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Exponential sampled-data fuzzy stabilization of nonlinear systems and its application to basic buck converters

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Abstract
This study focuses on the exponential stability and stabilization of nonlinear systems via fuzzy sampled-data control technique. The stability and stabilization conditions are obtained through constructing suitable Lyapunov functional which contains the sampling information and the solvable linear matrix inequalities. Then, the dynamics of the nonlinear buck converter system and Lorenz system with the sampled-data controller is analyzed and designed. Finally, the proposed method is validated with a basic buck converter system model designed to reflect the characteristics of the power metal-oxide-semiconductor field-effect transistors in the numerical section. In addition, the superiority of the sufficient conditions obtained is shown by comparing with the existing methods of the Lorenz system.

1 | INTRODUCTION

Since the middle of the 1980s, Takagi–Sugeno (T-S) fuzzy modelling has been demonstrated and its execution is deeply penetrate in nonlinear systems. On the other hand, it is well known that non-linear systems can be represented as the sum of the weights of several simple linear subsystems using the T-S fuzzy plant. Some of these models exhibit semi-linear properties that provide a stable structure for non-linear systems and facilitate stability analysis and controller synthesis in [1–6]. The T-S fuzzy technique gives a good representation of non-linear frameworks with the guide of fuzzy sets, fuzzy rules and a set of local linear subsystems. In this regard, the enormous merit of the T-S fuzzy model has been providing a good platform for analyzing the non-linear control via linear subsystems with IF-THEN rules. In model-based T-S fuzzy control strategies, a universal function approximates to describe the T-S fuzzy model which show the effectiveness of smoothing the non-linear functions in any convex compact set [7, 8]. Over the past few decades, T-S fuzzy model framework and proper controller design have been reported in the literature to help system analysis and synthesis of T-S fuzzy systems in [9–12].

DC–DC converters are used in a variety of applications, such as distributed DC systems, electric vehicles, electric traction, fuel cells, specialized motor drives and machine tools. Traditional analysis of DC–DC converters relies on a small-signal model and a pulse-width-modulation approach that involves a significant approximation at low switching frequencies, preventing high performance from being achieved. Recently, the development of hybrid system theory and the increased computational power provided by available hardware have made it possible to analyze and synthesize power converters as hybrid systems [13, 14]. The DC–DC converter can change low input voltage to high output voltage. As we all know, low-power electronics are increasingly used in various systems related to power generation and industrial equipment. In power generation systems, wind power is rapidly growing worldwide. As a result, wind turbines have been widely developed as alternative energy sources to provide cost-effective options in the energy market. Recently, the widespread use of DC–DC converters in electronic equipment has caused great interest in the modelling, analysis and control of such equipment. Several DC–DC converters have been proposed and explored for various forms in [13]. In grid-connected applications, the pulse width modulation converter acts as a control current source. In low-cost converters, as standard converters, low-cost converters also require active and reactive power between the DC storage capacitor and the grid. When the output load and input voltage fluctuate, it is necessary to control the output voltage of the DC–DC converter to a desired level. However, the control of a buck converter is still
a challenging task because such a system exhibits a non-linear behaviour with inherent uncertainties and disturbances. Thus, the linear control schemes cannot ensure satisfactory performances over a wide operating range [13]. To address this problem, non-linear and advanced control design methods have been proposed, such as sampled-data control [15–24].

In the literature, different types of controls are proposed such as fault-tolerant control [25, 26], fractional-order fault-tolerant control [27, 28] for stabilization of non-linear systems. Recently, sampled-data control strategy has been the hottest part of research. It is a method where the control signal is kept steady during the sampling time frame and permitted to change just at the instant of sampling. Besides, choosing the correct sample space in the sampled-data control frameworks is critical to planning fitting controllers. Recently, many researchers analyzed the instance of the standard model. Accordingly, due to its usefulness in many practical methods, the time-varying sampling is widely used. The sampled-data control methodology has been perceived as a powerful tool to manage T-S fuzzy system. Many interesting outcomes identified with sampled-data control signal in reference of T-S fuzzy approach for different kinds of systems have been accounted [15–18]. However, for infinite-dimensional systems, there are few results on sampled-data feedback control. Recently, the authors have discussed the stability of non-linear sampled-data control systems [19–23, 29, 30]. Consequently, real practical systems have been investigated with T-S fuzzy systems and sampled-data control in [9, 10, 20, 31, 32]. In the sampled-data controller, the discrete signal is applied into continuous systems which is more suitable for the chaotic systems. In this regard, the sampled-data controller has been widely utilized to control the continuous system for achieving the stability of both linear/non-linear dynamical systems. Recently, the chaotic systems have been considered extensively to incorporate sensitivity toward the underlying conditions in [33]. Many researchers have applied the fuzzy method to various control systems in order to stabilize the control power system in a limited time in [34–37]. In this paper, voltage-driven sampled-data control is an indirect method of controlling the active and reactive power of a static converter, which is very useful for the grid coupling of low-cost converters. It is the motivation of this current study.

On the other hand, well-recognized chaotic system equivalently is expressed into T-S fuzzy models via equivalent IF-THEN rules. Besides that, the conventional T-S fuzzy control techniques can be applied to the chaotic systems. In [38, 39], the free-weight matrix method and sampled-data control in [40] was connected to improve the productivity of fuzzy controlled in chaotic systems. In [41], the Lyapunov technique is used in the examination of T-S fuzzy chaotic systems via sampled-data control. However, T-S fuzzy schemes based on most of the existing literature have been studied using common control mechanisms, and the immediate problem of sampling instants does not suffer from these results. Therefore, the chaotic frameworks is very important from a theoretical point of view and has a very practical interest in the applications.

