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Intelligent Control, Filtering and Model Reduction Analysis for Fuzzy-Model-Based Systems

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To My Family

X. Su

To My Family

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Preface

Problem formulations of physical systems and processes can often lead to complex nonlinear systems, which may cause analysis and synthesis difficulties. Study of nonlinear systems is often problematic due to their complexities. One effective way of representing a complex nonlinear dynamic system is the so-called Takagi-Sugeno (T-S) fuzzy model, which is governed by a family of fuzzy IF-THEN rules that represent local linear input-output relations of the system. It incorporates a family of local linear models that smoothly blend together through fuzzy membership functions. This, in essence, is a multi-model approach in which simple sub-models (typically linear models) are fuzzily combined to describe the global behavior of a nonlinear system. Fuzzy logic method has been studied and developed for decades. It is known to be an effective control approach to some ill-defined and complex control processes. Thanks to fuzzy logic, expert knowledge about the control processes can be employed to heuristically design fuzzy controllers with some linguistic IF-THEN rules. Practically, human knowledge can be represented as linguistic statements and incorporated into the fuzzy logic controller. As a result, the design method can operate with intelligence.

Analysis and synthesis including state-feedback control, output-feedback control, tracking control, optical control, filtering, fault detection, and model reduction for a class of T-S fuzzy systems are all thoroughly studied. Fresh novel techniques including the Linear Matrix Inequality (LMI) techniques, the slack matrix method, and so on, are applied to such systems. This monograph is divided into four sections. First, we focus on stabilization synthesis and controller design for T-S fuzzy systems. The following problems are investigated in this book: (1) the problem of stability analysis and stabilization for T-S fuzzy systems with the time-varying delay; (2) the problem of Hankel-norm output feedback controller design for a class of T-S fuzzy stochastic systems; (3) the problem of $\mathcal{L}_2-\mathcal{L}_\infty$ dynamic output feedback controller design for nonlinear switched systems with nonlinear perturbations. Secondly, the reliable filtering and fault detection problems are solved for fuzzy systems. The below problems are studied: (1) the problem of the dissipativity-based filtering problem for fuzzy switched systems with stochastic perturbation; (2) the fault detection filtering problem for nonlinear switched stochastic system; (3) the problem of reliable filter design with strictly dissipativity for discrete-time T-S fuzzy time-delay systems.

Then the theories and techniques developed in the previous part are extended to the model reduction and model approximation of T-S fuzzy systems. The below problems are studied: (1) the reduced-order model approximation problem for discrete-time hybrid switched nonlinear systems; (2) the model approximation problem for dynamic systems with time-varying delays under the fuzzy framework; (3) the model approximation problem for T-S fuzzy switched systems with stochastic disturbance; (4) the $\mathcal{H}_\infty$ reduced-order filter design problem for discrete-time fuzzy delayed systems with stochastic perturbation. Finally, two real applications are proposed to demonstrate the feasibility and effectiveness of the fuzzy control design presented in the previous parts. The first application is the dissipative event-triggered fuzzy control of truck-trailer system. In view of the fuzzy model, the stability of the resulting system is analyzed in terms of Lyapunov stability theory. Additionally, the explicit expression of the desired controller is given in view of Linear Matrix Inequalities (LMIs), which ensures the resulting closed-loop system is asymptotically stable and strictly (X, Y, Z)–θ–*dissipative*. The second one is the event-triggered fuzzy control of inverted pendulum systems. By employing the parallel distributed compensation law, sufficient conditions for the resulting fuzzy system and the event-triggered fuzzy controller are presented for the nonlinear inverted pendulum system.

The main contents are suitable for a one-semester graduate course. This publication is a research reference whose intended audience includes researchers, postgraduate students.

