



Sigmoid-function Based Fixed-time Stability of Delayed Nonlinear Dynamic Systems

Guodong Zhang^{1,*}, Ardak Kashkynbayev², Dimitrios K. Gerontitis³ and Kuo-Shou Chiu⁴

¹School of Mathematics and Statistics, South-Central Minzu University, Wuhan 430074, China

²Department of Mathematics, Nazarbayev University, Nur-Sultan 010000, Kazakhstan

³Department of Information and Electronic Engineering, International Hellenic University, Thessaloniki, Greece

⁴Departamento de Matemática, Facultad de Ciencias Básicas, Universidad Metropolitana de Ciencias de la Educación, Josó Pedro Alessandri 774, Santiago 7760197, Chile

Abstract

This paper investigates fixed-time stability of delayed nonlinear dynamic systems. At first, by designing an inequality with sigmoid-function, a new kind of fixed-time stability lemma is constructed. Then, as an application, the new proposed lemma is applied to discuss fixed-time stabilization(FT) for a kind of delayed neural networks. At last, simulations are also given to show the effectiveness of the derived results.

Keywords: fixed-time stability, nonlinear dynamic systems, fixed-time stabilization, sigmoid-function, time delays.

1 Introduction

Convergence time of fixed-time stability is finite and its upper bound is a positive constant [1]. Theoretical results about fixed-time stability have better performance and more accurate, which have

some important engineering applications. Therefore, fixed-time stability of linear or nonlinear dynamic systems has attracted widespread interests from scholars in these days, and many interesting works have been reported, e.g., see [2–4].

In 2021, by improving fixed-time stability lemma, Hu *et al.* [5] studied fixed-time synchronization(FS) of complex networks, Aouiti *et al.* [6] investigated fixed-time stabilization(FT) for delayed neural networks with inertial items. In 2023, by using aperiodically switching control, Hu *et al.* [7] discussed FT of the spatiotemporal neural networks with discontinuous right-hand side. In 2024, by using event-triggered control, Zhang *et al.* [8] showed some new results on FS of discontinuous neural networks with time delays and inertial items. In 2026, Zhou *et al.* [9] gave novel results on FT and FS of inertial memristive neural networks with switching control, and Qiao *et al.* [10] studied FS of stochastic impulsive reaction-diffusion complex networks via internal and boundary control.

Noteworthy, the fixed-time stability lemmas used in above works are mainly based on the previous work [1], which usual has two power index terms. In this paper, without using two power index terms, we will use sigmoid-function to construct a kind of



Submitted: 01 September 2025

Accepted: 24 February 2026

Published: 27 February 2026

Vol. 2, No. 1, 2026.

doi:10.62762/JNDA.2026.431637

*Corresponding author:

✉ Guodong Zhang

zgd2008@mail.scuec.edu.cn

Citation

Zhang, G., Kashkynbayev, A., Gerontitis, D. K., & Chiu, K. S. (2026). Sigmoid-function Based Fixed-time Stability of Delayed Nonlinear Dynamic Systems. *Journal of Nonlinear Dynamics and Applications*, 2(1), 13–19.

© 2026 ICCK (Institute of Central Computation and Knowledge)

fixed-time stability lemma. And by using the proposed lemma and designing proper feedback control, FT for a kind of delayed neural networks will be investigated.

The following parts of this paper are: Sigmoid-function based fixed-time stability lemma is built in Section 2. In Section 3, FT of delayed neural networks are discussed via the proposed lemma. In Section 4, simulations are provided. At last, conclusions are showed.

Notations: Let $\Delta = \{1, 2, \dots, n\}$, $\mathbf{R}^n$ is Euclidean space in n -dimensional. For $\forall z = (z_1, z_2, \dots, z_n)^T \in \mathbf{R}^n$, which 1-norm is defined as $\|z\| = \sum_{k=1}^n |z_k|$. And $\mathbf{C}([-\tau, 0], \mathbf{R}^n)$ denotes all continuous function from $[-\tau, 0]$ to $\mathbf{R}^n$, where $\tau = \max_{t \geq 0} \{\tau(t)\}$.