The main objective of the study is to address the sampled-data stabilization of non-linear systems. To solve this non-linear model, the T-S fuzzy membership rules are designed to express the non-linearities into the linear form. Following that, the open-loop system is transformed into a closed-loop system under the sampled-data controller. In addition, the stability and stabilization conditions are derived for the closed-loop system through constructing the suitable Lyapunov functional with the information of the sampling period. The sampled-data controller is designed to depend on T-S fuzzy models of a basic buck converter system and Lorenz system under considered. The main feature of this article is summarized as follows:

- This article deals with the issue of sampled-data control for basic buck converter system and Lorenz system via T-S fuzzy stability theory.
- The decentralized sample-data control scheme is designed for the proposed model. Besides, the length of the sample period is considered with lower and upper limits in the interval.
- By building an appropriate Lyapunov function using relaxation-based integral inequalities, some sufficient conditions are proposed to ensure the asymptotic stability of the established in terms of LMIs.
- In this work, advanced stability and stabilization conditions are obtained for linear and non-linear sampled-data-based control systems, where non-linear sampled-data-based control systems can be modelled as linear sub-systems with the help of T-S fuzzy approach.
- Finally, numerical simulations have been proposed that show the performance and applicability of the proposed theory.

Notations: $\mathbb{R}^n$ denotes $n$ dimensional Euclidean space. $\mathbb{R}^{m \times n}$ denotes the space of real $n \times m$ matrices. $I_n$ denotes the identity matrix and $0_{m \times n}$ represents the $n \times m$ zero matrix, respectively. $\lambda_{\text{max}}(P)$ ($\lambda_{\text{min}}(P)$) is the maximum (minimum) eigenvalue of a real symmetric matrix $P$. $\|\cdot\|$ denotes the spectral norm for matrices or the Euclidean norm for vectors. Asterisk $\cdot^*$ in a symmetric matrix denotes the entry implied by symmetry.

## 2 | PRELIMINARIES

Consider the following non-linear model

$$\dot{x}(t) = f(x(t), u(t)).$$

Here, $x(t) \in \mathbb{R}^n$ is the state vector of the system, $u(t) \in \mathbb{R}^m$ is the control input of the system. The non-linear function is characterized as $f(x(t), u(t)) : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n$. In the form of T-S model, the system (1) can be represented as

Plant rule $i$: IF $z_i(t)$ is $M_{i1}$ and $\cdots$ and $z_p(t)$ is $M_{ip}$ THEN

$$\dot{z}(t) = A_i z(t) + B_i u(t), \quad i = 1, 2, \ldots, r$$

where $A_i \in \mathbb{R}^{n \times n}$ and $B_i \in \mathbb{R}^{n \times m}$ are real constant matrices with compatible dimensions. $M_{ij}$ ($i = 1, \ldots, r; j = 1, \ldots, p$) are the fuzzy sets, and the premise variables are $z(t) = [z_1(t), \ldots, z_p(t)]$. $r$ denotes the number of IF-THEN rules. The overall output is
expressed as

$$\dot{x}(t) = \frac{\sum_{i=1}^{r} w_i(\zeta(t)) A_i x(t) + \sum_{i=1}^{r} w_i(\zeta(t)) B_i u(t)}{\sum_{i=1}^{r} w_i(\zeta(t))}.$$ 

With centre-average defuzzier, product inference and singleton fuzzifier, (2) is described as

$$\dot{x}(t) = \sum_{i=1}^{r} b_i(\zeta(t))[A_i x(t) + B_i u(t)],$$

(3)

where $b_i(\zeta(t))$ is the normalized membership function and satisfies the following condition

$$b_i(\zeta(t)) = \frac{w_i(\zeta(t))}{\sum_{i=1}^{r} w_i(\zeta(t))}, w_i(\zeta(t)) = \prod_{j=1}^{p} M_{ij}(\zeta(t)),$$

and $M_{ij}(\zeta(t))$ represents the grade of membership of $\zeta(t)$ in $M_i$. It is obvious that $w_i(\zeta(t)) \geq 0$, $\sum_{i=1}^{r} w_i(\zeta(t)) > 0$ with $b_i(\zeta(t)) \geq 0$, $i = 1, 2, \ldots, r$, and $\sum_{i=1}^{r} b_i(\zeta(t)) = 1$.

The following sample-data controller is designed for system (3) corresponding to the fuzzy rule.

**Plant rule:** IF $\zeta_i(t_k)$ is $M_{i1}$ and $\ldots$ and $\zeta_r(t_k)$ is $M_{ir}$ THEN

$$u(t) = K_i x(t_k), \text{ for } t \in [t_k, t_{k+1}[, i = 1, 2, \ldots, r,$$

(4)

where $K_i$, $i = 1, 2, \ldots, r$, are the controller gains. The control signal holds a constant value $u(t_k)$ for $t \in [t_k, t_{k+1}[$ in which $u(t)$ denotes a control signal. At that point, the defuzzified output based fuzzy sampled-data controller (3) is designed as

$$u(t) = u(t_k) = \sum_{i=1}^{r} b_i(\zeta(t_k)) K_i x(t_k), t \in [t_k, t_{k+1}).$$

(5)

In this expression, fuzzy control rules have sample-data controllers in consequent or concluding parts. The schematic of the fuzzy-based control system is given in Figure 1.

