Input-to-State Stability Analysis for Stochastic Mixed Time-Delayed Neural Networks with Hybrid Impulses

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This paper investigates the mean-square exponential input-to-state stability (MEISS) of stochastic mixed time-delayed neural networks with hybrid impulses. A generalized comparison principle is introduced and a new inequality about the solution of an impulsive differential equation is established. Moreover, by utilizing the proposed inequality and average impulsive interval approach based on different kinds of impulsive sequences, some novel criteria on MEISS are established. When the external input is removed, several conclusions on mean-square exponential stability (MES) are also derived. Unusually, the hybrid impulses including destabilizing and stabilizing impulses have been taken into account in the presented system. Finally, two simulation examples are provided to demonstrate the validity of our theoretical results.

1. Introduction

Recently, neural networks have absorbed plenty of researchers' interests owing to their extensive applications in a variety of areas including system pattern identification, wireless communications, optimization problems, and machine learning [1, 2]. Actually, the majority of the applications are related to the stability of equilibrium points. Hence, it is of great significance to analyze the stability of network systems. Moreover, stochastic disturbances exist inevitably, which affect the dynamic properties of systems. Meanwhile, in view of the limited switching velocity of the amplifier in the hardware implementation, it is often encountered with time delay, which leads to the instability and oscillations of associated systems. Subsequently, abundant results about stability analysis of stochastic network systems are attained by utilizing various methods [3–7].

Since instantaneous perturbations or abrupt changes at certain moments appear unpredictably in the real environment, impulsive effects are incorporated to depict the phenomenon in neural networks. Generally, impulsive sequences can be classified into stabilizing impulses and destabilizing impulses. Impulsive sequences are called to be stabilizing impulses if they can promote the stability of differential systems, while destabilizing impulses can suppress the stability of differential systems. Stability and synchronization problems of a dynamical system with different categories of impulses have become an interesting research topic, and some results with respect to the problems have been reported in [8–16]. For instance, in [8], the asymptotic stability of impulsive recurrent neural networks with stochastic disturbances and time delays was discussed by virtue of the Lyapunov functional approach and LMI technique. In [9], the synchronization problem of stochastic memristor-based recurrent neural networks with impulsive effects was explored by utilizing the impulsive differential inequality. In the real world, some phenomena about hybrid impulses comprising stabilizing and destabilizing impulses simultaneously often occur. They can be observed in fishing management with impulsive harvesting and releasing, goods selling involving impulsive stocking and transferring, and ball motion process with impulsive accelerating and decelerating. Moreover, some stability results of neural network systems with hybrid impulses have been attained by...
using comparison theory in [10, 11]. Subsequently, instead of general impulses, the exponential synchronization issue of complex networks with hybrid impulses was also tackled in [12, 13], where the approach of average impulsive gain was introduced based on the average impulsive interval method in [14].

Additionally, the external inputs have great influences on the dynamic systems. To describe accurately how external perturbations impact the asymptotical properties of the control systems, the definition of input-to-state stability (ISS) was incorporated in [17]. Noting that the external disturbances or inputs also appear in the network systems, it is significant and meaningful to investigate the ISS of neural networks. Recently, many researchers paid considerable attention to the field, and plenty of achievements on ISS have emerged [18−26]. For instance, in [18], the ISS property for dynamical neural networks was analyzed by using the Lyapunov stability theory. In [19], a nice passive weight learning rule was designed for switched Hopfield neural networks, and some asymptotic stability and ISS results were proposed. Furthermore, some results about ISS analysis were extended to stochastic neural networks. Particularly, in [21, 22], MEISS of stochastic recurrent neural networks was discussed through the Lyapunov functional method. In [23], some algebraic conditions were derived to guarantee the mean-square stability ISS of stochastic network systems with Markovian switching on the basis of vector inequality methods and stochastic analysis techniques. Furthermore, robust input-to-state stability of stochastic neural networks with Markovian switching was examined in [24] under two circumstances by means of M-matrix theory. In [25], a novel criterion about MEISS of stochastic neural networks with multiproportional delays were established applying the variable transformations approach. More recently, the ISS of delay systems with hybrid impulses was studied in light of the Razumikhin method in [26]. As far as we know, up until now, although stability and synchronization problems of neural networks with multiple impulses have been resolved, the ISS properties of stochastic network systems with hybrid impulses have not been explored. Therefore, the analysis of influence for hybrid impulses and external input on system states becomes a significant topic.

Motivated by the previous considerations, this paper focuses on the MEISS of stochastic neural networks with hybrid impulses. The essential innovations are summarized as below. First of all, a generalized comparison principle is introduced and a new inequality about the solution of the impulsive differential equation is achieved. Secondly, different from the existing works, hybrid impulses including destabilizing impulses, stabilizing impulses, and external input are taken into account simultaneously, which reflected reality more accurately and makes the addressed system more complex. Finally, some new criteria on MEISS and MES of stochastic neural networks with hybrid impulses are established by the average impulsive interval approach based on different kinds of impulsive sequences. The structure of our paper is arranged appropriately. Section 2 proposes some preliminaries including mathematical models, assumptions, definitions, and lemmas. In Section 3, based on two proposed lemmas, several criteria on MEISS and MES of neural networks with hybrid impulses are established. Some simulation examples are provided in Section 4, and conclusions are drawn in the last section.