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Contents

Notations and Acronyms

$\triangleq$	is defined as
$\in$	belongs to
$\forall$	for all
$\sum$	sum
$\mathbf{R}$	field of real numbers
$\mathbf{R}^n$	space of n -dimensional real vectors
$\mathbf{R}^{n\times m}$	space of $n \times m$ real matrices
$\mathbf{Z}$	field of integral numbers
$\mathbf{Z}^+$	field of positive integral numbers
$\mathbf{E}\{\cdot\}$	mathematical expectation operator
$\mathbf{He}(A)$	$A + A^T$
lim	limit
max	maximum
min	minimum
sup	supremum
inf	infimum
$\mathrm{rank}(\cdot)$	rank of a matrix
$\mathrm{trace}(\cdot)$	trace of a matrix
$\lambda_{\min}(\cdot)$	minimum eigenvalue of a real symmetric matrix
$\lambda_{\max}(\cdot)$	maximum eigenvalue of a real symmetric matrix
I	identity matrix
I_n	$n \times n$ identity matrix
0	zero matrix
$0_{n\times m}$	zero matrix of dimension $n \times m$
X^T	transpose of matrix X
X^*	conjugate transpose of matrix X
X^{-1}	inverse of matrix X
$X > (<) 0$	X is real symmetric positive (negative) definite
$X \geq (\leq) 0$	X is real symmetric positive (negative) semi-definite
$\mathcal{L}_2\{[0, \infty), [0, \infty)\}$	space of square summable sequences on $\{[0, \infty), [0, \infty)\}$ (continuous case)

$\ell_2\{[0,\infty),[0,\infty)\}$	space of square summable sequences on $\{[0,\infty),[0,\infty)\}$ (discrete case)
$\lvert\cdot\rvert$	Euclidean vector norm
$\lVert\cdot\rVert$	Euclidean matrix norm (spectral norm)
$\lVert\cdot\rVert_2$	$\mathcal{L}_2$ -norm: $\sqrt{\int_0^\infty \lvert\cdot\rvert^2 dt}$ (continuous case) ℓ_2 -norm: $\sqrt{\sum_0^\infty \lvert\cdot\rvert^2}$ (discrete case)
$\lVert\cdot\rVert_E$	$\mathbf{E}\{\lVert\cdot\rVert_2\}$
$\lVert\mathbf{T}\rVert_\infty$	$\mathcal{H}_\infty$ norm of transfer function $\mathbf{T}$: $\sup_{\omega\in[0,\infty)}\lVert\mathbf{T}(j\omega)\rVert$ (continuous case) $\sup_{\omega\in[0,2\pi)}\lVert\mathbf{T}(e^{j\omega})\rVert$ (discrete case)
diag	block diagonal matrix with blocks $\{X_1,\ldots,X_m\}$
*	symmetric terms in a symmetric matrix
ADT	average dwell time
CCL	cone complementary linearization
DOF	dynamic output feedback
DOFC	dynamic output feedback control
FLC	fuzzy-logic-control
LKF	Lyapunov–Krasovskii function
LMI(s)	linear matrix inequality (inequalities)
MIMO	multiple-input multiple-output
NCSs	networked control systems
OFC	output feedback control
PDC	parallel distributed compensation
SISO	single-input single-output
SOFC	state-output feedback control
SOS	sum-of-squares
T-S	Takagi–Sugeno
TSK	Takagi–Sugeno–Kang

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Chapter 1
Introduction

1.1 Background

Many real-world systems are nonlinear and complex and thus challenging to synthesize and analyse using the conventional theory and approach. However, with the advent of fuzzy modelling and introduction of the “fuzzy sets” theory in [272], the Takagi–Sugeno (T-S) fuzzy model has emerged as an effective tool to analyse complex nonlinear systems [118, 153, 194, 202, 357]. By using IF-THEN rules, nonlinear equations can be approximated as a set of local linear input–output relations, and the complete fuzzy model can be obtained by mixing local linear models with piecewise fuzzy membership functions. Consequently, the results based on traditional linear system techniques can be extended to nonlinear systems. The resulting fuzzy system is described by a family of IF-THEN rules to express the local input–output relations of the nonlinear systems and realized by smoothly blending these local linear models together through the membership functions. Owing to the promising approximation ability of T-S fuzzy systems, the research concerning fuzzy systems has attracted increasing interest, and many researchers have focused on T-S fuzzy systems. For example, a stability analysis was conducted and stabilization issues were investigated in [115, 143, 321]; filtering problems were investigated in [10, 254, 337]; fault detection issues were reported in [83, 284, 341]; and model reduction problems were examined in [255, 256, 294].