2 Sigmoid-function based fixed-time stability

Consider the following delayed nonlinear dynamic systems

$$\frac{dz(t)}{dt} = f(t, z(t), z(t - \tau(t))), t \geq 0, \quad (1)$$

where $z(t) = (z_1(t), z_2(t), \dots, z_n(t))$ is state variable of the systems (1), $f(\cdot) = (f_1(\cdot), f_2(\cdot), \dots, f_n(\cdot))$ is nonlinear vector function and $f : \mathbf{R} \times \mathbf{R}^n \times \mathbf{R}^n \mapsto \mathbf{R}^n$, $\tau(t)$ is time delay that satisfies $0 < \tau(t) \leq \tau$. The initial values of system (1) are $z_k(s) = \varsigma_k(s) \in \mathbf{C}([-\tau, 0], \mathbf{R})$, $k \in \Delta = \{1, 2, \dots, n\}$.

For the convenience of rest discussion, the following Assumption 1 and Definition 1 of system (1) are given.

Assumption 1. For system (1), the nonlinear function $f_k(\cdot)$ is bounded continuous function and satisfies Lipschitz condition, and $z(t) = 0$ is the origin of system (1), here $k \in \Delta$.

Definition 1. ([8]). Nonlinear dynamic systems (1) is fixed-time stable, if origin of systems (1) is stable, and there is a constant $\mathcal{T}_M > 0$ that settling function $\mathcal{T}(z(0)) \leq \mathcal{T}_M$, $\lim_{t \rightarrow \mathcal{T}_M} \|z(t)\| = 0$ and $z(t) = 0$ when $t \geq \mathcal{T}_M$, where $\mathcal{T}_M$ is called settling-time.

Remark 1. Under Assumption 1, one can easily find that for each initial value, nonlinear dynamic systems (1) has unique solution $z(t)$ that is defined in the interval $[0, +\infty)$.

Now, by using C -regular function definition given in [11] and designing an inequality with sigmoid-function, we give following fixed-time stability Lemma 1 for this paper.

Lemma 1. Suppose there is a C -regular function $\mathbf{V}(\cdot)$, and following with any solutions of (1) that satisfies

$$\frac{d\mathbf{V}(z(t))}{dt} \leq -\frac{\alpha}{\sigma(\mathbf{V}(z(t))) [1 - \sigma(\mathbf{V}(z(t)))]}, \quad (2)$$

where $\alpha > 0$, $\sigma(\mathbf{V}(z(t))) = 1/[1 + \exp(-\mathbf{V}(z(t)))]$, then, systems (1) can get fixed-time stable, and settling-time is

$$\mathcal{T}_M = \frac{1}{2\alpha}. \quad (3)$$

Proof. From (2), we get that $\frac{d\mathbf{V}(t)}{dt} < 0$, because $\mathbf{V}(\cdot)$ is C -regular function. So, systems (1) is global asymptotic stable. Let $q = \mathbf{V}(z(t))$, from (2) and [11], we have the following settling-time function

$$\mathcal{T}(z(0)) = \frac{1}{\alpha} \int_0^{\mathbf{V}(z(0))} \sigma(q) [1 - \sigma(q)] dq, \quad (4)$$

because $\sigma'(q) = \sigma(q)[1 - \sigma(q)] > 0$, then, one has

$$\begin{aligned} \mathcal{T}(z(0)) &\leq \frac{1}{\alpha} \int_0^{+\infty} \sigma(q) [1 - \sigma(q)] dq \\ &= \frac{1}{\alpha} \int_0^{+\infty} \sigma'(q) dq \\ &= \frac{1}{\alpha} \sigma(q) \Big|_0^{+\infty} = \frac{1}{\alpha} \frac{1}{1 + \exp(-q)} \Big|_0^{+\infty} \\ &= \frac{1}{\alpha} \left(1 - \frac{1}{2}\right) = \frac{1}{2\alpha}. \end{aligned} \quad (5)$$

Now, based on [11], Definition 1 and from (5), one knows that systems (1) can get fixed-time stable, and settling-time is $\mathcal{T}_M = \frac{1}{2\alpha}$. The proof of Lemma 1 is finished.

Remark 2. The authors of this paper try their best to show a new method to realize fixed-time stability of nonlinear dynamic systems, that is, based on Sigmoid-function $\sigma(V(t)) = \frac{1}{1 + e^{-V(t)}}$ to derive fixed-time stability, which curve is shown in Figure 1. And under the above inequality (2), one knows that $V(t)$ is a non-increasing monotone function, so, $0 < \sigma(V(t)) < 1$. Therefore, the method used in this paper is completely different from the method of many previous works, such as [1, 6] that has two positive index variables λ, γ in $\dot{V}(t) < -\alpha V^\lambda(t) - \beta V^\gamma(t)$.

