Synchronization Control of Stochastic Delayed Neural Networks 
Communicating with Unreliable Links

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Abstract—This letter considers the problem of mean-square exponential synchronization control for a class of stochastic delayed neural networks. Different from the prior works, the master-response synchronization setup under consideration transmits its signals through unreliable links, which include network-induced delays, frame losses, and random fluctuations. We firstly introduce a mathematical model of networked synchronization control. By using Lyapunov method, some delay-dependent sufficient criteria are derived for the error system to be mean-square exponentially stable, which ensure the response systems synchronize with the master in the mean square sense. An illustrative example is provided to show the effectiveness and applicability of the proposed scheme.

I. INTRODUCTION

Synchronization control ensures two or more systems to share a common dynamical behavior by coupling or external forcing. In recent years, it has gained many researchers’ attention due to the strong background in engineering applications, such as secure communication, information processing, multiple robots formulation, and chemical reactions. Since Neural networks (NNs) can exhibit complex dynamics [1]–[3], the synchronization control of NNs has emerged as an important area of study. For example, in [4], a kind of Chua’s circuits which are periodic is employed to generate gait patterns for bio-inspired robots. When it comes to the robot formulation, some synchronization control schemes should be utilized. Nowadays, there has been increasing interest in synchronization scheme design for NNs [5]–[12]. In [5], synchronization of an array of linearly coupled identical connected NNs with or without delay has been discussed. Synchronization of coupled delayed NNs and applications to chaotic cellular neural networks in [6] have resulted in a theoretical condition for synchronization under the assumption that the coupling matrix is irreducible. The adaptive synchronization problems for NNs through output or state coupling have been investigated in [7]–[9]. In [7], Cao et al. proposed an analytical and rigorous adaptive feedback scheme for the synchronization of coupled uncertain NNs with time-varying delay using the invariant principles of functional differential equations. In [9], the adaptive control and parameters identification problem was investigated. Synchronization problem of recurrent NNs with time-varying and distributed delays was studied in [10] by using Lyapunov method. In [11], synchronization control of stochastic NNs with time-varying delays has been considered by using Lyapunov method and linear matrix inequalities (LMIs) technique.

In real-world applications of some synchronization control systems, signals transmission have to rely on the common communication channels. For example, in the reliable multiple robots formulation [13], the robots should transmit signals mutually through communication networks especially when they are numerous and distributed. What’s more, if we had to work in the adverse environments, the wireless links, which are always unreliable (not real–time, containing frame losses), might be utilized for mutually communicating. Two or more NNs, which are either chaotic or periodic, sharing a common dynamic behavior by coupling or external forcing and transmitting signals mutually through common communication networks fall into the category of networked synchronization control of NNs (NSCNN). In the communication networks, however, signals transmission are endowed with new features. They often involve network-induced time delays, frame losses, bit errors, environment disturbance, and so on, which will cause the signals can not be transmitted from one system to another in time. Accordingly, the existing synchronization control schemes can not work well in the networked synchronization systems. For example, it is known that secure communication is one of the hot spots in recent studies of wireless networks [14]. The existing secure communication schemes based on chaotic synchronization, however, can not be performed in it directly since the signals transmission can not complete in time, though which is a precondition in the existing chaotic synchronization schemes [15]. Therefore, to develop appropriative control schemes for networked synchronization control emerges as a topic of primary importance and significance nowadays.

However, little attention has been taken to the NSCNN. In the past a few years, networked control systems (NCSs) have been well investigated, see [16]–[18] for instance. But in the conventional NCSs, researchers often concern more about the stability and stabilization of certain linear systems. When it comes to the case of networked synchronization of various NNs which are obvious nonlinear, the dynamic behaviors of research object could be more complex, or even chaotic. To the best of our knowledge, this problem has not been investigated so far, and is still challenging and open.

This letter considers the problem of mean-square exponential synchronization control for a class of stochastic
NNs with time-varying delays. Different from the prior works, the reference signals are transmitted from the master system to the response through common communication networks, which include network-induced delays, frame losses, and random fluctuations. We firstly introduce a model of NSCNN, in which stochastic fluctuations are described in term of Brownian motion. By using Lyapunov method and some well known inequalities, some LMI-based delay-dependent sufficient conditions are derived for mean-square exponential stability of an error system, which will ensure the response system synchronizes with the master system in the mean square sense. An illustrative example is denoted to show the effectiveness and applicability of the proposed synchronization scheme.

