Cognitive Intelligence and Robotics

Kaushik Das Sharma
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Intelligent Control

A Stochastic Optimization Based Adaptive Fuzzy Approach

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Cognitive Intelligence and Robotics

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Dedicated to
our beloved students

Preface

Fuzzy control evolved as a superior alternative to the conventional classical control strategies mainly for nonlinear, complex, and mathematically ill-defined systems. The mathematical formulation of a fuzzy controller inherently contains the approximation capability, and the human expert knowledge can easily be incorporated to infer a decision directly to the real world. In the last decade of the twentieth century, the Lyapunov theory was successfully employed to study the stability of the fuzzy controllers and subsequently the concept of adaptation in the domain of stable fuzzy control was introduced. But in the early phases of adaptive fuzzy controller design procedures, the basic structure of a stable controller was usually assumed to be static. As time elapsed, gradual improvements over the early designs were proposed. Hybridization of genetic algorithm-based strategy with a Lyapunov theory-based strategy was proposed to adapt both controller structures and free parameters, containing center locations of input membership functions, scaling gains, learning rate, etc., in addition to the positions of the singletons describing output fuzzy sets of the fuzzy controller. But the main problem associated with such hybrid models is that the genetic algorithm-based Lyapunov method needed several thousands of fitness evaluations to achieve parameter convergence and to guarantee the closed-loop stability.

This book presents systematic designs of stable adaptive fuzzy logic controllers employing hybridizations of the Lyapunov strategy-based approach (LSBA) and contemporary stochastic optimization techniques. The book also presents another class of systematic hybrid adaptive fuzzy controller design techniques employing H^{∞} strategy-based robust approach (HSBRA) and contemporary stochastic optimization techniques. Particle swarm optimization (PSO), harmony search (HS), and covariance matrix adaptation (CMA) have been considered here as the candidate stochastic optimization techniques utilized in conjunction with the Lyapunov theory or H^{∞} control theory, to develop the hybrid models discussed in this book. The hybridization process attempts to combine strong points of both the Lyapunov theory or H^{∞} control theory-based local search methods and the stochastic optimization-based global search methods to evolve superior methods. The objectives of these design strategies are to perform simultaneous adaptations of both the structure of the fuzzy controller and its free parameters so that two competing requirements can be fulfilled: (i) to guarantee stability of the controllers designed and (ii) to achieve very high degrees of automation in the process of these controller designs, by employing global search methods. The LSBA/HSBRA helps to guarantee closed-loop stability with improved speed of convergence. On the other hand, the stochastic optimization algorithms help to achieve desired automation for the design methodologies of the adaptive fuzzy controller by getting rid of many manually tuned parameters, which are typical in LSBA/HSBRA design procedure. Hence, the objective is to design stable adaptive fuzzy controllers which can simultaneously provide a high degree of automation, guarantee asymptotic stability, and also achieve satisfactory transient performance.

In the present book, several novel variants of hybridization of locally operative LSBA/HSBRA and globally operative stochastic optimization techniques have been presented. These approaches have generally been named as hybrid adaptation strategy-based approaches (HASBA). Three modes of hybridizations, namely cascade, concurrent, and preferential modes of hybridizations, have been presented and discussed in detail here. To demonstrate the usefulness of these hybrid methodologies, several nonlinear benchmark problems available in the literature have been simulated and exhaustive performance studies have been carried out. Several real implementations in the areas of process control, vision-based robot navigation domains, and manipulator end-effector tracking have also been illustrated to show the effectiveness of the hybrid techniques presented in this book.

The following list articulates the key features of this book:

- Stochastic optimization techniques are hybridized with the Lyapunov theory/ H^{∞} control theory to design stable adaptive fuzzy controllers, in both simulation case studies and real implementations.
- The stable fuzzy adaptive controllers are designed for both fixed structure controller configurations and variable structure controller configurations.
- Three different variants of hybridizations of the Lyapunov theory/H^{∞} control theory and the stochastic optimization techniques are presented, namely cascade model, concurrent model, and preferential model.
- Stochastic optimization-based system identification methodology is developed, and temperature of an air heater process is controlled by means of the Lyapunov theory and stochastic optimization-based hybrid controllers, with the estimated process parameters.
- A novel idea for vision-based mobile robot navigation utilizing the stable adaptive fuzzy tracking controllers, designed by the Lyapunov theory and stochastic optimization-based hybrid methodologies, is implemented in real experiments.
- A novel idea for two-link manipulator control utilizing the stable adaptive fuzzy tracking controllers, designed by the H^{∞} control theory and stochastic optimization-based hybrid methodologies, is implemented in real experiments.

The materials presented in this book are divided into five parts, and these are composed as follows:

Part I: Prologue
This part of the book introduces the idea of adaptive fuzzy control and gives a preview of few very prominent contemporary stochastic optimization techniques applied in different fields of engineering. A non-adaptive fuzzy controller design technique is also presented employing a stochastic optimization algorithms.

