gives an impression of the wide range of MPC applications [25].

1.3.2 Advantage of Predictive Control

Predictive control is widely recognized as a high practical control technology with high performance. It has a significant and widespread impact on industrial process control. The penetration of predictive control into industrial practice has also been helped by the following facts [2, 26]:

- Its underlying ideas are easy to understand.
- It handles multivariable control problems naturally.
- It is more powerful than proportional integral derivative (PID) control, even for single loops without constraints. It is easier to tune than PID even on “difficult” loops such as those containing long time delay.
- It is the unique control method which can deal routinely with equipment and safety constraints.
- It often obtains very small mean square error (MSE) of process variables, which allows operation closer to constraints compared with conventional control, and then frequently leads to more profitable operation.

In addition, MPC is rather a methodology than a single technique. The difference in the various methods is mainly the way the problem is translated into a mathematical formulation. However, in all methods three important items are recognizable in the design procedure: the prediction model, receding horizon optimization, and the output feedback and correction.

1.4 Distributed Predictive Control

1.4.1 Why Distributed Predictive Control

For a class of large-scale system with hundreds or thousands of inputs and outputs variables (e.g., power and energy network, large chemical processes), the classical centralized MPC, where a control agent is able to acquire the information of the global system and could obtain a good global performance, is often impractical to apply to a large-scale system for some reasons: (1) there are hundreds of inputs and outputs. It requires large computational efforts in online implementation; (2) when the centralized controller fails, the entire system is out of control and the control integrity cannot be guaranteed when a control component fails; (3) in some cases, e.g., in a multi-intelligent vehicle system, the global information is unavailable to each controller. Thus, the DMPC appears and gradually substitutes the centralized MPC.

The distributed predictive not only inherits the advantages of MPC of directly handling constraints and good optimization performance, but also has the characteristics of a distributed control framework of less computational burden, high flexibility, and good error tolerance. Using distribute predictive control, the future state information of each subsystem is able to feed into its interacted subsystem-based MPC and then satisfy the versatile control objective, e.g., large lag system, and more restrict control performance requirements.

1.4.2 What is Distributed Predictive Control

For a class of large-scale systems with hundreds or thousands of input and output variables (e.g., power and energy network, large chemical processes), as shown in Figure 1.10, the whole system is properly partitioned into several interconnected subsystems and controlled in a distributed structure. Each subsystem is controlled by a local controller, and these local controllers are interconnected by a network. If the algorithm running in each local controller is predictive control, as shown in Figure 1.10, we call the whole control the distributed predictive control. In the distributed predictive control, each local predictive control coordinates with another one by exchanging the network information. More simplified, the distributed predictive control is the distributed implementation of a set of predictive controllers, and these predictive controllers consider the feedforward information from the predictive controllers corresponding to the subsystems they interacted with.

1.4.3 Advantage of Distributed Predictive Control

The distributed predictive control not only inherits the advantages of MPC of directly handing constraints and good optimization performance, but also has the characteristics of the distributed control framework of less computational efforts, high flexibility, good error

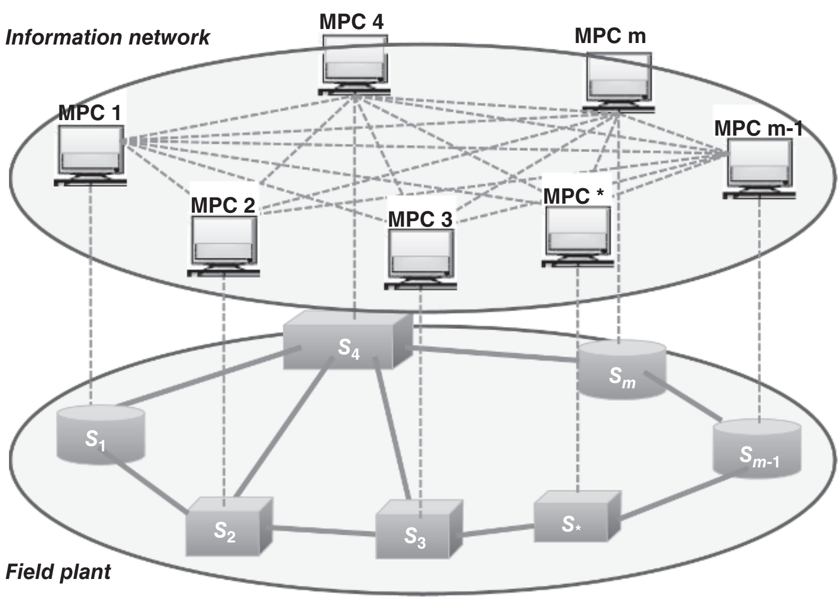

Figure 1.10 Distributed predictive control

tolerance, and no global information requirements [27, 28]. The advantages of the distributed predictive control are as follows:

