Model Free Adaptive Control

Theory and Applications

Zhongsheng Hou • Shangtai Jin

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Preface

During the past half century, modern control theory has developed greatly and many branches and subfields have emerged, for example, linear system theory, optimal control, system identification, adaptive control, robust control, sliding mode control, and stochastic system theory, etc. Meanwhile, lots of remarkable applications of modern control theory have been carried out in many practical fields, such as industrial processes, aerospace, urban transportation, and so on. However, we now face great challenges in studying and applying these control methods, because many new problems have been generated by the theoretical development of the control discipline itself and by practical control requirements of plants in the real world. Modern control theory was established and developed based on a fundamental assumption that the mathematical model or nominal model of a controlled plant is accurately known. As we know, building a model for a practical plant is a tough task, and sometimes it is impossible. Even if the model is properly derived, its accuracy is also in serious doubt. Therefore, difficulty in modeling, poor robustness, lack of safety, as well as a huge gap between theoretical analysis and practical performance, are common phenomena when applying modern control theory in practice. Some important theoretical problems, which are difficult to address within the framework of traditional model-based control theory, including accurate modeling versus model/controller simplification, unmodeled dynamics versus robustness, and unknown uncertainties versus assumption on their known upper bound required by robust design, and so on, hinder the healthy development of the modern control theory. Further, even when the mathematical model of the controlled plant is accurately built, it must be a very complicated one with strong nonlinearity and high order, due to the complexity of a practical system itself. Complex system model definitely leads to a complex controller, which renders unavoidable difficulties in controller design and system analysis. A complicated controller costs much, is hard to apply and maintain, and is unacceptable to engineers.

With the development of information science and technology in recent years, practical processes in many fields, such as chemical industry, metallurgy, machinery, electricity, transportation and logistics, and so on, have been undergoing significant changes. The scale of the enterprises is becoming increasingly large, the production process is becoming more and more complex, and the requirements on product quality are also becoming higher and higher. This challenges the existing control theory and methods since both of these are based on accurate mathematical model of the controlled plant. On the other hand, a huge amount of process data generated by practical plants and industrial processes could be obtained and stored, and it contains all the valuable state information about the process operations implicitly. In this case, how to utilize the collected data and the mined knowledge to develop efficient control and optimization methods for industrial processes when accurate process models are unavailable has become a vital issue faced by the control theory community. Therefore, developing data-driven control theory and methods is an inevitable choice for development of the control theory in the new era and is of great significance in both theory and practice.

Model-free adaptive control (MFAC), as a typical data-driven control method, was proposed by the first author of this book in his doctoral dissertation in 1994. For MFAC, only the measurement I/O data of the controlled plant are directly used for controller design and closed-loop system analysis, without any model dynamics involved. By applying MFAC, adaptive control for an unknown nonlinear system with time-varying parameters and time-varying structure is uniformly realized, and the existing difficulties in modern control methods, such as the dependence of controller design on system model, unmodeled dynamics, traditional robustness issues, and other related theoretical problems, are avoided within the data-driven control framework. Both the theoretical results incessantly developed and improved in the past two decades, and their successful practical applications in motor control, the chemical industry, machinery, and so on, have made MFAC become a novel control theory with a systematic and rigorous framework.

The main contents of the book cover the dynamic linearization approach, model-free adaptive control, model-free adaptive predictive control, and model-free adaptive iterative learning control for discrete-time SISO and MIMO nonlinear systems, with corresponding stability analysis and typical practical applications. Moreover, some more important issues are also studied in this monograph, including model-free adaptive control for complex connected systems, modularized controller designs between model-free adaptive control and other control methods, robustness of model-free adaptive control, and concept of the symmetric similarity for adaptive control system design.

The first author of this book would like to gratefully acknowledge the National Science Foundation of China for long-term support under grant No. 60834001, 61120106009, and 60474038, which helped to complete this monograph.

The first author expresses his sincere appreciation to his students whose contributions enriched and shaped the theory and applications of MFAC, namely Dr. Ronghu Chi, Dr. Weihong Wang, Dr. Chenkun Yin, Dr. Jingwen Yan, Dr. Xuhui Bu, and Dr. Xiangbin Liu, and PhD candidates Yongqiang Li, Heqing Sun, Yuanming Zhu, and Honghai Ji. Special thanks are due to Dr. Ronghu Chi and Dr. Chenkun Yin for their careful proofreading of this monograph. Many thanks

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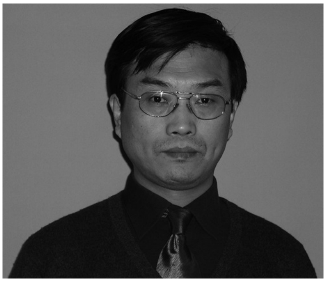
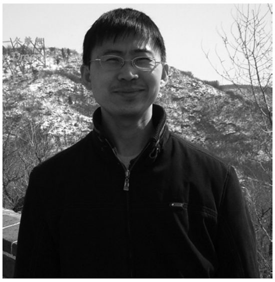


Zhongsheng Hou received his bachelor's and master's degrees from Jilin University of Technology, Changchun, China, in 1983 and 1988, respectively, and his PhD degree from Northeastern University, Shenyang, China, in 1994. He was a postdoctoral fellow with Harbin Institute of Technology, Harbin, China, from 1995 to 1997 and a visiting scholar with Yale University, New Haven, Connecticut, from 2002 to 2003. In 1997, he joined Beijing Jiaotong University, Beijing, China and is currently a full professor and the founding director of the Advanced Control Systems Lab and the dean of Department of Automatic Control in the School of Electronic and Information Engineering.

His research interests lie in the fields of data-driven control, model-free adaptive control, iterative learning control, and intelligent transportation systems. He has been the principal investigator for the state key program and the major international cooperation and exchange program of the National Natural Science Foundation of China. Up to now, he has over 110 peer-reviewed journal papers published and over 120 papers in prestigious conference proceedings. He is the author of the monograph *Nonparametric Model and Its Adaptive Control Theory*, Science Press of China, 1999. Dr. Hou has served as technical committee member for over 50 international and Chinese conferences and as associate editor and guest editor for a number of prestigious international and Chinese journals.



Shangtai Jin received his BS, MS, and PhD degrees from Beijing Jiaotong University, Beijing, China, in 1999, 2004, and 2009, respectively. He is currently a lecturer with Beijing Jiaotong University. His research interests include model-free adaptive control, data-driven control, learning control, and intelligent transportation systems.