- Chapter 1 introduces the adaptive fuzzy control with its journey from modern control theories. This chapter also elaborates the overall literature available for the interested readers in this domain.
- Chapter 2 describes the glimpses of some contemporary stochastic optimization techniques. GA, PSO, HS, and CMA are introduced in a nutshell.
- Chapter 3 describes the design techniques adopted for stable fuzzy controllers, employing stochastic optimization algorithm-based approach. A non-fuzzy supervisory control-based stable operation of fuzzy controllers has been evaluated for some benchmark nonlinear systems.

Part II: Lyapunov Strategy-Based Design Methodologies
This part of the book presents a detailed discussion about the Lyapunov theory-based adaptation procedure and different hybrid adaptive fuzzy controller design strategies.

- Chapter 4 describes the formulation of the control law for a class of nonlinear systems and the application of the Lyapunov theory to ensure the stability of the closed-loop system. The Lyapunov strategy-based approach of designing fuzzy controllers is developed and analyzed in detail.
- Chapter 5 describes the stochastic optimization algorithm-aided Lyapunov theory-based hybrid stable adaptive fuzzy controller design methodologies considered in this book. As mentioned before, three variants of the hybrid design schemes are discussed in this chapter.

Part III: H^{∞} Strategy-Based Design Methodologies
This part of the book presents another avenue with a discussion about the H^{∞} strategy-based robust control-based adaptation procedure and its hybrid variants.

- Chapter 6 describes the formulation of the H^{∞} strategy-based robust control law for a class of nonlinear systems with external disturbances. Here, the H^{∞} control-based robust direct adaptive fuzzy controller design methodology is discussed and analyzed in detail. The Riccati-like equation has been utilized here to ensure the stability of the closed-loop system with H^{∞} strategy-based control, with disturbance rejection phenomenon.
- Chapter 7 describes the stochastic optimization algorithm-aided H^{∞} strategy-based hybrid robust stable adaptive fuzzy controller design methodologies, considered in this book. Three variants of the hybrid design schemes, as discussed in Chap. 5, are discussed in this chapter.

Part IV: Applications

It is the most interesting part of the book where three real-life applications from diverse domains are presented. The first two chapters in this part discuss the applications developed utilizing the Lyapunov theory-based hybrid models of fuzzy controller design, whereas the third chapter utilizes the H^{∞} strategy-based robust control-based hybrid models to develop a real application.

- Chapter 8 describes the real implementation of temperature control of an air heater system, employing the hybrid controllers presented in Chaps. 4 and 5.
- Chapter 9 describes the real implementation of vision-based navigation of a mobile robot, employing the Lyapunov theory-based controller and hybrid controllers presented in Chaps. 4 and 5.
- Chapter 10 describes the real implementation of tracking control-based robot manipulator end-effector movement, employing the H^{∞} strategy-based controller and hybrid controllers presented in Chaps. 6 and 7.

Part V: Epilogue

- Chapter 11 concludes the book. This chapter describes some emerging areas of intelligent fuzzy control along with the future scope of research in this domain.

The book can be studied in two ways. For the readers interested only in the Lyapunov theory-based design, they can go through Chaps. 1–5 and 8, 9. On the other hand, if H^{∞} control theory is of prime interest, then the route will be Chaps. 1–3, 6, 7, and finally Chap. 10. Practicing engineers and senior researchers may skip Chaps. 1–4 and Chap. 6 as these chapters mostly deal with the basic theories. Chap. 11 may be beneficial to the new researchers as they can find some exciting ideas for their future research.

We are grateful to many people for their openhearted support and encouragement during the course of writing of this book. In particular, we thank Mr. Debasish Biswas, Research Scholar, Department of Applied Physics, University of Calcutta, for preparing the experimental arrangements utilized in Chap. 10. Finally, on a personal note, we would like to thank our families for their support and inspiration during this endeavor.

Kolkata, India
April 2018

Kaushik Das Sharma
Amitava Chatterjee
Anjan Rakshit

Contents

Part I Prologue

1 Intelligent Adaptive Fuzzy Control 3
1.1 Way to Modern Control Theory 3
1.2 Overview of Fuzzy Control 4
1.3 Overview of Adaptive Fuzzy Control 6
1.4 Stability Issues in Adaptive Fuzzy Control 7
1.5 Intelligent Adaptive Fuzzy Control 9
1.6 State of the Art 11
1.7 Summary 13
References 13

2 Some Contemporary Stochastic Optimization Algorithms: A Glimpse 23
2.1 Introduction 23
2.2 Genetic Algorithm (GA) 23
2.3 Particle Swarm Optimization (PSO) 26
2.4 Covariance Matrix Adaptation (CMA) 28
2.5 Harmony Search Algorithm (HSA) 32
2.6 Summary 34
References 34

3 Fuzzy Controller Design I: Stochastic Algorithm-Based Approach 37
3.1 Introduction 37
3.2 Stable Fuzzy Controllers 38
3.3 PSO-Based Design Methodology 42
3.3.1 PSO-Based Fuzzy Controller Design 43
3.3.2 The Design Algorithm 45