- Its underlying ideas are easy to understand: the distributed predictive control is the distributed implementation of a set of predictive controllers, and these predictive controllers consider the feedforward information from the predictive controllers which corresponds to the subsystems they interacted with.
- The local predictive control can deal routinely with equipment and safety constraints.
- The local predictive control handles multivariable control problems naturally. It is more powerful than PID control, even for single loops without constraints. It is not much more difficult to tune, even on "difficult" loops such as those containing long time delay.
- It allows operation closer to constraints compared with conventional control, which frequently leads to more profitable operation.
- Since the centralized predictive control is decomposed into many small-scaled predictive controllers, the computational efforts in each small-scaled predictive control are much less than that used for solving the centralized predictive control.
- If one or several errors occur in a subsystem, the other subsystem-based predictive controllers are still able to work. There is a good error-tolerance characteristic.
- If some new subsystems are appended into the current system, it is not necessary to modify all the local predictive controls. We should only modify the predictive control whose corresponding subsystem interacts with the new added subsystems. The distributed predictive control owns high flexibility to the system structure.
- The "plug-in and plug-out" is also able to be realized if a suitable algorithm and an appropriate program are designed.

Due to these advantages, the distributed predictive control gradually takes the place of a centralized predictive control for plant-wide systems. However, as pointed out in [27–33], the optimization performance of distributed predictive control, in most cases, is not as good as that of centralized predictive control. Thus, many different coordinating strategies are proposed to solve this problem [27, 29, 31–44]. In most cases, the coordinating strategies are very important to the performance of the closed-loop systems.

1.4.4 Classification of DMPC

To improve the global performance of the DMPC, several coordination strategies have appeared in the literature, and can be classified according to the information exchange protocol needed, and to the type of cost function which is optimized [6]. There are two classes of distributed predictive control if we catalog it by the information exchange protocol.

- *Noniterative-based algorithm*: in this kind of distributed predictive control, each local predictive control communicates only once with other local predictive control within every single control period, and solves the local control law once in a control period, e.g., [34, 44–47].
- *Iterative-based algorithm*: this kind of distributed predictive control assumes that the network communication resources are abundant enough for supporting the fact that each local

predictive control communicates with other interacted local predictive control many times in a single control period. And the time cost by communicating is very little, such that it could be ignored as compared to the control period. Each local predictive control solves its optimal control law based on the presumed control sequence. Then it transforms this control law to its interacted local predictive controllers. After that, each local predictive solves the new optimal control law based on the optimal control law based on its neighbors' optimal control laws solved at the last previous iteration, and then repeats this process until the iteration broken-down conditions are satisfied, e.g., [19, 29, 37, 48, 49].

The noniterative algorithms consume less communication resources than the iterative algorithms, and have a fast computation speed in comparison to the iterative algorithms. The iterative algorithms are able to achieve a better global performance than the noniterative algorithms.

There are three kinds of DMPCs if we classify DMPCs by the cost function of each local predictive control. And the DMPCs that accommodate the same kind of cost function for each subsystem-based MPC can be solved either by the iterative algorithm or by the noniterative algorithm. We briefly review these methods as motivations for the content to be presented later in the book.

- Local cost optimization-based DMPC (LCO-DMPC): distributed algorithms where each subsystem-based controller minimizes the cost function of its own subsystem were proposed in [1–4]

$$J_i(k) = \|\mathbf{x}_i(k+N)\|^2_{\mathbf{P}_i} + \sum_{s=0}^{N-1} \left(\|\mathbf{x}_i\,(k+s)\|^2_{\mathbf{Q}_i} + \|\mathbf{u}_i\,(k+s)\|^2_{\mathbf{R}_i} \right) \tag{1.1}$$

  When computing the optimal solution, each local controller exchanges state estimation with the neighboring subsystems to improve the performance of the local subsystem. This method is simple and very convenient for implementation. An extension of this stabilizing DMPC with input constraint for nonlinear continuous systems is given in [51, 52], and a stabilizing DMPC with input and state constraints is given in [50].