Symbols

L	Control input linearization length constant in the PFDL data model
L_y	Controlled output linearization length constant in the FFDL data model
L_u	Control input linearization length constant in the FFDL data model
$\phi_c(k)$	PPD in the CFDL data model for SISO discrete-time nonlinear systems at time instant k
$\phi_c(k,i)$	PPD in the iteration related CFDL data model for SISO discrete-time nonlinear systems at time instant k of the ith iteration
$\mathtt{f}_c(k)$	PG in the CFDL data model for MISO discrete-time nonlinear systems at time instant k
$\mathtt{f}_{c,i}(k)$	PG in the CFDL data model of the ith subsystem for interconnected systems at time instant k
$\mathtt{f}_{p,L}(k)$	L-dimensional PG in the PFDL data model for SISO discrete-time nonlinear systems at time instant k
$\bar{\mathtt{f}}_{p,L}(k)$	mL-dimensional PPG in the PFDL data model for MISO discrete-time nonlinear systems at time instant k
$\mathtt{f}_{i,pL}(k)$	L-dimensional PG in the PFDL data model of the ith subsystem for interconnected systems at time instant k
$\mathtt{f}_{f,L_y,L_u}(k)$	$L_y + L_u$-dimensional PG in the FFDL data model for SISO discrete-time nonlinear systems at time instant k
$\bar{\mathtt{f}}_{f,L_y,L_u}(k)$	$L_y + mL_u$-dimensional PPG in the FFDL data model for MISO discrete-time nonlinear systems at time instant k
$\mathtt{f}_S(k)$	PG in the PFDL data model for systems in series connection at time instant k
$\mathtt{f}_P(k)$	PG in the PFDL data model for systems in parallel connection at time instant k
$\mathtt{f}_F(k)$	PG in the PFDL data model for systems in feedback connection at time instant k
$\mathbf{\Phi}_c(k)$	$m \times m$-dimensional PJM in the CFDL data model for MIMO discrete-time nonlinear systems at time instant k

$\boldsymbol{\Phi}_{p,L}(k)$ — $m \times mL$-dimensional PPJM in the PFDL data model for MIMO discrete-time nonlinear systems at time instant k

$\boldsymbol{\Phi}_{f,L_y,L_u}(k)$ — $mL_y \times mL_u$-dimensional PPJM in the FFDL data model for MIMO discrete-time nonlinear systems at time instant k

$\boldsymbol{U}_L(k)$ — Vector in the PFDL data model for SISO discrete-time nonlinear systems, consisting of all control input signals within a moving time window $[k-L+1,k]$, that is, $\boldsymbol{U}_L(k)=[u(k),\ldots,u(k-L+1)]^T$

$\boldsymbol{U}_{i,L_i}(k)$ — Vector in the PFDL data model of the ith subsystem for interconnected systems, consisting of all control input signals within a moving time window $[k-L+1,k]$, that is, $\boldsymbol{U}_{i,L_i}(k)=[u_i(k),\ldots,u_i(k-L+1)]^T$

$\bar{\boldsymbol{U}}_L(k)$ — Vector in the PFDL data model for MIMO (MISO) discrete-time nonlinear systems, consisting of all control input signals within a moving time window $[k-L_y+1,k]$, that is, $\bar{\boldsymbol{U}}_L(k)=[\boldsymbol{u}^T(k),\ldots,\boldsymbol{u}^T(k-L+1)]^T$

$\boldsymbol{H}_{L_y,L_u}(k)$ — Vector in the FFDL data model for SISO discrete-time nonlinear systems, consisting of all control input signals within a moving time window $[k-L_u+1,k]$, and all system output signals within a moving time window $[k-L_y+1,k]$, that is, $\boldsymbol{H}_{L_y,L_u}(k)=[y(k),\ldots,y(k-L_y+1),u(k),\ldots,u(k-L_u+1)]^T$

$\bar{\boldsymbol{H}}_{L_y,L_u}(k)$ — Vector in the FFDL data model for MIMO discrete-time nonlinear systems, consisting of all control input signals within a moving time window $[k-L_u+1,k]$, and all system output signals within a moving time window $[k-L_y+1,k]$, that is, $\bar{\boldsymbol{H}}_{L_y,L_u}(k)=[\boldsymbol{y}^T(k),\ldots,\boldsymbol{y}^T(k-L_y+1),\boldsymbol{u}^T(k),\ldots,\boldsymbol{u}^T(k-L_u+1)]^T$

$\breve{\boldsymbol{H}}_{L_y,L_u}(k)$ — Vector in the FFDL data model for MISO discrete-time nonlinear systems, consisting of all control input signals within a moving time window $[k-L_u+1,k]$, and all system output signals within a moving time window $[k-L_y+1,k]$, that is, $\breve{\boldsymbol{H}}_{L_y,L_u}(k)=[y^T(k),\ldots,y^T(k-L_y+1),\boldsymbol{u}^T(k),\ldots,\boldsymbol{u}^T(k-L_u+1)]^T$

R — Real number set

R^n — n-dimensional real vector space

$R^{n\times m}$ — $n \times m$-dimensional real matrix space

Z^+ — Positive integer set

I — Identity matrix

q^{-1} — Unit delay operator

Δ — Difference operator

sign(x) — Sign function

round($\cdot$) — Round function

$|\cdot|$ — Absolute value

$\|\cdot\|_v$ — Consistent norm

$\hat{a}(k)$ — Estimation value of variable a at time k

$\tilde{a}(k)$	Estimation error of variable a, that is, $\tilde{a}(k) = \hat{a}(k) - a(k)$
$s(A)$	Spectral radius of A
A^{-1}	Inversion matrix of A
A^{T}	Transpose of A
A^{*}	Adjoint of A
$\det(A)$	Determinant of A
$\sigma_1(A)$	Condition number of A
$\lambda_{\max}[A]$	Largest eigenvalue of A
$\lambda_{\min}[A]$	Smallest eigenvalue of A
$\nabla J(\mathtt{q})$	Gradient of function $J(\mathtt{q})$ with respect to $\mathtt{q}$
$\nabla^2 J(\mathtt{q})$	Hessian matrix of function $J(\mathtt{q})$ with respect to $\mathtt{q}$