3.4 HSA-Based Design Methodology . . . 46
3.4.1 HSA-Based Fuzzy Controller Design . . . 47
3.4.2 The Design Algorithm . . . 48
3.5 Stochastic Algorithm-Based Design Methodology: *A Generalized Approach* . . . 51
3.5.1 The Generic Design Algorithm . . . 51
3.6 A Comparative Case Study of Different Algorithms . . . 52
3.6.1 Case Study I: DC Motor Containing Nonlinear Friction Characteristics . . . 53
3.6.2 Case Study II: Duffing's Oscillatory System . . . 62
3.7 Summary . . . 71
References . . . 74

Part II Lyapunov Strategy Based Design Methodologies

4 Fuzzy Controller Design II: Lyapunov Strategy-Based Adaptive Approach . . . 79
4.1 Introduction . . . 79
4.2 Stable Adaptive Fuzzy Controllers . . . 79
4.3 Lyapunov Strategy-Based Approach (LSBA) . . . 85
4.3.1 The Design Algorithm . . . 85
4.4 Case Studies . . . 88
4.4.1 Case Study I: DC Motor Containing Nonlinear Friction Characteristics . . . 88
4.4.2 Case Study II: Duffing's Oscillatory System . . . 90
4.5 Summary . . . 99
References . . . 99

5 Fuzzy Controller Design III: Hybrid Adaptive Approaches . . . 101
5.1 Introduction . . . 101
5.2 Hybrid Design Methodology Using Lyapunov Strategy . . . 102
5.2.1 Lyapunov Theory-Based Hybrid Cascade Model . . . 106
5.2.2 Lyapunov Theory-Based Hybrid Concurrent Model . . . 108
5.2.3 Lyapunov Theory-Based Hybrid Preferential Model . . . 109
5.3 Case Studies . . . 112
5.3.1 Case Study I: DC Motor Containing Nonlinear Friction Characteristics . . . 113
5.3.2 Case Study II: Duffing's Oscillatory System . . . 131
5.4 Summary . . . 149
References . . . 155

Part III H$^{\infty}$ Strategy Based Design Methodologies

6 Fuzzy Controller Design IV: H$^{\infty}$ Strategy-Based Robust Approach . . . 159
6.1 Introduction . . . 159
6.2 Robust Adaptive Fuzzy Controllers . . . 160
6.3 H$^{\infty}$ Strategy-Based Robust Approach (HSBRA) . . . 165
6.3.1 The Design Algorithm . . . 165
6.4 Case Studies . . . 167
6.4.1 Case Study I: DC Motor Containing Nonlinear Friction Characteristics . . . 167
6.4.2 Case Study II: Duffing's Oscillatory System . . . 169
6.5 Summary . . . 171
References . . . 173

7 Fuzzy Controller Design V: Robust Hybrid Adaptive Approaches . . . 175
7.1 Introduction . . . 175
7.2 Hybrid Design Methodology Using H$^{\infty}$ Strategy . . . 176
7.2.1 H$^{\infty}$ Strategy-Based Cascade Model . . . 179
7.2.2 H$^{\infty}$ Strategy-Based Concurrent Model . . . 181
7.2.3 H$^{\infty}$ Strategy-Based Preferential Model . . . 183
7.3 Case Studies . . . 185
7.3.1 Case Study I: DC Motor Containing Nonlinear Friction Characteristics . . . 186
7.3.2 Case Study II: Duffing's Oscillatory System . . . 187
7.4 Summary . . . 205
References . . . 205

Part IV Applications

8 Experimental Study I: Temperature Control of an Air Heater System with Transportation Delay . . . 209
8.1 Introduction . . . 209
8.2 Hardware Description of the Experimental Platform . . . 210
8.3 System Identification of the Air Heater System . . . 213
8.4 Hybrid Adaptive Fuzzy Controller Design . . . 216
8.4.1 Simulation Case Study . . . 217
8.4.2 Experimental Case Study I . . . 221
8.4.3 Experimental Case Study II . . . 226
8.5 Summary . . . 241
References . . . 241

9 Experimental Study II: Vision-Based Navigation of Mobile Robots . . . 243
9.1 Introduction . . . 243
9.2 Vision-Based Mobile Robot Navigation . . . 245
9.3 Vision-Based Mobile Robot Experimental Platform . . . 247
9.3.1 Mobile Robot Hardware Description . . . 247
9.3.2 Image Processing Technique . . . 247
9.3.3 Path Planning Algorithm . . . 249
9.4 Hybrid Adaptive Fuzzy Tracking Controller Design . . . 253
9.4.1 Simulation Case Study . . . 256
9.4.2 Experimental Case Study with Real Robot . . . 265
9.5 Summary . . . 276
References . . . 278

10 Experimental Study III: Control of Robot Manipulators . . . 281
10.1 Introduction . . . 281
10.2 Hardware Description of the Experimental Platform . . . 282
10.3 System Identification of the Two-Link Manipulator . . . 283
10.4 Hybrid Adaptive Fuzzy Controller Design . . . 286
10.4.1 Case Study: Simulation and Experimental . . . 287
10.5 Summary . . . 292
References . . . 292