Remark 3. The previous work [8] discussed predefined-time stable of delayed neural networks, in fact, from Lemma 1, if the following inequality holds

$$\frac{d\mathbf{V}(t)}{dt} \leq -\frac{\mathcal{T}_M}{\mathcal{T}_c} \frac{\alpha}{\sigma(\mathbf{V}(t)) [1 - \sigma(\mathbf{V}(t))]}, \quad (6)$$

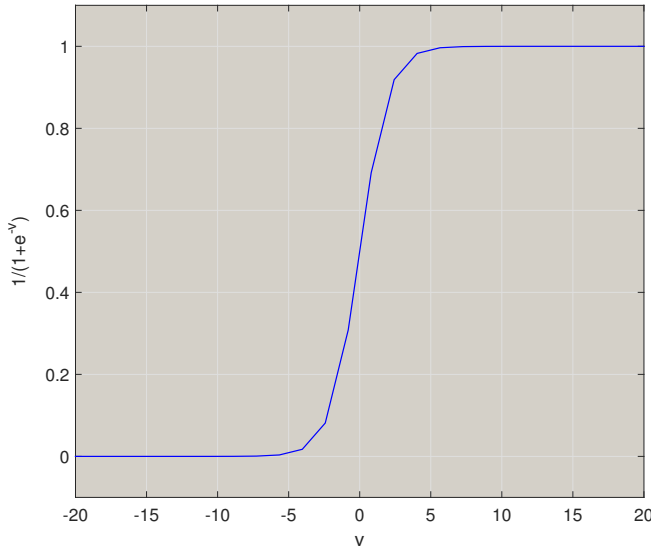


Figure 1. Curve of the Sigmoid-function.

where $\mathcal{T}_c > 0$ and other variables given as above, then, systems (1) can get predefined-time stable, and predefined-time is $\mathcal{T}_c$. Our paper mainly about fixed-time stability of nonlinear dynamic systems, and for more details of predefined-time stability, the readers can see [5] and [8].

3 Application of Lemma 1

In this section, as an application, we choose a kind of delayed neural networks as system (1). And we investigate the FT of the delayed neural networks based on Lemma 1.

Consider the following delayed neural networks

$$\begin{aligned} \frac{dz_k(t)}{dt} = & -d_k z_k(t) + \sum_{p=1}^n a_{kp} g_p(z_p(t)) \\ & + \sum_{p=1}^n b_{kp} g_p(z_p(t - \tau(t))) \\ & + \sum_{p=1}^n c_{kp} \int_{t-\tau(t)}^t g_p(z_p(s)) ds, \quad (7) \end{aligned}$$

where $d_k > 0$, $z_k(t)$ is the state of the k^{th} neural, a_{kp}, b_{kp}, c_{kp} are connect weights, $g_p(\cdot)$ is the nonlinear feedback function, $\tau(t)$ is defined as in (1), and initial values of systems (7) are $z_k(s) = \psi_k(s) \in \mathbf{C}([-\tau, 0], \mathbf{R}), t \geq 0, k, p \in \Delta$.

From Assumption 1, one has the following Assumption 2 for delayed neural networks (7).

Assumption 2. For system (7), the nonlinear feedback function $g_p(\cdot)$ is continuous function, which satisfies $g_p(0) = 0$ and for $\forall o_1, o_2 \in \mathbf{R}$ that

$$|g_p(o_1) - g_p(o_2)| \leq \mathcal{L}_p |o_1 - o_2|, |g_p(o_1)| \leq \mathcal{W}_p, \quad (8)$$

where $\mathcal{L}_p > 0, \mathcal{W}_p > 0$.

If delayed neural networks (7) is unstable, here, we consider its following stabilization model

$$\begin{aligned} \frac{dz_k(t)}{dt} = & -d_k z_k(t) + \sum_{p=1}^n a_{kp} g_p(z_p(t)) \\ & + \sum_{p=1}^n b_{kp} g_p(z_p(t - \tau(t))) \\ & + \sum_{p=1}^n c_{kp} \int_{t-\tau(t)}^t g_p(z_p(s)) ds \\ & + u_k(t), \quad (9) \end{aligned}$$

where $u_k(t)$ is the control input, which is designed as follows:

$$\begin{aligned} u_k(t) = & -\gamma_k z_k(t) - \frac{\alpha_k \text{sign}(z_k(t))}{\sigma(\mathbf{V}(t))(1 - \sigma(\mathbf{V}(t)))} \\ & - \delta_k \text{sign}(z_k(t)), \quad (10) \end{aligned}$$

and $\gamma_k, \alpha_k, \delta_k > 0, \mathbf{V}(t) = \sum_{k=1}^n |z_k(t)|$.