The basic structure of a fuzzy system consists of four conceptual components: knowledge base, fuzzification interface, interface engine, and defuzzification interface. Figure 1.1 shows the block diagram of a fuzzy system. The fuzzification interface maps the crisp inputs into fuzzy inputs through membership functions. The knowledge base is a collection of rules in the IF-THEN format, which describes the expert knowledge using linguistic rules. The interface engine performs reasoning based on the fuzzy inputs and rules to generate the fuzzy outputs. Subsequently, the defuzzification interface converts the fuzzy outputs into crisp outputs. The fuzzy system shown in Fig. 1.1 has been employed as a fuzzy controller, as proposed by

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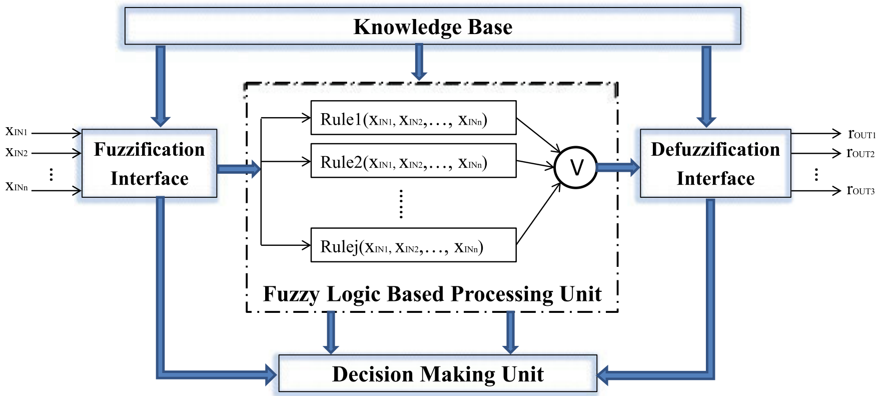

Fig. 1.1 Basic structure of a fuzzy system

Prof. Ebrahim Mamdani. By incorporating the knowledge of the control experts in the knowledge base, fuzzy controllers demonstrating human spirits have been successfully applied in various engineering applications such as industrial processes [119, 150, 170, 181], sludge waste water treatment [159, 229, 264], and construction engineering [13, 62, 71, 182].

Fuzzy control has been demonstrated to be a successful control approach for complex nonlinear systems. Moreover, the use of fuzzy control has been suggested as an alternative to conventional control techniques [117, 129, 216, 320]. In general, fuzzy sets can effectively capture the system nonlinearities, and the system dynamics of the nonlinear systems can be represented as an average weighted sum of certain local linear subsystems, with the weights characterized by the membership functions. In this context, stability analyses represent a key aspect in the field of fuzzy control systems [8, 148, 222].

1.2 Fuzzy-Model-Based Systems

Fuzzy-model-based control [19, 70, 312] is a powerful approach to address mathematically ill-defined nonlinear systems. To investigate the system stability, the T-S fuzzy model (also known as the Takagi–Sugeno–Kang (TSK) model) [59, 93, 235, 355] was proposed to provide a general and systematic framework to represent a nonlinear plant as a weighted sum of several linear subsystems. Each linear subsystem effectively models the dynamics of the nonlinear plant in the local operating domain. As the linear and nonlinear parts of the nonlinear plant are extracted, the T-S fuzzy model exhibits a semi-linear characteristic that can facilitate the realization of the stability analysis and controller synthesis. Based on the T-S fuzzy model, a fuzzy

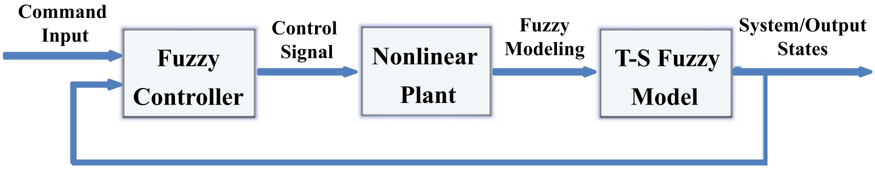

Fig. 1.2 A block diagram of the fuzzy-model-based control system

controller can be designed to close the feedback loop and form a fuzzy-model-based control system, as shown in Fig. 1.2.

In recent decades, fuzzy control has undergone rapid development in both theoretical research and industrial practice. In particular, since 1985, when Japanese scholars Takagi and Sugeno proposed the T-S fuzzy models [272], the design and analysis problem of fuzzy systems has evolved. Specifically, the T-S fuzzy model has emerged as the main method to address nonlinear problems because it can combine the strict mathematics theory with fuzzy logic theory to accurately approach nonlinear systems [2, 220, 286]. The dynamics of a nonlinear system can be expressed as a weighted average of linear subsystems. The linear and nonlinear characteristics of the nonlinear plant are extracted and expressed as the linear subsystems and nonlinear weights, respectively. In this manner, the T-S fuzzy model exhibits a favourable semi-linear property, enabling the use of certain linear analysis and design methods in performing the system analysis.