**Notations 1.** Let \((\Omega, \mathcal{F}, \mathcal{F}_t, \mathbb{P})\) be a complete probability space with a filtration \(\{\mathcal{F}_t\}_{t \geq t_0}\) satisfying the usual conditions, we set \(\mathbb{R}^+ = (0, +\infty)\), \(\mathbb{N}^* = \{1, 2, \ldots\}\). \(\mathcal{PC}(\mathbb{R}; \mathbb{R}^n)\) represents the family of all piecewise continuous functions from \([a, b]\) to \(\mathbb{R}^n\). \(L_{\mathcal{F}_t}^{(\mathbb{R}^n, \mathbb{N})}([t_0 − \tau_0, t_0]; \mathbb{R}^n)\) denotes the family of all \(\mathcal{F}_t\) measurable \(\mathcal{PC}(\mathbb{R}; \mathbb{R}^n)\) valued random processes \(\varphi = \{\varphi(s)| t_0 − \tau_0 \leq s \leq t_0\}\) such that \(\sup_{t_0 − \tau_0 \leq s \leq t_0} E[\varphi(s)^2] < \infty\). \(\lambda_{\text{max}}(\cdot)\) stands for the largest eigenvalue of a matrix. \(\|u\|_{\infty} = \sup_{t \geq t_0} |u(t)|\) denotes the infinite norm of the input function \(u(t)\). Dini-derivative \(D^+\) is defined by \(D^+ v(t) = \lim_{\varepsilon \to 0^+} v(t + \varepsilon) − v(t)/\varepsilon\).

### 2. Preliminaries

Consider the following class of neural networks with stochastic disturbances and mixed delays:

\[
\begin{aligned}
\frac{dx(t)}{dt} &= -\alpha x(t) + \mathcal{R} f(x(t)) + \mathcal{C} g(x(t) - \tau(t)) + \mathcal{D} \int_{t-\tau_0}^{t} h(x(s)) \, ds, \\
&= \varphi(t), \quad x(0) = \varphi(0), t_0 - \tau_0 \leq s \leq t_0
\end{aligned}
\]

where \(x(t) = (x_1(t), x_2(t), \ldots, x_8(t))^T \in \mathbb{R}^n\) denotes the state vector of the neurons. \(\alpha, \beta, \gamma > 0\) represents the state threshold. \(\mathcal{R} = (\delta_{ij})_{n \times n}, \mathcal{C} = (c_{ij})_{n \times n}, \mathcal{D} = (d_{ij})_{n \times n}\) represent the connection weight strength matrices. \(f(x(t)) = (f_1(x(t)), f_2(x(t)), \ldots, f_8(x_8(t)))^T, g(x(t)) = (g_1(x(t)), g_2(x(t)), \ldots, g_8(x_8(t)))^T, h(x(t)) = (h_1(x(t)), h_2(x(t)), \ldots, h_8(x_8(t)))^T\) are the activation vector functions. Additionally, \(w(t)\) denotes an \(n\)-dimensional independent standard Wiener process, and function \(\varphi(t, x(t), x(t - \tau(t)) \in \mathbb{R}^{n \times n}\) stands for the noise intensity. We suppose that \(\tau(t)\) satisfies that \(0 \leq \tau(t) \leq \tau_0\). Moreover, some assumptions are imposed on the neuron activation functions and noise intensity functions.
Assumption 1. Suppose that activation functions \( f_i(x), g_i(x), \) and \( h_i(x) \) with \( f_i(0) = 0, g_i(0) = 0, h_i(0) = 0 \) satisfy the globally Lipschitz continuous condition, i.e., there exist some positive constants \( l_i, p_i, q_i, \) and \( i = 1, 2, \ldots, n \) such that

\[
\begin{align*}
\left| f_i(t_1) - f_i(t_2) \right| & \leq l_i \left| t_1 - t_2 \right| , \\
\left| g_i(t_1) - g_i(t_2) \right| & \leq p_i \left| t_1 - t_2 \right| , \\
\left| h_i(t_1) - h_i(t_2) \right| & \leq q_i \left| t_1 - t_2 \right| ,
\end{align*}
\]

hold for any \( t_1, t_2 \in \mathbb{R}^n \), which indicate that

\[
\begin{align*}
\text{diag} \left[ \left| f_1(t_1) - f_1(t_2) \right| , \ldots, \left| f_n(t_1) - f_n(t_2) \right| \right] & \leq L \left| t_1 - t_2 \right| , \\
\text{diag} \left[ \left| g_1(t_1) - g_1(t_2) \right| , \ldots, \left| g_n(t_1) - g_n(t_2) \right| \right] & \leq P \left| t_1 - t_2 \right| , \\
\text{diag} \left[ \left| h_1(t_1) - h_1(t_2) \right| , \ldots, \left| h_n(t_1) - h_n(t_2) \right| \right] & \leq Q \left| t_1 - t_2 \right| ,
\end{align*}
\]

where \( L = \text{diag} \left[ l_1, l_2, \ldots, l_n \right] , \quad P = \text{diag} \left[ p_1, p_2, \ldots, p_n \right] , \) and \( Q = \text{diag} \left[ q_1, q_2, \ldots, q_n \right] \) are the diagonal matrices.

