Hybrid Compensation Control for Affine TSK Fuzzy Control Systems

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***Abstract*—The paper proposes a way of designing state feedback controllers for affine Takagi-Sugeno-Kang (TSK) fuzzy models. In the approach, by combining two different control design methodologies, the proposed controller is designed to compensate all rules so that the desired control performance can appear in the overall system. Our approach treats all fuzzy rules as variations of a nominal rule and such variations are individually dealt with in a Lyapunov sense. Previous approaches have proposed a similar idea but the variations are dealt with as a whole in a robust control sense. As a consequence, when fuzzy rules are distributed in a wide range, the stability conditions may not be satisfied. In addition, the control performance of the closed-loop system cannot be anticipated in those approaches. Various examples were conducted in our study to demonstrate the effectiveness of the proposed control design approach. All results illustrate good control performances as desired.**

***Index Terms*—Affine TSK fuzzy model, fuzzy control, hybrid compensation control.**

I. Introduction

THE STUDY of stable analysis and control design for fuzzy systems has attracted many researchers recently. In the control design study, there are two types of control design problems found in the literature. The first one is to design a fuzzy controller for a nonlinear or unknown system, and the other is to find a controller for a fuzzy system. In the former case, a so-called adaptive fuzzy control is usually used. Generally, the basic objective of adaptive control is to maintain consistent control performance in the presence of large uncertainties or unknown variations in plant parameters or structure [1]–[4]. In those papers, some adaptive laws are proposed to guarantee the stability of the system in the sense of Lyapunov. By combining other learning approaches, or by considering different control properties, various variations of adaptive fuzzy control approaches have been proposed in the literature [5]–[13]. In this paper, we reported our study on the issue of finding a suitable controller for a fuzzy system. In this study, the structure and parameters of the fuzzy controller are fixed and we shall find a way of designing fuzzy controllers to satisfy requirements.

For the analysis of stability of fuzzy system, based on the Lyapunov stability criterion, Tanaka and Sugeno (T–S) [14] have proposed a useful theory for conservatively assuring the stability of a Takagi-Sugeno-Kang (TSK) or T-S fuzzy model [15]. The theory states that if a common positive definite matrix required in Riccati equations can be found for all fuzzy rules, the fuzzy model is stable in the sense of Lyapunov. Thathachar *et al.* [16] also proposed a necessary condition and a sufficient condition for the stability of fuzzy systems. They showed that under a formal sufficient condition, a common Lyapunov matrix exists for all subsystems. It is easy to see that to analytically find such a matrix is a linear matrix inequality (LMI) problem [17], [41]. Based on the LMI concept, Kim *et al.* [18] proposed a numerical stability analysis method for singleton-type linguistic fuzzy control systems. Most of recent fuzzy control design approaches are to employ the parallel-distributed compensation (PDC) concept [19], in which controllers are designed individually for fuzzy rules and then stability condition is checked through LMI to validate the design. Some relaxed LMI stability conditions are also proposed in [20] and [21]. Parametric uncertainties regarding those approaches are dealt with in [22]–[24]. However, those methods are stability checking approaches instead of design approaches. When the designed controller cannot satisfy the stability criterion, another controller is tried. Such a process is somehow a trial-and-error design procedure. Lam *et al.* [25] proposed a designing method that can be used to help solving the relaxed LMI problem and in the approach, the feedback gains of the subsystem are determined by using a genetic algorithm, which can also be viewed as a trial-and-error procedure. Another problem rises when the number of rules is large because it may be difficult to find solutions for LMI in that case. Moreover, since the validation of LMI is only for stability, the control performance assured in individual rules cannot be anticipated in the overall system performance under those design approaches.

Several researchers [21], [26], [27] actually proposed ways of designing controllers by directly solving LMIs. Gao *et al.* [26] and Tanaka *et al.* [20] used LMIs combined with stable conditions of fuzzy systems to design a stable fuzzy system. When the control performance is considered, those approaches need to include performance constraints into LMIs for all fuzzy rules [27]. Korba *et al.* [28] proposed an extended fuzzy scheduler (EFS) controller that can guarantee the stability and the tracking performance requirements. The idea is to introduce an additional

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tracking-error state variable into the state variables of the controlled system, and then an extended-state feedback-gain matrix is design by means of LMIs. Cao *et al.* [29] also developed a two-part controller. One part is a state-feedback matrix like that in [17] and [20] and the other part is to satisfy global stable conditions. Note that in these approaches, the homogeneous fuzzy systems are considered. Here, "homogeneous" means that the consequent parts are linear equations without constant terms. Such fuzzy systems can only represent a certain class of nonlinear systems. Kim *et al.* [30] proposed a discrete iterative LMI approach to analyze stability for discrete affine fuzzy systems, where "affine" means that the consequent parts are linear equations with constant terms. However, the above approaches may become infeasible, when the number of rules is large. It is because the analysis techniques are to find a common positive definite matrix for all subsystems (fuzzy rules) to fulfill the Lyapunov stability analysis. It is difficult to find such a matrix when the rule number is large. Sometimes, there does not even exist such a matrix.