Now, we give the following Theorem 1 about FT of delayed neural networks (7) with control (10).

Theorem 1. Under Assumption 2 and control (10), and the following conditions hold

$$-d_k - \gamma_k + \sum_{p=1}^n \mathcal{L}_k |a_{pk}| < 0, \quad (11)$$

$$-\delta_k + \sum_{p=1}^n \mathcal{W}_p (|b_{kp}| + \tau |c_{kp}|) < 0, \quad (12)$$

then, delayed neural networks (7) gets FT, and settling-time is $\mathcal{T}_M = \frac{1}{2\alpha}$,

where $\alpha = \min_{1 \leq k \leq n} \{\alpha_k\}$.

Proof. Consider C -regular function as follows:

$$\mathbf{V}(t) = \sum_{k=1}^n |z_k(t)|. \quad (13)$$

Now, along the solutions of systems (9), and by using chain-rule [12], then, from (13), one gets

$$\begin{aligned}
 \left. \frac{d\mathbf{V}(t)}{dt} \right|_{(9)} &= \sum_{k=1}^n \dot{z}_k(t) \text{sign}(z_k(t)) \\
 &= \sum_{k=1}^n \text{sign}(z_k(t)) \left[-d_k z_k(t) + \sum_{p=1}^n a_{kp} g_p(z_p(t)) \right. \\
 &\quad + \sum_{p=1}^n b_{kp} g_p(z_p(t - \tau(t))) \\
 &\quad + \left. \sum_{p=1}^n c_{kp} \int_{t-\tau(t)}^t g_p(z_p(s)) ds + u_k(t) \right] \\
 &= \sum_{k=1}^n \text{sign}(z_k(t)) \left[-d_k z_k(t) + \sum_{p=1}^n a_{kp} g_p(z_p(t)) \right. \\
 &\quad + \sum_{p=1}^n b_{kp} g_p(z_p(t - \tau(t))) \\
 &\quad + \sum_{p=1}^n c_{kp} \int_{t-\tau(t)}^t g_p(z_p(s)) ds \\
 &\quad - \gamma_k z_k(t) - \frac{\alpha_k \text{sign}(z_k(t))}{\sigma(\mathbf{V}(t))(1 - \sigma(\mathbf{V}(t)))} \\
 &\quad \left. - \delta_k \text{sign}(z_k(t)) \right] \\
 &\leq \sum_{k=1}^n \left[-d_k |z_k(t)| + \sum_{p=1}^n |a_{kp}| |g_p(z_p(t))| \right. \\
 &\quad + \sum_{p=1}^n |b_{kp}| |g_p(z_p(t - \tau(t)))| \\
 &\quad + \sum_{p=1}^n |c_{kp}| \left| \int_{t-\tau(t)}^t g_p(z_p(s)) ds \right| \\
 &\quad - \gamma_k |z_k(t)| - \frac{\alpha_k}{\sigma(\mathbf{V}(t))(1 - \sigma(\mathbf{V}(t)))} \\
 &\quad \left. - \delta_k \right], \tag{14}
 \end{aligned}$$

by using Assumption 2 and from (14), one has

$$\begin{aligned}
 \left. \frac{d\mathbf{V}(t)}{dt} \right|_{(9)} &\leq \sum_{k=1}^n \left[-d_k |z_k(t)| + \sum_{p=1}^n \mathcal{L}_P |a_{kp}| |z_p(t)| \right. \\
 &\quad + \sum_{p=1}^n \mathcal{W}_p (|b_{kp}| + \tau |c_{kp}|) \\
 &\quad - \gamma_k |z_k(t)| - \frac{\alpha_k}{\sigma(\mathbf{V}(t))(1 - \sigma(\mathbf{V}(t)))} - \delta_k \Big] \\
 &= \sum_{k=1}^n \left[(-d_k - \gamma_k + \sum_{p=1}^n \mathcal{L}_k |a_{pk}|) |z_k(t)| \right.
 \end{aligned}$$

$$\begin{aligned}
 &\quad - \delta_k + \sum_{p=1}^n \mathcal{W}_p (|b_{kp}| + \tau |c_{kp}|) \\
 &\quad \left. - \frac{\alpha_k}{\sigma(\mathbf{V}(t))(1 - \sigma(\mathbf{V}(t)))} \right]. \tag{15}
 \end{aligned}$$