Assumption 2. Suppose that the noise intensity function \( q(t, x(t), x(t - \tau(t))) \) satisfies the globally Lipschitz condition \( q(t, 0, 0) = 0 \). Furthermore, there exist two symmetric real matrices \( M_1, M_2 \) such that

\[
\begin{align*}
\text{tr} \left[ q^T(t, x(t), x(t - \tau(t))) q(t, x(t), x(t - \tau(t))) \right] & \leq x^T(t) M_1 x(t) + x^T(t - \tau(t)) M_2 x(t - \tau(t)).
\end{align*}
\]

By incorporating impulsive jumps and external input function \( u(t) = (u_1(t), u_2(t), \ldots, u_n(t))^T \in PC \left( \left[ t_0, + \infty \right); \mathbb{R}^n \right) \), system (1) is rewritten as follows:

\[
\begin{align*}
\dot{x}(t) = & \left[ - \alpha_1 x(t) + \beta_1 f(x(t)) + \beta_2 \dot{g}(x(t - \tau(t))) + \beta_3 \int_{t-\tau_0}^{t} h(x(s))ds \right. \\
& + u(t) dt + \sigma(t, x(t), x(t - \tau(t))) d\omega(t), \quad t \neq t_k, \\
& x(t_k) = \gamma_{1k} x(t_k^-) = \gamma_{2k} u(t_k^-), \quad t = t_k, \\
x(s) = & \varphi(s), \quad t_0 - \tau_0 \leq s \leq t_0,
\end{align*}
\]

where \( \gamma_{1k}, \gamma_{2k} \) are bounded constants. Moreover, we assume that there exists a positive constant \( \gamma_0 \) satisfies \( |\gamma_{2k}| \leq \gamma_0 \).

Definition 1. The trivial solutions of system (1) are said to be MEISS, if for arbitrary \( \varphi \in L_{\infty} \left[ \left[ t_0, - \tau_0 \right]; \mathbb{R}^n \right) \) and \( u(t) \in PC \left( \left[ t_0 - \tau_0, + \infty \right); \mathbb{R}^n \right) \), there exist positive constants \( \alpha_0, \beta_0, \varepsilon_0 \) such that

\[
E \left[ \left| x(t, \varphi) \right|^2 \right] \leq \alpha_0 e^{-\beta_0 (t - t_0)} E \left[ \left| \varphi \right|^2 \right] + \varepsilon_0 \| u \|_{\infty}^2 .
\]

Lemma 1. Assume \( \theta(t), z(t), \zeta_1(t), \) and \( \zeta_2(t) \) are piecewise continuous functions. The time-varying delay \( \tau(t) \) and impulsive sequences \( \{t_k\} \) satisfy that \( 0 \leq \tau(t) \leq t_0 \) and \( t_{k+1} - t_k \geq \tau_0 \). If there exist some constants \( \alpha_p, \beta_k, \) and \( j = 1, 2, 3, k \in \mathbb{N}^+ \) satisfying the following inequalities:

\[
\begin{align*}
D^+ \left( \theta(t) \right) & \leq \alpha_{1j} \theta(t) + \alpha_{2j} \theta(t - \tau(t)) \\
& + \beta_3 \int_{t-\tau_0}^{t} \theta(s)ds + \zeta_1(t), \quad t \neq t_k, \\
\theta(t_k) & \leq \beta_2 \theta(t_k^-) + \zeta_2(t_k^-), \quad t = t_k,
\end{align*}
\]

and

\[
\begin{align*}
\left| f_i(t_1) - f_i(t_2) \right| & \leq l_i |t_1 - t_2| , \\
\left| g_i(t_1) - g_i(t_2) \right| & \leq p_i |t_1 - t_2| , \\
\left| h_i(t_1) - h_i(t_2) \right| & \leq q_i |t_1 - t_2| ,
\end{align*}
\]

\[
\begin{align*}
\left| f_i(t_1) - f_i(t_2) \right| & \leq l_i |t_1 - t_2| , \\
\left| g_i(t_1) - g_i(t_2) \right| & \leq p_i |t_1 - t_2| , \\
\left| h_i(t_1) - h_i(t_2) \right| & \leq q_i |t_1 - t_2| ,
\end{align*}
\]