Due to its simple modelling process, T-S fuzzy models have received considerable attention from domestic and foreign scholars, and many relevant studies have been conducted. In [63, 131, 213, 232], the stability analysis of a T-S fuzzy model was performed using the linear matrix inequality (LMI) toolbox. In [66, 136, 162, 273, 352], certain researchers designed observer-based controllers and output feedback controllers for a case involving unmeasurable system states. Furthermore, in [4, 30, 86], fault detection problems were considered to detect failures in real time. Moreover, in [51, 121, 292], the $\mathcal{H}_\infty$ filter problems were investigated; in particular, the filter error system was rendered asymptotically stable, and a certain performance was achieved in the presence of interfering signals.

1.2.1 T-S Fuzzy Dynamic Model

The T-S fuzzy model is a useful mathematical tool to model nonlinear plants. This model provides a fixed framework to represent nonlinear systems through several linguistic rules to facilitate the stability analysis and control synthesis by using the LMI or sum-of-squares (SOS) -based analysis approach. In particular, a complex nonlinear system can be modelled as the following T-S fuzzy system:

♦ **Plant Form**:

Rule i: IF $\theta_1(x(t))$ is $\mathcal{M}_{i1}$ and $\cdots$ and $\theta_p(x(t))$ is $\mathcal{M}_{ip}$, THEN

$$\delta x(t) = A_i x(t) + B_i u(t), \quad i = 1, 2, \ldots, r,$$

where $x(t) \in \mathbf{R}^n$ is the state vector, δ above denotes the derivative operator in continuous time $\big($i.e., $\delta x(t) = \dot{x}(t)\big)$ and the shift forward operator in discrete time $\big($i.e., $\delta x(t) = x(t+1)\big)$; $u(t) \in \mathbf{R}^m$ is the input vector. $\mathcal{M}_{im}$ is the fuzzy set of rule i corresponding to the function $\theta_m(x(t))$, $i = 1, 2, \ldots, r$, $m = 1, 2, \ldots, p$, and r is the number of IF-THEN rules; $A_i \in \mathbf{R}^{n \times n}$ and $B_i \in \mathbf{R}^{n \times m}$ are system parameter matrices.

The premise variables are assumed to be independent of the input variables $u(t)$. This assumption is implemented to avoid the complex defuzzification process of the fuzzy controllers [275]. Given a pair $(x(t), u(t))$, the T-S fuzzy dynamic model can be derived:

$$\delta x(t) = \sum_{i=1}^{r} h_i(x(t)) \left[A_i x(t) + B_i u(t)\right], \tag{1.1}$$

where $h_i(x(t))$ are the normalized grades of membership function with

$$h_i(x(t)) = \frac{\nu_i(x(t))}{\sum_{i=1}^{r} \nu_i(x(t))}, \quad \nu_i(x(t)) = \prod_{m=1}^{p} \mu_{\mathcal{M}_{im}}\big(\theta_m(x(t))\big),$$

where $\mu_{\mathcal{M}_{im}}\big(\theta_m(x(t))\big)$ are the membership functions corresponding to the fuzzy set $\mathcal{M}_{im}$. It is assumed that

$$\begin{aligned} \nu_i(x(t)) &\geq 0, \quad i = 1, 2, \ldots, r, \\ \sum_{i=1}^{r} \nu_i(x(t)) &> 0, \quad \forall t \geq 0. \end{aligned}$$

Therefore,

$$h_i(x(t)) \geq 0, \quad i = 1, 2, \ldots, r; \quad \sum_{i=1}^{r} h_i(x(t)) = 1. \tag{1.2}$$

In general, the T-S fuzzy model can be established using two approaches: (1) By using certain system identification algorithms [235, 272] based on the input–output data. This approach is suitable for nonlinear systems for which mathematical models are not available, but input–output data are available. (2) If the mathematical model of the nonlinear system is available, the T-S fuzzy model can be derived from the mathematical model by using the concept of sector nonlinearity or local approximation [275, 299]. Notably, in the second approach, the grades of the membership may be uncertain if they are in terms of uncertain system parameters. In this case, a nonlinear plant subject to parameter uncertainties can be represented as a T-S fuzzy model with uncertain grades of membership.