Other approaches also exist that do not make use of the common Lyapunov matrix validation scheme. Kang *et al.* [31] proposed a controller that is inferred by using their consistency conditions [32], but the desired performance has not yet been addressed. Kiriakidis *et al.* [33] viewed a TSK fuzzy model as a linear system subject to a class of nonlinear uncertainties and claimed that the computational cost of checking such a stability criterion is less than that of finding a common Lyapunov matrix. However, this approach leads to a convex programming problem and the design procedure is still in a trial-and-error manner. Feng [34] proposed a sufficient condition, which leads to a search algorithm for solving a Riccati equation, and then a state feedback can be designed accordingly for such a system. Zak [35] also proposed a design algorithm to obtain a controller, which is separated into two parts to stabilize the nominal system and variations residing in all fuzzy rules, respectively. This approach is to treat variations of all rules as a whole in a robust control sense. For those approaches, when subsystems are distributed in a wide range, the upper bound of such variations may become large, and then the stabilization algorithm may fail. In addition, the control performance of the closed-loop system cannot be anticipated. In this paper, we proposed a novel robust control design approach that can design controllers directly for affine continuous or discrete time fuzzy systems and the closed-loop performance can be theoretically anticipated.

This paper is organized as follows. Section II describes the affine TSK fuzzy model. The proposed controller is introduced in Section III. Both continuous-time cases and discrete-time cases are discussed. Section IV shows simulation results for both continuous and discrete-time examples. Finally, Section V concludes the paper.

II. Control Design for Affine TSK Fuzzy Models

The considered problem is that a system is described by a set of fuzzy rules and we want to develop a way of designing controllers for such a system. The considered fuzzy models are first introduced in [14] and the ith rule of a discrete system is

$$\begin{aligned} &\text{Rule } i\text{: IF } x_1(k) \text{ is } X_1^i \text{ and} \cdots \text{and } x_n(k) \text{ is } X_n^i \\ &\text{THEN } x_n(k+1) = a_0^i + a_1^i x_1(k) + a_2^i x_2(k) + \cdots + a_n^i x_n(k) \\ &\qquad + b_1^i u(k) + \cdots + b_m^i u(k-m+1) \end{aligned} \tag{1}$$

where $x_j(k) = x_{j-1}(k+1)$ for $j = 2, \ldots, n$, $u(k), \ldots,$ and $u(k-m+1)$ are the input and m past inputs, X_j^i are fuzzy sets, and $a_0^i, a_1^i, \ldots, a_n^i$, and $b_1^i, \ldots, b_m^i$ are parameters in describing the input and output relationships in the ith fuzzy rule. Note that the premise part is only determined by $x_1(k), x_2(k), \ldots,$ and $x_n(k)$ and is independent to $u(k), \ldots, u(k-m+1)$. This relationship matches the properties of common systems. Besides, the consequence part contains a constant term, a_0^i. Such a fuzzy model is referred to as a class of affine TSK fuzzy model [30]. The consequence part can be written in a state-space form as $x(k+1) = A^i x(k) + B^i u(k) + d^i$, where $x(k) = [x_1(k), \ldots, x_n(k)]^T$

$$A^i = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ a_1^i & a_2^i & a_3^i & \cdots & a_n^i \end{bmatrix}$$

$$B^i = [0, 0, \ldots, b_1^i]^T$$

and

$$d^i = [0, \quad \cdots \quad , a_0^i + b_2^i u(k-1) + \cdots + b_m^i u(k-m+1)]^T.$$

Let $\mu_j^i(x_j(k))$ be the membership degree of the $x_j(k)$ in the fuzzy set X_j^i. Then the overall system can be inferred as

$$x(k+1) = \sum_{i=1}^{r} w_i A^i x(k) + \sum_{i=1}^{r} w_i B^i u(k) + \sum_{i=1}^{r} w_i d^i \tag{2}$$

where r is the rule number

$$w_i = \left(\prod_{j=1}^{n} \mu_j^i(x_j(k)) / \sum_{i=1}^{r} \left(\prod_{j=1}^{n} \mu_j^i(x_j(k)) \right) \right)$$

with $0 \leq w_i \leq 1$, and $\sum_{i=1}^{r} w_i = 1$.
For a continuous TSK fuzzy model system, the ith rule is of the form

$$\begin{aligned} &\text{Rule } i: \text{IF } x_1(t) \text{ is } X_1^i \text{ and } \cdots \text{ and } x_n(t) \text{ is } X_n^i \\ &\text{THEN } \dot{x}_n(t) = a_0^i + a_1^i x_1(t) + a_2^i x_2(t) \\ &\qquad + \cdots + a_n^i x_n(t) + b_1^i u(t) \end{aligned} \tag{3}$$

where $x_j(t) = \dot{x}_{j-1}(t)$ for $j = 2, \ldots, n$ with $\dot{x}_{j-1}(t)$ is the time derivative of $x_{j-1}(t)$. Then, the consequence part can also be written as $\dot{x}(t) = A^i x(t) + B^i u(t) + d^i$, where $x(t) = [x_1(t), \ldots, x_n(t)]^T$, A^i and B^i are the same as those in the discrete case, and $d^i = [0, 0, \ldots, a_0^i]^T$. Similarly, the related items for a continuous affine TSK fuzzy model can be defined.

