NSS

Neutrosophic Sets and Systems, Vol. 56, 2023

University of New Mexico

Synchronization of Time Delay Neutrosophic Stochastic System

Suresh Rasappan[1], Sathish Kumar Kumaravel[2],
R. Narmada Devi[3], Regan Murugesan[4]

[1] Mathematics Section, College of Technology and Information Sciences, University of Technology and Applied Sciences- Ibri, Post Box- 466, Postal Code-516, Ibri, Sultanate of Oman.

E-mail: mrpsuresh83@gmail.com

[2,3,4]Department of Mathematics, Vel Tech Rangarajan Dr. Sagunthala R & D Institute of Science and Technology, Chennai-62, Tamilnadu, India.

E-mail: [2]k.sathi89@gmail.com, [3]narmadadevi23@gmail.com, [4]mreganprof@gmail.com

*Correspondence: Athour (narmadadevi23@gmail.com)

Abstract: This paper examines the asymptotic mean square solidness of a turbulent synchronization to time delay neutrosophic stochastic framework. The Lyapunov solidness hypothesis is utilized to plan a neutrosophic-based stochastic framework with time postpone that is supposed to be asymptotically mean square steady. The Takagi-Sugeno neutrosophic model had been made to make a neutrosophic spectator with a versatile refreshing system, as well as a neutrosophic spectator inside that presence. To communicate versatile update rules and control execution, direct framework disparity is utilized (LMI). A neutrosophic-based versatile control plot is assessed utilizing the idea of obscure. however, fixed boundary frameworks. The Lyapunov dependability hypothesis is utilized to foster the effectiveness of stochastic time delay tumultuous frameworks. For mathematical calculation, the Genesio-Tesi tumultuous framework is used. The neutrosophic fluffy framework yield is completed utilizing MATLAB. Hypothetical outcomes are approved by this recreation.

Keywords: Asymptotic mean square stability, T-S neutrosophic system, Chaos synchronization, Lyapunov function.

1 Introduction

Nonlinear dynamical frameworks that display perplexing and unusual way of behaving are known as tumultuous frameworks. The most intelligent qualities of turbulent frameworks are their touchy reliance on introductory circumstances and boundary varieties inside a given range[1-4]. Yamada and Fujisaka were quick to explore the synchronization of turbulent frameworks, trailed by Pecora and Carroll One way to deal with express delicate reliance on beginning circumstances is through turmoil syn- chronization The synchronization for turbulent frameworks has been far and wide to the degree, like summed up synchro- nization, stage synchronization , slack synchronization, projective synchronization , summed up projective syn- chronization and, surprisingly, hostile to synchronization [5-7]. The property of hostile to synchronization lay out a predominating peculiarity in even oscillators, in which the state vectors have similar outright qualities however inverse signs. At the point when synchronization and hostile to synchronization coincide, at the same time, in tumultuous frameworks, the synchronization is called half and half synchronization.

The hypotheses of vulnerability have equipped emphatically after the presentation of the fluffy set by zadeh and intuitionstic fluffy set where he presented the idea of parts capability of belongingness. Smarandache shows the possibility of a neutrosophic set. Neutrosophic set considers reality componentsthe indeterminacy parts capability, and the deception parts capability at the same time. Innovation of neutrosophic set plays a significant effect in science and designing examination area. In this ongoing age, it is for the most part utilized in direction (DM) issue and numerical demonstrating [8-12] . This supposition that is vital in a great deal of circumstances, for example, data combination when we attempt to join the information from various sensors. Neutrosophy was presented by Smarandache in 1995. ”It is a part of phi- losophy which concentrates on the beginning, nature and extent of neutralities, as well as their connections with various ideational spectra” . Neutrosophic set is a power general conventional structure which sums up the idea of the exemplary set, fluffy set, span esteemed fluffy set , intuitionistic fluffy set , and so forth [13-18]

Neutosophic fluffy based mayhem control has gotten a ton of interest as of late in an assortment of engineering applications. Versatile control configuration is an immediate mix of a control approach and some type of recursive framework recognizable proof, with the framework ID meaning to decide if the framework being controlled is direct or nonlinear. Just the qualities of a decent sort of model not set in stone for sys- tem ID, compelling parametric framework ID and parametric versatile control. In the hypothesis of questionable yet fixed boundary frameworks, versatile control configuration is contemplated and investigated [19-23].
This work proposes a neutosophic fluffy model for stochastic time-defer tumultuous frameworks with vulnerabilities in light of stochastic time-postpone turbulent frameworks with vulnerabilities. This technique is a deliberate plan procedure that guarantees the stochastic time-postpone tumultuous frameworks' worldwide mean square dependability. The versatile and supervi- siory control is resolved utilizing the Lyapunov capability to tune the regulator gain in view of the precalculated criticism control inputs. This paper is organized as follows. The issue is portrayed in Segment 2 alongside some fundamental data. The fundamental commitment of this study is referenced in Segment 3. The outline of the outcomes acquired in this paper is talked about in part 4.

2 Problem Statement and Preliminaries

Consider the stochastic time-delay chaotic system interms of T-S neutrosophic model with a time delay
$R^l : If Z_1(t_c)$ is M_1^l and $\ldots$ and $Z_j(t_c)$ is M_j^l then

$$\begin{aligned} dx(t_c) &= [(A_{1l}(t_c) + \Delta A_{1l}(t_c))x(t_c) + (A_{2l}(t_c) + \Delta A_{2l}(t_c))x(t_c - \tau_c)]dt_c + \\ &\quad [(A_{3l}(t_c) + \Delta A_{3l}(t_c))x(t_c) + (A_{4l}(t_c) + \Delta A_{4l}(t_c))x(t_c - \tau_c)]dw(t_c) \\ y(t_c) &= Cx(t_c),\ l = 1,\ 2,\ 3, \ldots, r. \end{aligned} \tag{2.1}$$

where $x(t_c) \in \mathbb{R}^n$is state vector,$y(t_c) \in \mathbb{R}^m$ is output vector $x(t_c - \tau_c)$ is time delay state vector, $A_{1l},\ A_{2l},\ A_{3l}, A_{4l}$ and C are system matrices, $\Delta A_{1l},\ \Delta A_{2l},\ \Delta A_{3l}, \Delta A_{4l}$ and C are corresponding uncertainties. τ_c is consider as constant time delay. M_j^l be the fuzzy set, r be the number of fuzzy rule, $z(t_c) = [z_1(t_c),\ z_2(t_c), \ldots\ z_j(t_c)]^T$ are premise variables associated with system states.

The center of gravity defuzzification method is used to get output of neutrosophic system.

$$\begin{array}{rcl} W_l & = & \langle t_c,\ \mu_{W_l},\ \sigma_{W_l},\ \gamma_{W_l} \rangle \\ dx & = & \langle t_c,\ \mu_{dx},\ \sigma_{W_{dx}},\ \gamma_{dx} \rangle \\ dt_c & = & \langle\ \mu_{dt_c},\ \sigma_{W_{dt_c}}\ \gamma_{dt_c} \rangle \\ dw(t_c) & = & \langle\ \mu_{dw},\ \sigma_{W_{dw}}\ \gamma_{dw} \rangle \\ y(t_c) & = & \langle \mu_{Cx(t_c)},\ \sigma_{W_x(t_c)},\ \gamma_{Cx(t_c)} \rangle \end{array} \tag{2.2}$$

where $\mu_{W_l}(z) = \prod_{i=1}^{j} \mu_{M_i^l}(z_j), \sigma_{W_l}(z) = \prod_{i=1}^{j} \sigma_{M_i^l}(z_j), \gamma_{W_l(z)} = \prod_{i=1}^{j} \gamma_{M_i^l(z_j)}$ and $\mu_{Cx(t_c)}, \sigma_{Cx(t_c)}, \gamma_{Cx(t_c)}$ are fuzzy matrices.

$$\begin{array}{rcl} \mu_{dx}(t_c) & = & \dfrac{\sum_{l=1}^{r} \mu_{W_l}(z)[(\mu_{A_{1l}}+\mu_{\Delta A_{1l}})(x(t_c))+(\mu_{A_{2l}}+\mu_{\Delta A_{2l}})(x(t_c-\tau_c))]\mu_{dt_c}+[(\mu_{A_{3l}}+\mu_{\Delta A_{3l}})x(t_c)+(\mu_{A_{4l}}+\mu_{\Delta A_{4l}})(x(t_c-\tau_c))]\mu_{dw(t_c)}}{\sum_{l=1}^{r} \mu_{W_l}(z)} \\ \sigma_{dx}(t_c) & = & \dfrac{\sum_{l=1}^{r} \sigma_{W_l}(z)[(\sigma_{A_{1l}}+\sigma_{\Delta A_{1l}})(x(t_c))+(\sigma_{A_{2l}}+\sigma_{\Delta A_{2l}})(x(t_c-\tau_c))]\sigma_{dt_c}+[(\sigma_{A_{3l}}+\sigma_{\Delta A_{3l}})x(t_c)+(\sigma_{A_{4l}}+\sigma_{\Delta A_{4l}})(x(t_c-\tau_c))]\sigma_{dw(t_c)}}{\sum_{l=1}^{r} \sigma_{W_l}(z)} \\ \gamma_{dx}(t_c) & = & 1-\mu_{dx}t_c \\ \text{and} & & \\ y(t_c) & = & Cx(t_c) \end{array} \tag{2.3}$$

$\mu_{M_i^l}(z_i), \sigma_{M_i^l}(z_i)$ and $\gamma_{M_i^l}(z_i)$ are the grades of components function and non components functions of M_i^l corresponding to z_i

$$\begin{array}{rcl} \mu_{M_l}(z_i) & = & \dfrac{\mu_{W_l}(z_i)}{\sum_{l=1}^{r} \mu_{W_l}(z_i)} \\ \sigma_{M_l}(z_i) & = & \dfrac{\sigma_{W_l}(z_i)}{\sum_{l=1}^{r} \sigma_{W_l}(z_i)} \\ \gamma_{M_l}(z_i) & = & \dfrac{\gamma_{W_l}(z_i)}{\sum_{l=1}^{r} \gamma_{W_l}(z_i)} \end{array} \tag{2.4}$$

Therefore the state of the neutrosophic system is given by

$$\begin{array}{rcl} \mu_{dx}(t_c) & = & \sum_{l=1}^{r} \mu_{M_l}(z_i)([(\mu_{A_{1l}}+\mu_{\Delta A_{1l}})(x(t_c))+(\mu_{A_{2l}}+\mu_{\Delta A_{2l}})x(t_c-\tau_c)]\mu_{dt_c}+ \\ & & [(\mu_{A_{3l}}+\mu_{\Delta A_{3l}})(x(t_c))+(\mu_{A_{4l}}+\mu_{\Delta A_{4l}})(x(t_c-\tau_c))]\mu_{dw(t_c)} \\ \sigma_{dx}(t_c) & = & \sum_{l=1}^{r} \sigma_{M_l}(z_i)([(\sigma_{A_{1l}}+\sigma_{\Delta A_{1l}})(x(t_c))+(\sigma_{A_{2l}}+\sigma_{\Delta A_{2l}})x(t_c-\tau_c)]\sigma_{dt_c}+ \\ & & [(\mu_{A_{3l}}+\sigma_{\Delta A_{3l}})(x(t_c))+(\sigma_{A_{4l}}+\sigma_{\Delta A_{4l}})(x(t_c-\tau_c))]\sigma_{dw(t_c)} \\ \gamma_{dx}(t_c) & = & 1-\mu_{dx}(t_c) \\ \text{and} & & \\ y(t_c) & = & Cx(t_c) \end{array} \tag{2.5}$$

Considering the assumptions

$$\begin{array}{l} \mu_{\Delta A}(t_c) = \sum_{l=1}^{r} \mu_{M_l}(z_i)\mu_{\Delta A_{1l}}(t_c), \sigma_{\Delta A}(t_c) = \sum_{l=1}^{r} \sigma_{M_l}(z_i)\sigma_{\Delta A_{1l}}(t_c) \quad \text{and} \quad \gamma_{\Delta A}(t_c) = \sum_{l=1}^{r} \gamma_{M_l}(z_i)\gamma_{\Delta A_{1l}}(t_c) \\ \mu_{\Delta A_{d_1}}(t_c) = \sum_{l=1}^{r} \mu_{M_l}(z_i)\mu_{\Delta A_{2l}}(t_c), \sigma_{\Delta A_{d_1}}(t_c) = \sum_{l=1}^{r} \sigma_{M_l}(z_i)\sigma_{\Delta A_{2l}}(t_c) \quad \text{and} \quad \gamma_{\Delta A_{d_1}}(t_c) = \sum_{l=1}^{r} \gamma_{M_l}(z_i)\gamma_{\Delta A_{2l}}(t_c) \\ \mu_{\Delta A_{d_3}}(t_c) = \sum_{l=1}^{r} \mu_{M_l}(z_i)\mu_{\Delta A_{4l}}(t_c), \sigma_{\Delta A_{d_3}}(t_c) = \sum_{l=1}^{r} \sigma_{M_l}(z_i)\sigma_{\Delta A_{4l}}(t_c) \quad \text{and} \quad \gamma_{\Delta A_{d_3}}(t_c) = \sum_{l=1}^{r} \gamma_{M_l}(z_i)\gamma_{\Delta A_{4l}}(t_c) \end{array} \tag{2.6}$$