Part V Epilogue

11 Emerging Areas in Intelligent Fuzzy Control and Future Research Scopes . . . 297
References . . . 298

Index . . . 301

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Part I
Prologue

Chapter 1
Intelligent Adaptive Fuzzy Control

1.1 Way to Modern Control Theory

Automatic control theory, predominantly the concept of feedback, has played a fundamental role to the development of automation [1]. A journey from classical control theory to modern control strategies spans over the time frame of few centuries. Classical control theory was applied for designing the controllers for the systems those are principally linear time invariant in nature [2]. The need for advanced control strategies arose when accurate control laws were required to be developed for detail mathematical modeling of the systems. Most of the practical systems that we encounter in real life are nonlinear in nature. The development of control laws for nonlinear systems necessitated the need for adopting modern approaches, e.g., state variable theory [3–6], which evolved as a general solution for the controller design problem. For the systems, which can be well described with a linear second-order mathematical model, there are a number of conventional procedures for designing the controllers [2, 7], while for the systems modeled with higher-order linear models, pole placement design technique [8, 9] or the frequency domain design procedures can be utilized [6, 7, 10]. Many of the current control applications involve complex, nonlinear single-input–single-output (SISO), multi-input–single-output (MISO), or multi-input–multi-output (MIMO) models, for which controller(s) is(are) required to deliver high-end performance specifications in the presence of plant uncertainty, input uncertainty (including noise or disturbances), and actuator constraints. Since classical control theories are not able to deal with such problems, several modern methodologies emerged in the past three decades that systematically address the fundamental limitations and capabilities of linear state feedback controllers, for such challenging systems, both in continuous-time case [6] and in digital implementations [11, 12]. Examples of such methodologies are the adaptive control [13, 14], H^{∞}-based robust control [15, 16], sliding mode control [17–19], optimal control [20, 21], etc., in conjunction with different intelligent techniques, such as neural networks [22, 23], fuzzy logic [24–26], machine

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learning [27, 28], evolutionary computations [29, 30], genetic algorithms [30, 31], etc. In some recent controller design strategies, intelligent control techniques have been utilized individually or in combinations to enhance the performance of the designed controllers.

Among the intelligent control techniques, "fuzzy logic controllers" (FLCs) are a class of nonlinear controllers that make use of human expert knowledge and an implicit imprecision to apply control to the systems which can be mathematically ill-defined. These controllers evolved as a popular domain of control system and control engineering more than three decades back. Although the original interest was initiated by the urge to design controllers for those systems which are very difficult to be characterized mathematically, with time, study on FLCs expanded extensively for both model-free and model-based systems.

1.2 Overview of Fuzzy Control

Fuzzy control emerged on the foundations of L. A. Zadeh's fuzzy set theory, introduced in 1965 [32, 33]. Fuzzy logic controllers have proven to be a successful control option for many complex and nonlinear systems or even for non-analytic systems too [34]. It has been suggested as an alternate approach to the conventional PID-type control techniques in many cases, even for linear systems where fuzzy controllers were exploited to obtain better performances [35].

One of the earliest fuzzy controllers was developed by E. H. Mamdani and S. Assilian in 1975, where control of a small laboratory prototype steam engine was considered [36, 37]. The primal fuzzy control algorithm consisted of fuzzy sets, a set of heuristic control rules and some methods to evaluate the rules. Since its emergence, fuzzy logic control has received huge attention from both the academic researchers and industrial practitioners. Many researchers have dedicated a great deal of time and effort equally in theoretical research and application techniques of fuzzy controllers in various fields like power systems [38–40], telecommunications [41–44], robotic systems [45–52], automobile [53–55], process control [56–59], medical services [56, 60–62], electronics [63–65], chaos control [66, 67] and nuclear reactors [68, 69], and many more.

In a nut shell, the basic structure of a fuzzy controller consists of four important components: (i) knowledge base (fuzzy rule base), (ii) fuzzification interface, (iii) inference engine, and (iv) defuzzification interface [70]. The block diagram of a generic fuzzy control system is shown in Fig. 1.1. The knowledge base encompasses all the knowledge about the controller (might be obtained from the input–output data set of the system to be controlled or may be obtained from a domain expert), and it contains a rule base for the fuzzy controller and a database. The description about the definition of membership functions (MFs) utilized in the fuzzy control rules, scaling gains, etc., is to be written in the knowledge base, which is the declarative part of the database. Whereas, the rule base of the fuzzy controller is the procedural part of the knowledge base. The rule base contains the information on

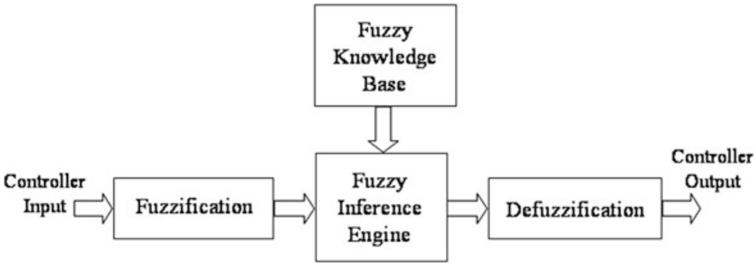

Fig. 1.1 Generic block diagram of a fuzzy logic controller

how this knowledge can be employed to infer new control actions in various situations. The inference procedure is performed by the inference engine part, which provides the reasoning mechanism to the control action under the physical constraints. It is the most essential part of a fuzzy control system. The fuzzifier, i.e., the fuzzification interface delineates a mapping from a real (crisp) space to a fuzzy space. Similarly, the defuzzifier, i.e., the defuzzification interface, delineates a mapping from a fuzzy space, guided by a universe of discourse for output variables, to a real (crisp) space [26].