Notation: $\mathbb{R}^n$ denotes the $n$-dimensional Euclidean space, $\mathbb{R}^{n \times m}$ is the set of real $n \times m$ matrices, $I$ is the identity matrix of appropriate dimensions, $||\cdot||$ stands for the Euclidean vector norm or spectral norm as appropriate. The notation $X > 0$ (respectively, $X < 0$), for $X \in \mathbb{R}^{n \times n}$ means that the matrix $X$ is a real symmetric positive definite (respectively, negative definite). The asterisk $*$ in a matrix is used to denote term that is induced by symmetry. $E \{ \cdot \}$ denotes the expectation. $(\Omega, \mathcal{F}, \mathbb{P})$ is a probability space, where $\Omega$ is the sample space, $\mathcal{F}$ is the $\delta$-algebra of subsets of the sample space and $\mathbb{P}$ is the probability measure on $\mathcal{F}$. $C([-\tau, 0], \mathbb{R})$ denotes the set of all continuous functions from $[-\tau, 0]$ to $\mathbb{R}$.

II. PROBLEM FORMULATION

Consider the networked synchronization control setup in Figure 1, where the sensors are clock-driven and the controller is event-driven. The master and response system are sampled simultaneously. The achieved state vectors of the master system are transmitted through unreliable communication networks. Sampled data from the response are stored in a buffer. Once the controller receives reference signals from the network, it will work out its outputs according to the differences between the received and the accordingly selected from the buffer. The detail description of the setup is as follows.

A. Master System

Consider the following neural network

$$\dot{x}_i(t) = -a_i x_i(t) + \sum_{j=1}^{n} b_{ij} g_j(x_j(t)) + \sum_{j=1}^{n} w_{ij} g_j(x_j(t - d(t))) \quad i = 1, \ldots, n \quad (1)$$

Its equivalent vector form is

$$\dot{x}(t) = -Ax(t) + Bg(x(t)) + Wg(x(t - d(t))) \quad (2)$$

$$x(t) = \phi(t) \quad t \in [-d, 0]$$

where $x(t) = [x_1(t), x_2(t), \ldots, x_n(t)]^T \in \mathbb{R}^n$ is the state vector associated with the $n$ neurons, the positive diagonal matrix $A = \text{diag}(a_1, a_2, \ldots, a_n)$ is the state feedback coefficient matrix, $B = (b_{ij})_{n \times n}$ and $W = (w_{ij})_{n \times n}$ are the connection weight matrix and the delay connection weight matrix, respectively, $g(x(t)) = [g_1(x(t)), g_2(x(t)), \ldots, g_n(x(t))]^T$ denotes the neuron activation function. $d(t)$ denotes the time-varying delay, and $d$ is the upper bound of $d(t)$. $\phi(t) = [\phi_1(t), \ldots, \phi_n(t)]^T \in C([-d, 0], \mathbb{R}^n)$ is the initial condition.

B. Networked Response System

The response systems ignoring the effects of communication networks are often considered as [11]

$$dy_i(t) = \left[ -a_i y_i(t) + \sum_{j=1}^{n} b_{ij} g_j(y_j(t)) + \sum_{j=1}^{n} w_{ij} g_j(y_j(t - d(t))) + u_i(t) \right] dt + \sum_{j=1}^{n} \sigma_{ij}(t, e(t), e(t - d(t))) dw_j(t) \quad (3)$$

or equivalently,

$$dy(t) = \left[ -Ax(t) + Bg(y(t)) + Wg(y(t - d(t))) + u(t) \right] dt + \sigma(t, e(t), e(t - d(t))) dw(t) \quad (4)$$

where $y(t) = [y_1(t), y_2(t), \ldots, y_n(t)]^T \in \mathbb{R}^n$ is the state vector, $A, B$ and $W$ are matrices which are the same as (2), $u(t)$ denotes the control. $e(t) = y(t) - x(t)$ is the error state vector. $\omega(t) = [\omega_1(t), \omega_2(t), \ldots, \omega_n(t)]^T$ is a $n$ dimension Brownian motion defined on a complete probability space $(\Omega, \mathcal{F}, \mathbb{P})$. Here, the white noise $dw(t)$ is independent of $dw_j(t)$ for mutually different $i$ and $j$, and $\sigma : \mathbb{R}^+ \times \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}^{n \times n}$ is called the noise intensity function matrix. This type of stochastic perturbation can be regarded as a result from the occurrence of random uncertainties of the neural network [11], [19]–[21].