The length of sampling intervals $t_{k+1} - t_k = b_k$ is assumed to satisfy $0 < b_Y \leq b_k \leq b_Y$, for all $k \geq 0$, where $b_Y$ and $b_Y'$ are known constants to denote the lower and upper bounds of the sampling interval, respectively.

Substituting (5) into (3), we get

$$\dot{x}(t) = \sum_{i=1}^{r} \sum_{j=1}^{r} b_j(\zeta(t)) b_i(\zeta(t)) x(t) \left[A_i x(t) + (B_i K_j) x(t)\right].$$

(6)

Denoting $\sum_{i=1}^{r} b_i(\zeta(t))$ by $\sum_{i=1}^{r} b_i$, for simplicity, we have

$$\dot{x}(t) = \sum_{i=1}^{r} \sum_{j=1}^{r} b_j b_i x(t) \left[A_i x(t) + (B_i K_j) x(t)\right].$$

(7)

**Remark 2.1.** Since $\sum_{i=1}^{r} b_i = 1$, we reach

$$\sum_{i=1}^{r} b_i A_i = [b_1 b_1 + b_1 b_2 + \ldots + b_r b_r] A_1 + \ldots + [b_1 b_1 + b_1 b_2 + \ldots + b_r b_r] A_r = \sum_{i=1}^{r} \sum_{j=1}^{r} b_j b_i A_i.$$  

(8)

Similarly, $\sum_{i=1}^{r} b_i B_i \sum_{j=1}^{r} b_j K_i$ can be written as:

$$\sum_{i=1}^{r} b_i B_i \sum_{j=1}^{r} b_j K_i = (b_1 B_1 + b_1 B_2 + \ldots + b_r B_r) \times (b_1 K_1 + b_1 K_2 + \ldots + b_r K_r) = \sum_{i=1}^{r} \sum_{j=1}^{r} b_j b_i B_i K_j.$$  

(9)

**Definition 2.2** [42]. The system (7) is said to be exponentially stable with convergence rate $\alpha > 0$, if there exists a positive constant $\alpha$ such that

$$\|x(t)\| \leq ae^{-\alpha(t-t_0)} \|x(t_0)\|, \forall t \geq t_0.$$  

(10)

### 3 Stability Analysis and Controller Design

This section first proposes the following theorem to verify the exponential stability of the T-S fuzzy system for given controllers.

**Theorem 3.1.** For given gains $K_i$ and positive scalars $b_Y$, $b_Y'$ and $\alpha$, the system (7) is exponentially stable with convergence rate $\frac{\alpha}{2}$ if there exist symmetric positive-definite matrices $P_1, P_2, Z \in \mathbb{R}^{n \times n}$ and any matrices $G_i, M_i, r, M_i, M_i$, with appropriate dimensions such that the following LMIs hold with $b \in \{b_Y, b_Y'\}$, for all $i, j = 1, 2, \ldots, r$,

$$\Sigma^A + b \Sigma^B < 0,$$

(11)
where

\[
\Sigma^A = e_T^2 P_{e_1} + e_T^2 P_{e_2} - [e_1 - e_3]^T P_3 [e_1 - e_3]
\]

\[\quad + \alpha e_T^2 P_{e_1} + e^{-\alpha h_V} \left( e_T^2 \left[ \mathbb{M}_1 + \mathbb{M}_2^T \right] e_T \right)
\]

\[\quad - e_T^2 \mathbb{M}_1 e_3 - (e_T^2 \mathbb{M}_2 e_3)^T + e_T^2 \mathbb{M}_2 e_1
\]

\[\quad + (e_T^2 \mathbb{M}_2 e_3)^T - e_T^2 \mathbb{M}_3 e_3 - \left( e_T^2 \mathbb{M}_3 e_3 \right)^T + e_T^2 \mathbb{M}_3 e_1
\]

\[\quad + (e_T^2 \mathbb{M}_3 e_3)^T - e_T^2 \left[ \mathbb{M}_3 + \mathbb{M}_3^T \right] e_T
\]

\[\quad + [e_T^2 + e_T^2] \mathbb{G} \left[ - e_2 + A_1 e_1 + (B_K) e_3 \right]
\]

\[\quad + \left( \left[ e_T^2 + e_T^2 \right] \mathbb{G} \left[ - e_2 + A_1 e_1 + (B_K) e_3 \right] \right)^T
\]

\[\Sigma^B = [e_1 - e_3]^T P_{e_2} e_T + e_T^2 P_{e_1} [e_1 - e_3]
\]

\[\quad + \alpha [e_1 - e_3]^T P_3 [e_1 - e_3] + e_T^2 Z e_2,
\]

\[\mathbb{M} = \left[ \begin{array}{cc} \mathbb{M}_1 & \mathbb{M}_2^T \\ \mathbb{M}_2 & \mathbb{M}_3^T \end{array} \right],
\]

\[e_3 = [0_{\mathbb{R}^3(\beta_1)} I_3 0_{\mathbb{R}^3(\beta_3)}], \quad i = 1, 2, 3.
\]