Acronyms

CFDL	Compact form dynamic linearization
CFDL–MFAC	Compact form dynamic linearization based model-free adaptive control
CFDL–MFAILC	Compact form dynamic linearization based model-free adaptive iterative learning control
CFDL–MFAPC	Compact form dynamic linearization based model-free adaptive predictive control
DDC	Data-driven control
FFDL	Full form dynamic linearization
FFDL–MFAC	Full form dynamic linearization based model-free adaptive control
FFDL–MFAPC	Full form dynamic linearization based model-free adaptive predictive control
IFT	Iterative feedback tuning
ILC	Iterative learning control
MBC	Model-based control
MFAC	Model-free adaptive control
MFAILC	Model-free adaptive iterative learning control
MFAPC	Model-free adaptive predictive control
MIMO	Multiple-input and multiple-output
MISO	Multiple-input and single-output
PFDL	Partial form dynamic linearization
PFDL–MFAC	Partial form dynamic linearization based model-free adaptive control
PFDL–MFAPC	Partial form dynamic linearization based model-free adaptive predictive control
PG	Pseudo gradient
PID	Proportional-integral-differential control
PJM	Pseudo-Jacobian matrix

PPD	Pseudo partial derivative
PPG	Pseudo partitioned gradient
PPJM	Pseudo partitioned Jacobian matrix
SISO	Single-input and single-output
VRFT	Virtual reference feedback tuning

Chapter 1

Introduction

In this chapter, the existing problems and challenges of the model-based control (MBC) theory are briefly reviewed, followed by a brief discussions of the available data-driven control (DDC) methods with definition, classifications, traits, insights, and applications. Finally, the outline of this book is given.

1.1 Model-Based Control

The introduction of state-space models by Kalman in 1960 [1,2] gave birth to modern control theory and methods. Modern control theory was founded and developed on a basis that the mathematical model or the nominal model of the controlled system is exactly known, thus, it is also called MBC theory. With the prosperous development of MBC theory including linear system theory, system identification theory, optimal control theory, adaptive control theory, robust control theory, filter and estimation theories, and so on, many successful applications of MBC are found in practical fields, especially in the fields of aerospace, national defense, and industry. On the other hand, the scale of industrial plants and enterprises becomes increasingly large, the production technology and processes also become more and more complex, and the requirements on product quality become higher and higher. All these, which were not exposed fully before, bring great challenges to the theoretical studies and practical applications of MBC theory.

1.1.1 Modeling and Identification

At present, almost all the control methods for linear and nonlinear systems are model-based. For the MBC methods, the first step is to build the mathematical model of the plant, then to design the controller based on the plant model obtained with the faith that the plant model represents the true system, and finally to analyze the closed-loop control system still in virtue of the mathematical model. The "certainty equivalence principle" is the cornerstone of modern control theory, and the plant model is the starting point and landmark for the controller design and analysis, as well as the evaluation criterion and control destination for the MBC methods.

There are two kinds of methods for modeling a plant: the first principles method and the system identification method. Modeling a plant using first principles means to establish the dynamic equations of the controlled plant according to some physical or chemical principles, and to determine the model parameters by a series of experiments. Modeling a plant by system identification is to develop an input–output plant model, which lies in a specified model set covering the true system and can approximate the true system in terms of bias or error, using the online or offline measurement data. It is recognized that modeling by first principles or system identification is just an approximation of the true system with some error, due to the complexities in system structure and operation environment. In other words, the unmodeled dynamics and other uncertainties always exist in the modeling process. Consequently, the application of the controllers designed on the inaccurate mathematical model may bring various practical problems. The corresponding closed-loop control system may have weak robustness and inherently possible lack of safety because of the unmodeled dynamics and external disturbances [3–6].

To preserve the obvious advantages of MBC design while increasing robustness against model errors, much effort has been put into the development of robust control theory. Various ways of describing model errors in the configuration of closed-loop systems have been considered. These include additive, multiplicative descriptions and the assumption on *a priori* bounds for noise, modeling errors, or uncertainties. However, the descriptions of these uncertainties upon which robust control design methods are based, cannot be obtained quantitatively or qualitatively by physical modeling or identification modeling. Even for the upper bound of the uncertainty, so far no identification method is able to supply its quantification. In other words, the descriptions of these uncertainties are not consistent with the results delivered by physical modeling or identification modeling [7]. Therefore, theoretically speaking, it is difficult to apply MBC methods to synthesize the controller for practical systems, and the control performance and safety may not be guaranteed when the model-based controller is connected to the practical plants [8].

For control system design, a very intuitive way is to first put a significant amount of effort to obtain a very accurate mathematical model (including uncertainties) for the unknown system by first-principles modeling or identification techniques, and then design a model-based controller based on this model for practical applications. However, there are both practical and theoretical difficulties in the establishment of a perfect plant model and the controller. First, unmodeled dynamics and the robustness are inevitable twinborn problems and they cannot be solved simultaneously within the conventional MBC theoretical framework. Up to now, there is no efficient tool or method, in mathematics theory or system identification, to produce an accurate plant model for complex nonlinear systems that exist everywhere in the real world. Accurate modeling sometimes is more difficult than control system design itself. If the plant dynamics is with time-varying structure or fast-varying parameters, it would be hard to determine the plant model, to design and analyze the control system using analytical mathematics tools. Second, the more accurate the model is, the more effort or cost we should spend, and the more complicated the controller is as well. In a sequel, the complex controller must lead to weak robustness and low reliability of the controlled system. Moreover, great difficulties would be brought in the implementation and application of the control system. If the system dynamics is of very high order, it is not suitable for practical controller design, since such a model would definitely lead to a controller with very high order, which possibly makes control system design, analysis, and application complicated and brings many difficulties in system monitoring and maintenance. In practice, reduction of the model or controller must be performed additionally to obtain a simple and practical control system. It seems paradoxical to build an accurate high-order model to target high performance for control system design, and then to perform model simplification for a low-order controller. The last but not least difficulty is the "persistent excitation" condition for modeling. It is a great challenge for input signals to satisfy the "persistent excitation" condition during modeling and closed-loop control. Without the persistently exciting inputs, an accurate model cannot be produced. In such a circumstance, most MBC theoretical results of a closed-loop control system, such as stability and convergence, cannot be guaranteed as what they claimed when they are used in practice [4–6,8]. "Persistent excitation" condition and control performance are also paradoxical, and cannot be handled within the framework of traditional MBC theory.

1.1.2 Model-Based Controller Design

For modern control theory, controller design is based on the mathematical model of a plant. Typical linear control system design methodologies are zero-pole assignment, linear quadratic regulator (LQR) design, optimal control design, and so on. For nonlinear systems, the inevitable controller design methods are the Lyapunov-based methods with backstepping controller design, feedback linearization, and so on. These controller design methodologies are recognized to be typical MBC system design methods. The key skill of MBC controller design and analysis is performed through mathematical analysis of the error dynamics of the closed-loop system, and the plant model is included in every phase of the control system design and applications, such as operation monitoring, evaluation, and diagnosis. The architecture of MBC theory is shown in Figure 1.1. This diagram shows that the system model and assumptions are the starting point for controller design, and also the destination for MBC control system analysis.