However, if the networks are involved in the signal communication from the master system to the response, the signal transmission will be endowed with the characteristic of networks. To establish the networked response system, we suppose that the data are transmitted with a single packet and time stamped. The real input $u(t)$ is realized through a
zeroth-order hold. Based on our previous works [18], [22], the response system is modeled as
\[ dy(t) = [-Ax(t) + Bg(y(t)) + Wg(y(t - d(t)))]dt + u(t) \sigma(t, e(i_k h))d\omega(t) \]
\[ t \in [i_k h + \tau_k, i_{k+1} h + \tau_{k+1}) \] (5)
where \( h \) is the sampling period, \( i_k (k = 1, 2, \ldots) \) are some integers and \( \{i_1, i_2, \ldots, i_k\} \in \{0, 1, 2, \ldots\} \). \( \tau_k \) is the time delay which denotes the time from the instant \( i_k h \) when the sensor node samples data from master system to the instant when the controller transfers the data to response system. Obviously, \( \bigcup_{k=1}^{\infty} [i_k h + \tau_k, i_{k+1} h + \tau_{k+1}) = [t_0, \infty), t_0 \geq 0. \)
In this letter, we assume that \( u(t) = 0 \) before the first control signal reaches the response system.

Remark 1: Let \( \kappa_k = i_{k+1} - i_k (k = 1, 2, \ldots) \). Obviously, \( \kappa_k \) are integers. The possible values of \( \kappa_k \) and their meanings are listed as follows:
\[
\kappa_k \begin{cases} 
> 1 & \kappa_k - 1 \text{ packets have been lost,} \\
= 1 & \text{No packet lost,} \\
= 0 & \text{Some errors occurred,} \\
< 0 & \text{The packet transmission is out of order.} 
\end{cases}
\]
It can be seen that when \( \kappa_k \leq 0, \) the received packets should be dropped since they are too old for the real time synchronization systems.

Definition 1: we define the following network performance index (NPI) \( \eta_k \),
\[ \eta_k = \kappa_k h + \tau_{k+1}, \] (6)
where \( \eta_k \) is bounded and satisfying \( \eta = \sup_k \{\eta_k\} \).

It is clearly that the NPI \( \eta_k \) is a comprehensive index which includes both packet dropping and the time delays in the signal transmission.

To proceed with our analysis, the following assumptions are needed.

Assumption 1: The time delay \( d(t) \) is a differentiable and bounded function satisfying
\[ 0 \leq d(t) \leq d \quad \text{and} \quad \dot{d}(t) \leq \mu < 1 \]
where \( d \) and \( \mu \) are known constants.

Assumption 2: For \( i \in \{1, 2, \ldots, n\} \), the neuron activation function \( g_i (\cdot) \) is continuous and bounded, which satisfies the following condition
\[ 0 \leq \frac{g_i(s_1) - g_i(s_2)}{s_1 - s_2} \leq \xi_i, \quad \forall \ s_1 \neq s_2 \in \mathbb{R}, \]
where \( \xi_i \) are known constants.

Remark 2: The condition in Assumption 2 has been used in [23], [24], which is more general than the usual sigmoid functions and the recently commonly used Lipschitz conditions. In addition, if \( g_i (s) \) is differentiable, we can conclude from Lagrangian mean-value theorem that \( \xi_i \) could be valued as the maximum values of \( g_i^{\prime}(\cdot) \).

Assumption 3: \( \sigma : \mathbb{R}^+ \times \mathbb{R}^n \rightarrow \mathbb{R}^{n \times n} \) which is locally Lipschitz continuous and satisfies the linear growth condition. Moreover, \( \sigma \) satisfies
\[ \text{trace} \left[ \sigma^T(t, e(i_k h)) \sigma(t, e(i_k h)) \right] \leq \| H e(i_k h) \|^2 \] (7)

where \( H \) is an appropriate dimension matrix.