In the literature, based on the Lyapunov theorem, several design approaches have been proposed to design stable controllers for homogenous fuzzy models; i.e., the constant vector is absent in (2). One of the most commonly used approaches is the parallel distributed compensation (PDC) control [19], [36], in which fuzzy controllers share the same premise parts with the considered fuzzy systems. The sufficient conditions for the stability of the closed-loop system are summarized in [20]. It is required that the stability of the overall system be checked by solving LMIs [17]. If the common Lyapunov matrix cannot be found, another design is tried. It should be noted that the number of inequalities to be solved is $r(r+1)/2$. It can be found that when the rule number is large, it may be very difficult to solve those inequalities.

As mentioned earlier, there is another kind of approach [33], [35] in which a controller is defined for the nominal system of fuzzy rules first, and then the deviations from this nominal system existing in all rules are dealt with in a robust control fashion. Our approach shared the same idea as this kind of approach. The nominal system can be defined as $A_0 \in conv(A^1,\ldots,A^r)$ and $B_0 \in conv(B^1,\ldots,B^r)$, where $conv(A^1,\ldots,A^r) = \{\sum_{i=1}^r w_i A^i : w_i \geq 0, \sum_{i=1}^r w_i = 1\}$ is a convex hull defined by the set of vertex matrices $A^1,\ldots,$ and A^r and a similar convex hull is defined for $conv(B^1,\ldots,B^r)$. Let

$$A_0 = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \\ a_1^0 & a_2^0 & \cdots & a_n^0 \end{bmatrix}$$

and $B_0 = [0,\ldots,b_0]^T$. The formation of A_0 and B_0 can be arbitrary as long as they are stabilizable. Usually, a simple arithmetic average is taken; that is, $a_j^0 = (\underset{i}{\mathrm{Max}}\{a_j^i\} + \underset{i}{\mathrm{Min}}\{a_j^i\})/2$ and $b_0 = (\underset{i}{\mathrm{Max}}\{b_1^i\} + \underset{i}{\mathrm{Min}}\{b_1^i\})/2$. The differences between (A^i,B^i) and (A_0,B_0) are

$$A_i = A^i - A_0 = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \\ a_{1i} & a_{2i} & \cdots & a_{ni} \end{bmatrix}$$
$$B_i = B^i - B_0 = [0,\ldots,b_i]^T \tag{4}$$

where $a_{ji} = a_j^i - a_j^0$ and $b_i = b_1^i - b_0$. Then, the system (2) can be rewritten as

$$x(k+1) = \sum_{i=1}^r w_i A^i x(k) + \sum_{i=1}^r w_i B^i u(k) + \sum_{i=1}^r w_i d^i$$
$$= (A_0+\Delta A)x(k) + (B_0+\Delta B)u(k) + \sum_{i=1}^r w_i d^i \tag{5}$$

where $\Delta A = \sum_{i=1}^r w_i A_i$ and $\Delta B = \sum_{i=1}^r w_i B_i$. Similarly, with the same definition as above, a continuous affine TSK fuzzy model can be written as

$$\dot{x}(t) = (A_0+\Delta A)x(t) + (B_0+\Delta B)u(t) + \sum_{i=1}^r w_i d^i. \tag{6}$$

Note that ΔA and ΔB are regarded as uncertainties in this kind of approaches.

III. Hybrid Compensation Control Design for Affine TSK Fuzzy Systems

The design idea is to design a controller for each local model under the idea of PDC control [19], [36], in which fuzzy controllers share the same premise parts with the considered fuzzy systems. Then, the ith control rule can be written as

$$\begin{array}{l}\text{Rule } i: \text{IF } x_1 \text{ is } X_1^i \text{ and } \cdots \text{ and } x_n \text{ is } X_n^i \\ \qquad \text{THEN } u = F_i(x)\end{array} \quad \text{for } i=1,\ldots,r.$$

Thus, the overall fuzzy controller is $u = \sum_{i=1}^r w_i F_i(x)$. In our study, a novel design approach, which consists of two parts of controllers to stabilize the nominal system and variations residing in all rules, respectively, is proposed. The propose feedback control law can be written as

$$u = Gx + G_C(x) \tag{7}$$

where G is to control the nominal system with the desired control performance and $G_C(x)$ is to compensate the variations in all rules individually. In the following, we shall introduce how the above control law is obtained. This type of control laws is called the hybrid compensation control (HCC) in our study. The control law proposed in [33] is referred to as the nominal compensation control (NCC) and the PDC controller [19], [36] is called the distributed compensation control (DCC). [35] also proposed a similar controller, in which the second part is to treat those variations as a whole instead of individually in a robust control sense. If those subsystems are distributed in a wide range, the required norm bound conditions may not be satisfied. In that case, the design algorithm will fail. This can be seen in our example shown later. For the proposed HCC, it is not required to find a common Lyapunov matrix for all subsystems. This advantage greatly increases the applicability of our approach, especially when the rule number of the system is large.

As mentioned earlier, ΔA and ΔB [in (5) for the discrete case or in (6) for the continuous case] are regarded as uncertainties in our approach. For those terms, the following assumptions are made.

- A1) The nominal part of the system (5) or (6) is stabilizable.
- A2) Uncertainties may vary with time within a prescribed bounded set.
- A3) There exists a $1 \times n$ vector $\tilde{a}$, a scalar $\tilde{b}$ such that $\Delta A = B_0 \tilde{a}$ and $\Delta B = \tilde{b} B_0$.

Those assumptions are also used in [37] and [38] in dealing with uncertainties in the system matrix and input channels. In our case, since those uncertainties are in fact the summation of the deviations of all rules, it is easy to see that those assumptions can easily be satisfied. This can be verified in our control design for various systems. The control law designing methods for discrete and continuous TSK fuzzy models are derived in the following two subsections.