Since the unmodeled dynamics and other uncertainties always exist in modeling and closed-loop control process, a model-based controller may not work well

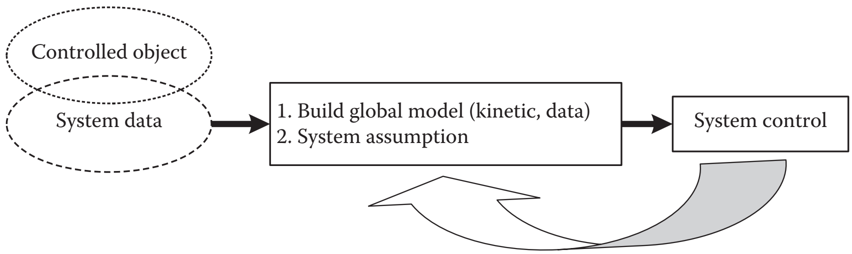


Figure 1.1 Architecture of MBC theory.

in practice, and even leads to bad performance or causes the closed-loop system unstable. An arbitrarily small modeling error could lead to a very bad closed-loop performance [9]. Rohr's counterexample in adaptive control is a warning bell for scholars to contemplate MBC theory and methods. The Rohr's counterexample has demonstrated that reported stable adaptive control systems, based on some assumptions made about the system model and the certainty equivalence principle, may show a certain unexpected behavior in the presence of unmodeled dynamics [10,11]. Thus, the correctness and applicability of MBC control system design methods are challenged.

Even when the model is accurate enough, the results of a theoretical analysis, such as the stability, convergence, and robustness of a closed-loop control system proven by rigorous mathematical derivation, are not always valuable if the additional assumptions made about the system are not reasonable. Taking adaptive control as an example, adaptive control methods often say that under assumptions A, B, C, D, and E, and with the use of algorithm F, all signals remain bounded as time goes to infinity, and then some other results occur. However, the uncertainties, including disturbances and the parameter shifting due to aging when the plant goes into operation, are inevitable for the adaptive control in practice. Those external factors and unmodeled dynamics may lead to an unstable closed-loop system. In other words, the stated conclusion in adaptive control does not rule out the possibility that at some time before time goes to infinity, the controller connected to the plant could make the closed-loop system unstable [6].

There are two kinds of uncertainties. One is the parametric uncertainties and the other is the nonparametric uncertainties. To enhance the robustness, many modification techniques and robust adaptive control design methods were proposed, such as normalization, dead-zone method, projection method, σ-modification and sliding mode adaptive method, and so on. The robustness issue of adaptive control systems is an intractable topic that attracts much research attention.

For MBC control system design, the modeling accuracy and correctness of the assumptions imposed on the plant mathematical model together determine the control system performance, reliability, and safety, since the available system model kinetics is embedded in the control system. If the system model is unavailable or the assumptions do not hold, then no conclusion on controller design and analysis could be obtained, and further we have no way to discuss applications. The MBC control method comes from the system model and ends up in the system model. To some extent, it may be called model theory rather than control theory.

1.2 Data-Driven Control

With the development of information science and technology, many industrial processes, for instance, chemical industry, metallurgy, machinery, electronics, electricity, transportation, and logistics, have been undergoing significant changes. As the scale of the enterprises becomes increasingly large, the production technology, equipment, and production process also become more and more complex, and the requirements on product quality become higher and higher. Hence, modeling these processes using the first-principles or identification method becomes more and more difficult, which leads us to conclude that using the traditional MBC theory to deal with the control issues in these kinds of enterprises would be impractical. On the other hand, however, many industrial processes generate and store a huge amount of process data, which contain all the valuable state information of the process operations and the equipments. In this case, it is of great significance to utilize these process data, gained online or offline, directly for controller design, monitoring, prediction, diagnosis, and assessment of the industrial processes when the accurate process models are unavailable. Therefore, the establishment and development of the DDC theory and methods are of significant importance in both control theory and applications.

Up to now, there exist a few DDC methods, such as proportion integral differential (PID) control, model-free adaptive control (MFAC), iterative feedback tuning (IFT), virtual reference feedback tuning (VRFT), iterative learning control (ILC), and so on. Although the studies on DDC are still in their embryonic stage, they attract much attention in the control theory community. The Institute for Mathematics and Its Applications (IMA) in the University of Minnesota held a workshop titled "IMA Hot Topics Workshop: Data-Driven Control and Optimization" in 2002. The Natural Science Foundation of China (NSFC) held a workshop titled "Data-Based Control, Decision, Scheduling, and Fault Diagnostics" in November 2008. A special issue with the same title as above in *Acta Automatica Sinica* was published in June 2009 that included 20 papers in these four directions [12]. NSFC and Beijing Jiaotong University jointly held another workshop on this topic titled "International Workshop on Data Based Control, Modeling and Optimization" in November 2010. The Chinese Automation Congresses, held by the Chinese Automation Association in 2009 and 2011, respectively, also listed this hot topic as one of main forums. Further, *IEEE Transactions on Neural Networks*, *Information Sciences*, and *IEEE Transactions on Industrial Informatics* also launched their call for papers for their special issues on this topic in 2010 and 2011, respectively, and the *IEEE Transactions on Neural Networks* has published its special issue in December 2011 [13].

1.2.1 Definition and Motivation of Data-Driven Control

There are three literal definitions of DDC in the literature so far, found by searching the Internet:

Definition 1.1 [14]

Data-driven control is the control theory and method, in which the controller is designed merely using online or offline I/O data of the controlled system or using knowledge from the data processing without explicitly or implicitly using information from the mathematical model of the controlled process, and whose stability, convergence, and robustness can be guaranteed by rigorous analysis under certain reasonable assumptions.

Definition 1.2 [15]

Data-driven control design is the synthesis of a controller using measurement data acquired on the actual system to be controlled, without explicitly using (non)parametric models of the system to be controlled during adaptation.

Definition 1.3 [16]

Measured data are used directly to minimize a control criterion. Only one optimization in which the controller parameters are the optimization variables is used to calculate the controller.