C. Error System
To establish the error system, we rearrange (2) as
\[ dx(t) = [-Ax(t) + Bg(x(t)) + Wf(e(t - d(t)))]dt + u(t) \sigma(t, e(i_k h))d\omega(t) \]
\[ t \in [i_k h + \tau_k, i_{k+1} h + \tau_{k+1}) \] (8)
Since \( e(t) = y(t) - x(t) \), combining (5) and (8), we get
\[ de(t) = [-Ax(t) + Bf(e(t)) + Wf(e(t - d(t)))]dt + u(t) \sigma(t, e(i_k h))d\omega(t) \]
\[ t \in [i_k h + \tau_k, i_{k+1} h + \tau_{k+1}) \] (9)
where \( f(e(t)) = g(y(t)) - g(x(t)) = g(x(t) + e(t)) - g(x(t)) \).

In previous works, it is a precondition that the state vectors of the master system, i.e. \( x(t) \), are available in time. For example, in [11], the controller is assumed to be \( u(t) = G(y(t) - x(t)) + G_1(y(t - d(t)) - x(t - d(t))) \) \( G \neq 0 \). In the networked synchronization systems, however, \( x(t) \) may not be obtained in time for the existence of network-induced delay, frame losses and other adverse conditions. Here, a zeroth-order hold controller is assumed to be
\[ u(t) = K(y(t - \tau_k) - x(t - \tau_k)) = Ke(i_k h) \]
\[ t \in [i_k h + \tau_k], k = 1, 2, 3 \ldots \] (10)
Substituting (10) into (9), we obtain
\[ de(t) = [-Ax(t) + Bf(e(t)) + Wf(e(t - d(t)))]dt + Ke(i_k h) \sigma(t, e(i_k h))d\omega(t) \]
\[ t \in [i_k h + \tau_k, i_{k+1} h + \tau_{k+1}) \] (11)
From Assumption 2, it is easy to verify that
\[ 0 \leq \frac{f_i(s)}{s} \leq g_i, \quad \forall \ s \in \mathbb{R}, \]
(12)
As noted in [18], we let \( \tau(t) = t - i_k h \), i.e. \( i_k h = t - \tau(t) \), then \( \sigma(t, e(i_k h)) = \sigma(t, e(t - \tau(t))) \). In addition, we assume \( d(t) \) and \( \tau(t) \) are independent since they are with respect to the neural networks and communication networks, respectively. The objective of this letter is to derive delay-dependent sufficient conditions to ensure the error system (11) to be global exponential stability in the mean square sense, which will imply that the system (5) is synchronized with system (2) in the mean square sense.

III. MAIN RESULTS

For convenience, we use the following notations:
\[ \xi^T(t) = [e^T(t), e^T(t - d(t)), e^T(i_k h), e^T (i_{k+1} h)] \]
\[ N^T = [N_1^T, N_2^T, N_3^T, N_4^T, N_5^T, N_6^T] \]
\[ M^T = [M_1^T, M_2^T, M_3^T, M_4^T, M_5^T, M_6^T] \]
\[ S^T = [S_1^T, S_2^T, S_3^T, S_4^T, S_5^T, S_6^T] \]
\[ \beta(t) = -Ax(t) + Bf(e(t)) + Wf(e(t - d(t))) \]
\[ + Ke(i_k h), \]
\[ \Sigma = \text{diag} (\varrho_1, \varrho_2, \ldots, \varrho_n), \quad \Lambda_i = \text{diag}(\lambda_{i,1}, \lambda_{i,2}, \ldots, \lambda_{i,n}) \quad (i = 1, 2). \]
Theorem 1: Suppose that Assumption 1-3 hold. For given scalars \( d, 0 \leq \mu < 1, \eta, \) and controller gain \( K, \) the system (11) is globally exponentially stable in the mean square sense, which ensures the system (5) is synchronized with the system (2) in the mean square sense, if there exist seven positive definite matrices \( P_i, Q_i, R_i, \) and \( T_j (j = 1, 2), \) two positive diagonal matrices \( \Lambda_i \) (\( i = 1, 2), \) matrices \( N_j, M_j, \) and \( S_j \) (\( j = 1, 2, \ldots, 6) \) of appropriate dimensions and a positive scalar \( \alpha > 0 \) such that the following LMIIs hold

\[
\begin{bmatrix}
\Omega & dN & \eta M \\
* & -dR_1 & 0 \\
* & * & -\eta T_1
\end{bmatrix} < 0 
\]  
(13)