Therefore the state of the neutrosophic systems is

$$\begin{array}{rcl} \mu_{dx}(t_c) &=& [\sum_{l=1}^{r} \mu_{M_l}(z_i)(A_{1l}(x(t_c)) + A_{2l}x(t_c-\tau_c)) + \mu_{\Delta A}(t_c)x(t_c) + \mu_{\Delta A_{d_1}}x(t_c-\tau_c)]dt_c \\ && +[\sum_{l=1}^{r} \mu_{M_l}(z_i)(A_{3l}(x(t_c)) + A_{4l}x(t_c-\tau_c)) + \mu_{\Delta A_{d_2}}(t_c)x(t_c) + \mu_{\Delta A_{d_3}}(t_c)x(t_c-\tau_c)]dw(t_c) \\ \sigma_{dx}(t_c) &=& [\sum_{l=1}^{r} \sigma_{M_l}(z_i)(A_{1l}(x(t_c)) + A_{2l}x(t_c-\tau_c)) + \sigma_{\Delta A}(t_c)x(t_c) + \sigma_{\Delta A_{d_1}}x(t_c-\tau_c)]dt_c \\ && +[\sum_{l=1}^{r} \sigma_{M_l}(z_i)(A_{3l}(x(t_c)) + A_{4l}x(t_c-\tau_c)) + \sigma_{\Delta A_{d_2}}(t_c)x(t_c) + \mu_{\Delta A_{d_3}}(t_c)x(t_c-\tau_c)]dw(t_c) \\ \gamma_{dx}(t_c) &=& 1-\mu_{dx}(t_c) \\ \text{and} && \\ y(t_c) &=& Cx(t_c) \end{array} \tag{2.7}$$

Assume that the uncertainties are imposed on matching condition. Therefore there exist an uniformly continuous function $E_A(t_c)$ and$E_d(t_c)$ exist such that $\Delta A(t_c) = BE_A(t_c),\ \Delta A_d(t_c) = BE_d(t_c),\ B\ in\ \mathbb{R}^{n\times p}$ are known matrix. Therefore the uncertainties in equation (2.7) are represented as

$$\begin{array}{rcl} \Delta A(t_c)x(t_c) &=& B\xi_1(x(t_c)t_c) \\ \Delta A_{d_1}(t_c)x(t_c-\tau_c) &=& B\xi_2(x(t_c-\tau_c)t_c) \\ \Delta A_{d_2}(t_c)x(t_c) &=& B\xi_3(x(t_c)t_c) \\ \Delta A_{d_3}(t_c)x(t_c-\tau_c) &=& B\xi_4(x(t_c-\tau_c)t_c) \end{array} \tag{2.8}$$

where $\xi_1,\ \xi_2,\ \xi_3,\ \xi_4$ are uncertainties, which are unknown, design of neutrosophic observer is required to estimate these uncertainties.

Therefore equation (2.7) becomes

$$\begin{aligned}
\mu_{dx}(t_c) &= [\sum_{l=1}^{r}\mu_l(z)(\mu A_{1l}(x(t_c)) + \mu A_{2l}x(t_c-\tau_c)) + \mu B\xi_1(x(t_c)t_c) + \mu B\xi_2(x(t_c-\tau_c)t_c)]dt_c \\
&\quad +[\sum_{l=1}^{r}\mu_l(z)(\mu A_{3l}(x(t_c)) + \mu A_{4l}x(t_c-\tau_c)) + \mu B\xi_3(x(t_c)t_c) + \mu B\xi_4(x(t_c-\tau_c)t_c)]\mu_{dw}(t_c) \\
\sigma_{dx}(t_c) &= [\sum_{l=1}^{r}\sigma_l(z)(\mu A_{1l}(x(t_c)) + \mu A_{2l}x(t_c-\tau_c)) + \sigma B\xi_1(x(t_c)t_c) + \sigma B\xi_2(x(t_c-\tau_c)t_c)]dt_c \\
&\quad +[\sum_{l=1}^{r}\mu_l(z)(\sigma A_{3l}(x(t_c)) + \sigma A_{4l}x(t_c-\tau_c)) + \sigma B\xi_3(x(t_c)t_c) + \sigma B\xi_4(x(t_c-\tau_c)t_c)]\sigma_{dw}(t_c) \\
\gamma_{dx}(t_c) &= 1-\mu_{dx}(t_c)\mu_{Al1}(x(t_c-\tau_c)) \\
&\text{and} \\
y(t_c) &= <\mu_y(t_c),\sigma_y(t_c),\gamma_y(t_c)>
\end{aligned} \tag{2.9}$$

where $\mu_y(t_c) = (\mu_c, \mu_x(t_c))$

Consider the following the neutrosophic system; that approximate the i^{th} components of the uncertainties $\xi_1(x(t_c)t_c),\ \xi_{li}$ as
$R^j : If x_1(t_c)$ is $\tilde{M}_1^j$ and ... and $x_n(t_c)$ is $\tilde{M}_n^j$, then $\hat{\xi}_{1i}$ is $\tilde{D}_{ij}, j = 1,\ 2,\ 3,\ 4\ldots\ q.$

The output of the neutrosophic inference is

$$\begin{aligned}
\mu(x/\theta_i) &= \frac{\sum_{j=1}^{q}\theta_{ij}(\prod_{h=1}^{n}\mu_{\tilde{M}_h^j}(x_h))}{\sum_{j=1}^{q}\prod_{h=1}^{n}\mu_{\tilde{M}_h^j}(x_h)} \\
\sigma(x/\theta_i) &= \frac{\sum_{j=1}^{q}\theta_{ij}(\prod_{h=1}^{n}\sigma_{\tilde{M}_h^j}(x_h))}{\sum_{j=1}^{q}\prod_{h=1}^{n}\sigma_{\tilde{M}_h^j}(x_h)} \\
\gamma(x/\theta_i) &= \frac{\sum_{j=1}^{q}\theta_{ij}(\prod_{h=1}^{n}\gamma_{\tilde{M}_h^j}(x_h))}{\sum_{j=1}^{q}\prod_{h=1}^{n}\gamma_{\tilde{M}_h^j}(x_h)} \\
\text{hence}\quad \hat{\xi}_{1i}(x/\theta_i) &= \theta_i^T\omega(x).
\end{aligned} \tag{2.10}$$

where $\theta_i = (\theta_{i1},\ \theta_{i2},\ \ldots,\ \theta_{iq})^T$ is an adjustable parameter vector.θ_{ij} is the center of $\tilde{D}_{ij}$ for $i = 1,\ 2,\ 3,\ \ldots,\ p;$ $j = 1,\ 2,\ 3,\ \ldots\ q,\ \omega(x)$ is the neutrosophic basic function.

The estimation of ξ_1 has the form $\hat{\xi}_{1i}(x/\theta) = \theta_i^T\omega(x), \theta \in \mathbb{R}^{p\times q}$.

The optimal parameter neutrosophic matrix θ^* is defined as $\theta^* =<\mu_{\theta*},\sigma_{\theta*},\gamma_{\theta*}>$

$$\mu_{\theta_*} = \text{arg}\ \text{min}_{\theta\in\Omega_\theta}(\sup\left\|\mu_{\hat{\xi}_1}(x/\theta) - \mu_{\hat{\xi}_1}(xt_ct_c)\right\|) \tag{2.11}$$

such that

$$\left\|\mu_{\hat{\xi}_1}(x/\theta^*) - \mu_{\hat{\xi}_1}(xt_c)\right\| \le \mu_{\xi_1} \tag{2.12}$$

$$\sigma_{\theta_*} = \text{arg}\ \text{min}_{\theta\in\Omega_\theta}(\sup\left\|\sigma_{\hat{\xi}_1}(x/\theta) - \sigma_{\hat{\xi}_1}(x(t_c)t_c)\right\|)$$

such that

$$\left\|\sigma_{\hat{\xi}_1}(x/\theta^*) - \sigma_{\hat{\xi}_1}(xt_c)\right\| \le \sigma_{\xi_1}$$

and

$$\gamma_{\theta^*}(t_c) = 1 - \mu_{\theta^*}(t_c)\mu_{Al1}(x(t_c - \tau_c))$$

where

$$\Omega_\theta = (\theta/\text{trace}(\theta^T\theta) < M_\theta^2), \tag{2.13}$$

here tr$(.)$ is trace of the matrix, M_θ is designed constant, ξ_1 is unknown upper bound such that

$$\|\xi_2(x(t_c - \tau_c))t_c\| \le \xi_2, \tag{2.14}$$

$\omega(x)$ is uniformly continuous then exist an Lipshiz constants

$$\|\omega(x) - \hat{\omega}(x)\| \le \gamma \|x - \hat{x}\|. \tag{2.15}$$

Thus, the neutrosophic observer for a stochastic time- delay chaotic system (2.1) is
$R^l : If Z_1(t_c)$ is M_1^l and ... and $Z_j(t_c)$ is M_j^l then $d\hat{x}(t_c) =< \mu_{d\hat{x}}(t_c), \sigma_{d\hat{x}}(t_c), \gamma_{d\hat{x}}(t_c) >$ where

$$\begin{aligned}
\mu_{d\hat{x}}(t_c) &= [\mu A_{1l}\hat{x}(t_c) + \mu A_{2l}\hat{x}(t_c - \tau_c) + \mu L_l(y(t_c) - \hat{y}(t_c)) + \mu B(\hat{\xi_1}(\hat{x})/\theta) + \mu u_1(t_c) + \mu u_2(t_c)]dt_c \\
&\quad +[\mu A_{3l}\hat{x}(t_c) + \mu A_{4l}\hat{x}(t_c - \tau_c) + \mu L_l(y(t_c) - \hat{y}(t_c)) + \mu B(\hat{\xi_1}(\hat{x}/\theta) + \mu u_1(t_c) + \mu u_2 t_c]\mu_{dw}(t_c), \\
\sigma_{d\hat{x}}(t_c) &= [\sigma A_{1l}\hat{x}(t_c) + \sigma A_{2l}\hat{x}(t_c - \tau_c) + \sigma L_l(y(t_c) - \hat{y}(t_c)) + \sigma B(\hat{\xi_1}(\hat{x})/\theta) + \sigma u_1(t_c) + \mu u_2(t_c)]dt_c \\
&\quad +[\sigma A_{3l}\hat{x}(t_c) + \sigma A_{4l}\hat{x}(t_c - \tau_c) + \sigma L_l(y(t_c) - \hat{y}(t_c)) + \sigma B(\hat{\xi_1}(\hat{x}/\theta) + \sigma u_1(t_c) + \sigma u_2(t_c)]\sigma_{dw}(t_c), \\
\gamma(dc\hat{x(t_c)}) &= 1 - \mu_{d\hat{x}}(t_c)\mu_{A_{l1}}(x(t_c - \tau_c)) \\
\text{and} & \\
\hat{y}(t_c) &= C\hat{x}(t_c),\ l = 1,\ 2,\ 3, \dots\ r.
\end{aligned} \tag{2.16}$$

where L_l is neutrosophic designed feedback gain matrices, u_1 and u_2 are neutrosophic supervisory control.

Therefore the output of the neutrosophic systems (2.16) is

$$\begin{aligned}
\mu_{d\hat{x}}(t_c) &= [\sum_{l=1}^{r} \mu_l(z)[\mu A_{1l}\hat{x}(t_c) + \mu A_{2l}\hat{x}(t_c - \tau_c) + \mu L_l(y(t_c) - \mu\hat{y}(t_c)) + \\
&\quad \mu B(\hat{\xi_1}(\hat{x}/\theta) + \mu u_1(t_c) + \mu u_2(t_c)]]dt_c + [\sum_{l=1}^{r} \mu_l(z)[\mu A_{3l}\hat{x}(t_c) + \mu A_{4l}\hat{x}(t_c - \tau_c) + \\
&\quad \mu L_l(y(t_c) - \hat{y}t_c) + B(\hat{\xi_1}(\hat{x}/\theta) + \mu u_1(t_c) + \mu u_2(t_c)]]\mu_{dw}(t_c), \\
\sigma_{d\hat{x}}(t_c) &= [\sum_{l=1}^{r} \sigma_l(z)[\sigma A_{1l}\hat{x}(t_c) + \sigma A_{2l}\hat{x}(t_c - \tau_c) + \sigma L_l(y(t_c) - \sigma\hat{y}(t_c)) + \\
&\quad \sigma B(\hat{\xi_1}(\hat{x}/\theta) + \sigma u_1(t_c) + \sigma u_2(t_c)]]dt_c + [\sum_{l=1}^{r} \sigma_l(z)[\sigma A_{3l}\hat{x}(t_c) + \sigma A_{4l}\hat{x}(t_c - \tau_c) + \\
&\quad \sigma L_l(y(t_c) - \hat{y}(t_c)) + B(\hat{\xi_1}(\hat{x}/\theta) + \sigma u_1 t_c + \sigma u_2 t_c]]\sigma_{dw} t_c, \\
\gamma_{d\hat{x}} t_c) &= 1 - \mu_{d\hat{x}} t_c \\
\text{and} & \\
\hat{y} t_c &= C\hat{x} t_c,\ l = 1,\ 2,\ 3 \dots\ r.
\end{aligned} \tag{2.17}$$