In Definition 1.1, the DDC controller design merely uses the plant measurement I/O data, not including any dynamics information and structure information of the controlled system. In Definition 1.2, the DDC controller design may include implicit use of the structure information of the controlled plant. In Definition 1.3, the DDC controller structure is assumed predetermined, and the controller's parameters are obtained via offline optimization. From the above three definitions, we could find that the motivation of DDC methodologies is to design the controller directly using the measurement input–output data of the controlled plant.

Summarizing all the three definitions above, a more generic definition of DDC is proposed as follows:

Definition 1.4 [17]

Data-driven control is the control theory and method, in which the controller is directly designed by using online or offline I/O data of the controlled system or

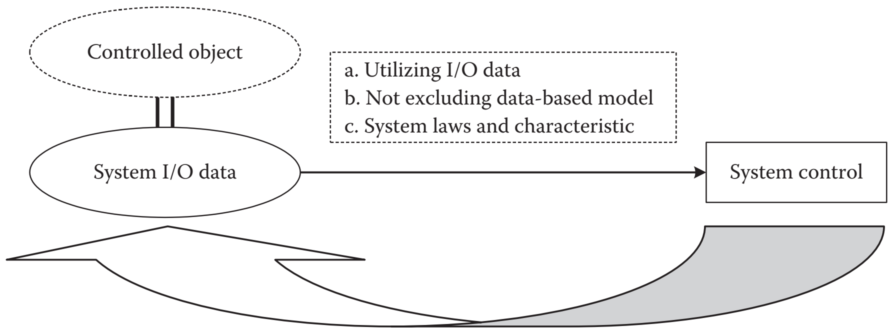


Figure 1.2 Architecture of DDC methodologies.

knowledge from the data processing without explicitly using the information from the mathematical model of the controlled process, and whose stability, convergence, and robustness can be guaranteed by rigorous analysis under certain reasonable assumptions.

The only difference between Definitions 1.4 and 1.1 lies in the fact that the former includes the methods that may implicitly use the information from the mathematical model of the controlled process. With Definition 1.4, direct adaptive control, subspace predictive control, and so on are in the scope of DDC.

The architecture diagram of the DDC methodologies is shown in Figure 1.2.

1.2.2 Object of Data-Driven Control Methods

The control system consists of two main parts: the controlled plant and the controller. The controlled plants can be categorized into the following four classes:

C1. The accurate first-principles or the identified model is available.
C2. The first-principles or the identified model is inaccurate with uncertainties.
C3. The first-principles or the identified model is known but complicated with very high order and very strong nonlinearities.
C4. The first-principles or the identified model is difficult to be established or is unavailable.

Generally speaking, C1 and C2 have been well addressed by the modern control theory, also called MBC theory. For C1, although controller design for general nonlinear systems is complicated, many well-developed approaches have been presented to deal with the linear or nonlinear system, such as zero-pole assignment, Lyapunov controller design methods, backstepping design methods, feedback linearization, and so on. For C2, adaptive control and robust control were developed to tackle uncertainties when the uncertainties could be parameterized or their bound is

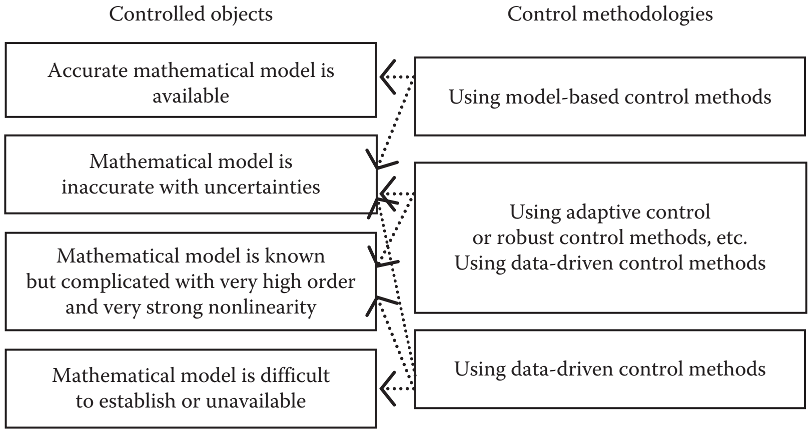


Figure 1.3 Controlled objects of DDC.

assumed known or available. Of course, many other well-developed modern control branches are also devoted to handling these two classes of controlled objects.

For C3, although the first-principles or the identified model is available with quite a high accuracy, its controller design and analysis is still quite a difficult task since the model is possibly with thousands of states, equations, high orders, and strong nonlinearity. As we know, the high-order nonlinear system model definitely leads to a controller with high order or strong nonlinearity. A complex high-order nonlinear controller must bring about a huge difficulty in implementation, performance analysis, practical application, and maintenance. In this case, the procedure of model reduction or controller reduction is inevitable. Usually, a complex high-order nonlinear model is not suitable for the controller design, analysis, and applications. Based on such an observation, we conclude that there is no available method to deal with these kinds of control problems both for C3 and C4.

For these four classes of controlled plants, only half of them or less are well addressed by the existing MBC methods, but there is not any good approach to deal with the other half and more up to now. System I/O data, however, can be always obtained regardless of the type of controlled objects. Therefore, it is recommended to apply DDC control methods. If the system model is unavailable or is with large uncertainty, DDC is an inevitable choice. The relationship between control methods and controlled objects is illustrated in Figure 1.3.

1.2.3 Necessity of Data-Driven Control Theory and Methods

A complete control theory should cover all the methodologies and theories for all the aforementioned controlled objects. From this point of view, MBC methods and DDC methods should be two inevitable parts of the complete control theory; namely, a perfect control theory must consist of MBC theory and DDC theory.

In the following, we will show the necessity of DDC theory and methods from three aspects: theory studies, applications, and historical development of control theory.

From the angle of basic theory: (1) Some difficult issues concerning unmodeled dynamics and robustness are inevitable for MBC theory and methods. On one hand, MBC methods are incapable of dealing with the control issue without the available system model. On the other hand, the unmodeled dynamics and robustness cannot be avoided for modeling and control. This is a dilemma. (2) The complexity in the system mathematical model determines the complexity in controller structure. Generally, a complicated high-order nonlinear system model definitely leads to a complicated high-order nonlinear controller. Therefore, it is necessary to consider model simplification, order reduction, and robustness of the MBC controller. (3) To implement a robust control, the upper bound of the uncertainties must be quantitatively given and described *a priori*; however, it can hardly be achieved in theory by existing modeling approaches.