Lemma 2. Let \( \alpha_1, \alpha_2 \geq 0, \alpha_3 \geq 0, \beta_k \geq 0, \) and \( \tau_0 \geq 0 \) be some constants. \( \zeta_1(t) \) and \( \zeta_2(t) \) are nonnegative bounded functions. Delay \( \tau(t) \) and impulsive sequences \( \{t_k\} \) satisfy that \( 0 \leq \tau(t) \leq t_0 \), \( t_{k+1} - t_k \geq \tau_0 \). If the following impulsive differential equation with initial value \( x(s) = \phi(s) \geq 0, t_0 - \tau_0 \leq s \leq t_0 \) holds

\[
\begin{align*}
\dot{z}(t) = & \alpha_1 z(t) + \alpha_2 z(t - \tau(t)) \\
& + \beta_3 \int_{t-\tau_0}^{t} z(s)ds + \zeta_1(t), \quad t \neq t_k, \\
z(t_k) = & \beta_2 z(t_k^-) + \zeta_2(t_k^-), \quad t = t_k, \quad k \in \mathbb{N}^+ ,
\end{align*}
\]

then one can derive that
In Lemma 2, when is reduced, and it converges to the equilibrium point. To be stabilizing impulses since the absolute value of the state is away from the equilibrium point. Hybrid impulses since the absolute value of the state is enlarged and it is away from the equilibrium point.

**Proof.** When \( t \in [t_0, t_1) \), by (9), one gets that

\[
\left( e^{-a_i(t-t_0)}z(t) \right)' = e^{-a_i(t-t_0)} \left[ a_2 z(t - \tau(t)) + a_3 \int_{s-t_0}^{s} z(\theta)d\theta + \tau_1(s) \right].
\]

By integrating the above equation, it yields that

\[
z(t) = z(t_0) e^{a_i(t-t_0)} + \int_{t_0}^{t} \left[ a_2 z(s - \tau(s)) + a_3 \int_{s-t_0}^{s} z(\theta)d\theta + \tau_1(s) \right] ds
\]

\[
\leq \beta_k z(t_0) e^{a_i(t-t_0)} + e^{a_i(t-t_0)} \left( \prod_{t_0 < t_m < t} \beta_m \right) z(t_0) e^{a_i(t-t_0)} + \left( \sum_{t_0 < t_m < t} \prod_{t_0 < t_m < t} \beta_m \right) \tilde{e}_2(t_k) e^{a_i(t-t_0)}
\]

\[
+ \int_{t_0}^{t} \left( \prod_{s < t_m < t} \beta_m \right) x e^{a_i(t-s)} \left[ a_2 z(s - \tau(s)) + a_3 \int_{s-t_0}^{s} z(\theta)d\theta + \tau_1(s) \right] ds
\]

\[
\leq \left( \prod_{t_0 < t_k < t} \beta_k \right) z(t_0) e^{a_i(t-t_0)} + \left( \sum_{t_0 < t_k < t} \prod_{t_0 < t_k < t} \beta_m \right) \tilde{e}_2(t_k) e^{a_i(t-t_0)}
\]

We can get the assertion (10).

**Remark 1.** In Lemma 2, when \( \beta_k < 1 \), the impulses are called to be stabilizing impulses since the absolute value of the state is reduced, and it convergences to the equilibrium point. When \( \beta_k > 1 \), the impulses are called to be destabilizing impulses since the absolute value of the state is enlarged and it is away from the equilibrium point. Hybrid impulses include stabilizing impulses and destabilizing impulses simultaneously. Recently, the stability and synchronization problems of neural networks or complex networks with multiple impulses have been discussed [11–14]. Furthermore, the ISS property of nonlinear delay systems with multiple impulses was examined by the Razumikhin method in the article [26]. Based on the existing results [26], this paper aims to investigate the MEISS of stochastic neural networks with hybrid impulses.

Taking the stabilizing and destabilizing impulses into account, we suppose that the values of stabilizing impulse strengths \( \{\beta_k\} \) belong to one finite set \( \{\delta_i | \delta_i < 1, i = 1, 2, \ldots, \tilde{I}_1\} \) while the values of destabilizing impulse strengths \( \{\beta_k\} \) belong to the other finite set \( \{\eta_j | \eta_j > 1, j = 1, 2, \ldots, \tilde{I}_2\} \). The following assumption is further introduced.

**Assumption 3.** Suppose that there exist positive constants \( N_0 > 0, \lambda_i > 0, \) and \( \mu_j > 0 (i = 1, 2, \ldots, \tilde{I}_1, j = 1, 2, \ldots, \tilde{I}_2) \) such that \( \chi_{1i}(T, t) \geq T - t/\lambda_i - N_0, \) \( \chi_{2j}(T, t) \leq T - t/\mu_j + N_0, \) where \( \chi_{1i}(T, t) \) and \( \chi_{2j}(T, t) \) respectively denote the amount of the stable impulse sequence with strength \( \delta_i \) and destabilizing impulse sequence with impulse strength \( \eta_j \) on the time interval \( (t, T) \). Besides, the impulsive activation times \( t_k \) satisfy that \( \inf\{t_k - t_{k-1}\} = \kappa \geq \tau_0 > 0 \).
Remark 2. From the above assumption, we can find that \( \lambda_i \) and \( \mu_i \) stand for the average dwell-time of stabilizing and destabilizing impulsive sequences, respectively. \( \delta_i \) and \( \eta_j \) represent the impulsive strength of stabilizing and destabilizing impulses. If \( \max_i \{ t_{jk} - t_{jk-1} \} = \lambda_i \) and \( \inf_i \{ t_{jk} - t_{jk-1} \} = \mu_i \), \( i = 1, 2, \ldots, I_i \), \( j = 1, 2, \ldots, I_j \), \( i \) and \( j \) represent the finite positive integers, then we have that \( \chi_{\lambda_i} (T, t) \geq T - t / \lambda_i - 1, \chi_{\mu_j} (T, t) \leq T - t / \mu_j + 1 \).