The observation error is defined as

$$de t_c = dx t_c - d\hat{x} t_c. \tag{2.18}$$

Therefore, the error dynamic is noted by

$$\begin{aligned}
\mu_{de}t_c &= [\sum_{l=1}^{r}\mu_l(z)[\mu(A_{1l}t_c-\mu L_lC)et_c+\mu A_{2l}e(t_c-\tau_c)]+\mu B(\xi_1(xt_ct_c)-\mu\hat{\xi}_1(\hat{x}/\theta)-\mu u_1t_c)\\
&+\mu B(\xi_1(x(t_c-\tau_c)t_c)-\mu u_2t_c)]dt+[\sum_{l=1}^{r}\mu_l(z)[\mu(A_{3l}t_c-\mu L_lC)et_c+\mu A_{4l}e(t_c-\tau_c)]\\
&-\mu B(\hat{\xi}_1(\hat{x}/\theta)+\mu u_1t_c)-\mu B(u_2t_c)]\mu_{dw}t_c.\\
\sigma_{de}t_c) &= [\sum_{l=1}^{r}\sigma_l(z)[\sigma(A_{1l}t_c-\sigma L_lC)et_c+\sigma A_{2l}e(t_c-\tau_c)]+\sigma B(\xi_1(xt_ct_c)-\sigma\hat{\xi}_1(\hat{x}/\theta)-\sigma u_1t_c)\\
&+\sigma B(\xi_1(x(t_c-\tau_c)t_c)-\sigma u_2t_c)]dt+[\sum_{l=1}^{r}\sigma_l(z)[\sigma(A_{3l}t_c-\sigma L_lC)et_c+\sigma A_{4l}e(t_c-\tau_c)]\\
&-\sigma B(\hat{\xi}_1(\hat{x}/\theta)+\sigma u_1t_c)-\sigma B(u_2t_c)]\sigma_{dw}t_c.\\
&\text{and}\\
\gamma_{de}t_c &= 1-\mu_{de}t_c
\end{aligned} \tag{2.19}$$

3 Main Result

Define the two state variables for stochastic time-delay chaotic system (2.6)

$$\begin{aligned}
\mu_f t_c &= \sum_{l=1}^{r}\mu_l(z)(\mu A_{1l}xt_c+\mu A_{2l}x(t_c-\tau_c))+\mu B\xi_1(xt_ct_c)+\mu B\xi_1(x(t_c-\tau_c)t_c)\\
\mu_g t_c &= \sum_{l=1}^{r}\mu_l(z)(\mu A_{3l}xt_c+\mu A_{4l}x(t_c-\tau_c))+\mu B\xi_3(xt_ct_c)+\mu B\xi_4(x(t_c-\tau_c)t_c).\\
\sigma_f t_c &= \sum_{l=1}^{r}\sigma_l(z)(\sigma A_{1l}xt_c+\sigma A_{2l}x(t_c-\tau_c))+\sigma B\xi_1(xt_ct_c)+\sigma B\xi_1(x(t_c-\tau_c)t_c)\\
\sigma_g t_c &= \sum_{l=1}^{r}\sigma_l(z)(\sigma A_{3l}xt_c+\sigma A_{4l}x(t_c-\tau_c))+\sigma B\xi_3(xt_ct_c)+\sigma B\xi_4(x(t_c-\tau_c)t_c).\\
\gamma_f t_c &= \sum_{l=1}^{r}\gamma_l(z)(\gamma A_{1l}xt_c+\gamma A_{2l}x(t_c-\tau_c))+\gamma B\xi_1(xt_ct_c)+\gamma B\xi_1(x(t_c-\tau_c)t_c)\\
\gamma_g t_c &= \sum_{l=1}^{r}\gamma_l(z)(\gamma A_{3l}xt_c+\gamma A_{4l}x(t_c-\tau_c))+\gamma B\xi_3(xt_ct_c)+\gamma B\xi_4(x(t_c-\tau_c)t_c).
\end{aligned} \tag{3.1}$$

Then the stochastic time delay chaotic system is

$$\begin{aligned}
\mu_x t_c-\mu_x(t_c-\tau_c) &= \int_{t-\tau_c}^{t}\mu dx(s)=\int_{t-\tau_c}^{t}\mu f(s)ds+\int_{t-\tau_c}^{t}\mu g(s)\mu_{dw}(s).\\
\sigma_x t_c-\sigma_x(t_c-\tau_c) &= \int_{t-\tau_c}^{t}\sigma dx(s)=\int_{t-\tau_c}^{t}\sigma f(s)ds+\int_{t-\tau_c}^{t}\sigma g(s)\sigma_{dw}(s).\\
\gamma_x t_c-\gamma_x(t_c-\tau_c) &= \int_{t-\tau_c}^{t}\gamma dx(s)=\int_{t-\tau_c}^{t}\gamma f(s)ds+\int_{t-\tau_c}^{t}\sigma g(s)\gamma_{dw}(s).
\end{aligned} \tag{3.2}$$

Theorem 3.1 Consider the stochastic time-delay chaotic system (2.1) and its corresponding neutrosophic observer (2.16). Suppose that positive definite matrices P, Q, S, R, D_0, D_1 and the feedback gain L_i, $i=1,\ 2,\ 3,\ 4,\ldots,r$, such that $PB=C^T$and the following condition holds

$$\begin{aligned}
[(A_{1i}-L_iC)^TP+P(A_{1i}-L_iC)+R+D_0+D_1+PA_{2i}R^{-1}A_{2i}^T] &\leq -Q_i,\\
\lambda_{\min}(Q_i) &\geq 2\gamma M_\theta\|C\|.
\end{aligned} \tag{3.3}$$

where $\lambda_{\min}$ denotes the minimum eigen value of a matrix.

Given the supervisory controls

$$u_1 = \hat{\xi}_1 \frac{B^T Pe}{\|B^T Pe\|},\ u_2 = \hat{\xi}_2 \frac{B^T Pe}{\|B^T Pe\|} \tag{3.4}$$

where $\hat{\xi}_1$ and $\hat{\xi}_2$ stand for estimators of ξ_1 and ξ_2.

The error dynamic is asymptotically stable in the mean square by applying

$$\begin{array}{rcl} \dot{\theta} & = & 2\eta\omega(\hat{x})B^T Pe, \\ \dot{\hat{\xi}}_1 & = & 2\eta_1 e^T PB, \\ \dot{\hat{\xi}}_2 & = & 2\eta_2 e^T PB. \end{array} \tag{3.5}$$

where $\eta,\ \eta_1,\ \eta_2$ denotes positive adaption constants.

Proof: Consider the Lyapunov-Krasovskii functional as follows:

$$Vt_c = e^T Pe + \frac{1}{2\eta} tr(\tilde{\theta}^T \tilde{\theta}) + \frac{1}{2\eta_1}\tilde{\xi}_1^2 + \frac{1}{2\eta_2}\tilde{\xi}_1^2 + \int_{t-\tau_c}^{t} e^T(\sigma)Se(\sigma)d\sigma, \tag{3.6}$$

where

$$\begin{array}{c} \tilde{\theta} = \theta^* - \theta, \\ \tilde{\xi}_1 = \xi_1 - \hat{\xi}_1, \\ \tilde{\xi}_2 = \xi_2 - \hat{\xi}_2, \end{array} \tag{3.7}$$

then its derivative can be obtained by $It\hat{o}$ formula that

$$\begin{array}{rcl} dvt_c & = & \mathbb{L}Vt_c dt + 2e^T Pgt_c dwt_c \\ \mathbb{L}Vt_c & = & V_t t_c + V_e t_c f t_c + \frac{1}{2}\text{trace}(g^T V_{ee} g) \end{array} \tag{3.8}$$

Therefore

$$\begin{array}{rcl} \mu_{\mathbb{L}V} t_c & = & 2e^T P([\sum_{i=1}^{r} \mu_i(z)[\mu(A_{1i}t_c - \mu L_i C)et_c + \mu A_{2i} e(t_c - \tau_c)] + \mu B(\xi_1(xt_c t_c) - \mu\hat{\xi}_1(\hat{x}/\theta) - \mu u_1 t_c) \\ & & +\mu B(\xi_2(x(t_c - \tau_c)t_c) - \mu u_2 t_c)]) + \mu e^T Se + \mu g^T Pg - \mu\frac{1}{\eta}\text{tr}(\tilde{\theta}^T \dot{\tilde{\theta}}) - \mu\frac{1}{\eta_1}\tilde{\xi}_1 \dot{\hat{\xi}}_1 \\ & & -\mu\frac{1}{\eta_2}\tilde{\xi}_2 \dot{\hat{\xi}}_2 - \mu e^T(t_c - \tau_c)Se(t_c - \tau_c). \\ \sigma_{\mathbb{L}V} t_c & = & 2e^T P([\sum_{i=1}^{r} \sigma_i(z)[\sigma(A_{1i}t_c - \sigma L_i C)et_c + \sigma A_{2i} e(t_c - \tau_c)] + \sigma B(\xi_1(xt_c t_c) - \sigma\hat{\xi}_1(\hat{x}/\theta) - \sigma u_1 t_c) \\ & & +\sigma B(\xi_2(x(t_c - \tau_c)t_c) - \sigma u_2 t_c)]) + \sigma e^T Se + \sigma g^T Pg - \sigma\frac{1}{\eta}\text{tr}(\tilde{\theta}^T \dot{\tilde{\theta}}) - \sigma\frac{1}{\eta_1}\tilde{\xi}_1 \dot{\hat{\xi}}_1 \\ & & -\sigma\frac{1}{\eta_2}\tilde{\xi}_2 \dot{\hat{\xi}}_2 - \sigma e^T(t_c - \tau_c)Se(t_c - \tau_c). \\ \gamma_{\mathbb{L}V} t_c & = & 1 - \mu_{\mathbb{L}V} t_c \end{array} \tag{3.9}$$

Now consider the relation

$$g^T Pg \leq e^T D_0 e + e^T(t_c - \tau_c)D_1 e(t_c - \tau_c). \tag{3.10}$$

Then

$$\begin{aligned}
\mu_{\mathbb{L}V}t_c &= 2e^TP([\sum_{i=1}^{r}\mu_i(z)[\mu(A_{1i}t_c-\mu L_iC)et_c+\mu A_{2i}e(t_c-\tau_c)]+\mu B(\xi_1(xt_ct_c)-\mu\hat{\xi}_1(\hat{x}/\theta)-\mu u_1t_c)\\
&\quad +\mu B(\xi_2(x(t_c-\tau_c)t_c)-\mu u_2t_c)])+\mu e^TSe+\mu e^TD_0e+\mu e^T(t_c-\tau_c)D_1e(t_c-\tau_c)\\
&\quad \mu-\frac{1}{\eta}\text{tr}(\tilde{\theta}^T\dot{\tilde{\theta}})-\mu\frac{1}{\eta_1}\tilde{\xi}_1\dot{\tilde{\xi}}_1-\mu\frac{1}{\eta_2}\tilde{\xi}_2\dot{\tilde{\xi}}_2-\mu e^T(t_c-\tau_c)Se(t_c-\tau_c)\\
&\leq \sum_{i=1}^{r}\mu_i[e^TP(A_{1i}-_iC)^Te+\mu e^T(A_{1i}-_iC)Pe+\mu 2e^TPA_{2i}e(t_c-\tau_c)]\\
&\quad +\mu 2e^TPB(\xi_1(xt_ct_c)-\mu\hat{\xi}_1(\hat{x}/\theta))\\
&\quad -\mu 2e^TPB(u_1)+\mu 2e^TPB(\xi_2(x(t_c-\tau_c))-\mu u_2)+\mu e^TSe+\mu e^TD_0e\\
&\quad +\mu e^T(t_c-\tau_c)D_1e(t_c-\tau_c)-\frac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta})-\mu\frac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1-\mu\frac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2-\mu e^T(t_c-\tau_c)Se(t_c-\tau_c).\\
\sigma_{\mathbb{L}V}t_c &= 2e^TP([\sum_{i=1}^{r}\sigma_i(z)[\sigma(A_{1i}t_c-\sigma L_iC)et_c+\sigma A_{2i}e(t_c-\tau_c)]+\sigma B(\xi_1(xt_ct_c)-\sigma\hat{\xi}_1(\hat{x}/\theta)-\sigma u_1t_c)\\
&\quad +\sigma B(\xi_2(x(t_c-\tau_c)t_c)-\sigma u_2t_c)])+\sigma e^TSe+\sigma e^TD_0e+\sigma e^T(t_c-\tau_c)D_1e(t_c-\tau_c)\\
&\quad \sigma-\frac{1}{\eta}\text{tr}(\tilde{\theta}^T\dot{\tilde{\theta}})-\sigma\frac{1}{\eta_1}\tilde{\xi}_1\dot{\tilde{\xi}}_1-\sigma\frac{1}{\eta_2}\tilde{\xi}_2\dot{\tilde{\xi}}_2-\sigma e^T(t_c-\tau_c)Se(t_c-\tau_c)\\
&\leq \sum_{i=1}^{r}\sigma_i[e^TP(A_{1i}-\sigma L_iC)^Te+\sigma e^T(A_{1i}-\sigma L_iC)Pe+\sigma 2e^TPA_{2i}e(t_c-\tau_c)]\\
&\quad +\sigma 2e^TPB(\xi_1(xt_ct_c)-\sigma\hat{\xi}_1(\hat{x}/\theta))\\
&\quad -\sigma 2e^TPB(u_1)+\sigma 2e^TPB(\xi_2(x(t_c-\tau_c))-\sigma u_2)+\sigma e^TSe+\sigma e^TD_0e\\
&\quad +\sigma e^T(t_c-\tau_c)D_1e(t_c-\tau_c)-\frac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta})-\sigma\frac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1-\sigma\frac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2-\sigma e^T(t_c-\tau_c)Se(t_c-\tau_c).\\
\gamma_{\mathbb{L}V}t_c &= 1-\gamma_{\mathbb{L}V}t_c
\end{aligned} \tag{3.11}$$

Now consider the relation

$$2e^TPA_{2i}e(t_c-\tau_c)\leq e^TPA_{2i}R^{-1}A_{2i}^TPe+e^T(t_c-\tau_c)Re(t_c-\tau_c). \tag{3.12}$$