From the angle of application, low-cost automation systems and equipments satisfying certain control criterions of decision makers are required in most of the practical fields, such as chemical process, industrial producing process, and so on. It costs, however, too much to build the first-principles model or global model mathematically. Especially for batch processes, it is impossible to precisely build the mathematical model for each subsystem in each batch in the name of improving production and quality. For a complicated system, building its global model is impossible since the system is with intrinsic complexity and external disturbances. Even in the local model, there is also discrepancy. Therefore, the MBC method may fail when it is used in practice. Rich theoretical achievements in control theory research versus poor control methods to tackle the practical control problems is the primary challenge to the management and control of many complicated systems in the field of process industry. In addition, the profound mathematical tools and the professional skills required by the MBC method make engineers feel unconfident and powerless when they use it to design and maintain control systems, particularly for complicated systems. The gap between control theory and its application becomes larger and larger. This strongly restricts the healthy development of control theory.

The historical development of control theory is in a spiral fashion, undergoing the following stages: simple regulation devices and PID control without the need of a mathematical model, the classical control theory based on the transfer function model, the MBC theory based on the state-space model, the control theory and methods depending on professional knowledge of the controlled plants including ruler-based model, neural-networks-based model and expert systems, and the DDC theory aiming at removing the dependence on the plant model. By DDC theory and methods, the controller is designed directly using I/O data of the controlled plant, which definitely accords with the developing trend of control theory.

According to the integrity of the theory, the existing control theory can be categorized into three classes: (1) control theory and methods fully depending on a mathematical model, such as control approaches in aerospace, optimal control, linear and nonlinear control, the coordinated control and decomposition technique for large systems and the zero-pole assignment technique, and so on; (2) control theory and methods partially depending on a mathematical model, including robust control, sliding mode control, adaptive control, fuzzy control, expert control, neural networks (NN) control, intelligent control, and so on; and (3) DDC theory and methods merely using the I/O data of the control plant, for example, PID control, ILC, and others. Establishing DDC theory and methods meets the integrity requirement of the control theory framework.

It is worth noting that DDC methods and MBC methods are not mutually exclusive, and they cannot be replaced with each other. DDC and MBC methods do have their own advantages and disadvantages. Based on this observation, DDC and MBC methods could separately develop and also work together in a complementary fashion. The primary difference between MBC and DDC is that the former is the model-based control design approach in case the accurate model is available and the latter is the data-based control design approach in case the accurate model is unavailable. The advantage of DDC theory and methods lies in the fact that the dependence on the mathematical model of a controlled plant is removed for control system design. Some important issues that are inevitable in traditional MBC methods, including unmodeled dynamics versus robustness, accurate modeling versus model simplification or controller reduction, robust control design versus the unavailable description on the upper bound of the uncertainties, good theoretical results versus bad practical performance, and so on, do not exist any longer within the framework of DDC.

1.2.4 Brief Survey on Data-Driven Control Methods

So far, there have been over 10 kinds of different DDC methods in the literature. According to the type of data usage, these methods could be summarized as three classes: the online data based DDC method; the offline data based DDC method, and the hybrid online/offline data based DDC method. According to controller structure, these methods could be divided into two classes: DDC methods with a known controller structure and DDC methods with an unknown controller structure. In the following, we briefly survey the existing DDC methods by virtue of these two observations.

1.2.4.1 DDC Classification According to Data Usage

Online Data Based DDC methods include Simultaneous Perturbation Stochastic Approximation (SPSA) based DDC, Model-Free Adaptive Control, and Unfalsified Control (UC), etc.

Simultaneous Perturbation Stochastic Approximation Based DDC Method — The simultaneous perturbation stochastic approximation (SPSA) based direct controller approximation method was first proposed by J. C. Spall in 1992 [18]. The method is solely using the closed-loop measured data, rather than the mathematical model of a class of discrete-time nonlinear plants, to tune the controller parameters. The SPSA-based control methods assume that the nonlinear dynamics of the controlled plant is unknown, and the controller is a function approximator, whose structure is fixed and the parameters are tunable. NN, polynomial, and so on, may be adopted as the approximators. The controller design is to find optimal controller parameters by minimizing a control performance index by using I/O data at each time instant. To solve the above optimal problem in case the system model is unknown, the SPSA algorithm is applied to estimate the gradient information of cost function with respect to the control input [19,20]. SPSA-based control algorithm has also been utilized in traffic control [21] and industrial control [22].

Model-Free Adaptive Control — The MFAC approach was first proposed by Zhongsheng Hou in 1994 for a class of general discrete-time nonlinear systems [23–26]. Instead of identifying a more or less nonlinear model of a plant, a virtual equivalent dynamical linearization data model is built at each dynamic operation point of the closed-loop system using a new dynamic linearization technique with a novel concept called pseudo partial derivative (PPD). With the help of the equivalent virtual data model, adaptive control of the nonlinear system is carried out by a proposed controller. The time-varying PPD is estimated merely using the I/O measurement data of a controlled plant. The dynamic linearization techniques include compact-form dynamic linearization (CFDL) data model, partial-form dynamic linearization (PFDL) data model, and full-form dynamic linearization (FFDL) data model. Compared with traditional adaptive control schemes, the MFAC approach has several merits, which make it more suitable for many practical control applications. First, MFAC is a pure DDC method, since it only depends on the real-time measurement I/O data of the controlled plant, but not on any model information of the plant. This implies that a general controller for a class of practical industrial processes could be designed independently. Second, MFAC does not require any external testing signals or any training process, which are necessary for the neural-networks-based nonlinear adaptive control; therefore, it is a low-cost controller. Third, MFAC is simple and easily implemented with small computational burden and has strong robustness. Fourth, under certain practical assumptions, the monotonic convergence and bounded-input bounded-output (BIBO) stability of the CFDL data model based MFAC and PFDL data model based MFAC can be guaranteed. It is a highlighted feature compared with other DDC approaches. Finally, the simplest CFDL data model based MFAC scheme has been successfully implemented in many practical applications, for example, the chemical industry [27,28], linear motor control [29], injection modeling process [30], pH value control [31], and so on.

Unfalsified Control — The unfalsified control (UC) method was first proposed by M. G. Safonov in 1995 [32]. It recursively falsifies control parameter sets that fails to satisfy the performance specification in order to derive the proper parameter and corresponding controller. The whole process is operated only by using the I/O data rather than the mathematical model of the controlled plant. UC belongs to a type of switching control method in essence, but is different from the traditional switching control. UC can falsify the controller that cannot stabilize the control system before being inserted into the feedback loop, so the transient performance is pretty good. UC includes three elements: an invertible controller candidate set, a cost detectable performance specification, and a controller switching mechanism [33,34]. The input–output stability of the unfalsified adaptive switching control system in a noisy environment is obtained in Ref. [35], and other modifications could be found in Ref. [36]. The UC method has been successfully used in the fields of missile guidance, robot arm control, and industrial process control [37].