3. Main Results

In this section, according to the proposed lemmas, several criteria on MEISS and MES of stochastic delay hybrid impulses neural networks are established by utilizing the comparison principle and stochastic Lyapunov function approach.

\[
\mathbb{L}V(t) = 2x^T(t) \left[ -\mathcal{A}x(t) + \mathcal{B}f(x(t)) + \mathcal{C}g(x(t - \tau(t))) + \mathcal{D} \int_{t - \tau_0}^{t} h(x(s))ds 
+ u(t) \right] + \text{tr}(\left[ \mathcal{A} - \mathcal{B}^T \right] x(t)) 
\leq -x^T(t) (\mathcal{A} + \mathcal{A}^T)x(t) + 2x^T(t) \mathcal{B}f(x(t)) + 2x^T(t) \mathcal{C}g(x(t - \tau(t))) 
+ 2x^T(t) \mathcal{D} \int_{t - \tau_0}^{t} h(x(s))ds + 2x^T(t) u(t) 
+ x^T(t) \mathcal{M}_1^T \mathcal{M}_1 x(t) + x^T(t - \tau(t)) \mathcal{M}_2^T \mathcal{M}_2 x(t - \tau(t)).
\]

Theorem 1. Let \( \beta_k = 2\gamma_k \) represent the impulsive strengths, which take values from two finite sets \( \{ \delta_i \mid 0 < \delta_i < 1, i = 1, 2, \ldots, I_i \} \) and \( \{ \eta_j \mid \eta_j > 1, j = 1, 2, \ldots, I_j \} \). Under Assumptions 1, 2, and 3, if there are some parameters \( \epsilon_i > 0, \epsilon_i \in \{1, 2, 3, 4\} \) satisfying the following inequality,

\[
\alpha_0 - q_0 \alpha_1 - q_0 \alpha_3 \tau_0 > 0,
\]

then system (1) is MEISS, where \( \alpha_0 = \sum_{i=1}^{I_i} \ln \delta_i / \lambda_i + \sum_{i=1}^{I_i} \ln \eta_i / \mu_i + \alpha_i \), \( \alpha_i = \lambda_{\max} \left[ - (\mathcal{A} + \mathcal{A}^T) + \epsilon_i \mathcal{B} \mathcal{B}^T + 1 / \epsilon_1 \right] 
+ \lambda_{\max} \left[ - (\mathcal{B} \mathcal{B}^T + \epsilon_3 \mathcal{B} \mathcal{B}^T + \epsilon_4 I + \mathcal{M}_1) \right] 
+ \lambda_{\max} \left[ 1 / \epsilon_2 P^T P + M_2 \right] 
\alpha_3 = \lambda_{\max} \left[ r_0 / \epsilon_2 Q^T Q \right] \), and \( q_0 = \prod_{i=1}^{I_i} 1 / \delta_i \right) \prod_{j=1}^{I_j} \eta_j \). 

Proof. The following Lyapunov function is chosen:

\[
V(t) = x^T(t)x(t).
\]

By the Itô formula, one can derive that

\[
2x^T(t) \mathcal{B}f(x(t)) \leq 2 \left[ \mathcal{B}^T \mathcal{B} \right] f(x(t)) \leq \epsilon_2 x^T(t) \mathcal{B} \mathcal{B}^T x(t) + \frac{1}{\epsilon_2} x^T(t) L^T L x(t). \tag{17}
\]

Similarly, one has that

\[
2x^T(t) \mathcal{C}g(x(t - \tau(t))) \leq \epsilon_3 x^T(t) \mathcal{C} \mathcal{C}^T x(t) + \frac{1}{\epsilon_3} x^T(t - \tau(t)) P^T P x(t - \tau(t)) 
2x^T(t) \mathcal{D} \int_{t - \tau_0}^{t} h(x(s))ds \leq \epsilon_3 x^T(t) \mathcal{D} \mathcal{D}^T x(t) + \frac{1}{\epsilon_3} \left( \int_{t - \tau_0}^{t} h(x(s))ds \right)^T \int_{t - \tau_0}^{t} h(x(s))ds 
\leq \epsilon_3 x^T(t) \mathcal{D} \mathcal{D}^T x(t) + \frac{\tau_0}{\epsilon_3} \int_{t - \tau_0}^{t} x^T(s) Q^T Q x(s)ds 
2x^T(t) u(t) \leq \epsilon_4 x^T(t) x(t) + \frac{1}{\epsilon_4} u^T(t) u(t).
\]
Then, we derive that