Therefore the equation (3.11) becomes

$$
\begin{aligned}
\mu_{\mathbb{L}V} t_c \ \leq\ & \sum_{i=1}^{r} \mu_i \, e^T[P(A_{1i}-L_iC)^T+(A_{1i}-L_iC)P+PA_{2i}R^{-1}A_{2i}^TP+S]e+e^T(t_c-\tau_c)Re(t_c-\tau_c) \\
& +2e^TPB(\xi_1(xt_ct_c)-\hat{\xi}_1(\hat{x}/\theta))-2e^TPB(u_1)+2e^TPB(\xi_2(x(t_c-\tau_c))-u_2)+ \\
& e^TD_0e+e^T(t_c-\tau_c)D_1e(t_c-\tau_c)-\tfrac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta})-\tfrac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1-\tfrac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2-e^T(t_c-\tau_c)Se(t_c-\tau_c). \\
\leq\ & \sum_{i=1}^{r} \mu_i \, e^T[P(A_{1i}-L_iC)^T+(A_{1i}-L_iC)P+R+D_0+D_1+PA_{2i}R^{-1}A_{2i}^TP]e+ \\
& +2e^TPB(\xi_1(xt_ct_c)-\hat{\xi}_1(\hat{x}/\theta))-2e^TPB(u_1)+2e^TPB(\xi_2(x(t_c-\tau_c)t_c)) \\
& -2e^TPBu_2-\tfrac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta})-\tfrac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1-\tfrac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2. \\
\sigma_{\mathbb{L}V} t_c \ \leq\ & \sum_{i=1}^{r} \sigma_i \, e^T[P(A_{1i}-L_iC)^T+(A_{1i}-L_iC)P+PA_{2i}R^{-1}A_{2i}^TP+S]e+e^T(t_c-\tau_c)Re(t_c-\tau_c) \\
& +2e^TPB(\xi_1(xt_ct_c)-\hat{\xi}_1(\hat{x}/\theta))-2e^TPB(u_1)+2e^TPB(\xi_2(x(t_c-\tau_c))-u_2)+ \\
& e^TD_0e+e^T(t_c-\tau_c)D_1e(t_c-\tau_c)-\tfrac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta})-\tfrac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1-\tfrac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2-e^T(t_c-\tau_c)Se(t_c-\tau_c). \\
\leq\ & \sum_{i=1}^{r} \sigma_i \, e^T[P(A_{1i}-L_iC)^T+(A_{1i}-L_iC)P+R+D_0+D_1+PA_{2i}R^{-1}A_{2i}^TP]e+ \\
& +2e^TPB(\xi_1(xt_ct_c)-\hat{\xi}_1(\hat{x}/\theta))-2e^TPB(u_1)+2e^TPB(\xi_2(x(t_c-\tau_c)t_c)) \\
& -2e^TPBu_2-\tfrac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta})-\tfrac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1-\tfrac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2. \\
\gamma_{\mathbb{L}V} t_c \ \leq\ & 1-\mu_{\mathbb{L}V} t_c
\end{aligned}
\tag{3.13}
$$

Again we consider the relation

$$
\begin{aligned}
\mu_{\xi_1}(xt_ct_c)-\mu\hat{\xi}_1(\hat{x}/\theta) &= \mu_{\xi_1}(xt_ct_c)-\mu_{\hat{\xi}_1}(\hat{x}/\theta)+\mu_{\hat{\xi}_1}(\hat{x}/\theta^*)-\mu_{\hat{\xi}_1}(\hat{x}/\theta^*)+\mu_{\hat{\xi}_1}(x/\theta^*)-\mu_{\hat{\xi}_1}(x/\theta^*) \\
&= \mu_{(\xi_1}-\mu_{\hat{\xi}_1}(\hat{x}/\theta^*))+\mu_{\hat{\xi}_1}((\hat{x}/\theta^*)-\mu(\hat{x}/\theta))+\mu_{\hat{\xi}_1}((x/\theta^*)-\mu(\hat{x}/\theta^*)) \\
&= (\mu_{\xi_1}-\mu_{\hat{\xi}_1}(\hat{x}/\theta^*))+\mu_{\tilde{\theta}^T\omega}(\hat{x})+\mu_{\theta^{*T}(\omega}(x)-\mu_\omega(\hat{x})), \\
\sigma_{\xi_1}(xt_ct_c)-\sigma\hat{\xi}_1(\hat{x}/\theta) &= \sigma_{\xi_1}(xt_ct_c)-\sigma_{\hat{\xi}_1}(\hat{x}/\theta)+\sigma_{\hat{\xi}_1}(\hat{x}/\theta^*)-\sigma_{\hat{\xi}_1}(\hat{x}/\theta^*)+\sigma_{\hat{\xi}_1}(x/\theta^*)-\sigma_{\hat{\xi}_1}(x/\theta^*) \\
&= \sigma_{(\xi_1}-\sigma_{\hat{\xi}_1}(\hat{x}/\theta^*))+\sigma_{\hat{\xi}_1}((\hat{x}/\theta^*)-\sigma(\hat{x}/\theta))+\sigma_{\hat{\xi}_1}((x/\theta^*)-\sigma(\hat{x}/\theta^*)) \\
&= (\sigma_{\xi_1}-\sigma_{\hat{\xi}_1}(\hat{x}/\theta^*))+\sigma_{\tilde{\theta}^T\omega}(\hat{x})+\sigma_{\theta^{*T}(\omega}(x)-\sigma_\omega(\hat{x})),
\end{aligned}
$$

$$
\gamma_{\xi_1}(xt_ct_c)-\gamma_{\hat{\xi}_1}(\hat{x}/\theta) \ = \ 1-[\mu_{\xi_1}(xt_ct_c)-\mu\hat{\xi}_1(\hat{x}/\theta)] \tag{3.14}
$$

and

$$
P(A_{1i}-L_iC)^T+(A_{1i}-L_iC)P+R+D_0+D_1+PA_{2i}R^{-1}A_{2i}^TP \leq -Q_i. \tag{3.15}
$$

Now, the equation (3.13) become

$$\begin{aligned}
\mu_{\mathbb{L}V} t_c &\leq \textstyle\sum_{i=1}^{r} \mu_i e^T(-Q_i)e + 2e^T PB(\xi_1(xt_ct_c) - \hat{\xi}_1(\hat{x}/\theta) + \hat{\xi}_1(\hat{x}/\theta^*) - \hat{\xi}_1(\hat{x}/\theta^*) + \hat{\xi}_1(x/\theta^*) \\
&\quad -\hat{\xi}_1(x/\theta^*)) - 2e^T PB(u_1) + 2e^T PB(\xi_2(x(t_c-\tau_c)t_c)) - 2e^T PBu_2 - \tfrac{1}{\eta} tr(\tilde{\theta}^T\dot{\theta}) - \tfrac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1 - \tfrac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2 \\
&\leq \textstyle\sum_{i=1}^{r} \mu_i e^T(-Q_i)e + 2e^T PB(\xi_1 - \hat{\xi}_1(\hat{x}/\theta^*)) + 2e^T PB(\tilde{\theta}^T\omega(\hat{x})) + 2e^T PB(\theta^{*T}(\omega(x) - \omega(\hat{x}))) \\
&\quad -2e^T PB(u_1) + 2e^T PB(\xi_2(x(t_c-\tau_c)t_c)) - 2e^T PBu_2 - \tfrac{1}{\eta} tr(\tilde{\theta}^T\dot{\theta}) - \tfrac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1 - \tfrac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2 \\
&\leq \textstyle\sum_{i=1}^{r} \mu_i e^T(-Q_i)e + 2\gamma\|e\|^2\|C\| M_\theta + \tfrac{1}{\eta} tr[\tilde{\theta}^T(2\eta\omega\hat{x}e^T PB - \dot{\theta})] \\
&\quad +2e^T PB(\hat{\xi}_1 - u_1) + 2e^T PB(\hat{\xi}_2 - u_2) + \tfrac{1}{\eta_1}(2\eta_1 e^T PB - \dot{\hat{\xi}}_1) + \tfrac{1}{\eta_2}(2\eta_2 e^T PB - \dot{\hat{\xi}}_2)\tilde{\xi}_2 \\
\sigma_{LV} t_c &\leq \textstyle\sum_{i=1}^{r} \sigma_i e^T(-Q_i)e + 2\gamma\|e\|^2\|C\| M_\theta + \tfrac{1}{\eta} tr[\tilde{\theta}^T(2\eta\omega\hat{x}e^T PB - \dot{\theta})] \\
&\quad +2e^T PB(\hat{\xi}_1 - u_1) + 2e^T PB(\hat{\xi}_2 - u_2) + \tfrac{1}{\eta_1}(2\eta_1 e^T PB - \dot{\hat{\xi}}_1) + \tfrac{1}{\eta_2}(2\eta_2 e^T PB - \dot{\hat{\xi}}_2)\tilde{\xi}_2 \\
&\text{and} \\
\gamma_{\mathbb{L}V} t_c &\geq 1 - [\mu_{\mathbb{L}V} t_c]
\end{aligned} \tag{3.16}$$

Now applying adaptive updating law (3.4) and (3.4) into (3.16), which yields

$$\mathbb{L}Vt_c \leq -e^T\beta e, \ \beta > 0 \tag{3.17}$$

Therefore

$$dVt_c = -e^T\beta e + 2e^T Pgt_c dwt_c \tag{3.18}$$

Taking expectation, then it follows that

$$\mathbb{E}[dVt_c] = \mathbb{E}[-e^T\beta e] + \mathbb{E}[2e^T Pgt_c dwt_c]. \tag{3.19}$$

Then it follows

$$dvt_c \leq -e^T\beta e. \tag{3.20}$$

Therefore $V \in L_\infty$, which indicate that $e, \ \tilde{\theta}, \ \tilde{\xi}_1, \ \tilde{\xi}_2, \ u_1, \ u_2 \in L_\infty$.

Integrating (3.20) from 0 to ∞ result in

$$\beta\int_0^\infty ee^T dt < V(0) - V(\infty) < \infty. \tag{3.21}$$

That mean that $e \in L_2$, applying the Lipschitz condition to the neutrosophic estimation lead to that $\dot{e} \in L_\infty$. Based on the Barbalat lemma, one may conclude that $e \to 0$ as $t \to \infty$.

Which is asymptotically stable in mean square.□

For neutrosophic observer, the output feedback control scheme is applied to stochastic chaotic time-delay.

The output feedback for a stochastic chaotic time-delay system is

$$\begin{aligned} \mu_{dx}t_c &= [\sum_{i=1}^{r}\mu_i(z)(\mu_{A_{1i}}+\Delta\mu_{A_{1i}})xt_c+(\mu_{A_{2i}}+\Delta\mu_{A_{2i})}(x(t_c-\tau_c))+\mu_{Bu}t_c]dt+ \\ &\quad [\sum_{i=1}^{r}\mu_l(z)(\mu_{A_{3i}}+\Delta\mu_{A_{3i}})xt_c+(\mu_{A_{4i}}+\Delta\mu_{A_{4i}})(x(t_c-\tau_c))+\mu_{Bu}t_c]\mu_{dw}t_c \\ \sigma_{dx}t_c &= [\sum_{i=1}^{r}\sigma_i(z)(\sigma_{A_{1i}}+\Delta\sigma_{A_{1i}})xt_c+(\sigma_{A_{2i}}+\Delta\sigma_{A_{2i})}(x(t_c-\tau_c))+\sigma_{Bu}t_c]dt+ \\ &\quad [\sum_{i=1}^{r}\sigma_l(z)(\sigma_{A_{3i}}+\Delta\sigma_{A_{3i}})xt_c+(\sigma_{A_{4i}}+\Delta\sigma_{A_{4i}})(x(t_c-\tau_c))+\sigma_{Bu}t_c]\sigma_{dw}t_c \\ \gamma_{dx} &= 1-\mu_{dx}t_c \\ &\text{and} \\ yt_c &= Cxt_c \end{aligned} \tag{3.22}$$

and the corresponding neutrosophic observer is

$$\begin{aligned} \mu_{d\hat{x}}t_c &= [\sum_{i=1}^{r}\mu_i(z)(\mu_{\mu_{A_{1i}}}\hat{x}t_c+\mu_{A_{2i}}t_c)x(t_c-\tau_c)+\mu_{L_i}(yt_c-\hat{y}t_c)-\mu_{BK_i}\hat{x}t_c]dt \\ &\quad +[\sum_{i=1}^{r}\mu_i(z)(\mu_{A_{3i}}\hat{x}t_c+\mu_{A_{3i}}t_c)x(t_c-\tau_c)+\mu_{L_i}(yt_c-\hat{y}t_c)-\mu_{BK_i}\hat{x}t_c]\mu_{dw}t_c \\ \sigma_{d\hat{x}}t_c &= [\sum_{i=1}^{r}\sigma_i(z)(\sigma_{\mu_{A_{1i}}}\hat{x}t_c+\mu_{A_{2i}}t_c)x(t_c-\tau_c)+\mu_{L_i}(yt_c-\hat{y}t_c)-\mu_{BK_i}\hat{x}t_c]dt \\ &\quad +[\sum_{i=1}^{r}\mu_i(z)(\mu_{A_{3i}}\hat{x}t_c+\mu_{A_{3i}}t_c)x(t_c-\tau_c)+\mu_{L_i}(yt_c-\hat{y}t_c)-\mu_{BK_i}\hat{x}t_c]\mu_{dw}t_c \\ \gamma_{d\hat{x}}t_c &= 1-\mu_{dx}t_c \\ &\text{and} \\ \hat{y}t_c &= C\hat{x}t_c. \end{aligned} \tag{3.23}$$