A. Discrete-Time Case

Consider a discrete TSK fuzzy model described by (5). Let the control input be (7), where $G = [\,g_1 \quad g_2 \quad \cdots \quad g_n\,]$ is to stabilize the nominal model in (5) and $G_C(x)$ is to compensate the variations of all rules. Substituting (7) into (5), we have

$$\begin{aligned} x(k+1) &= (A_0 + B_0 G)x(k) + B_0(\tilde{a}x(k) + \tilde{b}G_C(x) + \tilde{d}) \\ &= \overline{A}_0 x(k) + B_0 h(x) \end{aligned} \quad (8)$$

where $\tilde{a} = \sum_{i=1}^{r} k_i \tilde{a}_i$ with $\tilde{a}_i = [(a_{1i} + b_i g_1)/b_0, \ (a_{2i} + b_i g_2)/b_0, \ \cdots \ (a_{ni} + b_i g_n)/b_0]$, $\tilde{b} = \sum_{i=1}^{r} k_i \tilde{b}_i$ with $\tilde{b}_i = 1 + (b_i/b_0)$, $\tilde{d} = \sum_{i=1}^{r} k_i \tilde{d}_i$ with $\tilde{d}_i = d^i/b_0$, and $h(x) = \tilde{a}x(t) + \tilde{b}G_C(x) + \tilde{d}$. In order to let the system be stable, there must exist symmetry positive definite matrices P and Q such that $\overline{A}_0^T P \overline{A}_0 - P = -Q$. Define $V(x(k)) = x^T(k)Px(k)$ and we have

$$\Delta V(x(k)) = -x^T(k)Qx(k) + h(x)[\alpha h(x) + 2\beta(x)]$$

where $\alpha = B_0^T P B_0$, $\beta(x) = B_0^T P \overline{A}_0 x(k)$. It is easy to verify that when $h(x)[\alpha h(x) + 2\beta] \le 0$, the system is stable. Since $h(x) = \tilde{a}x(t) + \tilde{b}G_C(x) + \tilde{d}$, if the compensation part is set as $G_C(x) = -(\tilde{a}x(k) + \tilde{d})/\tilde{b}$, then $h(x) = 0$. Hence, we have

$$G_C(x) = -\frac{\tilde{a}x(k) + \tilde{d}}{\tilde{b}} = -\frac{\sum_i w_i \tilde{a}_i}{\sum_i w_i \tilde{b}_i} x(k) - \frac{\sum_{i=1}^{r} w_i \tilde{d}_i}{\sum_i w_i \tilde{b}_i}. \quad (9)$$

We then have the following theorem.

Theorem 1: Suppose that the chosen nominal system matrix (A_0, B_0) for the discrete fuzzy model system (1) is stabilizable. Then, the closed-loop system driven by the control law (7) is asymptotically stable in the large, where G is the stable state-feedback gain for the nominal model and $G_C(x)$ is given by (9).

Proof: With the compensation part of the control law in (9), the equation $h(x) = 0$ holds. Thus, the closed-loop system (8) becomes

$$x(k+1) = (A_0 + B_0 G)x(k). \quad (10)$$

Since (A_0, B_0) is stabilizable, it proves the Theorem. $Q.E.D.$

From Theorem 1, we can also conclude the following lemmas.

Lemma 1: The behavior of the discrete fuzzy model (1) controlled by the control law (7) is the same as the closed-loop nominal model (10).

The closed-loop system is a linear system (nominal model) whose eigenvalues can be arbitrarily assigned by the state-feedback gain G. Hence, we can employ various stability design approaches, such as pole-placement, linear optimal control or other design techniques in designing controllers for the nominal model.

Lemma 2: Consider the fuzzy model system (1) without the constant term. Suppose that the eigenvalues assigned for each subsystem are the same as that for the nominal model. Then the state feedback gain of the ith subsystem is

$$F_i = G - \frac{\tilde{a}_i}{\tilde{b}_i} \quad (11)$$

where $i = 1, \ldots, r$, and F_i, and G are the state feedback gains of the ith subsystem and of the nominal model, respectively.

It is easy to verify this lemma by simply substituting the feedback gain into rules.

In (9), if b_1^is are the same sign in all rules that implies $\tilde{b} \neq 0$. In most of existing approaches, $\tilde{b} \neq 0$ is always assumed. When b_1^i changes sign among rules for some $i \in \{1, \ldots, r\}$, $\tilde{b}$ may be near 0 or equal to 0. If such a situation occurs, it means that in a transition instant, the input can hardly change the system states. In other words, the system becomes uncontrollable. We think $\tilde{b} = 0$ is only a transition state and usually, the system can still work well without this assumption. In our implementation, a threshold ε is used to avoid large input values for such situations. As shown in Example 1, when b_1^i changes signs among rules, the control input transits from large negative values to large positive values. By using a threshold, the input is limited to a reasonable range and the system still works well. We further analyze such a case in the following. If $\tilde{b} = 0$, it means that the inferred system is $x(k+1) = Ax(k)$. It is an unforced system, and no matter what input is, the system behavior is uncontrollable. If the current uncontrollable state is an equilibrium state of $x(k+1) = Ax(k)$, then there is no way of moving out this uncontrollable state. This is rarely the case and it is the problem of the system and is not caused by our control law. If not, the system will transit and then it is easy to find that $\tilde{b} \neq 0$ because the system state is changed.