Offline Data Based DDC methods include PID Control, Iterative Feedback Tuning, Correlation-Based Tuning, and Virtual Reference Feedback Tuning, etc.

PID Control — The body of literature on the PID control methods is large. The techniques are well developed and widely used in practical applications. Up to now, 95% of the control methods utilized in the industrial process are PID [38]. It is worth pointing out that PID control may be considered as the earliest DDC method, although parameter tuning methods and techniques for PID control are still under development.

Iterative Feedback Tuning — The IFT method was first proposed by H. Hjalmarsson in 1994 [39]. It is a data-driven controller tuning scheme, which iteratively optimizes the parameter of a feedback controller by using an offline gradient estimation of a control performance criterion with respect to the control input. At each iteration, the gradient is estimated by using a finite set of data obtained partly from the normal operating condition of the closed-loop system, and partly from a special experiment whose reference signal is a specified signal. Under suitable assumptions, the algorithm converges to a local minimum of the control performance criterion [40]. Some extension results of IFT to nonlinear systems could be found in Refs. [41–44]. The industrial and experimental applications of IFT are summarized in Refs. [40,45].

Correlation-Based Tuning — The correlation-based tuning (CbT) method was proposed by K. Karimi, L. Miskovic, and D. Bonvin in 2002 [46]. It is a kind of data-driven iterative controller tuning method. The underlying idea is inspired by the well-known correlation approach in system identification. The controller parameters are tuned iteratively either to decorrelate the closed-loop output error between the designed and achieved closed-loop systems with the external reference signal (decorrelation procedure) or to reduce this correlation (correlation reduction). It is necessary to point out that CbT and IFT are closely related methods, but they differ in two aspects:

the underlying control objective and the way of obtaining the gradient estimate. CbT is extended to the multiple-input and multiple-output (MIMO) systems in Ref. [47] and applied to the suspension system in Refs. [48,49].

Virtual Reference Feedback Tuning — The VRFT method was proposed by G. O. Guardabassi and S. M. Savaresi in 2000 [50]. It is a direct data-driven method to optimize the parameters of the controller with a prespecified controller structure for a linear time-invariant (LTI) system. VRFT transforms the controller design problem into a controller parameter identification problem by introducing a virtual reference signal. VRFT and IFT belong to the same class of controller design methods but their features are quite different. IFT is a gradient descent based iterative algorithm. VRFT is a "one-shot" batch method that searches for the global minimum of the performance index, without the need for iteration or initialization. It makes use of a set of input–output data collecting in an open or closed loop, and does not require specific elaborate experiments [51]. In Ref. [52], the VRFT approach is extended to a nonlinear setup. In Ref. [53], VRFT is extended to the MIMO system. VRFT has been successfully applied to some practical systems, such as a vertical-type one-link arm [54], an active suspension system [55], and velocity controllers in self-balancing industrial manual manipulators [56], and so on.

Online/Offline Data Based DDC methods include Iterative Learning Control and Lazy Learning (LL), etc.

Iterative Learning Control — The ILC was first proposed by M. Uchiyama in 1978 in Japanese [57], which did not draw enough attention. Since Ref. [58] was published in English in 1984, ILC has been extensively studied with significant progress in theory and has been widely applied in many fields. For a system that repeats the same task over a finite interval, ILC is an ideal control method, since it targets control performance improvement by learning from the repetitive operations via output tracking errors and control input signals at previous iterations. ILC is of a very simple controller structure, which is considered as an integrator in the iteration domain. ILC as a kind of DDC control method requires little prior knowledge of the system and can guarantee learning error convergence when the iteration number goes to infinity. Recent research results [59–63] of ILC are summarized comprehensively and systematically, and the contraction mapping method forms the theoretical basis of most ILC studies [64,65]. In addition, ILC has been widely applied in many practical fields [66,67]. Compared with other DDC approaches, ILC uses the collected online/offline data in a more abundant and systematic way. It is worth noting that ILC does not tune controller parameters using the I/O data, but finds the optimal control input signal directly.

Lazy Learning — Lazy learning (LL) algorithm is one of the supervised machine learning algorithms. S. Schaal and C. G. Atkeson first applied LL algorithms to the control field in 1994 [68]. Similar to other supervised machine learning algorithms, the goal of LL algorithms is to find the relationship between input and output from a collection of input/output data, called the training set. LL-based control, using the historical data, builds online a local linear dynamic model for the nonlinear plant, and then designs a local controller at every time instant. Owing to the real-time updating of the historical dataset, LL-based control can be considered as an intrinsically adaptive control method. Its computational cost, however, is high. Besides this main shortcoming of LL-based control, there is also a lack of theoretical analysis of the stability [69,70]. In the literature, there are some other methods similar to LL, such as just-in-time learning (JITL) [71], instance-based learning [72], local weighted model [73], model-on-demand [74,75], and so on.

1.2.4.2 DDC Classification According to Controller Structure Design

In this section, we will use another criterion, that is, whether the structure of the controller is known or not, to classify DDC approaches in order to make the readers understand them well.

DDC Methods with Known Controller Structure include PID, IFT, VRFT, UC, SPSA-based control, CbT, etc.

For this kind of DDC method, controller design is carried out by using a plant's I/O measurement data on the basis of a known controller structure with unknown parameters. The controller parameters are obtained by some procedure of optimization, such as batch and recursive algorithms. In other words, the controller design problem for this kind of DDC method is transformed into controller parameter identification with the help of the assumption that the controller structure is known *a priori* and linear in controller parameters. Typical ones are PID, IFT, VRFT, UC, SPSA-based control, CbT, and so on. No explicit information of the plant model and the dynamics model is involved in these methods. The focus, however, is how to determine the controller structure. Generally speaking, it is quite difficult to construct a proper controller with unknown parameters for a particular plant, especially the one with a general nonlinear structure. Sometimes, the difficulty is equal to that of accurately building a plant model. Another obstacle to apply this kind of DDC method is the lack of a stability analysis methodology for a closed-loop system.

DDC Methods with Unknown Controller Structure include model-related DDC methods and model-unrelated DDC methods.