**Proof.** Consider the following Lyapunov–Krasovskii functional (LKF):

\[
V(t) = \sum_{i=1}^{3} V_i(t), \quad t \in [t_k, t_{k+1}),
\]

where

\[
V_1(t) = x^T(t) P_1 x(t),
\]

\[
V_2(t) = (t_{k+1} - t) [x(t) - x(t_k)]^T P_2 [x(t) - x(t_k)],
\]

\[
V_3(t) = (t_{k+1} - t) \int_{t_k}^{t} e^{(t-s)Z} (t) \dot{x}(s) ds.
\]

Since \( \lim_{t \to t_k^-} V_2(t) = V_2(t_k) = 0 \) and \( \lim_{t \to t_k^+} V_3(t) = V_3(t_k) = 0 \), we note that \( \{P_2, Z\}\)-dependent terms \( V_2(t) \) and \( V_3(t) \) evaporate at the sampling instant \( t_k \). In this manner, \( \lim_{t \to t_k^-} V_1(t) = V_1(t_k) = x^T(t_k) P_1 x(t_k) \), which implies that \( V_1(t) \) is continuous in time and turns into a quadratic function at sampling instants.

Now, taking a derivative along with the state trajectories of the system (7), we can get

\[
\dot{V}_1(t) = -\alpha V_1(t) + \dot{x}^T(t) P_1 x(t) + x^T(t) P_1 \dot{x}(t)
\]

\[\quad + \alpha x^T(t) P_1 x(t),
\]

\[\cdots
\]

\[
V_2(t) = -\alpha V_2(t) - [x(t) - x(t_k)]^T P_2 [x(t) - x(t_k)]
\]

\[\quad + (t_{k+1} - t) [x(t) - x(t_k)]^T P_2 \dot{x}(t)
\]

\[\quad + (t_{k+1} - t) \dot{x}^T(t) P_2 [x(t) - x(t_k)]
\]

\[\quad + \alpha (t_{k+1} - t) [x(t) - x(t_k)]^T
\]

\[\quad \times P_3 [x(t) - x(t_k)],
\]

\[
(15)
\]

\[
V_3(t) = (t_{k+1} - t) \int_{t_k}^{t} e^{(t-s)Z} (t) \dot{x}(s) ds - \alpha V_3(t).
\]

Based on the formula of integration by parts, the following zero equality holds for any matrices \( \mathbb{M}_1, \mathbb{M}_2, \) and \( \mathbb{M}_3 \) with appropriate dimensions:

\[
0 = e^{-\alpha h_V} \times 2 [x^T(t) \mathbb{M}_1 + \dot{x}^T(t) \mathbb{M}_2 + x^T(t_k) \mathbb{M}_3]
\]

\[\times \left( x(t) - x(t_k) - \int_{t_k}^{t} \dot{x}(s) ds \right)
\]

\[\quad = e^{-\alpha h_V} \times 2 \zeta^T(t) \mathbb{M} \left( x(t) - x(t_k) - \int_{t_k}^{t} \dot{x}(s) ds \right),
\]

\[
(17)
\]

where \( \zeta^T(t) = [x^T(t) \dot{x}^T(t) x^T(t_k)] \). Then one can easily get

\[
0 \leq (t - t_k) \zeta^T(t) \mathbb{M} Z^{-1} \mathbb{M}^T \zeta(t)
\]

\[\quad + (\int_{t_k}^{t} \dot{x}(s) ds) \left( Z \int_{t_k}^{t} \dot{x}(s) ds \right)
\]

\[\quad + 2 \zeta^T(t) \mathbb{M} \left( x(t) - x(t_k) \right)
\]

\[\quad + 2 \zeta^T(t) \mathbb{M} \left( x(t) - x(t_k) \right)
\]

\[
(18)
\]

Then, we have

\[
\dot{V}_3(t) \leq (t_{k+1} - t) \dot{x}^T(t) Z \dot{x}(t)
\]

\[\quad + e^{-\alpha h_V} \left[ (t - t_k) \zeta^T(t) \mathbb{M} Z^{-1} \mathbb{M}^T \zeta(t)
\]

\[\quad + 2 \zeta^T(t) \mathbb{M} \left( x(t) - x(t_k) \right) - \alpha V_3(t),
\]

\[
(19)
\]
Based on the system (7), the following equality holds:

\[
0 = 2[x^T(t) + \dot{x}(t)]G[\dot{x}(t) + \ddot{x}(t)]
\]
\[
= 2[x^T(t) + \dot{x}(t)]G \left[ -\dot{x}(t) + \sum_{i=1}^{r} \sum_{j=1}^{r} b_j(\xi(t))b_j(\xi(t_k)) \right]
\]
\[
\quad \times \left\{ A_i x(t) + (B_i K_j) x(t_k) \right\}
\]
\[
= \sum_{i=1}^{r} \sum_{j=1}^{r} b_j(\xi(t))b_j(\xi(t_k)) \left\{ -2x^T(t)G\dot{x}(t) + 2x^T(t) \right. 
\]
\[
\left. \times G A_i x(t) + 2x^T(t)G B_i K_j x(t_k) - 2\dot{x}(t)G\dot{x}(t) \right. 
\]
\[
+ 2\dot{x}(t)G A_i x(t) + 2\dot{x}(t)G B_i K_j x(t_k) \right\}. \tag{20}
\]