B. Continuous-Time Case

Similarly, we can derive the control law for continuous-time systems. The control law (7) is also used for a continuous TSK fuzzy model system (6). Since $\overline{A}_0$ is Hurwitz stable, there exist symmetry positive definite matrices P and Q such that $\overline{A}_0^T P + P^T \overline{A}_0 = -Q$. Let $V(x) = x^T(t)Px(t)$, and we have

$$\dot{V}(x) = -x^T(t)Qx(t) + 2h(x)B_0^T Px(t).$$

Obviously, if the inequality $2h(x)B_0^T Px(t) \le 0$ holds, the system is asymptotically stable. We let $2h(x)B_0^T Px(t) = 0$; i.e., $h(x) = \tilde{a}x(t) + \tilde{b}G_C(x) + \tilde{d} = 0$. Therefore

$$G_C(x) = -\frac{\tilde{a}x(t) + \tilde{d}}{\tilde{b}} = -\frac{\sum_{i=1}^{r} k_i \tilde{a}_i}{\sum_{i=1}^{r} k_i \tilde{b}_i} x(t) - \frac{\sum_{i=1}^{r} k_i \tilde{d}_i}{\sum_{i=1}^{r} k_i \tilde{b}_i}. \quad (12)$$

Clearly, (12) is the same as that for the discrete case; i.e., (9). In other words, *Theorem 1* can also work for continuous fuzzy models. Consequently, *Lemmas 1* and *2* also work for continuous fuzzy models.

Finally, the proposed HCC design method is summarized as follows.

Step 1) Select a stabilizable central rule as the nominal fuzzy model and calculate the variations for all subsystems by (3).

Step 2) Find a state feedback matrix G such that the nominal fuzzy model in (8) is assigned the desired eigenvalues. Such a G can be designed by various techniques to provide specified system behaviors.

Step 3) Get the compensation part $G_C(x)$ by using (8) and (9).

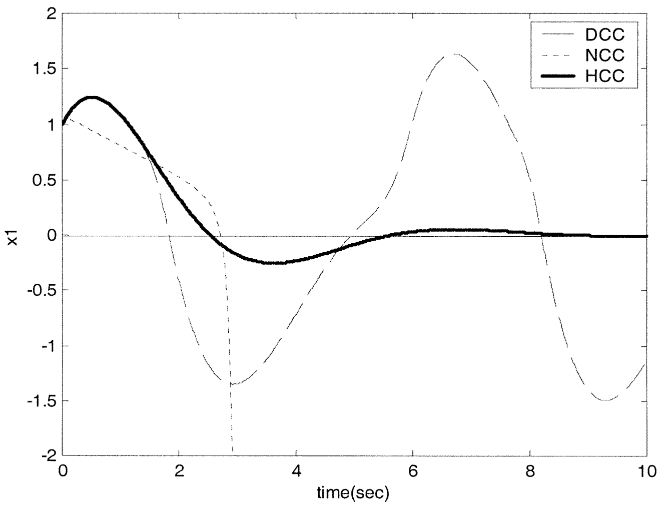

Fig. 1. Responses of using various controllers for the system in Example 1.

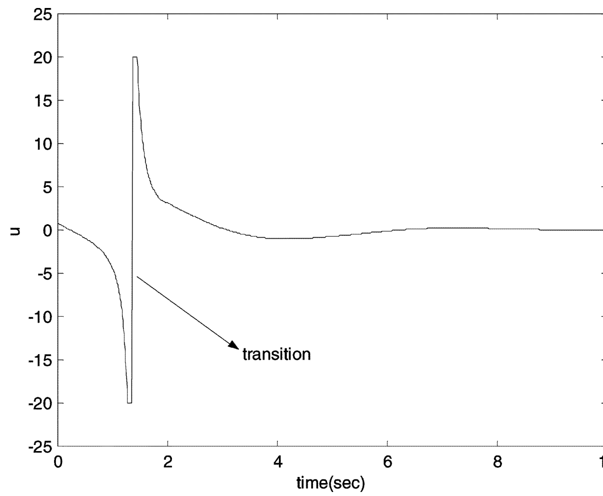

Fig. 2. Control input by using the proposed HCC for the system in Example 1.

IV. Design Examples

In this section, various examples are considered to illustrate good design performance of the proposed HCC design scheme.

Example 1: Consider an unstable continuous model, in which there are two rules in the model and the system matrices are

$$A_1 = \begin{bmatrix} 0 & 1 \\ -0.588 & 2.718 \end{bmatrix},\ B_1 = \begin{bmatrix} 0 \\ 0.603 \end{bmatrix}$$
$$A_2 = \begin{bmatrix} 0, & 1 \\ -0.361 & 2.256 \end{bmatrix},\ B_2 = \begin{bmatrix} 0 \\ -1.12 \end{bmatrix}.$$

Define the nominal system matrices as

$$A_0 = 1/2(A_1 + A_2) = \begin{bmatrix} 0 & 1 \\ -0.4745 & 2.487 \end{bmatrix}$$

and $B_0 = 1/2(B_1 + B_2) = \begin{bmatrix} 0 \\ -0.2611 \end{bmatrix}$.