where \( \Omega = (\Xi_{ij})_{6 \times 6} \) is a symmetric matrix and its elements in the upper triangular are given by:

\[
\begin{align*}
\Xi_{11} & = Q_1 + N_1 + N_1^T + M_1 + M_1^T - S_1A - A^T S_1^T, \\
\Xi_{12} & = N_2 - N_1 + M_2 - A^T S_2^T, \\
\Xi_{13} & = N_3 + M_3 - M_1 - A^T S_3^T + S_1K, \\
\Xi_{14} & = P + N_4^T + M_4^T - A^T S_4^T - S_1, \\
\Xi_{15} & = \Sigma A_1 + N_5^T + M_5^T - A^T S_5^T + S_1B, \\
\Xi_{16} & = N_6^T + M_6^T - A^T S_6^T + S_1W, \\
\Xi_{22} & = -(\mu)Q_1 - N_2 - N_2^T, \\
\Xi_{23} & = -N_3^T - M_2 + S_2K, \\
\Xi_{24} & = -N_4^T - S_2, \\
\Xi_{25} & = -N_5^T + S_2B, \\
\Xi_{26} & = \Sigma A_2 - N_6^T + S_2W, \\
\Xi_{33} & = \alpha H^T H - M_3 - M_4^T + S_3K + K^T S_3^T, \\
\Xi_{34} & = -M_4^T + K^T S_4^T - S_3, \\
\Xi_{35} & = -M_5^T + K^T S_5^T + S_3B, \\
\Xi_{36} & = -M_6^T + K^T S_6^T + S_3W, \\
\Xi_{43} & = dR_1 + \eta T_1 - S_4 - S_4^T, \\
\Xi_{45} & = -S_5^T + S_4B, \\
\Xi_{46} & = -S_6^T + S_4W, \\
\Xi_{55} & = Q_2 - 2A_1 + S_6B + B^T S_5^T, \\
\Xi_{66} & = -(\mu)Q_2 - 2A_2 + S_6W + W^T S_6^T.
\end{align*}
\]

Remark 3: To process the proof of Theorem 1, the following Lyapunov-Krasovskii functional is needed.

\[
V(t, e(t)) = e^T(t)Pe(t) + \int_{t-d(t)}^{t} e^T(s)Q_1e(s)ds + \int_{t-d(t)}^{t} f^T(e(s))Q_2f(e(s))ds + \int_{t-d(t)}^{t} e^T(s)Q_2f(e(s))ds + \int_{t-d(t)}^{t} e^T(s)Q_2f(e(s))ds + \int_{t-d(t)}^{t} e^T(s)Q_2f(e(s))ds + \int_{t-d(t)}^{t} e^T(s)Q_2f(e(s))ds + \int_{t-d(t)}^{t} e^T(s)Q_2f(e(s))ds + \int_{t-d(t)}^{t} e^T(s)Q_2f(e(s))ds
\]

with \( P, Q_1, Q_2, R_1, \) and \( T_1 \) are positive definite matrices. The proof can be achieved by following a similar line in our recent paper [25]. Due to the limit of space, the detail has been omitted, and will be presented in our future paper.

Based on Theorem 1, a transformation is made to derive the feedback gain \( K. \)

Proof: Let \( S = [1_{2 \times 2} \rho_2 \rho_3 \rho_4 \rho_5 \rho_6]X \) and \( Y = XK \) in Theory 1, it is obvious.

Remark 4: In our main results, the mean-square synchronization control problems are solved with a class of stochastic delayed NNs. Some LMI-based delay-dependent sufficient conditions are derived for the stability of the addressed error system, which will ensure the response system is synchronized with the master system in the mean square sense. We would like to point out that the controller design of (10) seems conservative since \( y(t - \tau_k) \) is older than the available state vector \( y(t). \) Therefore, it can be expected that a more appropriate design of controller by employing the state estimation [26], [27] or filtering [28] technique, which will be left for our further study.
IV. ILLUSTRATIVE EXAMPLE

In this section, an illustrative example is presented to demonstrate the effectiveness and application of the developed method.