Under conditions (11) and (12), from (15), one obtains

$$\begin{aligned}
 \left. \frac{d\mathbf{V}(t)}{dt} \right|_{(9)} &\leq \sum_{k=1}^n \left[-\frac{\alpha_k}{\sigma(\mathbf{V}(t))(1 - \sigma(\mathbf{V}(t)))} \right] \\
 &\leq -\frac{\alpha}{\sigma(\mathbf{V}(t))(1 - \sigma(\mathbf{V}(t)))}. \tag{16}
 \end{aligned}$$

Now, by using Lemma 1, one gets that the delayed neural networks (7) gets FT with control scheme (10), and settling-time is $\mathcal{T}_M = \frac{1}{2\alpha}$. The proof of Theorem 1 is completed.

If $c_{pk} = 0, p, k \in \Delta$, then, the stabilization model (9) is changed into

$$\begin{aligned}
 \frac{dz_k(t)}{dt} &= -d_k z_k(t) + \sum_{p=1}^n a_{kp} g_p(z_p(t)) \\
 &\quad + \sum_{p=1}^n b_{kp} g_p(z_p(t - \tau(t))) \\
 &\quad + u_k(t), \tag{17}
 \end{aligned}$$

where $u_k(t)$ is the control input as given in (10).

For (17), and from Theorem 1, we has the following Corollary 1.

Corollary 1. Under Assumption 2 and control (10), and the following condition (11) hold and

$$-\delta_k + \sum_{p=1}^n \mathcal{W}_p |b_{kp}| < 0, \tag{18}$$

then, delayed neural networks (17) is fixed-time stable, and settling-time is $\mathcal{T}_M = \frac{1}{2\alpha}$.

Remark 4. From Figure 1, one can find that the control input (10) do not produce extremely large control inputs near the zero, so, we believe that the fixed-time stability results of this paper still holds when the control input is bounded. And in this paper, we only discuss a simple application, that is, FT of delayed neural networks, we believe that our results can be used to discuss fixed-time stability for other more complex nonlinear dynamic models, such as circuit

systems, switched systems and neural networks with inertial items, complex-valued or reaction-diffusion terms.

4 Example simulations

Example 1. Discuss two-dimensional delayed neural networks as follows:

$$\begin{aligned} \frac{dz_k(t)}{dt} = & -d_k z_k(t) + \sum_{p=1}^2 a_{kp} g_p(z_p(t)) \\ & + \sum_{p=1}^2 b_{kp} g_p(z_p(t - \tau(t))) \\ & + \sum_{p=1}^2 c_{kp} \int_{t-\tau(t)}^t g_p(z_p(s)) ds, \\ & t \geq 0, \end{aligned} \quad (19)$$

where $d_1 = d_2 = 1$, $\tau(t) = \frac{\exp(t)}{1+\exp(t)}$, $g_p(z_p(t)) = \tanh(z_p(t))$, $k, p = 1, 2$, and other parameter values are given as in Table 1.

Table 1. Parameter values of delayed neural networks (19).

a_{11}	a_{12}	b_{11}	b_{12}	c_{11}	c_{12}
2	-0.1	-1.5	-0.1	-0.01	0.01
a_{21}	a_{22}	b_{21}	b_{22}	c_{21}	c_{22}
-5	2.5	-3	-2.5	0.01	-0.01

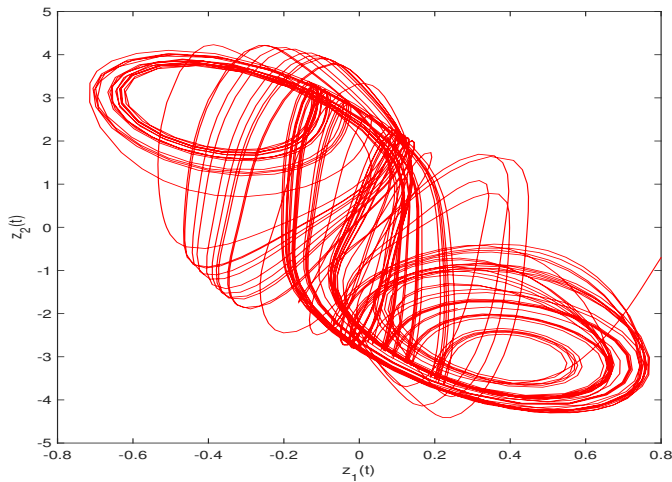


Figure 2. Chaotic behaviors of delayed neural networks (19).