Let the desired eigenvalues are $[-0.5 + j,\ \ -0.5 - j]$ and then $G = [2.9703 \quad 13.3558]$. Define $Q = I$, we have $v = 23.4183 > 1$ [33] for NCC. Such a design cannot guarantee the stability of the system. Using our HCC approach, the compensation parts are $\tilde{a}_1 = [-9.3957 \quad -45.087]$, $\tilde{b}_1 = -2.3096$ and $\tilde{a}_2 = [9.3369 \quad 44.8226]$, $\tilde{b}_2 = 4.8298$. Suppose that the same eigenvalues are assigned for all subsystem (DCC). From *Lemma 2*, we obtain $F_1 = [-1.0978 \quad -6.1658]$ and $F_2 = [-0.7937 \quad -2.9071]$. The solution for LMIs cannot be obtained for this case. In other words, the stability condition is not satisfied, and the controllers for all rules must be redesigned in the PDC approach. Fig. 1 shows the response of the three closed-loop systems for the initial condition $x = [1 \quad 0]$. Simulations confirm the above assertions. Now, consider the approach in [35], since the norm bound of uncertainties is bigger than 1, that approach fails in this case. It should be noted that in this example b_i changes signs among rules. We can find that the control input transits from large negative values to large positive values as shown in Fig. 2. By using a threshold, the input is limited to a reasonable range.

Example 2: Consider a nonlinear discrete system in [39]

$$y(k+1) = \frac{y(k)y(k-1)y(k-2)u(k-1)(y(k-2)-1)+u(k)}{1+y(k-2)^2+y(k-1)^2}.$$

The TSK fuzzy model of such a system is derived in [31] and shown as follows:

$$\begin{aligned}
&R^1: \text{IF } x_2(k) \text{ is A1 and } x_1(k) \text{ is } B1\\
&\text{THEN } x_3(k+1) = 0.08 + 0.974x_3(k) + 0.333x_2(k)\\
&\qquad -0.279x_1(k) + 0.494u(k) - 0.468u(k-1)\\
&R^2: \text{IF } x_2(k) \text{ is A1 and } x_1(k) \text{ is B2}\\
&\text{THEN } x_3(k+1) = 0.021 - 0.03x_3(k) + 0.058x_2(k)\\
&\qquad -0.127x_1(k) + 0.419u(k) + 0.029u(k-1)\\
&R^3: \text{IF } x_2(k) \text{ is A2 and } x_1(k) \text{ is C1}\\
&\text{THEN } x_3(k+1) = 0.004 - 0.173x_3(k) + 0.211x_2(k)\\
&\qquad +0.009x_1(k) + 0.619u(k) + 0.111u(k-1)\\
&R^4: \text{IF } x_2(k) \text{ is A2 and } x_1(k) \text{ is C2}\\
&\text{THEN } x_3(k+1) = 0.002 - 0.012x_3(k) + 0.005x_2(k)\\
&\qquad +0.007x_1(k) + 0.977u(k) + 0.007u(k-1)\\
&R^5: \text{IF } x_2(k) \text{ is A2 and } x_1(k) \text{ is C3}\\
&\text{THEN } x_3(k+1) = 0.003 - 0.099x_3(k) + 0.011x_2(k)\\
&\qquad -0.02x_1(k) + 0.587u(k) + 0.058u(k-1)\\
&R^6: \text{IF } x_2(k) \text{ is A3 and } x_1(k) \text{ is } D1\\
&\text{THEN } x_3(k+1) = -0.003 - 0.062x_3(k) + 0.01x_2(k)\\
&\qquad -0.192x_1(k) + 0.38u(k) + 0.079u(k-1)\\
&R^7: \text{IF } x_2(k) \text{ is A3 and } x_1(k) \text{ is D2}\\
&\text{THEN } x_3(k+1) = -0.112 + 0.131x_3(k) - 0.001x_2(k)\\
&\qquad +0.144x_1(k) + 0.382u(k) - 0.138u(k-1)
\end{aligned}$$

where $x_3(k) = y(k)$, $x_2(k) = x_3(k-1)$, and $x_1(k) = x_2(k-1)$. Define the state vector $x = [x_1 \quad x_2 \quad x_3]$ and the membership functions are the same as those used in [31]. It can be found that the rule number is 7, LMI kinds of approaches may have difficulties in solving it. Now, the optimum control design is used. The considered cost function is of the form $J =$

$\sum_{k=0}^{\infty}[x^T(k)Qx(k)+u^T(k)Ru(k)]$. Two situations are tested here

$$\text{(I) } J_1: Q=\begin{bmatrix}10&0&0\\0&0&0\\0&0&0\end{bmatrix} \text{ and } R=1$$

$$\text{and (II) } J_2: Q=\begin{bmatrix}10&-10&0\\-10&10&0\\0&0&0\end{bmatrix} \text{ and } R=1.$$