The fuzzy logic controllers can be approximately categorized, according to their methods of rule generation and the construction of the inference engine, into the following classes:

(i) Conventional fuzzy control which is a classical Mamdani-type design [34, 37] and early version of Sugeno-type design [36] of fuzzy controller.

(ii) Fuzzy proportional–integral–derivative (PID) control where a fuzzy controller is designed to generate control actions like a conventional PID controller [71], while some other alternate definitions are also there in few literatures [72, 73].

(iii) Neuro-fuzzy control where the complementary features of artificial neural network-based control, providing learning abilities and high efficacy in terms of computational burden in parallel implementation, and fuzzy control, providing a efficient framework for expert knowledge representation, are combined together to enhance the flexibility, data processing capability, and adaptability of the designed controller [58, 69, 74, 75].

(iv) Fuzzy sliding mode control for controlling processes with parameter uncertainties and/or load disturbances, where fuzzy control and sliding mode control are combined in such a way that can eliminate the chattering in sliding mode control by fuzzy-based switching and the robustness of the designed controller is achieved with the traditional philosophy of sliding mode control [17, 18, 47, 55, 76–78]. In this context, hybridization of robust stabilization concept with fuzzy control method has given rise to another active branch of fuzzy control in recent times, termed as robust fuzzy control [79–82].

(v) Adaptive fuzzy control where control action is taken for partially known or fully unknown systems with some kind of adaptation mechanism based on the function approximation capability of fuzzy systems [24, 83–93].

(vi) Takagi–Sugeno (T-S) model-based fuzzy control which is a fuzzy dynamic model, based on a set of fuzzy rules to describe a nonlinear system, in terms of a set of linear models which are smoothly connected by fuzzy membership functions [24–26, 87, 88, 92–94].

Several researchers are exploring different aspects of fuzzy controllers both in theoretical domain and in application arena in different categories as stated before [70, 95]. As the present book mainly deals with the domain of stable adaptive fuzzy control, thus, the development of this category of adaptive fuzzy controllers is scrutinized in brief further.

1.3 Overview of Adaptive Fuzzy Control

The non-adaptive fuzzy control [24, 25, 27] were initially in use in some applications long time back. However, it is sometimes difficult to specify the configurations of the fuzzy controllers, i.e., controller structure, scaling gains, rule base parameters for some plants, or it might be needed to tune those nominal parameters with the variation of the plant dynamics to provide a minimum desired performance. In some cases, to cope with the temporal variations in the reference input signal applied to the plant, the rigorous adjustments of the fuzzy controller configurations are required. This provides the motivation for adaptive fuzzy control, where the focus is on the automatic synthesis and tuning of fuzzy controller parameters, fulfilling the requirements of control objectives.

The very first adaptive fuzzy controller was introduced by Procyk and Mamdani in [96], called the linguistic self-organizing controller (SOC). Later Layne and Passino have studied several applications of this method in [97], and further, they introduced the "fuzzy model reference learning controller" (FMRLC) in [98–100]. Kwong and Passino developed some extensions of FMRLC in [101]. The FMRLC had also been successfully implemented for rotational inverted pendulum, a single-link flexible robot, and an induction machine [100, 102] and also been applied to the multiple-input–multiple-output (MIMO) problem of a two-link rigid robot [103, 104].

Many other adaptive fuzzy control techniques have also been employed for several applications [83, 105–108]. In [94], Ordonez et al. provided a comparative analysis of FMRLC with conventional adaptive and/or non-adaptive nonlinear control methods for experimental studies on rotational inverted pendulum system. The main problem with the SOC and the FMRLC that were developed in [101, 102], by Passino et al., was that although the developed approaches emerged as adaptive fuzzy control strategies, the closed-loop stability of the system was not guaranteed.

Su and Stepanenko [86], Wang [87], Johansen [108], and other researchers in [84, 85, 90, 93, 109] explored the ideas derived from conventional adaptive control to establish stability conditions for a variety of adaptive fuzzy control techniques. On the whole, these techniques can be split into two categories: direct and indirect adaptive fuzzy control [24, 25, 84, 87, 91, 95, 109–112]. In indirect adaptive fuzzy control, there is an estimation mechanism that produces a model of the plant which is then used to specify the controller configurations. In direct adaptive control, on the contrary, the model of the plant is not estimated; instead, the controller parameters are directly tuned by using input–output data of the plant.

Along with the property of adaptability of a fuzzy controller, it is always desired that the system should be stable in behavior. The notion of stability in fuzzy controller, and in control theory in general, should be a major concern during the design process of the controller. Thus, the next section briefly describes the different approaches available in the literature for stability analysis of a fuzzy controller.