Model-Related DDC Methods — It seems that this kind of DDC method is merely dependent on the plant I/O measurement data, but in essence the plant model structure and the dynamics information are implicitly involved in the controller design. Control system design and theoretical analysis approaches for these kinds of DDC methods are similar to those of MBC design. However, model-related DDC methods are also of significance for the control system design because strong robustness can be achieved when they are used in practice. Typical ones are direct adaptive control, subspace predictive control, and so on.

Model-Unrelated DDC Methods — For these kinds of DDC methods, the controller is designed only using the plant measurement I/O data without involving any explicit or implicit model information. Model-unrelated DDC methods can uniformly fulfill the control task for linear and nonlinear systems. Another outstanding feature of these kinds of DDC methods is that it has a systematic framework for controller design and provides a systematic stability analysis means. Typical ones are ILC and MFAC. Compared with other DDC methods, the effectiveness or rationality of the controller structure or controller design in model-unrelated DDC methods is theoretically guaranteed.

1.2.5 Summary of Data-Driven Control Methods

Toward a comprehensive understanding of DDC methods for the readers, some brief remarks are listed here:

1. Theoretically speaking, ILC, SPSA, UC, and MFAC are originally developed for nonlinear systems by directly using the I/O data of the controlled plants. Other methods, such as IFT and VRFT, are proposed for LTI systems and then extended to nonlinear systems.
2. SPSA, MFAC, UC, and LL have adaptive features, while other DDC methods are nonadaptive control methods. The adaptability of SPSA may be affected by variation of plant structure or parameters.
3. Essentially, SPSA, IFT, and VRFT are controller parameter identification approaches. Specifically, VRFT is a one-shot direct identification method, that is, only one experiment is needed for I/O data collection, and controller parameters are directly identified through offline optimization. The other two are iterative identification methods.
4. Both MFAC and LL are based on dynamic linearization. Specifically, MFAC gives a systematic dynamic linearization framework, including several virtual data models and a series of controller design strategies, with contraction-mapping-like stability analysis and error convergence of closed-loop systems. No framework is formed yet for the LL-based control method.
5. Most of the DDC methods except for PID, ILC, and VRFT need to estimate the gradient using measured I/O data. SPSA, IFT, and gradient-based UC estimate a gradient of a certain cost function with respect to the controller parameters. The dynamic linearization based MFAC and LL, however, calculate the gradient of the system output with respect to the control input online at each instant.
6. SPSA, UC, and MFAC use online measured I/O data, and PID, IFT, and VRFT use offline measured I/O data, and ILC and LL use both online and offline data. It is worth noting that ILC provides a systematic way to use the online/offline I/O measurement data. Moreover, ILC approximates directly

to the desired control signal in the iteration domain rather than tuning controller parameter.

7. For ILC, a perfect systematic framework is put forward in both the controller design and performance analysis. MFAC has the similar feature, but the other DDC methods need further study.
8. Almost all the DDC methods mentioned above are designed based on controller parameter tuning approaches except ILC. Some of them are online tuning, such as MFAC, UC, and SPSA, while the others are offline tuning. The key of the DDC methods is that the controller structure does not depend on the plant model, although controller structure is assumed known *a priori* in some DDC methods. Comparatively, MFAC and LL go one step ahead since their controller structure is based on the dynamic linearization data model and certain optimization criterions that are theoretically supported, while the assumption in the other DDC methods that the controller structure is known inevitably leads to a problem of how to determine the controller structure. Sometimes, the difficulty in determining a proper controller structure for a given plant is equivalent to that of building an accurate plant model.
9. Moreover, as we know, controller parameter tuning is an optimization problem in mathematics, but the optimization in DDC controller design is quite different from traditional optimization because the system model during DDC controller design is unknown, while the model in MBC is known *a priori*. From this point of view, an outstanding feature of MFAC, SPSA, and IFT is that the technique to calculate or estimate the gradient information using the I/O data of the controlled plant is developed when the objective function is unknown. Specifically, MFAC and IFT use the deterministic approach, and SPSA uses the stochastic approximation approach.
10. The key to distinguish DDC methods and MBC methods lies in whether or not its control design is only dependent on I/O data of the controlled system, that is, whether or not the information about dynamic model structure or dynamics (including other forms of expression such as NN, fuzzy rules, expert knowledge, etc.) is embedded in the controller. If only I/O data of the controlled system is utilized, but neither any information about the model structure nor dynamics equality is involved in the control design, it is a DDC method; otherwise, it is an MBC method.

1.3 Preview of the Book

There are 12 chapters in this book. Chapters 2 through 10 focus on the design and analysis of the MFAC theory and methodology, Chapter 11 is dedicated to MFAC applications, and Chapter 12 presents the conclusions.

Chapter 1 first surveys the issues on modeling, identification, and control within the framework of MBC theory and then gives the definition, classification, and highlights on the existing DDC methods.

Chapter 2 introduces the online parameter estimation algorithms, which intends to make the monograph self-contained.

Chapter 3 presents a novel dynamic linearization method for a class of discrete time single-input single-output (SISO), multiple-input and single-output (MISO), and MIMO nonlinear systems, which serves as the theoretical foundation for the design and analysis of MFAC. By this dynamic linearization method, the CFDL data model, the PFDL data model, and the FFDL data model are introduced.

Chapters 4 and 5 study the design, stability analysis, and simulation verification of the dynamic linearization based MFAC schemes for discrete-time SISO, MISO, and MIMO nonlinear systems, respectively.

Chapter 6 describes the design, stability analysis, and simulation verification of model-free adaptive predictive control (MFAPC) schemes for discrete-time SISO nonlinear systems.

Chapter 7 presents the model-free adaptive iterative learning control (MFAILC) scheme for a class of discrete-time SISO nonlinear systems, and shows that the scheme guarantees monotonic convergence of the maximum learning error in the iteration domain.

Chapter 8 extends the MFAC control system design to complicated interconnected nonlinear systems, and the modularized controller design between MFAC and other existing control methods, such as adaptive control and ILC, are also presented in this chapter.

Chapter 9 discusses robustness issues for the MFAC scheme by considering external disturbance and data dropout.

Chapter 10 introduces a conceptual description of the symmetric similarity structure and design principle. The similarity among different control methods, especially for MFAC and MFAILC, adaptive control and ILC, is analyzed.

Chapter 11 lists several applications of the MFAC scheme to practical plants, including a three water tank system, a linear motor system, a traffic system, the welding process, and a wind turbine.

Chapter 12 concludes this book and points out several future research directions closely related to MFAC theory and implementation.

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