We select the initial values of delayed neural networks (19) are $z_1(s) = 0.8$, $z_2(s) = -0.7$, $\forall s \in [-1, 0)$, and delayed neural networks (19) exist chaotic behaviors, which is showed in Figure 2. Without control, state

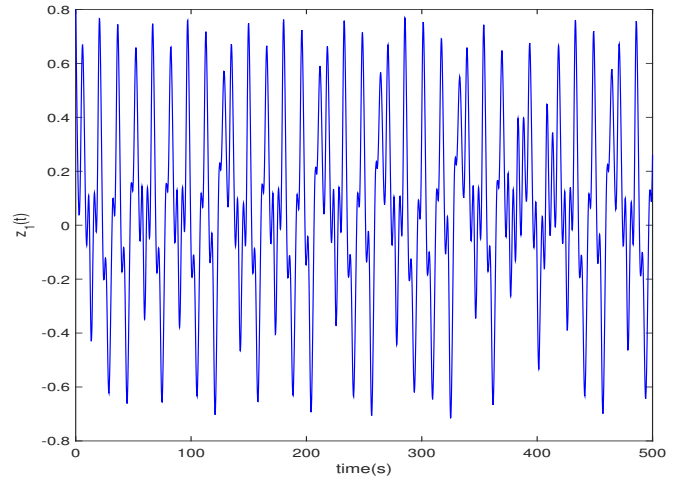


Figure 3. State trajectory $z_1(t)$ of system (19) without control.

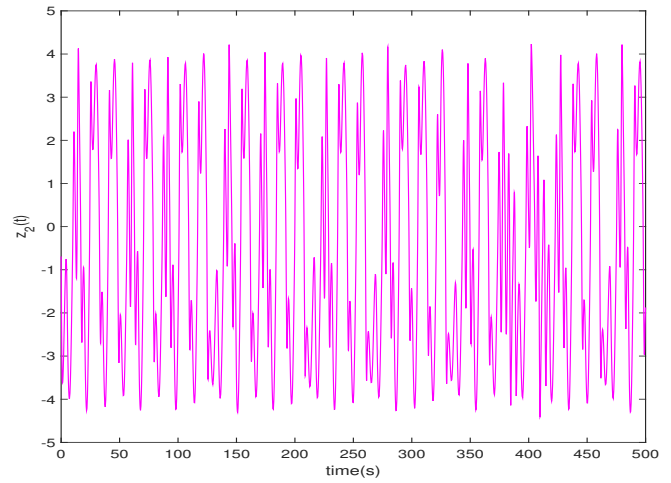


Figure 4. State trajectory $z_2(t)$ of system (19) without control.

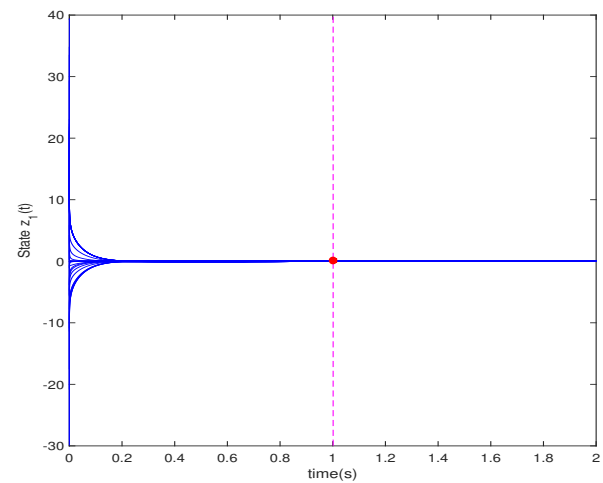


Figure 5. State trajectories $z_1(t)$ of system (19) with control (10).

trajectories $z_1(t)$, $z_2(t)$ of delayed neural networks (19) are displayed in Figures 3 and 4, respectively.