Combining (14)–(20), we obtain

\[
\dot{V}(t) \leq -\alpha V(t) + \sum_{j=1}^{r} \sum_{j=1}^{r} b_j(\xi(t))b_j(\xi(t_k)) \times \xi^T(t) \left[ \Sigma A + (t_k+1 - t) \Sigma B \right] 
\]
\[
+(t - t_k)e^{-\alpha h_k} \mu^T \mathbb{Z}^{-1} \mu \right] \xi(t). \tag{21}
\]

In addition, since \( b_k \in [b_l, b_u] \), the following inequality holds:

\[
\dot{V}(t) \leq -\alpha V(t) + \sum_{j=1}^{r} \sum_{j=1}^{r} b_j(\xi(t))b_j(\xi(t_k)) \times \xi^T(t) \left[ \frac{t_{k+1} - t}{b_k} \Sigma A + \frac{t - t_k}{b_k} \Sigma B \right] 
\]
\[
+ \frac{(t - t_k)e^{-\alpha h_k}}{b_k} \mu^T \mathbb{Z}^{-1} \mu \right] \xi(t)
\]
\[
= -\alpha V(t) + \sum_{j=1}^{r} \sum_{j=1}^{r} b_j(\xi(t))b_j(\xi(t_k)) \times \xi^T(t) \left[ \frac{t_{k+1} - t}{b_k} \Sigma A + \frac{t - t_k}{b_k} \Sigma A + \frac{t_{k+1} - t}{b_k} \Sigma B \right] 
\]
\[
+ \frac{(t - t_k)e^{-\alpha h_k}}{b_k} \mu^T \mathbb{Z}^{-1} \mu \right] \xi(t)
\]
\[
= -\alpha V(t) + \sum_{j=1}^{r} \sum_{j=1}^{r} b_j(\xi(t))b_j(\xi(t_k)) \times \xi^T(t) \left[ \frac{t_{k+1} - t}{b_k} \Sigma A + \frac{t - t_k}{b_k} \Sigma B \right] 
\]
\[
+ \frac{(t - t_k)e^{-\alpha h_k}}{b_k} \mu^T \mathbb{Z}^{-1} \mu \right] \xi(t). \tag{22}
\]

It is noted that

\[
\Sigma A + b_k \Sigma B = \frac{b_{lV} - b_k}{b_{U} - b_{lV}} (\Sigma A + b_V \Sigma B) + \frac{b_k - b_{lV}}{b_{U} - b_{lV}} (\Sigma A + b_U \Sigma B),
\]
\[
\Sigma A + b_k (\mathbb{M}^T \mathbb{Z}^{-1} \mathbb{M}) = \frac{b_{lV} - b_k}{b_{U} - b_{lV}} (\Sigma A + b_V (\mathbb{M}^T \mathbb{Z}^{-1} \mathbb{M})) + \frac{b_k - b_{lV}}{b_{U} - b_{lV}} (\Sigma A + b_U (\mathbb{M}^T \mathbb{Z}^{-1} \mathbb{M})).
\]

At that point, by Schur complement, \( \dot{V}(t) < 0 \) is equal to LMIs (11) and (12). From (22), we can presume that

\[
\dot{V}(t) + \alpha V(t) \leq 0,
\]
\[
\frac{d}{dt} [e^{\alpha t} V(t)] \leq 0, \quad t \in [t_k, t_{k+1}). \tag{23}
\]

When \( t_k \leq t < t_{k+1} \), integrating both sides of (23) from \( t_k \) to \( t \) gives

\[
\int_{t_k}^{t} \frac{d}{dt} [e^{\alpha t} V(t)] \leq 0
\]
\[
e^{\alpha t} V(t) \leq e^{\alpha t_k} V(t_k), \tag{24}
\]

which implies

\[
V(t) \leq e^{-\alpha (t-t_k)} V(t_k), \quad t_k \leq t < t_{k+1}. \tag{25}
\]

It follows from the Lyapunov functional (13) that

\[
\lim_{t \to t_{k+1}^-} V(t) = V(t_k). \tag{26}
\]

By substituting (25) into (26), we have

\[
V(t) \leq e^{-\alpha (t-t_k)} V(t_k)
\]
\[
= e^{-\alpha (t-t_k)} V(t_k)
\]
\[
\leq e^{-\alpha (t-t_{k-1})} [e^{-\alpha (t_{k-1}-t_{k-2})} V(t_{k-1})] \]
\[
= e^{-\alpha (t-t_{k-1})} V(t_{k-1})
\]
\[
\vdots
\]
\[
\leq e^{-\alpha (t-t_0)} V(t_0) = e^{-\alpha t} V(0), \tag{27}
\]

Moreover,

\[
V(0) = \xi^T(0) P_l x(0)
\]
On the other hand, from $V_1(t)$, we know that

$$V'(t) \geq \lambda_{\min}(P_1) \|x(t)\|^2$$

and

$$\|x(t)\|^2 \leq \frac{V(t)}{\lambda_{\min}(P_1)}.$$

(29)

From equation (27), we have

$$\|x(t)\| \leq \frac{\sqrt{e^{\alpha t} \lambda_{\max}(P_1) \|x(0)\|^2}}{\lambda_{\min}(P_1)}.$$  

(30)

From Definition 2.2, the closed-loop system (7) is exponentially stable with the exponential convergence rate $\frac{\alpha}{2}$. This completes the proof.