1.2.2 Fuzzy-Model-Based Control System

The most widely used approach to design the fuzzy controller pertains to the state-feedback fuzzy controller [122, 226, 338], which has a structure similar to the T-S fuzzy model and is a weighted sum of several linear state-feedback sub-controllers. The control action is described by certain linguistic rules. Let us consider the following state-feedback fuzzy controller:

♦ **Controller Form**:

Rule j: IF $\vartheta_1(x(t))$ is $\mathcal{N}_{j1}$ and ... and $\vartheta_q(x(t))$ is $\mathcal{N}_{jq}$, THEN

$$u(t) = K_j x(t), \quad j = 1, 2, \ldots, s,$$

where $\mathcal{N}_{jn}$ is the fuzzy set of rule j corresponding to the function $\vartheta_n(x(t))$, $j = 1, 2, \ldots, s$, $n = 1, 2, \ldots, q$, and s is the number of IF-THEN rules. $K_j \in \mathbf{R}^{m \times n}$ is the gain matrix of the state feedback controller in each rule, and a compact form of the controller is given by

$$u(t) = \sum_{j=1}^{s} g_j(x(t)) K_j x(t), \tag{1.3}$$

where

$$g_j(x(t)) = \frac{\nu_j(x(t))}{\sum_{j=1}^{s} \nu_j(x(t))}, \quad \nu_j(x(t)) = \prod_{n=1}^{q} \mu_{\mathcal{N}_{jn}}\big(\theta_n(x(t))\big),$$

with

$$g_j(x(t)) \geq 0, \quad j = 1, 2, \ldots, s; \quad \sum_{j=1}^{s} g_j(x(t)) = 1, \tag{1.4}$$

$g_j(x(t))$ are the normalized grades of membership function, and $\mu_{\mathcal{N}_{jn}}\big(\vartheta_n(x(t))\big)$ are the membership functions corresponding to the fuzzy set $\mathcal{N}_{jn}$.

A fuzzy-model-based control system consists of a nonlinear plant represented by the T-S fuzzy model (1.1) and fuzzy controller (1.3) connected in a closed loop.

Throughout this book, as derived from (1.2) and (1.4), the following property is used during the system performance analysis:

$$\sum_{i=1}^{r} h_i(x(t)) = \sum_{j=1}^{s} g_j(x(t)) = \sum_{i=1}^{r}\sum_{j=1}^{s} h_i(x(t))g_j(x(t)) = 1. \tag{1.5}$$

Consider (1.1), (1.3) and (1.5), the closed-loop fuzzy-model-based control system can be described by

$$\begin{aligned}\delta x(t) &= \sum_{i=1}^{r} h_i(x(t))\big[A_i x(t) + B_i \sum_{j=1}^{s} g_j(x(t))K_j x(t)\big] \\ &= \sum_{i=1}^{r}\sum_{j=1}^{s} h_i(x(t))g_j(x(t))A_{ij}x(t),\end{aligned}$$

where $A_{ij} \triangleq A_i + B_i K_j$, $x(t) \in \mathbf{R}^n$ is the state vector, δ denotes the derivative operator in continuous time $\big($i.e., $\delta x(t) = \dot{x}(t)\big)$ and the shift forward operator in discrete time $\big($i.e., $\delta x(t) = x(t+1)\big)$.

1.2.3 Stability Analysis of Fuzzy Control Systems

The stability analysis and control synthesis are essential aspects in fuzzy-model-based control problems. The most popular approach to investigate the stability of fuzzy-model-based control systems is based on the Lyapunov method [151, 225, 324]. The stability analysis process can be realized using the following steps:

1. Construct a fuzzy model representing the nonlinear plant.
2. Select the type of fuzzy controller for the control process.
3. Formulate a fuzzy-model-based control system by connecting the fuzzy model and fuzzy controller in a closed loop, as displayed in Fig. 1.2.
4. Define a Lyapunov function candidate, which is a scalar positive function.
5. Set the stability conditions based on the Lyapunov stability method.