1.4 Stability Issues in Adaptive Fuzzy Control

The area of stability analysis of fuzzy control systems is receiving an ever increasing attention from many researchers for the last two decades, primarily due to the advancements made in the theoretical perspectives of fuzzy control and their several possible applications. A brief overview of some popular approaches adopted for stability analysis of fuzzy controller is summarized as follows:

Kalman and Bertram in [113], Chand and Hansen in [114] and Chiu and Chand in [115] presented some earlier studies based on Lyapunov methods for analyzing stability of fuzzy control systems. Langari et al. in [116, 117] also used Lyapunov's direct method and generalized theorem of Popov [118] to provide sufficient conditions for stability of fuzzy control systems. In [119], Aracil, Ollero, and Garcia-Cerezo introduced stability indices for fuzzy control systems using phase portrait for characterizing and understanding the dynamical behavior of low-order fuzzy control systems [120, 121]. The circle criterion [69] is used by Ray et al. in [122, 123] to provide sufficient conditions for stability of fuzzy control systems. The stability analysis of fuzzy control systems, developed using sliding mode control technique, was detailed in [76, 124]. Some earlier treatments of stabilizing a gain scheduling type of T-S fuzzy control systems [125] were presented in [26]. In [110, 125, 126, 128] Tanaka et al. explored the Lyapunov theory-based stability analysis and implementation of stable fuzzy controllers in different applications like model car control, backing up control of a track trailer, chaos control, and the robustness of the designed controllers were also studied in [129, 130]. Nonlinearities in control systems, such as the systems with fuzzy controllers, sometimes cause limit cycle oscillations in the system response [131]. The circle criterion can be used to prove the absolute stability of the system and therefore the absence of limit cycles. Similarly, using a steady-state error prediction procedure [131], one can prove the absence of limit cycles, if the steady-state error is zero. However, neither of these methods is able to calculate the amplitude or frequency of limit cycles when they do exist in practice. In [132], Jenkins presented how describing function analysis [133] can be used to predict the existence of limit cycles, thus, the stability of the fuzzy control systems. Jenkins and Passino also presented a method in [134] for calculating frequency and amplitude of limit cycle in fuzzy control systems [135, 136]. Some other methods for stability analysis of fuzzy control systems using linear matrix inequalities (LMIs) method were presented in [110, 126, 127, 130, 137]. Similarly, Chen in [138, 139] and Fei and Isik in [140] provided another alternate approach, called "cell-to-cell mapping" [141, 142], for analysis of stability in fuzzy dynamical systems.

Among the different stability analysis methodologies for fuzzy control systems, Lyapunov theory -based analyses are most popular in fuzzy control research fraternity. The possible reason can be that it can provide a systematic technique which can easily infer the stability of a closed-loop system. There are many variations of Lyapunov theory applied to the fuzzy controller stability analysis, such as (i) stability analysis based on common quadratic Lyapunov function [128, 143, 144], (ii) stability analysis based on piecewise quadratic Lyapunov function [145–147], and (iii) stability analysis based on fuzzy Lyapunov function [148–150]. In [151], Curtis and Beard developed a graphical method for understanding the Lyapunov-based nonlinear control.

Robustness is another issue, along with stability of the adaptive fuzzy controller that was also rigorously investigated by the researchers for last two decades [42, 89, 112, 152–166]. Chen et al. in [89] presented the earlier most work on H^∞ theory-based robust tracking control applied on fuzzy controller design. The adaptation rule and robust control law, augmented with the fuzzy control action, were developed utilizing the Riccati-like equation. The attenuation of tracking error, when the non-linear plant is subjected to the external disturbances, was ensured by the use of H^∞ theory-based optimal control.

Assawinchaichote et al. in [152, 154] described design strategies of output feedback fuzzy controllers, based on H^∞ control scheme, for a class of nonlinear systems that may be singularly perturbed employing T-S-type fuzzy modeling. Linear matrix inequality (LMI) approach had been utilized to develop H^∞ output feedback fuzzy controllers that regulated the L_2-gain of the system in such a manner that the overall stability of the system was guaranteed. Moreover, in [154], authors successfully applied their formulation of LMI-based H^∞ robust tracking control scheme for the Markovian jump nonlinear systems. In [155], the authors also presented a similar methodology for LMI-based H^∞ robust tracking control scheme and it was validated by applying it for a real-time non-minimum phase system.

Wu et al. in [156] studied the T-S-type fuzzy controller design problem by minimizing the mixed H^2/H^∞ norm. The concept of fuzzy region clustering in connection with fuzzy rule base design and the H^∞-based robust control technique was employed to stabilize all clustered plant rules, for each fuzzy region.

Wu et al. in [157] proposed a H^∞ fuzzy observer-based controller design technique for a class of nonlinear parabolic partial differential equation (PDE) systems. The characteristics of the system, in terms of eigenspectrum, was divided into a finite-dimensional slower one and an infinite-dimensional stable fast component. A T-S-type fuzzy observer-based indirect controller was developed to stabilize the nonlinear PDE system, and H^{∞} disturbance attenuation was also achieved in an optimal manner, considering the control constraints.

Guan et al. in [158] formulated a feedback H^{∞} control problem for discrete time T-S-type fuzzy systems utilizing the output measured by a memoryless logarithmic quantizer. The asymptotical stability of the closed-loop system was guaranteed by the full-order dynamic output feedback controller while the prescribed H^{∞} performance level was also ensured to attenuate the disturbances. On the other hand, Pan et al. in [159] focused on the H^{∞} control-based robust stabilization problem of fuzzy controller for a class of continuous-time T-S-type systems.