□

Remark 3.2. It is noted that the condition (12) tends to be satisfied with small $h_T$ and $b_T$, while larger $b_T$ is desirable in controller implementation because we do not want frequent sampling in real systems. Thus, there is a kind of trial and error for choosing $b_T$ and $b_T$ to meet the condition in Theorem 3.1. We suggest that $b_T$ be chosen first according to implementation specification, and then increase $b_T$ gradually so that both (11) and (12) are satisfied. In standard digital control theory, a fixed sampling interval is used, that is, $b_T = b_T$. For that special case, we can also use the condition of Theorem 3.1 to increase the sampling period gradually.

Next, controller design criteria are introduced based on the stability conditions described above. If the controller is unknown, Theorem 3.1 is no longer an LMI-based condition due to the product of $GBK$. To solve this problem, we present the following theorem for obtaining controller parameters.

Theorem 3.3. For given positive scalars $h_T$, $b_T$ and $\alpha$, the system (7) is exponentially stable with convergence rate $\frac{\alpha}{2}$ by a sampled-data controller (4), if there exist positive-definite matrices $\bar{P}_1$, $\bar{P}_2$, $\bar{Z} \in \mathbb{R}^{n \times n}$, non-singular matrix $\bar{G}$, and any matrices $\bar{M}_1$, $\bar{M}_2$, $\bar{M}_3$, and $H$ with suitable dimensions such that the following LMIs hold with $b = \{b_T, b_T\}$, for all $i, j = 1, 2, \ldots, r$,

$$\begin{bmatrix} \Sigma^A & A \bar{G} \\ \bar{G}^T & -\frac{\alpha}{2} \bar{M} \end{bmatrix} < 0,$$

(31)

and $\Sigma^A$ is defined by

$$\Sigma^A = \begin{bmatrix} \xi_1^T \bar{P}_1 \xi_1 + \xi_2^T \bar{P}_2 e_3 - [\xi_1 - e_3]^T \bar{P}_2 [\xi_1 - e_3] \\
\xi_1^T e_1 + e^{\alpha b_T} \left( e_1^T [\bar{M}_1 + \bar{M}_3^T] e_1 + \xi_2^T [\bar{M}_2 + \bar{M}_3^T] e_1 + \xi_3^T [\bar{M}_3 + \bar{M}_3^T] e_1 \right) \\
+ [e_1^T + e_2^T] e_1 + [\xi_2^T + \xi_3^T] e_1 \end{bmatrix}.$$  

(32)

where

$$\begin{bmatrix} \xi_1^T \bar{P}_1 \xi_1 + \xi_2^T \bar{P}_2 e_3 - [\xi_1 - e_3]^T \bar{P}_2 [\xi_1 - e_3] \\
\xi_1^T e_1 + e^{\alpha b_T} \left( e_1^T [\bar{M}_1 + \bar{M}_3^T] e_1 + \xi_2^T [\bar{M}_2 + \bar{M}_3^T] e_1 + \xi_3^T [\bar{M}_3 + \bar{M}_3^T] e_1 \right) \\
+ [e_1^T + e_2^T] e_1 + [\xi_2^T + \xi_3^T] e_1 \end{bmatrix}.$$  

(33)

□

4 SIMULATION RESULTS

This section examines the important role of flexible regions in fuzzy position sharing for non-smooth systems such as base buck converters and Lorentz systems.

4.1 Case study for the basic buck converter system

Example 4.1. Power metal oxide semiconductor field-effect transistors (MOSFETs) are a type of MOSFETs designed to handle critical power conditions. Compared to other power semiconductor devices such as insulated gate bipolar transistors (IGBTs) and thyristors, their main advantages are fast switching speed and excellent performance at low voltages. Easily, the current is driving in the circuit because the insulated gate is shared with the IGBTs. The converter equivalent circuit is shown and the test is performed according to the buck converter induced current, output voltage, and duty cycle as shown in Figure 2. In the circuit, the current $i_L$ is measured by Hall sensor in [13].
where $GUNASEKARAN$ $ET$ $AL.$
is the threshold voltage of the diode, $\text{Equivalent}$ $circuit$ $of$ $basic$ $buck$ $converter$ $in$ $FIGURE$ $2$

The buck power converter is known to exhibit a highly non-linear dynamics. Its averaged model can be found in [13] and is recalled as

$$\dot{x}(t) = f(x(t)) + g(x(t))u(t), \quad (33)$$

where

$$f(x(t)) = \begin{bmatrix} \frac{-1}{L} \left( R_L + \frac{R R_C}{R + R_C} \right) i_L(t) - \frac{R}{L(R + R_C)} n_0(t) \\ \frac{R}{C(R + R_C)} i_L(t) - \frac{1}{C(R + R_C)} n_0(t) \end{bmatrix} \quad \text{and} \quad g(x(t)) = \begin{bmatrix} \frac{-1}{L} \left( R_M i_L(t) - V_{in} - V_D \right) u(t) \end{bmatrix}.$$ 

Here, $R_M$ is the resistance of the transistor (MOSFET), $V_D$ is the threshold voltage of the diode, $R_C$ is the equivalent series resistance of the filter capacitor and $V_{in}$ is the input voltage. $i_L$, $n_0$ and $a$ represent, respectively, the inductance current, the output voltage and the duty cycle of the buck converter. The location of the non-linear state space of the buck converter is given in the form

$$\dot{x}(t) = Ax(t) + B(i_L)u(t), \quad (34)$$

where $x(t) = [x_1(t) \quad x_2(t)]^T = [i_L(t) \quad n_0(t)]^T$ and

$$A = \begin{bmatrix} \frac{-1}{L} \left( R_L + \frac{R R_C}{R + R_C} \right) & -\frac{R}{L(R + R_C)} \\ \frac{R}{C(R + R_C)} & -\frac{1}{C(R + R_C)} \end{bmatrix},$$

$$B(i_L) = \begin{bmatrix} \frac{-1}{L} \left( R_M i_L(t) - V_{in} - V_D \right) \quad 0 \end{bmatrix}^T.$$

Let us consider the premise variable $\zeta_1 = x_1(t)$ is bounded as: $i_{L2} \leq i_L(t) \leq i_{L1}$. The non-linear model (34) can be expressed by using the following IF-THEN rules.