Now the system can be represented as

$$\begin{aligned} \mu_{dx}t_c &= \sum_{i=1}^{r}\mu_i(z)[\mu_{A_{1i}}xt_c+\mu_{A_{2i}}x(t_c-\tau_c)+\mu_{B\xi_1}(xt_ct_c)+\mu_{B\xi_2}(x(t_c-\tau_c)t_c)+\mu_B ut_c]dt \\ &\quad +\sum_{i=1}^{r}\mu_i(z)[\mu_{A_{3i}x}t_c+\mu_{A_{4i}x}(t_c-\tau_c)+\mu_{B\xi_1}(xt_ct_c)+\mu_{B\xi_2}(x(t_c-\tau_c)t_c)+\mu_B ut_c]\mu_{dw}t_c \\ \sigma_{dx}t_c &= \sum_{i=1}^{r}\sigma_i(z)[\sigma_{A_{1i}}xt_c+\sigma_{A_{2i}}x(t_c-\tau_c)+\sigma_{B\xi_1}(xt_ct_c)+\sigma_{B\xi_2}(x(t_c-\tau_c)t_c)+\sigma_B ut_c]dt \\ &\quad +\sum_{i=1}^{r}\sigma_i(z)[\mu_{A_{3i}x}t_c+\sigma_{A_{4i}x}(t_c-\tau_c)+\sigma_{B\xi_1}(xt_ct_c)+\sigma_{B\xi_2}(x(t_c-\tau_c)t_c)+\sigma_B ut_c]\sigma_{dw}t_c \\ \gamma_{dx}t_c &= 1-\mu_{dx}t_c \\ &\text{and} \\ yt_c &= Cxt_c. \end{aligned} \tag{3.24}$$

Theorem 3.2 Let the neutrosophic controller in (3.24) be chosen as

$$\begin{aligned} \mu_{ut_c} &= \textstyle\sum_{l=1}^{r}\mu_i[-\mu_{K_i}-\mu_{L_i}\mu_M]\hat{x}-\mu_{\hat{\xi}_1}(\hat{x}/\theta)-u_1-u_2, \\ \sigma_{ut_c} &= \textstyle\sum_{l=1}^{r}\sigma_i[-\sigma_{K_i}-\sigma_{L_i}\sigma_M]\hat{x}-\sigma_{\hat{\xi}_1}(\hat{x}/\theta)-u_1-u_2, \\ \gamma_{ut_c} &= 1-\mu_u t_c \end{aligned} \tag{3.25}$$

where M is a positive definite matrix and $K_i$is neutrosophic feedback gain. Suppose definitions of $\hat{\xi}_1(\hat{x}/\theta)$, u_1, u_2, and the stability conditions in theorem(1) hold. If the positive definite neutrosophic matrices M, W, U, V_0, V_1 and N_i for $i = 1,\ 2,\ 3, \ldots, r$ exist, the following conditions are satisfied

$$(A_{1i} - BK_i)^T M + M(A_{1i} - BK_i) + U + V_0 + V_1 + MA_{2i}U^{-1}A_{2i}^T M^T \leq -N_i \vee i \tag{3.26}$$

the observer-based control system is asymptotically mean square stable.
Proof: Consider the Lyapunov-Krasovskii functional as follows:

$$\begin{aligned}
Vt_c &= \hat{x}^T M\hat{x} + e^T Pe + \tfrac{1}{2\eta}\text{tr}(\tilde{\theta}^T\tilde{\theta}) + \tfrac{1}{2\eta}\tilde{\xi}_1^2 + \tfrac{1}{2\eta}\tilde{\xi}_2^2 + \\
&\quad \textstyle\int_{t-\tau_c}^{t} e^T(\sigma)Se(\sigma)d\sigma + \int_{t-\tau_c}^{t} \hat{x}^T(\sigma)S\hat{x}(\sigma)d\sigma, \\
\mu_{\mathbb{L}V}t_c &= [\sum_{i=1}^{r}\mu_i(2\hat{x}^T(\mu_{A_{1i}} - \mu_B\mu_{K_i)}\hat{x}t_c + 2\hat{x}^T\mu_{A_{2i}}\hat{x}(t_c-\tau_c)) + 2\hat{x}^T\mu_M\mu_{L_i}\mu_C e] \\
&\quad +[\sum_{i=1}^{r}\mu_i[2e^T\mu_P(\mu_{A_{1i}} - \mu_{L_iC)}et_c + 2e^T\mu_P\mu_{A_{2i}}e(t_c-\tau_c)]] + 2e^T\mu_P\mu_B\mu_{\xi_1} \\
&\quad +2e^T\mu_P\mu_B\mu_{\xi_2} + 2e^T\mu_P\mu_B ut_c + 2e^T\mu_P\mu_B\mu_{K_i}\hat{x} - \tfrac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta}) - \tfrac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1 \\
&\quad -\tfrac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2 - e^T t_c Set_c - e^T(t_c-\tau_c)\mu_S e(t_c-\tau_c) + \hat{x}^T\mu_W\hat{x} - \hat{x}(t_c-\tau_c)^T\mu_W\hat{x}(t_c-\tau_c) + \\
&\quad g^T t_c\mu_w gt_c + g^T t_c\mu_P gt_c \\
\sigma_{\mathbb{L}V}t_c &= [\sum_{i=1}^{r}\sigma_i(2\hat{x}^T(\sigma_{A_{1i}} - \sigma_B\sigma_{K_i)}\hat{x}t_c + 2\hat{x}^T\sigma_{A_{2i}}\hat{x}(t_c-\tau_c)) + 2\hat{x}^T\sigma_M\sigma_{L_i}\sigma_C e] \\
&\quad +[\sum_{i=1}^{r}\sigma_i[2e^T\sigma_P(\sigma_{A_{1i}} - \sigma_{L_iC)}et_c + 2e^T\sigma_P\sigma_{A_{2i}}e(t_c-\tau_c)]] + 2e^T\sigma_P\sigma_B\sigma_{\xi_1} \\
&\quad +2e^T\sigma_P\sigma_B\sigma_{\xi_2} + 2e^T\sigma_P\sigma_B ut_c + 2e^T\sigma_P\sigma_B\sigma_{K_i}\hat{x} - \tfrac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta}) - \tfrac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1 \\
&\quad -\tfrac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2 - e^T t_c Set_c - e^T(t_c-\tau_c)\sigma_S e(t_c-\tau_c) + \hat{x}^T\sigma_W\hat{x} - \hat{x}(t_c-\tau_c)^T\sigma_W\hat{x}(t_c-\tau_c) + \\
&\quad g^T t_c\sigma_w gt_c + g^T t_c\sigma_P gt_c \\
\gamma_{\mathbb{L}V}t_c &= 1 - \mu_{LV}t_c
\end{aligned} \tag{3.27}$$

Now consider the relation

$$\begin{aligned}
g^T t_c W gt_c &\leq \hat{x}^T V_0\hat{x} + \hat{x}^T(t_c-\tau_c)V_1\hat{x}(t_c-\tau_c) \\
g^T t_c P gt_c &\leq e^T D_0 e + e^T(t_c-\tau_c)D_1 e(t_c-\tau_c)
\end{aligned} \tag{3.28}$$

$$\begin{aligned}
\mu_{\mathbb{L}V}t_c &\leq \sum_{i=1}^{r}\mu_i et_c^T[(\mu_{A_{1i}} - \mu_{L_i}\mu_C)^T\mu_P + \mu_P(\mu_{A_{1i}} - \mu_{L_i}\mu_C) + \mu_R + \mu_{D_0} + \mu_{D_1} + \mu_P\mu_{A_{2i}R^{-1}}\mu_{A_{2i}^T}\mu_P]et_c \\
&\quad +2e^T\mu_P\mu_B\xi_1 + 2e^T\mu_P\mu_B\xi_2 + 2e^T PBut_c - \tfrac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta}) - \tfrac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1 - \tfrac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2 \\
&\quad +\sum_{i=1}^{r}\mu_i 2\hat{x}^T\mu_M\mu_{L_i}\mu_C e + \sum_{i=1}^{r}\mu_i\hat{x}^T[(\mu_{A_{1i}} - \mu_B\mu_{K_i})^T\mu_M \\
&\quad +\mu_M(\mu_{A_{1i}} - \mu_B\mu_{K_i}) + \mu_M\mu_{A_{2i}}\mu_{U^{-1}}\mu_{A_{2i}^T}\mu_M + \mu_U + \mu_{V_0} + \mu_{V_1}]\hat{x}t_c \\
\sigma_{\mathbb{L}V}t_c &\leq \sum_{i=1}^{r}\sigma_i et_c^T[(\sigma_{A_{1i}} - \sigma_{L_i}\sigma_C)^T\sigma_P + \sigma_P(\sigma_{A_{1i}} - \sigma_{L_i}\sigma_C) + \sigma_R + \sigma_{D_0} + \sigma_{D_1} + \sigma_P\sigma_{A_{2i}R^{-1}}\sigma_{A_{2i}^T}\sigma_P]et_c \\
&\quad +2e^T\sigma_P\sigma_B\xi_1 + 2e^T\sigma_P\sigma_B\xi_2 + 2e^T PBut_c - \tfrac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta}) - \tfrac{1}{\eta_1}\tilde{\xi}_1\dot{\hat{\xi}}_1 - \tfrac{1}{\eta_2}\tilde{\xi}_2\dot{\hat{\xi}}_2 \\
&\quad +\sum_{i=1}^{r}\sigma_i 2\hat{x}^T\sigma_M\sigma_{L_i}\sigma_C e + \sum_{i=1}^{r}\sigma_i\hat{x}^T[(\sigma_{A_{1i}} - \sigma_B\sigma_{K_i})^T\sigma_M \\
&\quad +\sigma_M(\sigma_{A_{1i}} - \sigma_B\sigma_{K_i}) + \sigma_M\sigma_{A_{2i}}\sigma_{U^{-1}}\sigma_{A_{2i}^T}\sigma_M + \sigma_U + \sigma_{V_0} + \sigma_{V_1}]\hat{x}t_c
\end{aligned}$$

$$\gamma_{\mathbb{L}V} t_c \;=\; 1 - [\mu_{\mathbb{L}V} t_c] \tag{3.29}$$

Now we put

$$\begin{aligned} \mu_u t_c &= \textstyle\sum_{l=1}^{r} \mu_i[-\mu_{K_i} - \mu_{L_i}\mu_M]\hat{x} - \hat{\xi}_1(\hat{x}/\theta) - u_1 - u_2 \\ \sigma_u t_c &= \textstyle\sum_{l=1}^{r} \sigma_i[-\sigma_{K_i} - \sigma_{L_i}\sigma_M]\hat{x} - \hat{\xi}_1(\hat{x}/\theta) - u_1 - u_2 \\ \gamma_u t_c &= 1 - \mu_u t_c \end{aligned} \tag{3.30}$$

Therefore

$$\begin{aligned} \mu_{\mathbb{L}V} t_c &\leq \sum_{i=1}^{r} \sigma_i e t_c^T[(\mu_{A_{1i}} - \mu_{L_i}C)^T\mu_P + \mu_P(\mu_{A_{1i}} - \mu_{L_i}\mu_C) + \mu_R + \mu_{D_0} + \mu_{D_1} + \mu_P\mu_{A_{2i}}\mu_{R^{-1}}\mu_{A_{2i}^T}\mu_P]et_c \\ &\quad + 2e^T\mu_P\mu_B(\xi_1 - \mu_{\hat{\xi}_1}(\hat{x}/\theta) - u_1)2e^T\mu_P\mu_B\mu_{(\xi_2} - u_2 - \tfrac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta}) - \tfrac{1}{\mu_{\eta_1}}\tilde{\xi}_1\mu_{\dot{\hat{\xi}}_1} - \tfrac{1}{\mu_{\eta_2}}\tilde{\xi}_2\mu_{\dot{\hat{\xi}}2} \\ &\quad + \sum_{i=1}^{r} \mu_i\hat{x}^T[(\mu_{A_{1i}} - \mu_B\mu_{K_i})^T\mu_M + \mu_M(\mu_{A_{1i}} - \mu_{Bi}) + \mu_M\mu_{A_{2i}}\mu_{U^{-1}}\mu_{A_{2i}^T}\mu_M + U + V_0 + V_1]\hat{x}t_c \\ \sigma_{\mathbb{L}V} t_c &\leq \sum_{i=1}^{r} \sigma_i e t_c^T[(\sigma_{A_{1i}} - \sigma_{L_i}C)^T\sigma_P + \sigma_P(\sigma_{A_{1i}} - \sigma_{L_i}\sigma_C) + \sigma_R + \sigma_{D_0} + \sigma_{D_1} + \sigma_P\sigma_{A_{2i}}\sigma_{R^{-1}}\sigma_{A_{2i}^T}\sigma_P]et_c + \\ &\quad 2e^T\sigma_P\sigma_B(\xi_1 - \sigma_{\hat{\xi}_1}(\hat{x}/\theta) - u_1)2e^T\sigma_P\sigma_B\sigma_{(\xi_2} - u_2 - \tfrac{1}{\eta}tr(\tilde{\theta}^T\dot{\theta}) - \tfrac{1}{\sigma_{\eta_1}}\tilde{\xi}_1\sigma_{\dot{\hat{\xi}}_1} - \tfrac{1}{\sigma_{\eta_2}}\tilde{\xi}_2\sigma_{\dot{\hat{\xi}}2} \\ &\quad + \sum_{i=1}^{r} \sigma_i\hat{x}^T[(\sigma_{A_{1i}} - \sigma_B\sigma_{K_i})^T\sigma_M + \sigma_M(\sigma_{A_{1i}} - \sigma_{Bi}) + \sigma_M\sigma_{A_{2i}}\sigma_{U^{-1}}\sigma_{A_{2i}^T}\sigma_M + U + V_0 + V_1]\hat{x}t_c \\ \gamma_{\mathbb{L}V} t_c &\leq 1 - \mu_{LV} t_c \end{aligned} \tag{3.31}$$

adopting the results from the theorem 1 yields

$$\begin{aligned} \mu_{\mathbb{L}V} t_c &\leq -\beta e^T e + \sum_{i=1}^{r} \mu_i\hat{x}^T[(\mu_{A_{1i}} - \mu_B\mu_{K_i})^T\mu_M + \mu_M(\mu_{A_{1i}} - \mu_B\mu_{K_i}) \\ &\quad + \mu_M\mu_{A_{2i}}\mu_{U^{-1}}\mu_{A_{2i}^T}\mu_M + \mu_U + \mu V_0 + \mu_{V_1}]\hat{x}t_c \\ \sigma_{\mathbb{L}V} t_c &\leq -\beta e^T e + \sum_{i=1}^{r} \sigma_i\hat{x}^T[(\sigma_{A_{1i}} - \sigma_B\sigma_{K_i})^T\sigma_M + \sigma_M(\sigma_{A_{1i}} - \sigma_B\sigma_{K_i}) \\ &\quad + \sigma_M\sigma_{A_{2i}}\sigma_{U^{-1}}\sigma_{A_{2i}^T}\sigma_M + \sigma_U + \sigma V_0 + \sigma_{V_1}]\hat{x}t_c \\ \gamma_{\mathbb{L}V} t_c &\geq 1 - \mu_{\mathbb{L}V} t_c \end{aligned} \tag{3.32}$$