Now, we can easily get $\mathcal{L}_1 = \mathcal{L}_2 = \mathcal{W}_1 = \mathcal{W}_2 = \tau = 1$, and choose $\gamma_1 = \gamma_2 = 7$, $\delta_1 = 1.7$, $\delta_2 = 5.6$, $\alpha_1 = \alpha_2 = 0.5$, then, one has $\alpha = 0.5$ and

$$\begin{aligned} -d_1 - \gamma_1 + \sum_{p=1}^2 \mathcal{L}_1 |a_{p1}| &< 0, \\ -d_2 - \gamma_2 + \sum_{p=1}^2 \mathcal{L}_2 |a_{p2}| &< 0, \\ -\delta_1 + \sum_{p=1}^2 \mathcal{W}_p (|b_{1p}| + |c_{1p}|) &< 0, \\ -\delta_2 + \sum_{p=1}^2 \mathcal{W}_p (|b_{2p}| + |c_{2p}|) &< 0, \end{aligned}$$

so, all conditions of Theorem 1 are hold, then, from Theorem 1, we get delayed neural networks (19) is fixed-time stable with control input (10). And settling-time $\mathcal{T}_M = 1$, randomly selecting 30 initial values in interval $[-50, 50]$ and under control (10), state trajectories $z_1(t)$, $z_2(t)$ of delayed neural networks (19) are fixed-time stable, which are displayed in Figures 5 and 6, respectively.

Remark 5. From above analysis, one finds control (10) has $\text{sign}(\cdot)$, to avoid chattering phenomenon, we use $\tanh(w \cdot (\cdot))$ stands for $\text{sign}(\cdot)$ in the simulation, where w is a big positive constant. In our simulation, we choose $w = 20$, that is, we use $\tanh(20 \cdot z_k(t))$ substitutes $\text{sign}(z_k(t))$ in our simulations.

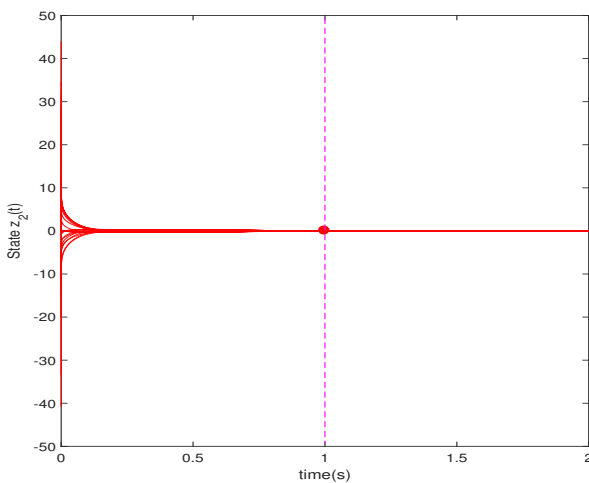


Figure 6. State trajectories $z_2(t)$ of system (19) with control (10).

5 Conclusions

Based on sigmoid-function, a new kind of fixed-time stability Lemma 1 was constructed. And FT of a kind of delayed neural networks was investigated by using the proposed Lemma 1. Compared with some previous works, our fixed-time stability Lemma 1 does not have two power index terms, which is more convenient for practical applications. And our results can be used to discuss fixed-time stability and synchronization for other general nonlinear dynamic systems, which will be further investigated in our future works.

Data Availability Statement

Data will be made available on request.

Funding

This work was supported by the National Science Foundation of China under Grant 62476292, and the Fundamental Research Funds for Central University of South-Central Minzu University under Grant CZQ24020.

Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

References

- [1] Polyakov, A. (2012). Nonlinear feedback design for fixed-time stabilization of linear control systems. *IEEE Transactions on Automatic Control*, 57(8), 2106-2110. [\[CrossRef\]](#)
- [2] Yang, X., Lam, J., Ho, D. W., & Feng, Z. (2017). Fixed-time synchronization of complex networks with impulsive effects via nonchattering control. *IEEE Transactions on Automatic Control*, 62(11), 5511-5521. [\[CrossRef\]](#)
- [3] Kong, F., Zhu, Q., Sakthivel, R., & Mohammadzadeh, A. (2021). Fixed-time synchronization analysis for discontinuous fuzzy inertial neural networks with parameter uncertainties. *Neurocomputing*, 422, 295-313. [\[CrossRef\]](#)
- [4] Ma, Z. F., Tong, D. B., Chen, Q. Y., & Zhou, W. N. (2025). Fixed/prescribed-time synchronization and

energy consumption for Kuramoto-oscillator networks. *IEEE Transactions on Cybernetics*, 55(7), 3379-3389. [CrossRef]