Design Case (I): $A_0=\begin{bmatrix}0&1&0\\0&0&1\\-0.0675&0.166&0.4005\end{bmatrix}$

and

$$B_0=\begin{bmatrix}0\\0\\0.6792\end{bmatrix}.$$

It is easy to verify that (A_0,B_0) is stabilizable. By minimizing J_1, the required eigenvalues are $[-0.1123+0.2661j \quad -0.1123-0.2661j \quad 0.2392]$ and then the state-feedback gain is $G=[0.1288 \quad -0.2881 \quad -0.5682]$. The compensation parts are

$$\begin{aligned}
\tilde{a}_1&=[-0.3465 \quad 0.3244 \quad 0.9993], &\tilde{b}_1&=0.7273\\
\tilde{a}_2&=[0.237 \quad -0.0486 \quad -0.4162], &\tilde{b}_2&=0.6169\\
\tilde{a}_3&=[0.1012 \quad 0.0918 \quad -0.7941], &\tilde{b}_3&=0.9114\\
\tilde{a}_4&=[0.1662 \quad -0.3634 \quad -0.8565], &\tilde{b}_4&=1.4385\\
\tilde{a}_5&=[0.0525 \quad -0.1891 \quad -0.6583], &\tilde{b}_5&=0.8643\\
\tilde{a}_6&=[-0.24 \quad -0.1028 \quad -0.4307], &\tilde{b}_6&=0.5595\\
\tilde{a}_7&=[0.2551 \quad -0.1198 \quad -0.1482], &\tilde{b}_7&=0.5624.
\end{aligned}$$

Design Case (II): By minimizing the cost function J_2, the desired eigenvalues become $[-0.0059+0.1458j \quad -0.0059-0.1458j \quad 0.766]$. Thus, the state feedback gain is $G=[0.123 \quad -0.263 \quad 0.521]$ and the compensation parts are $\tilde{a}_1=[-0.35 \quad 0.32 \quad 0.70]$ $\tilde{a}_2=[0.24 \quad -0.06 \quad -0.83]$, $\tilde{a}_3=[0.11 \quad 0.09 \quad -0.90]$ $\tilde{a}_4=[0.16 \quad -0.35 \quad -0.38]$, $\tilde{a}_5=[0.05 \quad -0.19 \quad -0.81]$ $\tilde{a}_6=[-0.24 \quad -0.11 \quad -0.91]$ $\tilde{a}_7=[0.26 \quad -0.13 \quad -0.62]$, and $\tilde{b}_1,\ldots,$ and $\tilde{b}_7$ are the same as those in case (I).

The simulation results are shown in Fig. 3 for the initiate state (1, −1, 1). It can be found that the overall system can indeed have good control performance as expected.

Example3: Consider the problem of balancing an inverted pendulum on a cart. The dynamic equations are [40]

$$\dot{x}_1=x_2$$
$$\dot{x}_2=\frac{g\sin(x_1)-\frac{amlx_2^2\sin(2x_1)}{2}-a\cos(x_1)u}{\frac{4l}{3}-aml\cos^2(x_1)}$$

where x_1 and x_2 are the angle of the pendulum from the vertical and the angle velocity, m is the mass of the pendulum, M is the mass of the cart, $a=1/(m+M)$, $g=9.8\ \mathrm{m/s^2}$ is the gravity constant, $2l$ is the length of the pendulum, and u is the force applied to the cart. Similar to [17], $m=2.0\,\mathrm{kg}$ and $M=8.0\,\mathrm{kg}$. The fuzzy model can be approximated as [17]

$$R^1: \text{IF } x_1 \text{ is about 0 THEN } \dot{x}=A_1x+B_1u$$
$$R^2: \text{IF } x_1 \text{ is about } \pm\frac{\pi}{2}\left(|x_1|<\frac{\pi}{2}\right)$$
$$\text{THEN } \dot{x}=A_2x+B_2u$$

where

$$A_1=\begin{bmatrix}0&1\\g/(4l/3-aml)&0\end{bmatrix}$$

$$B_1=\begin{bmatrix}0\\-a/(4l/3-aml)\end{bmatrix}$$

$$A_2=\begin{bmatrix}0&1\\2g/(\pi(4l/3-aml\beta^2))&0\end{bmatrix}$$

$$B_2=\begin{bmatrix}0\\-a\beta/(4l/3-aml\beta^2)\end{bmatrix}$$

and $\beta=\cos(88^\circ)$. The design specification is considered as no overshoot with the rising time 2 s.

We select the nominal fuzzy model as

$$A_0=\begin{bmatrix}0&1\\13.3271&0\end{bmatrix}$$

and

$$B_0=\begin{bmatrix}0\\-0.0918\end{bmatrix}$$

It is easy to verify that (A_0,B_0). is stabilizable. For the given specifications, the required two pole locations are $(-2,-2)$. Then, we have $G=[188.8267 \quad 43.5911]$. From (8), the compensation parts are

$$\begin{aligned}
\tilde{a}_1&=[131.0811 \quad 40.2407], &\tilde{b}_1&=1.9231\\
\tilde{a}_2&=[-134.8203 \quad -41.1039], &\tilde{b}_2&=0.0571.
\end{aligned}$$

The controller is used for the initial conditions $(x_1,x_2)=(80^\circ,0^\circ/\mathrm{s})$. For the same desired pole locations, the PDC approach in [17] and the approach in [35] are also considered. The simulation results are shown in Fig. 4 and corresponding

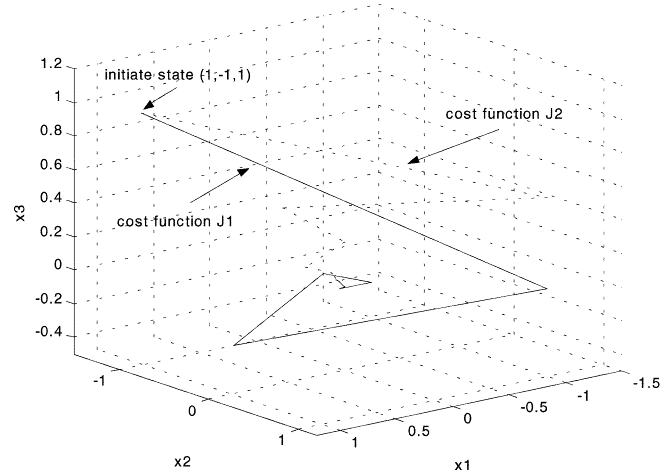

Fig. 3. State trajectories of the nonlinear discrete system in Example 2.