Given the stability conditions (3.26), it follows that

$$\begin{aligned} \mathbb{L}V t_c &\leq -\beta e^T e - \textstyle\sum_{i=1}^{r} \mu_i \lambda_{min}(N_i)\, \|\hat{x}\|^2, \\ &\leq \beta e^T e - \alpha\hat{x}^T\hat{x},\ \alpha > 0 \end{aligned} \tag{3.33}$$

Therefore

$$dVt_c = -e^T\beta e - \alpha\hat{x}^T\hat{x} + 2e^TPgt_c dwt_c \tag{3.34}$$

Taking expectation, then it follows that

$$\begin{aligned} \mathbb{E}[dVt_c] &= \mathbb{E}[(-e^T\beta e - \alpha\hat{x}^T\hat{x})] + \mathbb{E}[2e^TPgt_c dwt_c] \\ dvt_c &\leq -e^T\beta e - \alpha\hat{x}^T\hat{x} \end{aligned}$$

Using the Barbalat lemma, both e and $\hat{x}$ will eventually approach zero.□

As a general rule, a tumultuous framework has unsound fixed focuses or temperamental circles. The synchronization of the framework typically centers around fostering a control technique that powers framework directions to join to unsound fixed places or circles.

The stochastic time postpone tumultuous framework is planned as the following reference model.

The neutrosophic reference model for stochastic time-delay chaotic system is

$$\begin{aligned}
\mu_{dx_m}t_c &= [\sum_{i=1}^{r}\mu_i(\mu_{\overline{A}_{1i}}x_mt_c+\mu_{\overline{A}_{2i}}x_m(t_c-\tau_c)+\mu_{\overline{B}_i}rt_c)]dt \\
&\quad +[\sum_{i=1}^{r}\mu_i(\mu_{\overline{A_{3i}}}x_mt_c+\mu_{\overline{A}_{4i}}x_m(t_c-\tau_c)+\mu_{\overline{B}_i}rt_c)]\mu_{dw}t_c, \\
\sigma_{dx_m}t_c &= [\sum_{i=1}^{r}\sigma_i(\sigma_{\overline{A}_{1i}}x_mt_c+\sigma_{\overline{A}_{2i}}x_m(t_c-\tau_c)+\sigma_{\overline{B}_i}rt_c)]dt \\
&\quad +[\sum_{i=1}^{r}\sigma_i(\sigma_{\overline{A_{3i}}}x_mt_c+\sigma_{\overline{A}_{4i}}x_m(t_c-\tau_c)+\sigma_{\overline{B}_i}rt_c)]\sigma_{dw}t_c, \\
\gamma_{dx_m}t_c &= 1-\mu_{dx_m}(t_c-\tau_c) \\
\text{and} & \\
y_mt_c &= Cx_mt_c
\end{aligned} \tag{3.35}$$

where$\overline{A}_{1i}=A_{1i}-BK_i,\ \overline{A}_{2i}=A_{2i}\overline{A}_{3i}=A_{3i}-BK_i,\ \overline{A}_{4i}=A_{4i},\ \overline{B}_i=BK_{mi},K_{mi}$ is a known real matrix and rt_c is reference input.

The observer for tracking control is

$$\begin{aligned}
\mu_{d\hat{x}}t_c &= \sum_{i=1}^{r}[(\mu_{A_{1i}}-\mu_B\mu_{K_i})\hat{x}t_c+\mu_{A_{2i}}\hat{x}(t_c-\tau_c)+\mu_{L_i}(yt_c-\hat{y}t_c)+\mu_B\mu_{K_{mi}}rt_c]dt \\
&\quad +\sum_{i=1}^{r}[(\mu_{A_{3i}}-\mu_B\mu_{K_i})\hat{x}t_c+\mu_{A_{4i}}\hat{x}(t_c-\tau_c)+\mu_{L_i}(yt_c-\hat{y}t_c)+\mu_B\mu_{K_{mi}}rt_c]\mu_{dw}t_c \\
\sigma_{d\hat{x}}t_c &= \sum_{i=1}^{r}[(\sigma_{A_{1i}}-\sigma_B\sigma_{K_i})\hat{x}t_c+\sigma_{A_{2i}}\hat{x}(t_c-\tau_c)+\sigma_{L_i}(yt_c-\hat{y}t_c)+\sigma_B\sigma_{K_{mi}}rt_c]dt \\
&\quad +\sum_{i=1}^{r}[(\sigma_{A_{3i}}-\sigma_B\sigma_{K_i})\hat{x}t_c+\sigma_{A_{4i}}\hat{x}(t_c-\tau_c)+\sigma_{L_i}(yt_c-\hat{y}t_c)+\sigma_B\sigma_{K_{mi}}rt_c]\sigma_{dw}t_c \\
\gamma_{d\hat{x}}t_c &= 1-\mu_{d\hat{x}}t_c \\
\hat{y}t_c &= C\hat{x}t_c.
\end{aligned} \tag{3.36}$$

Therefore the neutrosophic reference model can be written as

$$\begin{aligned}
\mu_{dx_m}t_c = \sum_{i=1}^{r}\sigma_i[(\mu_{A_{1i}}-\mu_B\mu_{K_i})x_mt_c+\mu_{A_{2i}}x_m(t_c-\tau_c)+\mu_B\mu_{K_{mi}}rt_c]dt \\
+\sum_{i=1}^{r}\mu_i[(\mu_{A_{3i}}-\mu_B\mu_{K_i})x_mt_c+\mu_{A_{4i}}x_m(t_c-\tau_c)+\mu_B\mu_{K_{mi}}rt_c]\mu_{dw}t_c
\end{aligned} \tag{3.37}$$

$$\begin{aligned}
\sigma_{dx_m}t_c = \sum_{i=1}^{r}\sigma_i[(\sigma_{A_{1i}}-\sigma_B\sigma_{K_i})x_mt_c+\sigma_{A_{2i}}x_m(t_c-\tau_c)+\mu_B\sigma_{K_{mi}}rt_c]dt \\
+\sum_{i=1}^{r}\sigma_i[(\sigma_{A_{3i}}-\sigma_B\sigma_{K_i})x_mt_c+\sigma_{A_{4i}}x_m(t_c-\tau_c)+\sigma_B\sigma_{K_{mi}}rt_c]\sigma_{dw}t_c
\end{aligned} \tag{3.38}$$

$$\begin{aligned} \gamma_{dx_m}t_c &= 1-\mu_{dx_m}t_c \qquad (3.39)\\ \text{and} & \\ y_mt_c &= Cx_mt_c. \qquad (3.40)\end{aligned}$$

Define the error vectors $et_c = xt_c - \hat{x}_mt_c,\ \overline{x}t_c = x_mt_c - \hat{x}t_c$ The error dynamics system of et_c and $\overline{x}$ is

$$\begin{aligned}
\mu_{de}t_c &= \sum_{i=1}^{r}\mu_i[(\mu_{A_{1i}}-\mu_{L_i}\mu_C)et_c+\mu_{A_{2i}}e(t_c-\tau_c)+\mu_B\xi_2-\mu_B\mu_{K_{mi}}rt_c+\mu_But_c]dt\\
&+\sum_{i=1}^{r}\mu_i[(\mu_{A_{3i}}-\mu L_i\mu_C)et_c+\mu_{A_{4i}}e(t_c-\tau_c)+\mu_B\xi_2-\mu_B\mu_{K_{mi}}rt_c+\mu_But_c]\mu_{dw}t_c\\
\sigma_{de}t_c &= \sum_{i=1}^{r}\sigma_i[(\sigma_{A_{1i}}-\sigma_{L_i}\sigma_C)et_c+\sigma_{A_{2i}}e(t_c-\tau_c)+\sigma_B\xi_2-\sigma_B\sigma_{K_{mi}}rt_c+\sigma_But_c]dt\\
&+\sum_{i=1}^{r}\sigma_i[(\sigma_{A_{3i}}-\sigma L_i\sigma_C)et_c+\sigma_{A_{4i}}e(t_c-\tau_c)+\sigma_B\xi_2-\sigma_B\sigma_{K_{mi}}rt_c+\sigma_But_c]\sigma_{dw}t_c\\
\gamma_{de}t_c &= 1-\mu_{de}t_c\\
\text{and} & \qquad (3.41)\\
\mu_{d\overline{x}} &= \sum_{i=1}^{r}\mu_i[(\mu_{A_{1i}}-\mu_B\mu_{K_i})\overline{x}t_c+\mu A_{2i}\overline{x}(t_c-\tau_c)-\mu_{L_i}\mu_{C\overline{x}}t_c]dt\\
&+\sum_{i=1}^{r}\mu_i[(\mu_{A_{3i}}-\mu_B\mu_{K_i})\overline{x}t_c+\mu_{A_{4i}}\overline{x}(t_c-\tau_c)-\mu_{L_i}\mu_{C\overline{x}}t_c]\mu_{dw}t_c\\
\sigma_{d\overline{x}} &= \sum_{i=1}^{r}\sigma_i[(\sigma_{A_{1i}}-\sigma_B\sigma_{K_i})\overline{x}t_c+\sigma A_{2i}\overline{x}(t_c-\tau_c)-\sigma_{L_i}\sigma_{C\overline{x}}t_c]dt\\
&+\sum_{i=1}^{r}\sigma_i[(\sigma_{A_{3i}}-\sigma_B\sigma_{K_i})\overline{x}t_c+\sigma_{A_{4i}}\overline{x}(t_c-\tau_c)-\sigma_{L_i}\sigma_{C\overline{x}}t_c]\sigma_{dw}t_c\\
\mu_{d\overline{x}} &= 1-\mu_{d\overline{x}}
\end{aligned}$$

Theorem 3.3 Suppose that the fuzzy controller in (3.24) is

$$\begin{aligned}
\mu_ut_c &= \textstyle\sum_{i=1}^{r}\mu_i(-\mu_{K_i}\hat{x}-\mu_{Li}\mu_M\hat{x}+\mu_{Kmi}rt_c)-\hat{\xi}_1(\hat{x}/\theta)-u_1-u_2,\\
\sigma_ut_c &= \textstyle\sum_{i=1}^{r}\sigma_i(-\sigma_{K_i}\hat{x}-\sigma_{Li}\sigma_M\hat{x}+\sigma_{Kmi}rt_c)-\hat{\xi}_1(\hat{x}/\theta)-u_1-u_2, \qquad (3.42)\\
\mu_ut_c &= 1-\mu_ut_c
\end{aligned}$$

and the stability conditions addressed in Theorems 3.1 and 3.2 hold. Then, the mean square asymptotic stabilities of the closed-loop systems (3.41) are guaranteed.