- [5] Hu, C., He, H., & Jiang, H. (2021). Fixed/preassigned-time synchronization of complex networks via improving fixed-time stability. *IEEE Transactions on Cybernetics*, 51(6), 2882-2892. [CrossRef]
- [6] Aouiti, C., Hui, Q., Jallouli, H., & Moulay, E. (2021). Fixed-time stabilization of fuzzy neutral-type inertial neural networks with time-varying delay. *Fuzzy Sets and Systems*, 411, 48-67. [CrossRef]
- [7] Hu, X., Wang, L., Zhang, C. K., Wan, X., & He, Y. (2023). Fixed-time stabilization of discontinuous spatiotemporal neural networks with time-varying coefficients via aperiodically switching control. *Science China Information Sciences*, 66(5), 152204. [CrossRef]
- [8] Zhang, G. D., & Cao, J. D. (2023). New results on fixed/predefined-time synchronization of delayed fuzzy inertial discontinuous neural networks: Non-reduced order approach. *Applied Mathematics and Computation*, 440, 127671. [CrossRef]
- [9] Zhou, X., Zhang, G., Wang, L., & Xiao, Q. (2026). Novel results on fixed-time stabilization and synchronization for delayed memristive inertial neural networks via aperiodically switching control. *Communications in Nonlinear Science and Numerical Simulations*, 156, 109683. [CrossRef]
- [10] Qiao, Y., Tohti, R., Lu, B. L., Abdurahman, A., & Jiang, H. J. (2026). Internal and boundary control-based fixed-time synchronization for stochastic impulsive reaction-diffusion complex networks. *Chaos, Solitons & Fractals*, 206, 117910. [CrossRef]
- [11] Forti, M., Grazzini, M., Nistri, P., & Pancioni, L. (2006). Generalized Lyapunov approach for convergence of neural networks with discontinuous or non-Lipschitz activations. *Physica D: Nonlinear Phenomena*, 214(1), 88-99. [CrossRef]
- [12] Clarke, F. H., Ledyaev, Yu. S., Stern, R. J., & Wolenski, R. R. (1998). A short course in control theory. In *Nonsmooth analysis and control theory* (pp. 177-256). Springer. [CrossRef]



Guodong Zhang received his Ph.D. degree in System analysis and integration from the School of Automation, Huazhong University of Science and Technology in 2014. He is currently a Full Professor and the Supervisor in the School of Mathematics and Statistics, South-Central Minzu University, Wuhan, China.

He has published over 80 international journal papers, he received the 2012 Outstanding Master's Degree Thesis Award of Hubei Province, 2015 Outstanding PhD Dissertation Award of Hubei Province and 2016 Chinese Association of Automation Outstanding PhD Dissertation Award. He is selected as the World Top 2% scientists

in 2020-2022, 2024 and 2025, and he is also selected for the World Top 2% Scientists Lifetime Impact List in 2025. He is an IEEE Senior Member and Editorial Board Member of several SCI or EI journals, such as Scientific Reports, Neural Computing & Applications and Franklin Open.

His current research interests include fixed-time stability of nonlinear dynamic systems, synchronization control of neural networks, event-triggered control and adaptive control. (Email: zgd2008@mail.scuec.edu.cn)



Ardak Kashkynbayev obtained his Ph.D. degree in Mathematics from Middle East Technical University, Turkey. Currently, he is an Associate Professor at the Department of Mathematics, School of Sciences and Humanities, Nazarbayev University, Astana, Kazakhstan. His research interest includes discontinuous dynamical systems, control theory, neural networks, mathematical biology, and mathematical medicine. Dr.

Kashkynbayev has been PI and co-PI of several research projects with a budget of over 1.5M. He has published one monograph, two book chapters and over 40 articles in high-impact journals. (Email: ardak.kashkynbayev@nu.edu.kz)



Dimitrios K. Gerontitis received the B.S. degree in mathematics and the M.S. degree in theoretical informatics and systems and control theory from the Aristotle University of Thessaloniki, Thessaloniki, Greece, in 2013 and 2016, respectively, and the Ph.D. degree from the Department of Information and Electronic Engineering, International Hellenic University, Thessaloniki, Greece, in 2025.

His main research interests include neural networks, optimization, and numerical linear algebra. (Email: dimitrios_gerontitis@yahoo.gr)



Kuo-Shou Chiu received his Ph.D. in Mathematics from the University of Chile, Chile, in 2010. He is currently a Full Professor in the Department of Mathematics at the Metropolitan University of Educational Sciences, Santiago, Chile.

His research focuses on differential equations with piecewise constant arguments, impulsive dynamical systems, stability theory, periodic and oscillatory behavior, neural networks, and mathematical modeling. He has participated in and led several research projects related to neural network models and dynamical systems.

Professor Chiu has authored more than 40 research articles published in peer-reviewed international journals. (Email: kschiu@umce.cl)