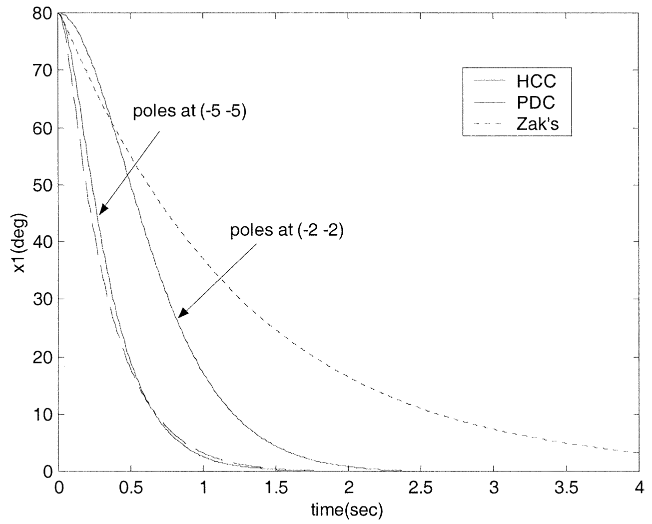

Fig. 4. Angle responses of using various controllers for the system in Example 3.

TABLE I
RISE-TIMES OF ZAK'S, PDC AND HCC FOR EXAMPLE 3

	Zak's Poles at (-2 –2)	PDC Poles at (-2 –2)	HCC Poles at (-2 –2)	HCC Poles at (-5 –5)
Rise-time	3 sec	0.75 sec	1.31 sec	0.74 sec

rise-time are listed in Table I. It can be found that our approach is the nearest one. Moreover, when the rise-time is 0.75 sec, the required two poles are about $(-5, -5)$. By using our HCC approach, the simulation result and the rise-time are also shown in Fig. 4 and in Table I, respectively. It is clearly that HCC could achieve such a specification.

Since our approach is to directly compensate the uncertainties, robustness again parameter changes is an important issue. Nevertheless, our approach is derived in a Lyapunov control fashion. The obtained controller is always stable under a certain range of uncertainty. Thus, if a parameter slightly changes, we believe the proposed controller is robust. Fig. 5 shows the simulation results of changing m (the mass of the pendulum), M (the mass of the cart) and l (the length of the pendulum), respectively, within $\pm 10\%$, and without redesigning the controllers (two poles are located at $(-2, -2)$). It is evident that the responses of using our controller are only slightly changed even though the direct compensation is implemented. For the other two approaches, the changes are much less in our simulation. It is because those two approaches do not directly compensate those uncertainties and as a consequence, the effects of parameter changes are small.

V. CONCLUSIONS

In this paper, we have proposed a method of designing controllers for affine TSK fuzzy models. In this approach, the controller is separated into two parts. The first one is to move the eigenvalues of the central rule to the desired locations. The second one is to individually compensate the variations residing in all rules. The design procedure is simple and effective. The stability analysis becomes the Lyapunov theorem for linear systems. Such an approach not only can result in the use of various control design techniques but also can guarantee desired performance of the closed- loop system. Various examples are conducted in the paper. Some of them even cannot be solved by other existing approaches. All results illustrated good control performances as desired.

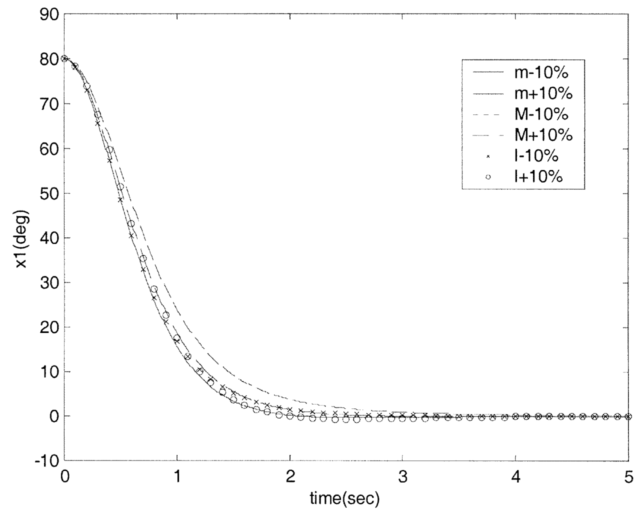

Fig. 5. Angle responses of using the same HCC for the system with various parameter variations in Example 3.

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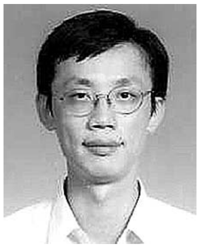

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