Proof: The Lyapunov − Krasovskii functional candidate is chosen as

$$\begin{aligned}
Vt_c &= \overline{x}^TM\overline{x}+e^TPe+\tfrac{1}{2\eta}tr(\tilde{\theta^T}\tilde{\theta})+\tfrac{1}{2\eta}\tilde{\xi}_1^2+\tfrac{1}{2\eta}\tilde{\xi}_2^2+\\
&\int_{t-\tau_c}^{t}e^T(\sigma)Se(\sigma)d\sigma+\int_{t-\tau_c}^{t}\overline{x}^T(\sigma)S\overline{x}(\sigma)d\sigma \qquad (3.43)
\end{aligned}$$

Suppose the derivative of (3.43) as

$$\begin{aligned}
\mu_{\mathbb{L}V}t_c \le & \sum_{i=1}^{r}\mu_i\, e^T[(\mu_{A_{1i}}-\mu_{L_i}\mu_C)^T\mu_P+\mu_P(\mu_{A_{1i}}-\mu_{L_i}\mu_C)+\mu_{D_0}+\mu_{D_1}+\mu_R+\mu_P\mu_{A_{2i}}\mu_{R^{-1}}\mu_{A_{2i}}^T\mu_P]e\\
&+2e^T\mu_P\mu_B\xi_1+2e^T{}_{-}P\mu_B\xi_2+\sum_{i=1}^{r}2e^T\mu_P\mu_B\mu_{Ki}\hat{x}+\sum_{i=1}^{r}2e^TPB(-K_i)\hat{x}-2e^T\mu_P\mu_B\hat{\xi}_1(\hat{x}/\theta)\\
&-2e^T\mu_P\mu_Bu_1-2e^T\mu_P\mu_Bu_2-\sum_{i=1}^{r}\mu_i2\overline{x}^T\mu_M\mu_{Li}c\overline{x}+\sum_{i=1}^{r}\mu_i(-J)\overline{x}^T\overline{x}
\end{aligned}$$

$$
\begin{aligned}
\sigma_{\mathbb{L}V} t_c &\leq \sum_{i=1}^{r} \sigma_i\, e^T[(\sigma_{A_{1i}} - \sigma_{L_i}\sigma_C)^T\sigma_P + \sigma_P(\sigma_{A_{1i}} - \sigma_{L_i}\sigma_C) + \sigma_{D_0} + \sigma_{D_1} + \sigma_R + \sigma_P\sigma_{A_{2i}}\sigma_{R^{-1}}\sigma_{A_{2i}}^T\sigma_P]e \\
&\quad + 2e^T\sigma_P\sigma_B\xi_1 + 2e^T{}_-P\sigma_B\xi_2 + \sum_{i=1}^{r} 2e^T\sigma_P\sigma_B\sigma_{Ki}\hat{x} + \sum_{i=1}^{r} 2e^T PB(-K_i)\hat{x} - 2e^T\sigma_P\sigma_B\hat{\xi}_1(\hat{x}/\theta) \\
&\quad - 2e^T\sigma_P\sigma_B u_1 - 2e^T\sigma_P\sigma_B u_2 - \sum_{i=1}^{r}\sigma_i 2\overline{x}^T\sigma_M\sigma_{Li}c\overline{x} + \sum_{i=1}^{r}\sigma_i(-J)\overline{x}^T\overline{x} \\
\gamma_{\mathbb{L}V} t_c &\geq 1 - \mu_{\mathbb{L}V} t_c
\end{aligned} \tag{3.44}
$$

adopting the results from the theorem 1 and theorem 2 and Given the stability conditions (3.42), it follows that

$$\mathbb{L}Vt_c \leq \beta e^T e - \delta\overline{x}^T\overline{x},\ \delta > 0 \tag{3.45}$$

Therefore

$$dVt_c = -e^T\beta e - \delta\overline{x}^T\overline{x} + 2[e^T P + \overline{x}^T M]gt_c dwt_c \tag{3.46}$$

Taking expectation, then it follows that

$$
\begin{aligned}
\mathbb{E}[dVt_c] &= \mathbb{E}[(-e^T\beta e - \delta\overline{x}^T\overline{x})] + \mathbb{E}[2[e^T P + \overline{x}^T M]Pgt_c dwt_c] \\
&\leq -e^T\beta e - \delta\overline{x}^T\overline{x}
\end{aligned}
$$

Using the Barbalat lemma, both β and $\overline{x}$ will eventually approach zero.

Which is asymptotically mean square stable.

4 Numerical Simulations

Gensio-Tesi is a three-dimensional autonomous chaotic system. The system is defined by the following set of differential equations:

$$
\begin{aligned}
\dot{x}_1 &= -x_3 - x_2 \\
\dot{x}_2 &= x_1 + ax_2 \\
\dot{x}_3 &= b + x_3(x_1 - c)
\end{aligned} \tag{4.1}
$$

where a, b, and c are system parameters. The Gensio-Tesi system has been studied extensively in the field of chaos theory and has been used as a benchmark system for testing various chaos analysis methods.

The Gensio Tesi chaotic delay system is a nonlinear dynamic system that exhibits chaotic behavior. The mathematical representation of the Gensio Tesi chaotic delay system is given by the following set of delay differential equations:

$$
\begin{aligned}
\dot{x}_1 &= -ax_1 + \beta x_2(t_c - \tau_c) \\
\dot{x}_2 &= \gamma x_1 + \delta x_2(t_c - \tau_c) + \epsilon x_3(t_c - \tau_c) \\
\dot{x}_3 &= \mu x_3 + v x_1 x_2
\end{aligned} \tag{4.2}
$$

The Gensio Tesi chaotic delay system has been applied in various fields such as secure communication, chaos control, and image encryption. Its complex and unpredictable behavior makes it a useful tool in these applications.

The system exhibits chaotic behavior under certain parameter regimes, which means that small perturbations in the initial conditions can lead to vastly different outcomes over time. The delay term introduces a time lag in the system's response, while the stochastic term adds random fluctuations to the dynamics. The system

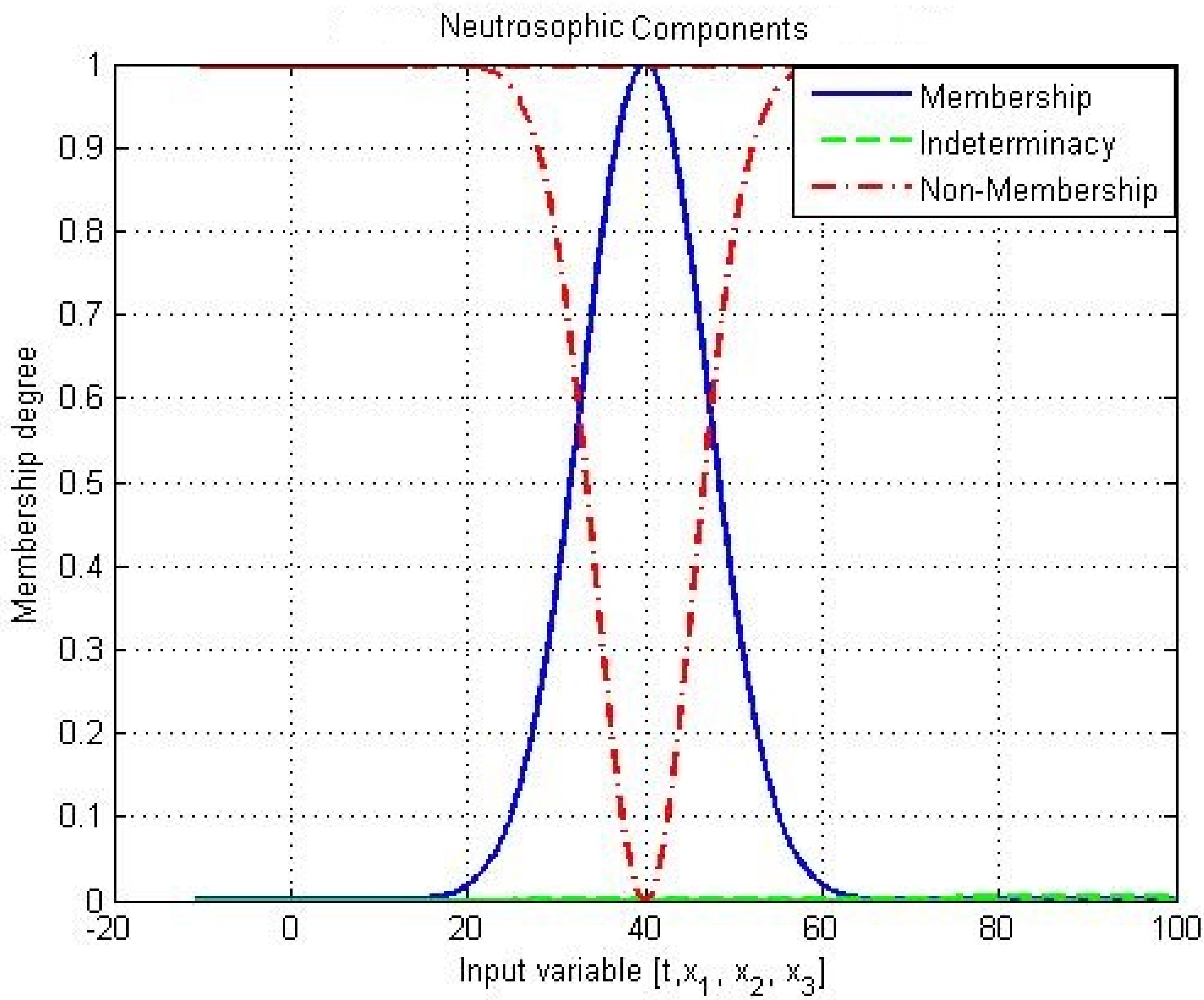

Figure 1: Neutrosophic components Function for Timet$_{c}andstatevariables$x$_1, x_2, x_3$

is defined by the following set of differential equations:

$$\begin{aligned} dx_1t_c &= [-ax_1 + \beta x_2(t_c - \tau_c)]dt + \sigma_1[-ax_1]dwt_c \\ dx_2t_c &= [\gamma x_1 + \delta x_2(t_c - \tau_c) + \epsilon x_3(t_c - \tau_c)]dt + \sigma_2[\delta x_2(t_c - \tau_c)]dwt_c \\ dx_2t_c &= [\mu x_3 + vx_1x_2]dt + \sigma_3[x_1x_2]dwt_c \end{aligned} \quad (4.3)$$

The system (4.3) is the stochastic differential equation that gives the Gensio Tesi chaotic delay system. Here $\sigma_1, \sigma_2, \sigma_3$ are the noise parameter. For this problem these parameter values are vary inbetween 0 and 1. wt_c is the *wiener.*

The MATLAB is used for numerical simulation. Calculation is performed using the exponential fuzzy components function.

Figure 1 shows neutrosophic components function for timet$_{c}andstatevariables$x$_1, x_2, x_3$.

Figure 2 shows neutrosophic components function the state variables x_1 without time t.

Figure 3 portraits neutrosophic components function the state variables x_2 without time t.

