

# Finite-time anti-synchronization of memristive stochastic BAM neural networks with probabilistic time-varying delays



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## ARTICLE INFO

### Article history:

Received 4 October 2017

Revised 25 May 2018

Accepted 11 June 2018

### Keywords:

Memristor

Stochastic BAM neural networks

Finite-time anti-synchronization

Probabilistic time-varying delays

Leakage delays

## ABSTRACT

This paper investigates the drive-response finite-time anti-synchronization for memristive bidirectional associative memory neural networks (MBAMNNs). Firstly, a class of MBAMNNs with mixed probabilistic time-varying delays and stochastic perturbations is first formulated and analyzed in this paper. Secondly, a nonlinear control law is constructed and utilized to guarantee drive-response finite-time anti-synchronization of the neural networks. Thirdly, by employing some inequality technique and constructing an appropriate Lyapunov function, some anti-synchronization criteria are derived. Finally, a number simulation is provided to demonstrate the effectiveness of the proposed mechanism.

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## 1. Introduction

In the past decades, a large amount of attention has been devoted to the bidirectional associative memory neural networks (BAMNNs) owing to their potential applications from signal processing, pattern recognition, associative memory, and so on [1–5]. Nowadays, with the increasing amount of data [6,7] and complex neural networks (NNs) [8,9], scientists conceive that we can get a new type of BAMNNs named MBAMNNs, which the self-feedback connection weights are implemented by memristors [10–16] rather than resistances. From the system theoretic point of view, MBAMNNs can be treated as a class of state-depend nonlinear system [17], and it is a challenging topic. With the research and development of memristor, plenty of researchers from various fields show skyscraping enthusiasm to this kind of memristive neural networks (MNNs) [18–22]. The MBAMNNs have remarkable properties such as satisfactory convergence rate, computer implementation, a large number of equilibrium points, and so on [23]. Therefore, this type of model can better emulate the human brain than the traditional neural networks.

Synchronization, which means the dynamical signals of chaotic coupled system achieve an identical behavior with time moving. In reality, it is significant to consider the synchronization of its different potential applications including biological systems, intelligent control, secure communication, and image protection. As a typical collective behavior, the stability and synchronization of MNNs have been widely discussed, including lag synchronization [24], exponential synchronization, anti-synchronization [25–28], finite time synchronization [29,30], and so on. Recently, chaotic synchronization of MBAMNNs has gained much attention due to its successful applications in various areas [31–34].

However, in addition to this result, there are few results on the anti-synchronization for MBAMNNs. Additionally, among these synchronization works of MBAMNNs, most are asymptotic, implying the stability or synchronization of chaotic systems can be accomplished only when time towards to infinity. But from the point of practical, owing to the life span of human and machine [35], it is more pressing to achieve synchronization within the finite time, that is, finite time synchronization [37–40]. Besides, finite-time synchronization can illustrates the faster synchronous rate after a finite time-interval named setting time. Therefore, it is more practical and valuable to investigate the finite-time anti-synchronization control of the MBAMNNs.

In the process of studying MBAMNNs, it is detected that the delays frequently appears owing to the limited transfer speed and the

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information processing. Actually, in the electronic implementation of analog NNs, time delay frequently occurring in the response and communication of neurons. And the time delay can lead to a series of questions, to a certain extent, affected the instability and oscillation to the NNs [41–44]. In the view of this, it is rewarding and reasonable to study the delayed NNs [45–49]. Nevertheless, time delays often occurring in a random way in the view of probabilistic reasons. This often occurs in real systems where the probability to taking vary large values of delay is very small [50].

Under these situations, probabilistic measurement delays would be regarded as a Bernoulli distributed white sequence [51] to depict more property of the real systems. Furthermore, it should not be neglected that in a real nervous system, there is a typical time delay named leakage delay which has tendency to impact on the dynamical behavior of NNs [52–54]. From the above discussions, it is significant and necessary to investigate some reasonable and practical systems for MBAMNNs. The actual communication between NNs is inevitably disturbed by a stochastic perturbation. The stochastic perturbation mainly comes from various uncertainties which probably results in package losses or influences the signal transmission. Hence, it is important to discuss the effect of probabilistic delays and stochastic perturbations. It should be mentioned that, the finite-time anti-synchronization results for stochastic MBAMNNs with probabilistic time-varying delays has not been studied yet, this motivates our present study.

Motivated by the aforementioned concerns, the aim of this paper is to investigate the finite-time anti-synchronization results for stochastic MBAMNNs with probabilistic time-varying delays. With the aid of the set-valued map, memristor mathematical model, differential inclusion, linear feedback controller, adaptive linear feedback controller, and the definition of anti-synchronization, two new sufficient criteria are derived to guarantee the finite-time anti-synchronization of MMAMNNs with mixed probabilistic time-varying delay. The main contributions of this paper can be summarized as follows.

1. We focus on the study of MBAMNNs models with stochastic perturbation and various time-varying delays, which including non-delay, discrete time-varying delays and a constant delay in the leakage term. Many other MBAMNNs models with delays are the special cases of our considered model.
2. We first attempt to address the finite-time anti-synchronization control problem for a class of proposed MBAMNNs models. By utilizing sign function and the definition of finite-time stability, a suitable nonlinear state feedback controller is designed. We consider and analysis the complex randomness of the time-varying delays rather than treat them as the same stability. Some main results are derived by utilizing the Lyapunov function, finite-time stability theorem, stochastic analysis theory and Wirtinger-type inequality.
3. Finally, we provided the numerical examples to illustrated the effectiveness and rationality of the proposed conclusions.