1.5 Intelligent Adaptive Fuzzy Control

Computational intelligence (CI), termed as soft computing in many cases, provides a framework to address design, analysis, and modeling in control problems, in the presence of uncertain and imprecise information [29, 30, 167]. The main components of intelligent computing technologies are fuzzy logic, neural networks, and stochastic optimization, and these are considered as complementary and synergistic to each other. CI components, individually or in a hybrid mode, have been applied to improve the performances of the design strategies in the domains of parameter estimation and nonlinear control systems, which are characterized by imprecise data and incomplete knowledge [53]. Neuro-fuzzy systems [168] are the most well-known representative of hybrid systems in terms of number of applications in the field of control system design. Compared to neuro-fuzzy systems, genetic fuzzy systems, i.e. genetic algorithm-based design of fuzzy controllers, are not put into practice until the end of the twentieth century, in the industrial applications. The earliest genetic algorithm-based fuzzy control systems were introduced in the following four pioneering works described next.

Karr in his seminal work in [169] introduced genetic tuning of linguistic fuzzy rule base systems (FRBSs). The definition of the fuzzy database was encoded in the chromosome, which contained the concatenated parameters of the input and output fuzzy sets.

In [170], Valenzuela-Rendon presented the first genetic fuzzy system for learning fuzzy rule bases with disjunctive normal form (DNF) of fuzzy rules, employing a supervised learning algorithm. In [171], the author further extended his original proposal to incorporate the concept of reinforcement learning.

In [172], Thrift presented another pioneering work for learning fuzzy rule bases. This method works by using a complete decision table that represents a special case of crisp relation, defined over the collections of fuzzy sets corresponding to the input and output variables. In this work, genetic algorithm employed an integer coding.

Pham and Karaboga, in [173], presented a quite different approach for designing fuzzy controllers that uses a fuzzy relation, instead of the decision table-based classical crisp relation. The genetic algorithm (GA) was used to modify the fuzzy relational matrix of a SISO fuzzy model.

After the initiation, the application of genetic algorithm for designing the fuzzy controllers and neuro-fuzzy controllers gained tremendous attention from the researchers during 1990s. A brief overview of some prominent applications of genetic algorithm for designing fuzzy or neuro-fuzzy controllers is presented here next:

Bonissone et al. in [54] and Hwang in [174] described genetic tuning schemes for optimization of a fuzzy controller applied in transportation systems. The design goal that was successfully achieved in [54] was a controller that could accurately track a desired velocity profile while at the same time could maintain a smooth ride in order to minimize the stress load on the couplers connecting the rail cars. In [174], fuzzy c-means clustering and genetic algorithm were applied in conjunction to identify the structure and parameters of a linguistic fuzzy model, which was used by the railway operators to build efficient and economic control strategies.

In [77], Huang et al. designed a fuzzy sliding mode controller using a real-coded GA in a position control application for an industrial XY-table. By using laser as a sensor, the table could be positioned with submicron-level accuracy. This work also showed that the evolutionary optimization of fuzzy controllers is feasible for hardware-in-the-loop systems and can help to reduce the costs for controller design and tuning.

In [175], Shim et al. reported an application of evolutionary computation, in combination with neural networks and fuzzy systems, for intelligent consumer products. Here, the role of the evolutionary algorithm was to adapt the number of rules and to fine-tune the membership functions to improve the performance of fuzzy systems for estimation and control. This work also mentioned evolutionary computation for fuzzy rule generation applied to process control.

In [176], Alcala et al. considered GA to develop a smart tuning strategy for fuzzy logic controllers applied to the control of heating, ventilating and air conditioning systems, considering energy performance and indoor comfort requirements. To solve this problem, a quick convergence GA was proposed based on an aggregated fitness function, considering trustable weights provided by the experts.

Homaifar and McCormick in [177] proposed a method for knowledge base learning using GA for control problems, where both membership functions and fuzzy rules were determined simultaneously in order to address their codependency. This method considered the simple GA, with integer coding, for both rule consequents [172] and for membership function support amplitude, in the same chromosome.

In [178] Ishibuchi, Nozaki, Yamamoto and Tanaka utilized GAs for selecting a small number of fuzzy IF-THEN rules with high classification performance. The proposed algorithm was based on a simple GA with binary coding, representing whether a rule should be selected or not from an initial set of candidate rules.

In [179], Setnes and Roubos proposed a two-step approach for function approximation, dynamic systems modeling, and data classification problems, by learning approximate T-S rules. In this work, first a compact initial knowledge base was obtained using fuzzy clustering technique and then this model was optimized by a real-coded GA, subjected to constraints in order to maintain the semantic properties of the rules. Each chromosome represents the parameters defining each candidate fuzzy model containing membership functions of the antecedents and coefficients of the consequents. To obtain a more interpretable approximate T-S model using GA, this work contributed significantly in this domain.