  Also, an iterative algorithm for DMPC based on *Nash optimality* was developed in [1]. The whole system will arrive at Nash equilibrium if the convergence condition of the algorithm is satisfied.
- Cooperative distributed MPC (C-DMPC): to improve the global performance, distributed algorithms, where each local controller minimizes a global cost function

$$J_i(k) = \sum_{j\in\mathrm{P}} J_j(k) \tag{1.2}$$

  were proposed in [31, 37, 44, 48, 53]. In this method, each subsystem-based MPC exchanges information with all other subsystems. And some iterative stabilizing designs are proposed which take the advantages of the model of the whole system, and are used in each subsystem-based MPC. This strategy may result in a better performance but consumes much more communication resources, in comparison with the method described in (1.1).
- Networked DMPC with information constraints (N-DMPC): to balance the performance, communication cost, and the complexity of the DMPC algorithm, a novel coordination strategy was recently proposed in [19, 47, 54]. Here each subsystem-based controller minimizes

its corresponding subsystem's cost function and the cost function of the subsystems directly impacts on

$$\overline{J}_i(k) = \sum_{j \in \mathcal{P}_i} J_j(k) \tag{1.3}$$

where $\mathcal{P}_i = \{j : j \in \mathcal{P}_{-i} \text{ or } j = i\}$ is the set of subscripts of the downstream subsystems of subsystem $\mathcal{S}_i$, that is the region impacted on by subsystem $\mathcal{S}_i$. The resulting control algorithm is termed as an impacted-region cost optimization-based DMPC (ICO-DMPC) [55–57] or N-DMPC with communication constraints. It could achieve a better performance than the first method, and its communication burden is much less than the second method. Clearly, this coordination strategy as proposed in [19, 47, 54] and described in (1.3) is a preferable method to trade off the communication burden and global performance.

Some other kinds of DMPC formulations are also available in [11, 13, 29, 46, 48, 51–54, 58–64]. Among them, the methods described in [52, 62] are proposed for a set of decoupled subsystems, and the extension of [52] could handle systems with weakly interacting subsystem dynamics [51]. There is no absolute priority among these different distributed predictives. One could select different algorithms according to their purpose of employing the control system.

1.5 About this Book

This book systematically introduces the distributed predictive control with different coordination strategies for the plant-wide system, including the system decomposition, classification of distributed predictive control, unconstrained distributed predictive control, and the stabilized distributed predictive control with different coordinating strategies for different purposes, as well as the implementation examples of distributed predictive control. The major new contribution of this book is to show how the DMPCs can be coordinated efficiently for different control requirements, namely the network connectivity, error tolerance, performance of the entire closed-loop system, calculation speed, etc. This book also describes how to design DMPC. The latest theory and technologies of DMPC for coupling discrete-time linear systems are introduced in this book. The rest of this book is structured into four parts, as shown in Figure 1.11, and are organized as follows.

In the first part, Chapters 2 and 4, we recall the main concepts and some fundamental results of the predictive control for discrete-time linear systems. Some existing results about the solution and the stability of the closed-loop system under the control of MPC are provided in this part. The system model, structure model, and some decomposition methods, e.g., the relative gain array (RGA), N-step accessible matrix-based decomposition, are also introduced in this chapter to present how to divide the entire system into the interacted subsystems according to the specific control requirements. Then some coordination strategies are introduced according to the classification of coordination degree (the optimization index of each subsystem-based MPC).

Our intent is to provide only the necessary background for the understanding of the rest of the book.

In the second part, Chapters 5–7, the unconstrained DMPCs with different coordination strategies are introduced for primary readers, since the major ideas and the characteristics of