\[
\mathcal{L} \mathbf{V}(t) \leq \mathbf{x}^T(t) \left[ - (\mathbf{A} + \mathbf{A}^T) + \varepsilon_1 \mathbf{B} \mathbf{B}^T + \frac{1}{\varepsilon_1} \mathbf{I}^T \mathbf{L} + \varepsilon_2 \mathbf{C} \mathbf{C}^T + \varepsilon_3 \mathbf{D} \mathbf{D}^T + \varepsilon \mathbf{I} ight] \mathbf{x}(t) + \mathbf{x}^T(t - \tau(t)) \left[ \frac{1}{\varepsilon_2} \mathbf{P} + \mathbf{M}_1^T \mathbf{M}_1 \right] \mathbf{x}(t - \tau(t)) + \frac{\tau_0}{\varepsilon_3} \int_{t - \tau}^t \mathbf{x}^T(s) \mathbf{Q} \mathbf{x}(s) ds + \frac{1}{\varepsilon_4} \mathbf{x}^T(t) \mathbf{u}(t)
\]

(19)

where \( \alpha_1 = \lambda_{\text{max}} \left[ - (\mathbf{A} + \mathbf{A}^T) + \varepsilon_1 \mathbf{B} \mathbf{B}^T + \frac{1}{\varepsilon_1} \mathbf{I}^T \mathbf{L} + \varepsilon_2 \mathbf{C} \mathbf{C}^T + \varepsilon_3 \mathbf{D} \mathbf{D}^T + \varepsilon \mathbf{I} \right] \), \( \alpha_2 = \lambda_{\text{max}} \left[ \frac{1}{\varepsilon_2} \mathbf{P} + \mathbf{M}_1^T \mathbf{M}_1 \right] \), and \( \alpha_3 = \lambda_{\text{max}} \tau_0 \varepsilon_3 \mathbf{Q}. \)

In addition, we have that

\[
EV(t_k) \leq 2y_{1k}^2 \mathbf{V}(t_k) + 2y_{2k}^2 \mathbf{u}(t_k) \mathbf{u}(t_k)^T \leq \beta_k \mathbf{V}(t_k) + \zeta_k(t_k),
\]

(21)

where \( \beta_k = 2y_{1k}^2 + y_{2k}^2 \mathbf{u}(t_k)^2. \)

Together with (20) and (21), we can conclude that

\[
\begin{align*}
D^+ \mathbf{V}(t) &\leq E \mathbf{Z} \mathbf{V}(t) \\
&\leq \alpha_1 \mathbf{V}(t) + \alpha_2 EV(t - \tau(t)) + \alpha_3 \int_{t - \tau}^t EV(s) ds + \zeta_1(t),
\end{align*}
\]

(20)

Moreover, for \( t \neq t_k, \) one can see that

\[
EV(t) \leq z(t) \leq \left( \prod_{t_k < t_k \leq t} \beta_k \right) H_0 e^{\alpha_1(t - t_0)} + \sum_{t_k < t_k \leq t} \left( \prod_{t_k < t_m \leq t} \beta_m \zeta_2(t_m) e^{\alpha_1(t - t_m)} \right) + \int_{t_0}^t \left( \prod_{t_k < t_k \leq t} \beta_k \right) e^{\alpha_1(s - t)} \left[ \alpha_2 EV(s - \tau_1(s)) + \alpha_3 \int_{s - \tau}^s EV(u) du + \zeta_1(s) + \theta \right] ds,
\]

(23)

where \( H_0 = \sup_{-\tau_0 \leq s \leq 0} E|\mathbf{x}(s)|^2. \) Let \( q_0 = \left( \prod_{i=1}^{l_1} 1/\delta_i \prod_{j=1}^{l_2} \eta_j \right)^{N_2}, \) \( \alpha_0 = -\left[ \sum_{i=1}^{l_1} \ln \delta_i/\lambda_i + \sum_{j=1}^{l_2} \ln \eta_j/\mu_j + \alpha_1 \right]. \) From Assumption 3, it easily follows that \( t - t_0/\lambda_i - N_0 \leq \chi_{1i} \) and

\[
\left( \prod_{t_k < t_k \leq t} \beta_k \right) e^{\alpha_1(t - t_0)} \leq \left( \prod_{i=1}^{l_1} q_{1i} \prod_{j=1}^{l_2} \eta_{1j} \right) e^{\alpha_1(t - t_0)} \leq \left( \prod_{i=1}^{l_1} \delta_{1i} \prod_{j=1}^{l_2} \eta_{1j} \right) e^{\alpha_1(t - t_0)} \leq q_0 e^{-\alpha_0(t - t_0)}.
\]