**Example 1:** We consider the NN (2) with the following parameters [11]

\[
A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 2.0 & -0.1 \\ -5.0 & 2.8 \end{bmatrix},
\]

\[
W = \begin{bmatrix} -1.6 & -0.1 \\ -0.3 & -2.5 \end{bmatrix}, \quad g(s) = \tanh(s), \tau(t) \equiv 1.
\]

The dynamic of system (18) has been investigated in [29], [30] by numerical simulation. It has been shown that the addressed system will exhibit chaotic dynamics. The response system here is assumed to be

\[
dy(t) = \left[ -Ay(t) + Bg(y(t)) + Wg(y(t - 1)) \right] dt + \sigma(t, e(i_kh))d\omega(t)
\]

with \( H = 0.1I \).

**A. Numerical results**

It is easy to verify from (18) that \( d = 1 \) and \( \mu = 0 \). By selecting \( p_2 = 0.01, p_3 = 2.5, p_4 = p_5 = p_6 = 1 \) and \( \eta = 0.1 \) in Theorem 2, we verify that LMIs (16)(17) are feasible, which implies that the addressed error system (9) is globally exponential stable in the mean-square sense which means the response system is synchronized with the master system. Furthermore, the corresponding controller gain can be worked out and given by

\[
K = X^{-1}Y = \begin{bmatrix} -3.5260 & 0.2211 \\ 3.0618 & -6.1443 \end{bmatrix}.
\]

**B. Simulation results**

Now we will simulate the synchronization control with the controller gain given by (19) in TrueTime simulation platform. The master system informs its state vectors to the response system through wireless channels and the simulation setup is shown by Figure 2. In the setup, the master system is stationed at the origin. Its sampling period is 0.02s and initial condition is assumed to be \([0.5 \ 0.3]\). The response system is moving along the trajectory of \( x(t) = 2\cos \frac{t}{5} + 2, \)

\( y(t) = 3\sin \frac{t}{5} + 4 \), and is disturbed by a band-limited white noise. Its sampling period is 0.02s and initial condition is \([0 \ 0]\).

The parameters of the used wireless networks are shown in Table I. It can be found out that the maximum signal reach is 18.31 meters. We further set three stationary interference nodes and their coordinates are \( A(-1, -1), B(3, -1) \) and \( C(-1, 3) \). Interference node \( A \) sends 1K bits data to \( B \) every 0.015s with a probability of 0.5. As soon as \( B \) receives the data, it will send them to \( C \). Then \( C \) will send the packet to \( A \) immediately.

<table>
<thead>
<tr>
<th>Network Type</th>
<th>IEEE 802.15.4(ZigBee)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Rate (bit/s)</td>
<td>( 2.5 \times 10^7 )</td>
</tr>
<tr>
<td>Minimum Frame (bit)</td>
<td>248</td>
</tr>
<tr>
<td>Transmit Power</td>
<td>-3</td>
</tr>
<tr>
<td>Pathloss Exponent</td>
<td>3.5</td>
</tr>
<tr>
<td>Retry Limit</td>
<td>3</td>
</tr>
<tr>
<td>Error Coding Threshold</td>
<td>0.02</td>
</tr>
</tbody>
</table>

**Remark 5:** In the traditional sampled systems, more detailed sampling often results in better synchronization performance. While in the NSCNN, the faster sampling will
increase the communication burden of networks. We further detail the sampling period of sensors to 0.002s in the above simulation setup and fix other parameters. In this case, the maximum network performance is detected to be 0.6198 in 200s. Fig. 5(a) shows the network performance $\eta_k$ and Fig. 5(b) denotes the trajectories of the corresponding error system in the simulation. Obviously, it leads to a poor control performance through such sampling period. From the above analysis, a unified design method between the control system parameters and the network protocols should be concerned in the near future.

\[
\begin{array}{ll}
\text{(a) The network performance} & \text{(b) The error system} \\
\end{array}
\]

Fig. 5. Network performance and errors ($h = 0.002s$)

V. CONCLUSION

A networked master-response synchronization control frame has been established in this letter. Different from the prior works, signals here were transmitted from the master systems to the response through the common communication networks, which included network-induced delays, frame losses, and stochastic external fluctuations. A model of networked synchronization control of stochastic delayed NNs has been firstly proposed. And then, the global mean-square exponential networked synchronization problem has been transformed to stabilize the address error system. By using Lyapunov method and LMI techniques, some delay-dependent sufficient conditions have been derived which ensured the response system to be synchronized with the master in the mean square sense. An illustrative example has been given to show the effectiveness and applicability of the proposed synchronization scheme.

REFERENCES