Plant Rule $i$: IF $\zeta_1$ is $M_{i1}$, THEN

$$\dot{x}(t) = \sum_{i=1}^{2} b_i(\zeta_1)[A_i x(t) + B_i u(t)], \quad (35)$$

FIGURE 2 Equivalent circuit of basic buck converter in [13]

where

$$A_1 = A_2 = \begin{bmatrix} \frac{-1}{L} \left( R_L + \frac{R R_C}{R + R_C} \right) & -\frac{R}{L(R + R_C)} \\ \frac{R}{C(R + R_C)} & -\frac{1}{C(R + R_C)} \end{bmatrix},$$

$$B_1 = \begin{bmatrix} \frac{-1}{L} \left( R_M i_L - V_{in} - V_D \right) \quad 0 \end{bmatrix}^T,$$

$$B_2 = \begin{bmatrix} \frac{-1}{L} \left( R_M i_L - V_{in} - V_D \right) \quad 0 \end{bmatrix}^T,$$

and the membership functions are given by:

$$b_1(\zeta_1) = \frac{x_1(t) - i_{L2}}{i_{L1} - i_{L2}}, \quad b_2(\zeta_1) = 1 - b_1(\zeta_1).$$

The schematic diagram of the closed-loop structure of the base converter shown in the Figure 3.

The system parameters of the base converter are the values listed in Table 1. Each cycle of the base buck converter has two stages. First, when the MOSFETs are enabled, the trigger charges from the source. Second, when the power MOSFETs turn off, the inductor is discharged through the load. The gain may be low, and in some cases, the gate voltage must be greater than the control voltage.

The sampled-data fuzzy controllers are as follows:

Plant Rule $i$: IF $x_i$ is $M_{i1}$, THEN

$$u(t) = K_i x(t), \quad t \in [t_k, t_{k+1}).$$

According to LMs (31) and (32), when $\alpha = 0.2$, $b_0 = 0.1$ and $b_L = 0.3$, the control gains obtained via Robust Control

FIGURE 3 Closed-loop structure of the basic buck converter in [13]
TABLE 1 Parameters of the basic buck converter in [13]

| Parameters of the converter | Value | Unit |
|-----------------------------|-------|------|
| Nominal input voltage, $V_i$ | 30    | V    |
| Reference voltage, $V_{ref}$ | 12    | V    |
| Inductance, $L$              | 98.58 | μH   |
| Parasitic resistance for $L$, $R_L$ | 48.5  | mΩ   |
| Capacitance, $C$             | 202.5 | μF   |
| Parasitic resistance for $C$, $R_C$ | 162   | mΩ   |
| Parasitic resistance for MOSFET, $R_M$ | 0.27  | Ω    |
| Forward voltage of diode, $V_D$ | 0.82  | V    |
| Load resistance, $R$         | 6     | Ω    |

FIGURE 4 Inductance current $i_L$ in Example 4.1

Toolbox of MATLAB are given as follows:

$$K_1 = [1.0616 \quad 0.0888], \quad K_2 = [0.9133 \quad 0.0778].$$

Based on the above gain matrices and an initial condition $x(0) = [2, 12]^T$, the state $i_L(t)$ response and control input of the unified basic buck converter system (1) is shown in Figures 4 and 5. The control response curves are exploited in Figure 6.

4.2 Case study for Lorenz system and comparative result

In this subsection, for comparison purposes, Lorenz system is used to show the benefits and efficiencies of the proposed method.

Example 4.2. Consider the following Lorenz system:

$$
\begin{align*}
\dot{x}_1(t) &= a(x_2(t) - x_1(t)), \\
\dot{x}_2(t) &= c x_1(t) - x_2(t) - x_1(t)x_3(t), \\
\dot{x}_3(t) &= x_1(t)x_2(t) - bx_3(t), \\
\end{align*}
$$

where $x_1(t)$ denotes the convective fluid motion, $x_2(t)$ denotes the horizontal temperature variation, $x_3(t)$ denotes the vertical temperature variation and $a$, $b$, $c$ are positive scalars.