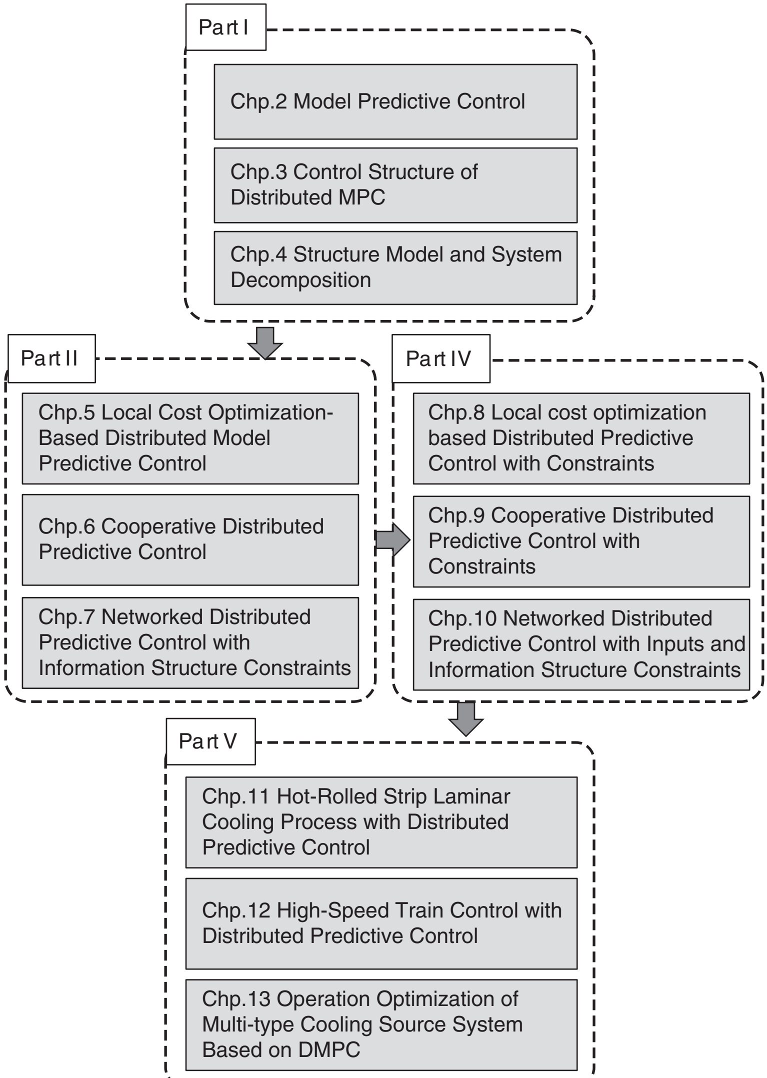

Figure 1.11 Content of this book

DMPCs can be clearly explained in a simple way without constraints. Chapter 5 presents the LCO-DMPC (the simplest and most practical one) and Nash optimization-based DMPC (the solution of which could obtain Nash optimality). Chapter 6 provides the C-DMPC which could obtain very good performance of the entire system but each subsystem-based MPC of which requires the information of the whole system. Chapter 7 introduces the N-DMPC with information constraints which is a tradeoff between the two methods mentioned above. Both iterative algorithm and noniterative algorithm for solving the optimal solution of subsystem-based MPC are given in each coordinating strategy. The predictive model, explicit solution, and stability analysis of each algorithm are also detailed in this part.

In the third part, Chapters 8–10, we focus on introducing the design methods of the stabilizing DMPCs with constraints for the advanced readers. In Chapter 8, a design method for the LCO-DMPC is developed, which is based on a dual mode scheme and is able to handle input constraints. The feasibility and stability of this method are analyzed. In addition, Chapter 9 introduces a stabilizing DMPC with constraints, in which each subsystem-based MPC optimizes the cost of whole system. The consistency constraints, which limit the error between the optimal input sequence calculated at the previous time instant, referred to as the presumed inputs, and the optimal input sequence calculated at the current time instant to within a prescribed bound, are designed and included in the optimization problem of each local predictive control. The noniterative algorithm for the related fast process is designed for solving each local predictive control. Both the feasibility and stability of this method are analyzed. Chapter 10 provides a networked distributed predictive control with inputs and information constraints, where each local predictive control optimizes not only its own performance but also that of the systems it directly impacted on. The consistency and stability constraints are designed to guarantee the recursive feasibility and the asymptotical stability of the closed-loop system if the initial feasible solution exists.

In the last part, Chapters 11–13, three practical examples are given to illustrate how to implement the introduced DMPC into the industrial process. At first, the implementation of DMPC to accelerated cooling processes in heavy plate steel mills is introduced. The control problem, the system model, the system decomposition, the control strategy, and the performance of the closed-loop system under the control of DMPC are provided. Then, different from the metallurgical process, one example of the speed train control with DMPC is presented and the technical details are also provided. Finally, a load control of a high building in Shanghai with multicooling resources system is studied, and the distributed predictive with a scheduling layer is developed and detailed in Chapter 14.

In conclusion, this book tries to give systematic and latest distributed predictive control technologies to the readers. We hope this book could help engineers to design their control systems in their daily work or in their new projects. In addition, we believe that this book is fit for the graduate students who are pursuing their master's or doctor's degree in control theory and control engineering. We will be very pleased if this book could really do something for you if you are interested in the control of a plant-wide system or predictive control.