(24)
Accordingly, we acquire that
\[
\left( \prod_{t_k \leq t \leq t_{k+1}} \beta_m \right) \zeta_2(t_k) e^{\alpha_1(t-t_k)} \leq q_0 \zeta_2(t_k) e^{-\alpha_0(t-t_k)},
\]
\[
\left( \prod_{s \leq t \leq t_s \leq t} \beta_k \right) e^{\alpha_1(t-s)} \leq q_0 e^{-\alpha_0(t-s)}.
\]
(25)

Hence, it follows that
\[
EV(t) \leq z(t) \leq q_0 H_0 e^{-\alpha_0(t-t_k)} + q_0 \sum_{t_k \leq t \leq t_{k+1}} \zeta_2(t_k) e^{-\alpha_0(t-t_k)} + \int_{t_0}^{t} q_0 e^{-\alpha_0(t-u)} \left[ \alpha_2 EV(s - \tau_1(s)) + \alpha_3 EV(u) du + \zeta_1(s) + \theta \right] ds.
\]
(26)

Considering the following equation:
\[
\xi - \alpha_0 + \alpha_2 q_0 e^{\xi_0} + \alpha_3 q_0 e^{\xi_0} - 1 = 0.
\]
(27)

Let \( \Phi(\xi) = \xi - \alpha_0 + \alpha_2 q_0 e^{\xi_0} + \alpha_3 q_0 e^{\xi_0} - 1/\xi \). Since \( \Phi(0^+) = - (\alpha_0 - \alpha_2 q_0 - \alpha_3 q_0) < 0, \) \( \Phi(+\infty) > 0 \), and \( \Phi(\xi) \) is a continuous function in the time interval \((0, +\infty)\), there is a root satisfying (27). Besides, it is obvious that \( \Phi'(\xi) > 0 \). Thus, there exists a unique positive root \( \sigma \) such that the above equation holds. Subsequently, we will claim that
\[
EV(t) \leq q_0 H_0 e^{-\sigma(t-t_k)} + q_0 \left[ \zeta_1(t) \right]_{t_0}^{t} + \theta \]
\[
\frac{\alpha_0 q_0 \zeta_2(t)}{1 - e^{-\alpha_0(t-t_k)}} + \frac{\alpha_0 q_0 \zeta_2(t)}{1 - e^{-\alpha_0(t-t_k)}}(1 - e^{-\alpha_0(t-t_k)}) (a_0 - q_0 a_2 - q_0 a_3 r_0).
\]
(28)

When \( t \in [t_0 - \tau_0, t_0] \), it can be easily verified that what assertion (28) holds. Let \( H_1 = q_0 \left( \left\| \zeta_1(t) \right\|_{t_0} + \theta \right) / \alpha_0 - q_0 a_2 - q_0 a_3 r_0 + a_0 q_0 \zeta_2(t) \left( 1 - e^{-\alpha_0(t)} \right) (a_0 - q_0 a_2 - q_0 a_3 r_0) \). For \( t > t_0 \), if inequality (3.6) is not true, on the contrary, then there exists a \( T \) such that
\[
EV(t) \geq q_0 H_0 e^{-\sigma(t-t_k)} + H_1,
\]
(29)

and for \( t \in [-t_0, T) \)
\[
EV(t) \leq q_0 H_0 e^{-\sigma(t-t_k)} + H_1.
\]
(30)

Then, we obtain that
\[
EV(t) \leq q_0 H_0 e^{-\alpha_0(t-t_k)} + q_0 \sum_{t_k \leq t \leq t_{k+1}} \zeta_2(t_k) e^{-\alpha_0(t-t_k)} + \int_{t_0}^{t} q_0 e^{-\alpha_0(t-u)} \left[ \alpha_2 EV(s - \tau_1(s)) + \alpha_3 EV(u) du + \zeta_1(s) + \theta \right] ds.
\]
(31)

By means of (30), it is noted that
\[
\int_{t_0}^{t} q_0 e^{-\alpha_0(t-u)} \alpha_2 EV(s - \tau_1(s)) du \leq q_0 \int_{t_0}^{t} \alpha_2 e^{-\alpha_0(t-u)} \left[ q_0 H_0 e^{-\sigma(t-t_k)} + H_1 \right] du
\]
\[
\leq q_0^2 H_0 \alpha_2 e^{\sigma t} e^{-\alpha_0(t-u)} \left[ 1 - e^{-\alpha_0(t-t_k)} \right] \alpha_0
\]
\[
\leq q_0^2 H_0 \alpha_2 e^{\sigma t} \left[ e^{-\sigma(t-t_k)} - e^{-\alpha_0(t-t_k)} \right] \alpha_0.
\]
(32)