By letting $\dot{x}_1(t) = \dot{x}_2(t) = \dot{x}_3(t) = 0$ in (36), the equilibrium points $(x_1(t), x_2(t), x_3(t))$ can be calculated as $(0, 0, 0)$, $(\sqrt{b(c-1)}, \sqrt{b(c-1)}, c-1)$, and $(-\sqrt{b(c-1)}, -\sqrt{b(c-1)}, c-1)$, for $c > 1$. The solutions of the Lorenz equations are also extremely sensitive to perturbations in the initial conditions. The Lorenz system (36) is chaotic if it displays long-term aperiodicity and sensitive dependence on initial conditions. Specifically, chaotic behaviours are shown in Figure 7. From Figure 7, one can see that while expanding the $a$ esteem, the non-linear system displays various kinds of complex nature, for example, stable, chaotic and periodic behaviours, respectively. In this paper, the parameters are chosen as $a = 10$, $b = 8/3$, $c = 28$, which are frequently utilized for the examination of Lorenz framework. The initial conditions are set as $x(0) = [0.1, 0.2, 0.3]^T$. The stage pictures and state reactions of the dynamics in Lorenz frameworks are portrayed by Figures 8 and 9, respectively. It can be seen from Figure 8 that the dynamic conduct of the Lorenz framework displays a two-lobed example called the butterfly attractor. The chaotic nature of the state response is shown in Figure 9.
FIGURE 7  Butterfly attractors for the non-linear system (36) with respect to $a$ are shown in the sub-figures.

FIGURE 8  Chaotic behaviour of Lorenz systems in Example 4.2.
FIGURE 9 State responses of Lorenz systems in Example 4.2

Note that the solution oscillates back and forth between among positive and negative qualities in a rather erratic manner. To be sure, the chart of \( x \) versus \( t \) takes after an arbitrary vibration, in spite of the fact that the Lorenz conditions are totally deterministic and the arrangement is totally controlled by the initial conditions. All things considered, the arrangement likewise displays a specific normality in that the frequency and amplitude of the motions are basically consistent in time. We accept that the state variable \( x(t) \in [-20, 50] \), and any scope of \( x(t) \), respectively, to develop a fuzzy model.

Defining \( z(t) = x(t) \) for the non-linear term, the equation (36) can be written as

\[
\dot{x}(t) = \begin{bmatrix} -a & a & 0 \\ \varepsilon & -1 & -z(t) \\ 0 & z(t) & -b \end{bmatrix} x(t) + \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} u(t).
\]

Next, we calculate the minimum and maximum values of \( z(t) \) under \( x(t) \in [-20, 50] \), and obtain \( \min z(t) = -20 \), \( \max z(t) = 50 \). Then, the membership functions can be set as

\[
b_1(z(t)) = \frac{z(t) + 20}{50 + 20}, \quad -20 \leq z(t) \leq 50, \\
b_2(z(t)) = 1 - b_1(z(t)) = \frac{-z(t) + 50}{50 + 20}.
\]

With the maximum and minimum value, \( z(t) \) can be represented by

\[
z(t) = x(t) = b_1(z(t)) \times (-20) + b_2(z(t)) \times 50.
\]

Thus, Lorenz systems (36) can be represented by the following T-S fuzzy model:

\[
\dot{x}(t) = \sum_{i=1}^{2} b_i(z(t)) \left[ A_i x(t) + B_i u(t) \right], \tag{38}
\]

where \( x = [x_1, x_2, x_3]^T \) and

\[
A_1 = \begin{bmatrix} -10 & 10 & 0 \\ 28 & -1 & 20 \\ 0 & -20 & -8/3 \end{bmatrix},
A_2 = \begin{bmatrix} -10 & 10 & 0 \\ 28 & -1 & -50 \\ 0 & 50 & -8/3 \end{bmatrix},
B_1 = B_2 = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}^T.
\]

Consider the fuzzy controller (5) such that the chaotic system (36) with an input constraint is exponentially stable. Particularly, when \( \alpha = 0.2, b_V = 0.01 \) and \( h^* = 0.0662 \), we can get the corresponding gain matrices in (5) as follows

\[
K_1 = \begin{bmatrix} -0.0958 & -2.5307 & -0.0045 \end{bmatrix},
K_2 = \begin{bmatrix} -0.0958 & -2.5313 & -0.0036 \end{bmatrix}.
\]

Based on the above gains and an initial condition \( x(0) = [-10, 10, 10]^T \), the state \( x(t) \) and control responses of the unified chaotic systems (36) are shown in Figures 10 and 11.

Theorem 3.1 and 3.3 obtained here are not only less conservative but has wider application scopes than that of [10] as well. In addition, if \( b_V = b^*_{V} = 0.0662 \), we can use Theorem 3.3 to deal with the standard sample periods. It is clear that Theorem 3.3 of this paper provides better result with the maximum allowable upper bound of sampling intervals, that is, \( b_V = b^*_{V} = 0.0662 \). Therefore, the proposed method gives less conservative condition, which is computationally better than that obtained in [10, 39, 43]. By using LMI-based sufficient condition in Theorem 3.3, and using similar steps (as in Equation (38)), we have calculated the maximum allowable upper bound (MAUB) of \( b_V = b^*_{V} \), which is listed in Table 2. It is observed that the derived sufficient condition provides the improved allowable upper bound of \( b_k \) than the existing results.
CONCLUSION
This paper analyzes the appropriate LMI-based conditions of a T-S fuzzy system via a sampled-data controller. Based on suitable LKF and zero inequality, the sufficient conditions for the LMI-based asymptotic conditions have been proposed. The designed control gains are achieved by solving the feasibility problem up to the LMIs. Finally, the simulation results for basic buck converter system and the Lorentz model have been presented to demonstrate the feasibility of the proposed control design strategy.

| Method            | $h_T$         |
|-------------------|---------------|
| Example 4.2       | $h_T = h_T^*$ |
| [39]              | 0.0158        |
| [10]              | 0.0347        |
| [43]              | 0.0442        |
| Theorem 3.3       | 0.0662        |

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