In [180], Park et al. used a new fuzzy reasoning method to enhance the performance of fuzzy controllers designed from prior knowledge provided by an expert. As the design method mostly relied on the expert's knowledge about the system, so to avoid the subjective selection of fuzzy reasoning models, genetic algorithm was used to find simultaneously the optimal fuzzy relation matrix and the fuzzy membership functions, extending the fuzzy controller design model proposed by Pham and Karaboga in [173]. In this way, each chromosome is divided into two parts, one part representing the fuzzy relation matrix and the other part representing the fuzzy membership functions.

Similar works for designing fuzzy controllers utilizing genetic algorithm are also reported in [175, 181–190].

The survey of the genetic algorithm- based hybrid design methodologies for fuzzy controllers reveals that it can successfully solve industrial and commercial problems. The chief motivation behind this development, during last two decades, is the need for low-cost solutions that utilize intelligent methodologies for information processing, design and optimization, where the controller designs are essentially performed off-line.

1.6 State of the Art

Lyapunov theory-based strategies, in many forms, are utilized in conventional control theory for long to design controllers that can guarantee closed-loop stability of the system. Wang in [87] and Fischle and Schroder in [88] described two of the earliest design methods of Lyapunov-based direct adaptive fuzzy controllers.

In [87], Wang developed a direct adaptive fuzzy controller which guaranteed the global stability of the resulting closed-loop system in the sense that all signals involved were uniformly bounded and the convergence of the plant output towards a given reference signal is guaranteed. He also showed how a supervisory control forced the states to be within the constraint set. Despite that the controller in [87] had a drawback that it needed adaptation of controller parameters for every variation in reference signal, which implied that for temporally varying reference signals the controller parameters would never converge.

In [88], Fischle and Schroder demonstrated that a modified form of stable AFLC can be proposed where the controller parameters would converge even in presence of a temporally varying reference signal. The main problem in these methods is that it requires a considerable amount of time to track the reference input and also the inherent approximation error in striving to achieve an unknown theoretical control law leads the system towards larger integral absolute error (*IAE*). Another major drawback of many existing designs of adaptive fuzzy logic controllers is that they are developed for systems with unlimited actuation authority. It was also commented in [88] that some further developments are necessary to reduce the learning time, which tend to become unacceptably large for systems of higher order. If it is possible to overcome this drawback, stable adaptive fuzzy control has the potential to provide uncomplicated, reliable and easy-to-understand solutions for a large variety of nonlinear control objectives. However, those designs of controllers were proposed based on control laws adapting a parameter vector containing the positions of the fuzzy sets of the controller outputs only.

As mentioned before, several approaches have also been developed to utilize stochastic optimization techniques, specially genetic algorithm, to automatically design the fuzzy controllers. In [190], Giordano et al. proposed and successfully implemented stable adaptive fuzzy controller where they combined conventional Lyapunov theory and real-coded genetic algorithm to design variable structure fuzzy controller. In this seminal paper, they utilized Lyapunov theory for local adaptation of consequent parts of the T-S fuzzy system and genetic algorithm was used to determine the structure and scaling gains of the fuzzy controller. They had successfully implemented the proposed hybrid stable adaptive fuzzy controller for controlling the speed of a real DC motor. In [190], it was also presented that the stability of closed-loop system and the convergence of the plant output to a desired reference signal were precisely guaranteed.

In the last few decades, optimal control theory-based on robust control strategy has been well developed and applied extensively to cater to the robust stabilization and external disturbance rejection problems [42, 89, 112]. However, in the classical H^{∞} control strategy, the model of the plant must be known a priori. In [89], Chen et al. extended the conventional H^{∞} control strategy towards the nonlinear systems with unknown or uncertain models employing adaptive fuzzy logic concept. In [165], an adaptive fuzzy controller was introduced to guarantee the stability of the adaptive fuzzy controller. In that study the H^{∞} tracking design technique has also been utilized to attenuate the effect of the matching error and external disturbance on the tracking error. The design method, for the first time, showed the way to combine the H^{∞}-based attenuation scheme, T-S-type fuzzy approximation, and adaptive control law for the robust tracking controller design for nonlinear plants with uncertainty and/or unknown variation in plant parameters.

Over the last decade, designs of optimized adaptive fuzzy controllers for various types of nonlinear plants are of focal interest of the researchers around the globe [92, 93]. Various population-based optimization techniques are very popular for hybridization with adaptive fuzzy control strategies based on Lyapunov theory [191]. Further, H^{∞} control-based robust adaptive fuzzy controllers are also hybridized with the contemporary stochastic optimization techniques and successfully implemented for many real-life applications [165].

1.7 Summary

This chapter has introduced the concepts of basic fuzzy controllers and their different forms in a nutshell. The adaptive fuzzy controller and the stability issues, especially in light of Lyapunov theory, has also been scrutinized in brief. The H^{∞} strategy-based robust fuzzy control schemes are also discussed in brief. The developmental introduction of hybrid fuzzy controller design methodology, particularly GA-based design, has been explored too. Finally, the inspiration for the present book is put forward, the concepts of designing hybrid stable adaptive fuzzy controllers employing Lyapunov theory or H^{∞} strategy-based robust control theory and stochastic optimization techniques are introduced, and the works carried out within the scope of this book are put forward, in brief.

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