Moreover, in the stability analysis of fuzzy-model-based control systems, the conservativeness is related to several factors:

1. **Types of Lyapunov Functions**: A Lyapunov function is a mathematical tool to investigate the stability problem for fuzzy-model-based control systems. By employing different types or forms of Lyapunov function candidates to approximate the domain of the feasible solution, different stability conditions pertaining to different levels of conservativeness are obtained.
2. **Types of Stability Analyses**: The type of stability analysis determines the information of the membership functions to be considered, which influences

the conservativeness of the stability conditions. In particular, in membership-function-independent and membership-function-dependent stability analyses, the information of the membership functions is not considered and considered to set the stability conditions, respectively. In the latter case, the stability analysis results depend on the considered nonlinear model and often correspond to relaxed stability conditions.

3. **Methods of Stability Analyses**: The methods used to realize the stability analysis, such as those for managing and incorporating the membership functions influence the degree of conservativeness for the stability conditions.

For T-S fuzzy-model-based control systems, as shown in Fig. 1.3, the approaches to realize the stability analysis based on the Lyapunov stability theory can be classified into two types, specifically, membership-function-independent and membership-function-dependent approaches depending on whether the information of the membership functions is considered in the stability analysis. As the membership-function-independent stability analysis does not consider the membership functions, the stability analysis results are often more conservative than those based on the membership-function-dependent approach, in which the membership functions are considered in the stability analysis.

1.2.3.1 Membership-Function-Independent Stability Analysis

In the membership-function-independent stability analysis, the information of the membership functions is not considered, and only the local control subsystems of the fuzzy-model-based control systems are managed. Thus, the stability conditions do not involve any membership functions. Once there exists a feasible solution to the stability conditions, the fuzzy-model-based control system is guaranteed to be stable for any shape of the membership functions. However, when membership functions are not considered in the stability analysis, certain information of the nonlinearity is ignored. Therefore, the membership-function-independent stability results are potentially conservative.

1.2.3.2 Membership-Function-Dependent Stability Analysis

The membership-function-dependent stability conditions take into account the membership functions of the fuzzy model and fuzzy controller in the stability analysis. The obtained stability conditions include the information of the membership functions. In general, more relaxed stability conditions are obtained compared with those in the membership-function-independent stability analysis as more information of the fuzzy-model-based control system is considered. However, as the information of the membership functions is implemented in the form of slack matrices in the stability analysis and the number of stability conditions is generally high, the computational demand to determine a feasible solution for the stability conditions is high. Moreover,

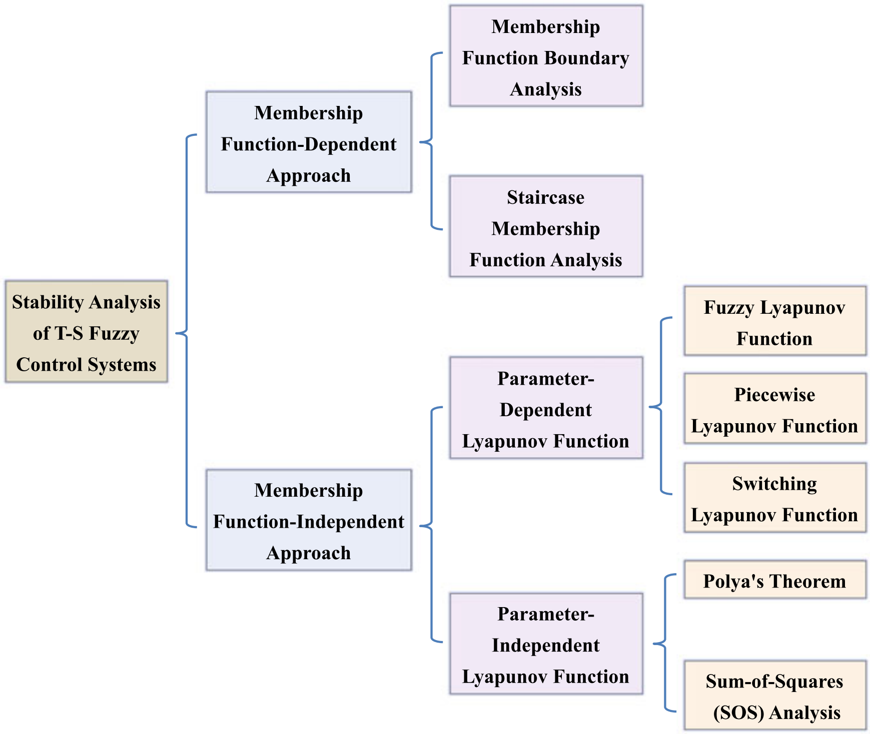

Fig. 1.3 Stability analysis approaches for T-S fuzzy-model-based control systems

the obtained stability conditions are specific to the fuzzy-model-based control system to be controlled and not generalized for all shapes of the membership functions.