The rest of this paper is organized as follows. Some definitions, lemmas and assumptions about the proposed model are presented in Section 2. In Section 3 derives some sufficient conditions of finite time anti-synchronization based our considered MBAMNNs. Numerical simulations are demonstrated to verify the effectiveness of the obtained results in Section 4. Finally, the conclusion is given in Section 5.

*Notations.* For  $r > 0$ ,  $\mathbf{C}([-r, 0], \mathbb{R}^n)$  denotes the Banach space of all continuous functions mapping  $[-r, 0]$  into  $\mathbb{R}^n$  with  $q$ -norm or  $\infty$ -norm by the following forms, respectively.  $\mathbb{R}^n$  denotes the  $n$ -dimensional Euclidean space. The superscript  $T$  represents matrix or vector transposition. We define the norm of the vector as  $\|x_i\|$  indicates the 2-norm of a vector  $x_i$ , i.e.,  $\|x_i\| = (\sum_{i=1}^n x_i^2)^{\frac{1}{2}}$ .  $co[a, b]$  denotes the convex hull (closure) of  $\{a, b\}$ .

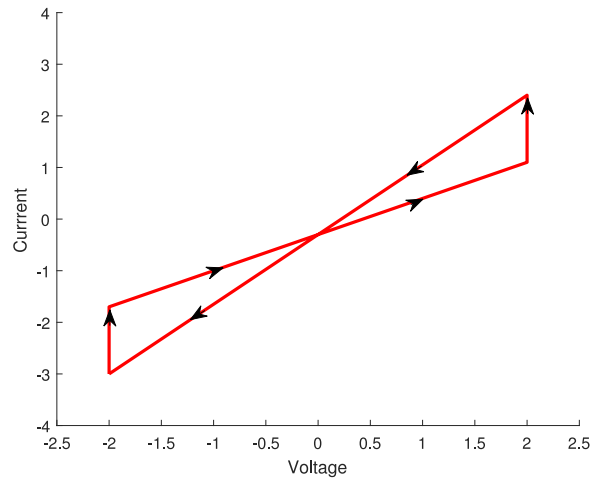


Fig. 1. Typical current-voltage characteristic of a memristor.

### 2. Model description and preliminaries

Based on the physical properties of memristor, a class of stochastic MBAMNNs with time-varying delays is described as follows

$$\begin{aligned} \dot{x}_i(t) &= -a_i x_i(t - \tau) + \sum_{j=1}^m b_{ji}(x_i(t)) f_j(y_j(t)) \\ &\quad + \sum_{j=1}^m c_{ji}(x_i(t - \tau(t))) f_j(y_j(t - \tau(t))), \quad (1) \\ \dot{y}_j(t) &= -d_j y_j(t - \sigma) + \sum_{i=1}^n q_{ij}(y_j(t)) g_i(x_i(t)) \\ &\quad + \sum_{i=1}^n p_{ij}(y_j(t - \sigma(t))) g_i(x_i(t - \sigma(t))), \end{aligned}$$

where  $x_i(t)$  and  $y_j(t)$  denote the voltages of capacitor  $C_i$  and  $\tilde{C}_j$  at time  $t$ , for  $t \geq 0$  and  $i = 1, 2, \dots, n$  and  $j = 1, 2, \dots, m$ .  $a_i > 0$  and  $d_j > 0$  represent the self-feedback connection weight.  $f_j(y_j(t))$  and  $g_i(x_i(t))$  are the feedback functions.  $\tau(t)$  and  $\sigma(t)$  are the time-varying delays which satisfied  $0 \leq \tau(t) \leq \tau_2$  and  $0 \leq \sigma(t) \leq \sigma_2$ .  $b_{ji}(x_i(t))$ ,  $c_{ji}(x_i(t - \tau(t)))$ ,  $q_{ij}(y_j(t))$  and  $p_{ij}(y_j(t - \sigma(t)))$  represent memristor-based weights, and  $b_{ji}(x_i(t)) = \frac{W_{(1)ji}}{\tilde{C}_j} \times \text{sgn}_{ij}$ ,  $c_{ji}(x_i(t - \tau(t))) = \frac{W_{(2)ji}}{\tilde{C}_j} \times \text{sgn}_{ij}$ ,  $q_{ij}(y_j(t)) = \frac{W_{(3)ij}}{C_i} \times \text{sgn}_{ij}$ ,  $p_{ij}(y_j(t - \sigma(t))) = \frac{W_{(4)ij}}{C_i} \times \text{sgn}_{ij}$ ,

$$\text{sgn}_{ij} = \begin{cases} 1, & i \neq j, \\ -1, & i = j, \end{cases} \quad \text{sgn}_{ji} = \begin{cases} 1, & j \neq i, \\ -1, & j = i, \end{cases}$$

then  $W_{(1)ji}$ ,  $W_{(2)ji}$ ,  $W_{(3)ij}$  and  $W_{(4)ij}$  denote the memductance of memristors  $R_{(1)ji}$ ,  $R_{(2)ji}$ ,  $R_{(3)ij}$  and  $R_{(4)ij}$ , respectively. In addition,  $R_{(1)ji}$  presents the memristor between the feedback function  $f_j(y_j(t))$  and  $y_j(t)$ ,  $R_{(2)ji}$  presents the memristor between the feedback function  $f_j(y_j(t - \tau(t)))$  and  $y_j(t - \tau(t))$ ,  $R_{(3)ij}$  presents the memristor between the feedback function  $g_i(x_i(t))$  and  $x_i(t)$ ,  $R_{(4)ij}$  presents the memristor between the feedback function  $g_i(x_i(t - \sigma(t)))$  and  $x_i(t - \sigma(t))$ .

According to the feature of memristor and the current-voltage characteristic, Fig. 1 can illustrates the simplification current characteristic of a memristor. And we apply the state-dependent parameters of the system (1) are satisfy the following conditions

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