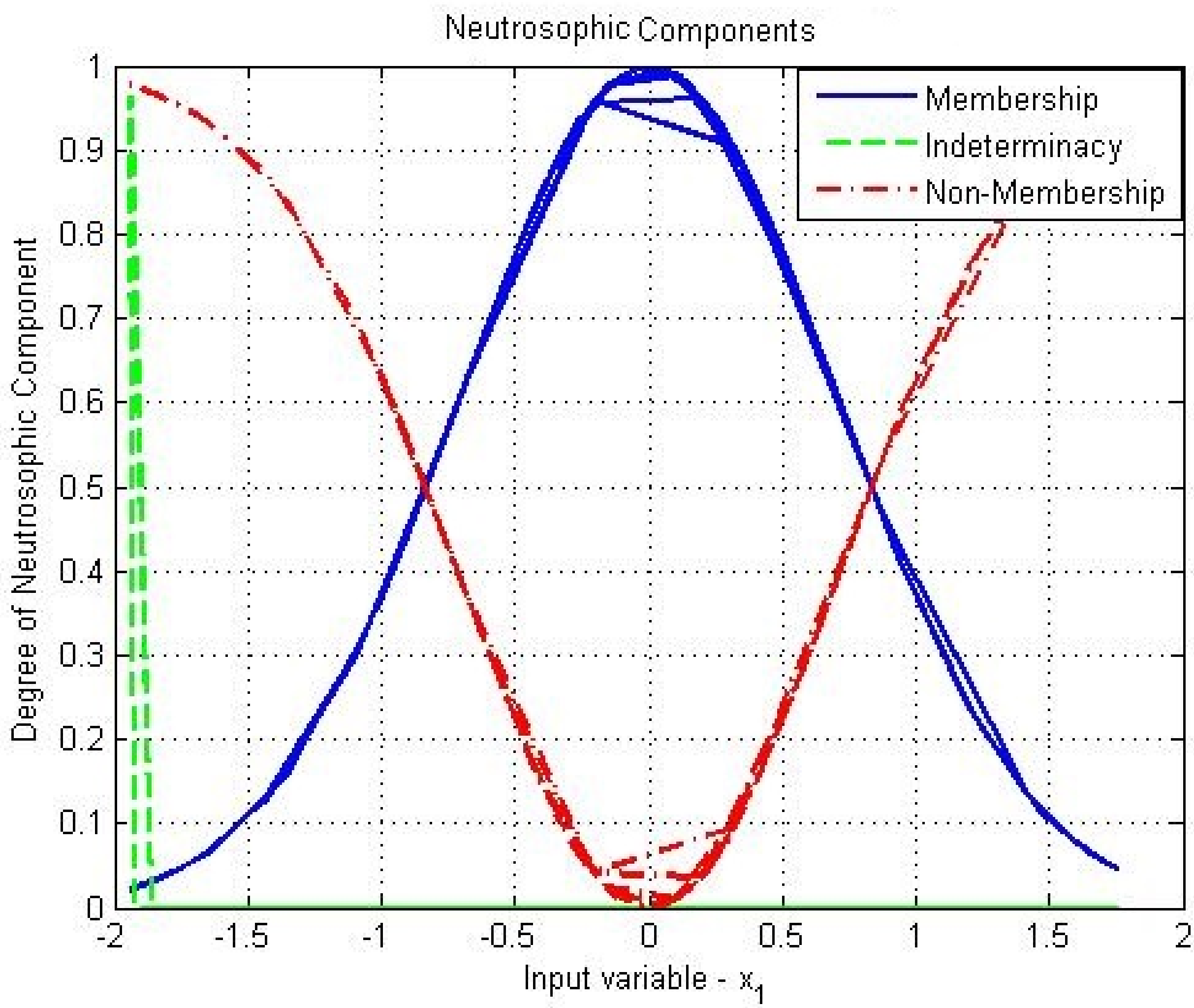

Figure 2: Neutrosophic components Function for state variables $x1$

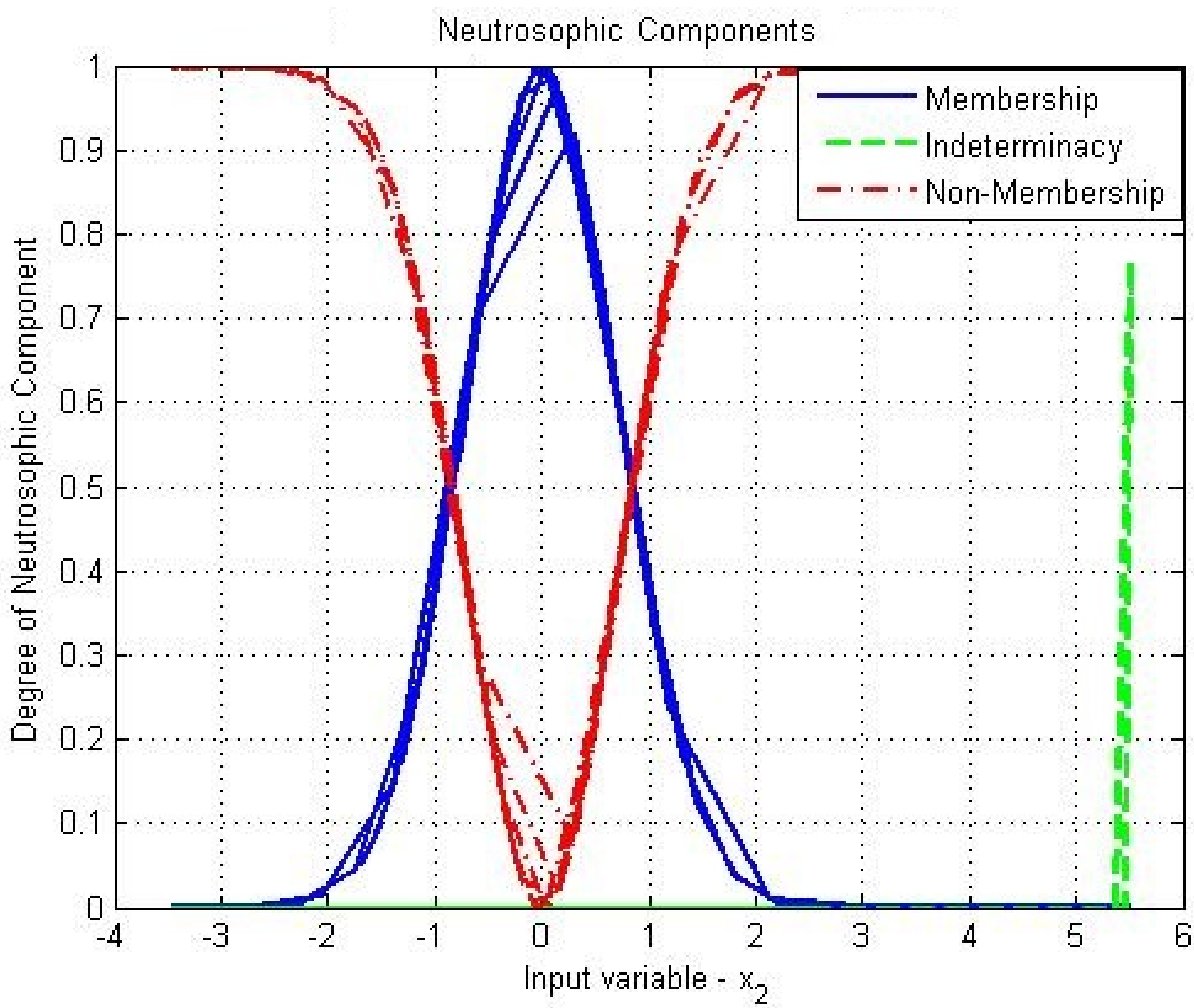

Figure 3: Neutrosophic components Function for state variables $x2$

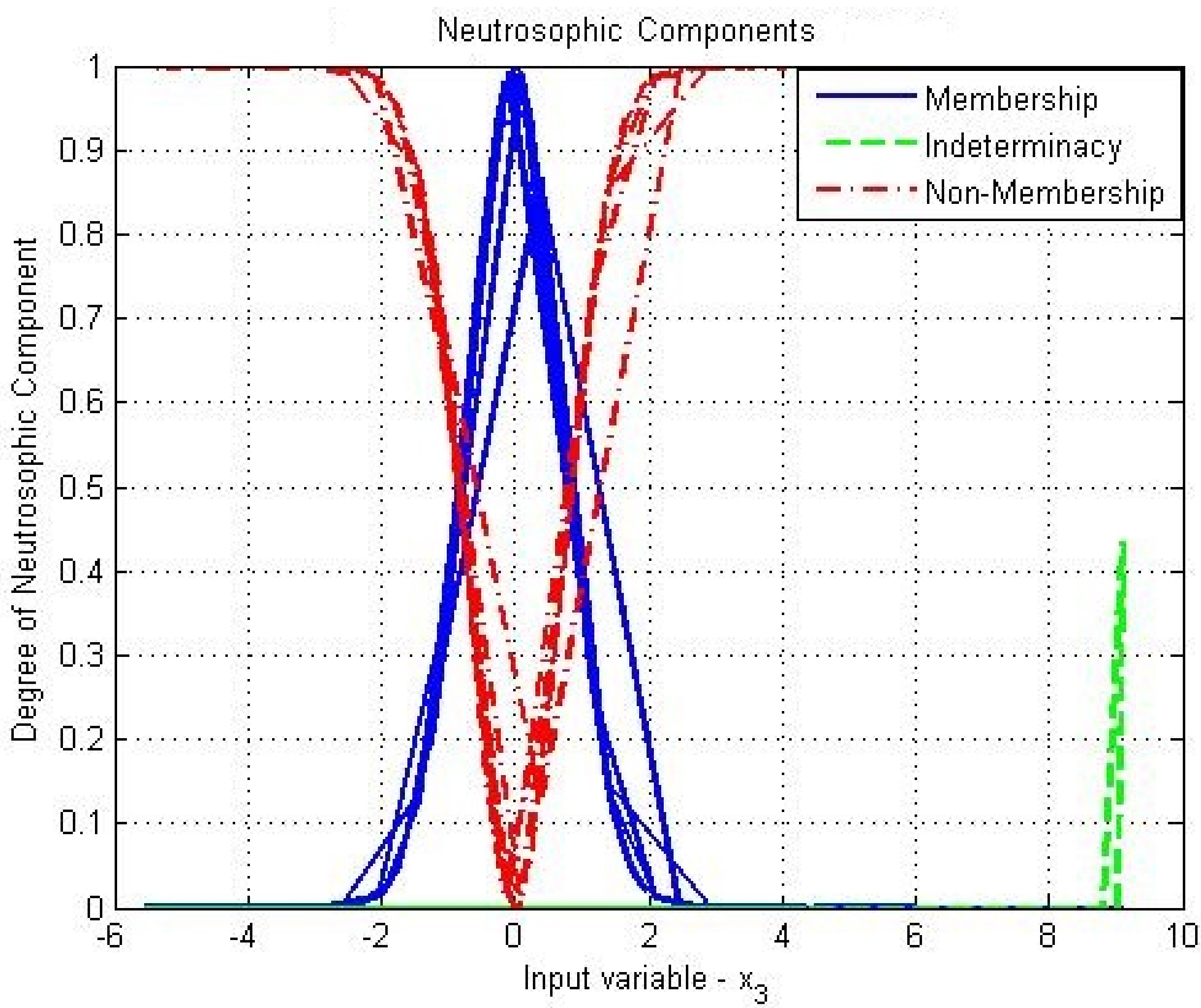

Figure 4: Neutrosophic components Function for state variables $x3$

Figure 4 portraits neutrosophic components function the state variables x_3 without time t.

5 Conclusion

This work proposes a neutrosophic T-S stochastic turbulent framework with time delay using an eyewitness based approach. A fluffy versatile administrative control strategy has been utilized to survey the asymptotic mean square soundness of tumultuous frameworks. To infer the neutrosophic versatile update regulation and control execution, direct lattice imbalance is utilized (LMI). Since the Lyapunov examples are not required for these computations, the versatile administrative control engineering is extremely proficient and advantageous for acquiring asymptotic mean square synchronization. For mathematical reenactment, the Genisio Tesi turbulent defer framework is utilized. The given hypothetical outcome is approved by the mathematical reenactment. The article is quick to address stochastic tumultuous frameworks with time delays and neutrosophic fuzzy.

References

[1] H. Fujisaka and T. Yamada, *Stability theory of synchronized motion in coupled-oscillator systems*, Progress of Theoretical Physics 63 (1983), pp.32–47.

[2] L. M. Pecora and T. L. Carroll, *Synchronizing chaotic circuits*, IEEE Trans. Circ. Sys. 38 (1991), pp.453–456.

[3] K. Murali and M. Lakshmanan, *Secure communication using a compound signal using sampled-data feedback*, Applied Mathematics and Mechanics 11 (2003), pp.1309–1315.

[4] Jiang Wang, Lisong Chen, Bin Deng, , *Synchronization of ghostburster neurons in external electrical stimulation via H_∞ variable universe fuzzy adaptive control*, Chaos, Solitons and Fractals 39 (2009), 2076–2085.

[5] F. M. Moukam Kakmeni,J. P. Nguenang, and T. C. Kofane, *Chaos synchronization in bi-axial magnets modeled by bloch equation*, Chaos, Solitons and Fractals, 30 (2006), 690–699.

[6] J.L. Hindmarsh and R. M. Rose, *A model of neuronal bursting using 3-coupled 1 st order differential equations*, Proc. Roy. Soc. Lond. B. Biol 221 (1984), 81–102.

[7] Yan-Qiu Che, Jiang Wang, Kai-Ming Tsang and Wai-Lok Chen, *Unidirectional synchronization for Hindmarsh-Rose neurons via robust adaptive sliding mode control*, Nonlinear Analysis: Real world Application 11 (2010), 1096–1104.

[8] Guang Zhao Zeng, Lan Sun Chen and Li Hua Sun, , *Complexity of an SIR epidemic dynamics model with impulsive vaccination control*, Chaos, Solitons and Fractals 26 (2005), 495–505.

[9] J. H. Park, *Adaptive control for modified projective synchronization of a four-dimensional chaotic system with uncertain parameters* , J. Computational and Applied Math. 213 (2008), 288–293.

[10] H. T. Yau, *Design of adaptive sliding mode controller for chaos synchronization with uncertainties*, Chaos, Solitons and Fractals 22 (2004), 341–347.

[11] V. Sundarapandian , *Global chaos synchronization of the Pehlivan systems by sliding mode control*, International J. Computer Science and Engineering 03 (2011), 2163-2169.

[12] V. Sundarapandian and R. Suresh, *Global chaos synchronization for Rossler and Arneodo chaotic systems by nonlinear control*, Far East Journal of Applied Mathematics 44 (2010), 137-148.

[13] Chen-Sheng Ting, *An observer-based approach to controlling time-delay chaotic systems via Takagi-Sugeno fuzzy model*, Information Sciences, An International Journal 177 (2007), 4314–4328.

[14] H. Layeghi, M. Tabe Arjmand, H. Salarieh and A. Alasry, *Stabilizing periodic orbits of chaotic systems using fuzzy adaptive sliding mode control*, Chaos, Solitons and Fractals 37 (2008), 1125–1135.

[15] M. Bonakdar, M. Samadi, H. Salarieh and A. Alasry, *Stabilizing periodic orbits of chaotic systems using fuzzy control of poincare map*, Chaos, Solitons and Fractals 36 (2008), 682–693.

[16] R. Suresh and V. Sundarapandian, *Hybrid synchronization of n-scroll Chua and Lur'e chaotic systems using backstepping control via novel feedback*, Archives of Control Sciences, 22(LVIII)(2012), pp. 255–278.

[17] R. Suresh and V. Sundarapandian, *Synchronization of n-scroll hyperchaotic Chua circuit using backstepping control with recursive feedback*, Far East Journal of Mathematical Sciences, 73(2013), pp. 73–95.

[18] R.Narmada Devi and G.Muthumari, Properties on Topologized Domination in Neutrosophic Graphs, Neutrosophic Sets and Systems, 47(2021), 511-519.

[19] R.Narmada Devi and G.Muthumari, View On Neutrosophic Over Topologized Domination Graphs, Neutrosophic Sets and Systems, Vol. 47(2021), 520-532.

[20] H. Wang, F. Smarandache, Y.Q. Zhang, R. Sunderraman, Single-valued neutrosophic sets, Multisp. Multistruct. 4(2010), 410–413.

[21] Devi, R.N, Muthumari, G., and Bravelin Jersha ,J., (2022),"Properties of Detour Central and Detour Boundary Vertices in Neutrosophic Graphs , International journal of Neutrosophic science, Vol. 18, No. 3,pp. 84-92.

[22] L. A. Zadeh. Fuzzy sets, Information and Control, 8(1965), 338–353.

[23] F. Smarandache. A Unifying Field in Logics: Neutrosophic Logic. Neutrosophy, Neutrosophic Set, Neutrosophic Probability., American Research Press, Rehoboth, NM,(1999).

Received: March 20, 2023. Accepted: July 18, 2023