1.3 Intelligent Control of Nonlinear Systems

1.3.1 Intelligent Control

Since the 20th century, the requirements for control systems have evolved with the development of science and technology [107, 112, 114, 309]. From linear to nonlinear systems and from single-input single-output (SISO) control systems to multiple-input multiple-output (MIMO) control systems, multiple control approaches have been integrated to complement the strengths of different techniques [46, 68, 178, 271, 313]. Intelligent control, as a novel technology, can help realize the preset control tasks of a system autonomously without human intervention [60, 75, 85, 201, 236]. Through this control implementation, the system control mode evolves from ordinary automatic control to a more advanced intelligent control mode. Intelligent control strategies transform the control model from certain to uncertain and provide a more convenient path for the information exchange between the input and output devices of the control system and the external environment. Moreover, when using intelligent control schemes, the control task of the system changes from a single task to a more complex control task. Thus, a more ideal solution exists for the control problem of nonlinear systems, which cannot be easily solved using ordinary automatic control systems. Intelligent control strategies enable an automatic control system to achieve self-adaptation, self-organization, self-learning, and self-coordination [197, 279, 301, 317]. Intelligent control represents the development trend of the control theory, which can effectively solve complex control problems, and several related techniques can be applied to industry, agriculture, service industry, military aviation, and other fields beyond control pertaining to finance, management, civil engineering, and design, among other domains.

Most control systems are designed under the assumption of perfect data transmission in both the sensor-to-controller and controller-to-actuator channels. This assumption is valid for most point-to-point control structures, but not for the widely used networked control systems (NCSs), in which the control loop is closed through a certain form of communication networks. Compared with traditional point-to-point control systems, the main advantages of NCSs are the low cost, flexibility and easy reconfigurability, inherent reliability and robustness to failure, and adaptation capability [20, 101, 108, 155, 265]. Consequently, NCSs have been applied in a broad range of areas such as power grids, water distribution networks, transportation networks, haptics collaboration over the Internet, mobile sensor networks, and unmanned aerial vehicles [78, 160, 234, 344, 348]. However, the introduction of communication channels in the control loop induces several network-induced critical issues or constraints such as variable transmission delays, data-packet dropouts, packet disorder, and quantization errors, which can significantly degrade the system performance and even destabilize the system in certain conditions. In recent years, the issues induced by the NCSs have posed considerable challenges to conventional control and communication theory and have attracted considerable attention from researchers of multiple disciplines including control, communication, and mathematics [65, 92, 174, 354]. The typical research topics pertaining to NCSs include the stability of NCSs under various network constraints, state estimation over lossy networks, controller/filter design of NCSs with guaranteed stability, and performance optimization [134, 198, 263, 339].

Moreover, recently, the benefit of using wireless communication technology in large-scale industrial processes has become evident [64, 145, 282, 283, 314], especially in the form of cyber-physical systems. The utilization of wireless networks in industrial process control enables the realization of new system architectures and designs. Nevertheless, many industrial control processes involve severe nonlinear characteristics, which renders the analysis and design highly challenging. In recent decades, fuzzy-logic-control (FLC) has received considerable attention from both academic and industrial communities. Notably, the FLC has been demonstrated to be a simple and powerful strategy for the analysis and synthesis of many complex nonlinear systems and nonanalytic systems [224, 227, 233, 336]. Significant research efforts have been devoted for both theoretical advances and implementation techniques for fuzzy controllers, and many industrial applications of the FLC have been reported in the existing literature [203, 228, 274]. Among various model-based fuzzy control methods, the approach based on the T-S model is well suited to design model-based nonlinear system controller [80, 126, 149, 244]. The research interest in the systematic analysis and design of networked nonlinear systems via T-S fuzzy dynamic models has increased, and multiple significant results have been reported [88, 165, 215, 346, 356].

1.3.2 Fuzzy Control

The mathematical modelling of physical systems and processes often generates complex nonlinear systems, the synthesis and analysis of which is highly difficult. The research on nonlinear systems is often problematic due to their complexities. One effective way of representing a complex nonlinear dynamic system is by using the T-S fuzzy model [5, 16, 27, 126, 142], which is governed by a family of fuzzy IF-THEN rules that represent the local linear input–output relations of the system. This model incorporates a family of local linear models smoothly blended through fuzzy membership functions. This approach, in essence, is a multi-model approach, in which simple sub-models (typically linear models) are fuzzily combined to describe the global behaviour of a nonlinear system [7, 21, 23, 260]. Within these fuzzy models, the local dynamics in different state space regions are represented by linear models [24, 29, 37, 41, 48]. An overall fuzzy model of the system is created by fuzzily 'blending' these linear models. Based on the fuzzy model, the control design can be realized based on the parallel distributed compensation (PDC) scheme. In particular, a linear state-feedback controller is designed for each local linear model. The obtained overall controller is usually nonlinear and represents a fuzzy 'blending' of each individual linear controller [33, 44, 56, 61, 69, 72].

Nevertheless, because only a part of the state information may be known in real-world engineering, the state-feedback control is not entirely effective to ensure the desired performance level [11, 12, 189, 257]. Consequently, intensive research has been conducted in the area of output feedback control (OFC) design. Although the state-output feedback control (SOFC) technique (see, for instance, [100, 110, 188]) can be used to address the dynamic output feedback control (DOFC) problem, the process involves several analytical difficulties. Nonetheless, several solutions have been obtained for DOFC problems. For instance, the DOFC problems for T-S fuzzy systems were addressed in [40, 128, 147, 191, 345], the corresponding results for Markovian hybrid jump systems were reported in [9, 156, 177, 240**?**], and the feasibility conditions for stochastic switched systems were defined in [54, 90, 91, 175, 361]. In addition, the mixed $\mathcal{H}_2/\mathcal{H}_\infty$ fuzzy OFC design techniques were introduced in [49, 81, 221, 305]. However, to the best of our knowledge, only a few studies have focused on the fuzzy output feedback controller design with the $\mathcal{L}_2$–$\mathcal{L}_\infty$ performance for nonlinear switched systems. Furthermore, the previously obtained results in this domain must be further investigated in terms of multiple aspects, for instance, the mechanism of selecting the fuzzy piecewise Lyapunov functions for nonlinear complex systems to reduce conservativeness and the design strategy for switched DOFC to ensure the system stability and achieve $\mathcal{L}_2$–$\mathcal{L}_\infty$ performance level. These problems are the motivation for the current research.

Practical systems, especially those pertaining to chemical processes and communication, commonly involve time delays, which reduce the system performance and may lead to instability. The prevalent use of stochastic systems has led to the widespread application of stochastic modelling in science and engineering domains [247, 303]. Many key results have been reported for the T-S fuzzy model [42, 239, 262, 360], switched systems [34, 158, 252, 291], and Markovian jumping systems [14, 36, 241, 248, 332]. The general control synthesis methodologies cannot satisfy the requirements for T-S fuzzy systems that incorporate intelligent control method, filtering, and model reduction analysis. Considering these aspects, this monograph presents the innovative research developments and methodologies pertaining to the synthesis and analysis of T-S fuzzy systems in a unified matrix inequality setting. Researchers exploring the problems of intelligent control, filtering, and model reduction for fuzzy-model-based systems can find valuable reference material in this text. The aspects of stability analysis and stabilization, dynamic output feedback (DOF) control, full- and reduced-order filter design, fault detection, and model reduction problems for a class of T-S fuzzy systems are thoroughly investigated. Moreover, novel techniques are applied to systems, including the delay-partitioning method, slack matrix method, reciprocally convex approach, and event-triggered strategy, [15, 22, 31, 288, 349].

1.4 Reduced-Order Method Synthesis

1.4.1 Model Reduction

With the increasing demands of higher security, reliability, and performance in several engineering domains, fault detection techniques have attracted considerable attention. Model-based fault diagnosis represents an effective approach to solve the fault detection problems in technical processes [45, 87, 102, 231, 269, 277]. The key strategy for fault detection involves two parts, specifically, the construction of a residual signal and computation of a residual evaluation function to be compared against a predefined threshold. A fault alarm is generated when the residual evaluation function exceeds the threshold. To detect faults in a timely manner and avoid false alarms, the residual signal should be sensitive to faults and robust against modelling errors or disturbances for a fault detection problem [26, 35, 38, 79, 280]. Recently, several model-based approaches for fault detection problems have been reported for dynamic systems, along with several significant results. For example, the authors of