Similarly, we have that
\[
\int_{t_0}^{T} q_0 e^{-a_1 (t - t_0)} \int_{s-t_0}^{s} \mathbf{E} V(u) \, duds \\
\leq q_0 \int_{t_0}^{T} a_0 e^{-a_1 (t - s)} \left[ \int_{s-t_0}^{s} q_0 H_0 e^{-\sigma (t - s)} + H_1 \right] \, dvds \\
\leq q_0^3 H_0 a_3 e^{\sigma T_1} - 1 \frac{q_0 \alpha_3 \tau_0}{\sigma} H_1 \left[ 1 - e^{-a_1 (t - t_0)} \right] \\
\leq q_0^3 H_0 a_3 e^{\sigma T_1} - 1 \left[ e^{-\sigma (t - T_1)} - e^{-a_1 (t - T_1)} \right] + q_0 \alpha_3 \tau_0 H_1 \left[ 1 - e^{-a_1 (t - t_0)} \right], \\
\int_{t_0}^{T} q_0 e^{-a_1 (t - s)} (\zeta_1 (s) + \theta) \, ds \leq \frac{q_0 \mathcal{H}_1 (s) + \theta}{\alpha_0} \left[ 1 - e^{-a_1 (t - t_0)} \right].
\]

Therefore, one gets that

\[
\mathbf{E} V(T) \leq q_0 H_0 e^{-a_1 (t - t_0)} + q_0 \left[ \frac{q_0 \mathcal{H}_1 (s) + \theta}{\alpha_0} \left[ 1 - e^{-a_1 (t - t_0)} \right] \right]
\]

Noting that \( a_0 + a_2 q_0 e^{\sigma T_1} + \alpha_3 q_0 e^{\sigma T_1} - 1/\sigma = 0 \) and \( H_1 = q_0 (\mathcal{H}_1 (t) + 2 \zeta_1 (s) + \theta) \), we have that

\[
\mathbf{E} V(T) \leq q_0 H_0 e^{-\sigma (T - t_0)} + q_0 \mathcal{H}_1 (s) + \theta \\
+ \frac{1}{\alpha_0} \left[ q_0 H_1 \left[ \frac{q_0 \zeta_1 (t) + \theta}{\alpha_0} \left[ 1 - e^{-a_1 (t - t_0)} \right] \right] \right],
\]

which implies that

\[
\mathbf{E} V(T) \leq q_0 H_0 e^{-\sigma (t - t_0)} + H_1.
\]

It yields a contradiction with (29). Then, we have that

\[
\mathbf{E} V(T) \leq q_0 H_0 e^{-\sigma (t - t_0)} + \frac{q_0 \mathcal{H}_1 (s) + \theta}{\alpha_0} \left[ 1 - e^{-a_1 (t - t_0)} \right] \\
+ \frac{q_0 \alpha_3 \tau_0}{\alpha_0} \left[ 1 - e^{-a_1 (t - t_0)} \right],
\]

which implies that system (1) is MEISS. \( \square \)

Remark 3. In [21, 22], the MEISS of stochastic recurrent neural networks and Cohen-Grossberg neural networks have been investigated. In this paper, impulsive sequences
are composed of destabilizing impulses, stabilizing impulses, and external input, which makes our model complicated. Meanwhile, some novel ISS criteria are established by employing impulsive differential inequality and average impulsive interval approach based on different kinds of impulsive sequences. On the other hand, the ISS property of impulsive delay systems with multiple impulses was also analyzed by means of the Razumikhin method in [26], and some restrictive conditions are required such that \( \beta_2 = \beta_{N+1} \). It implies that the impulsive sequences are periodic, which is not necessary for our results. Besides, compared with the existing results [26], our results are applied to stochastic neural networks and the sufficient conditions are more easily verified.

**Remark 4.** It is worth pointing out that the method applied in [12, 13] is not suitable in this paper since the impulsive part includes the external input. Therefore, this paper constructs the new impulsive inequality to overcome the difficulties.

If the stochastic disturbances and distributed delays are removed (1) immediately, it yields the following system:

\[
\begin{align*}
\dot{x}(t) &= \left[-\alpha x(t) + Bf(x(t)) + Cg(x(t - \tau(t)))\right] + u(t) dt, t \neq t_k, \\
x(t_k) &= y_{1k}(t_k) + y_{2k}(t^-), t = t_k, \\
x(s) &= \phi(s), t - \tau_0 \leq s \leq t_0.
\end{align*}
\]

(40) 

Accordingly, we have the following result.

**Corollary 1.** Let \( \beta_2 = 2\gamma_{1k} \) represent the impulsive strengths, which take values from two finite sets \( \{\delta_i, 0 < \delta_i < 1, i = 1, 2, \ldots, 1\} \) and \( \{\eta_j, |\eta_j| > 1, j = 1, 2, \ldots, 1\} \). Under Assumptions 1 and 3, if there exist positive constants \( \epsilon_1, \epsilon_2 \in \{1, 2, 3\} \), then such that

\[
\alpha_0 - q_0 \alpha_2 > 0,
\]

(41) 

where \( \alpha_0 = -[\sum_{i=1}^{N_1} \ln \delta_i/\lambda_i + \sum_{j=1}^{N_2} \ln \eta_j/\mu_j + \alpha_1], \quad \alpha_1 = \lambda_{\max} \left[-(\alpha + \alpha^T) + \epsilon_1 B^T B + \epsilon_2 \|B^T C + C^T\|_2^2 + \epsilon_3 \|B^T D + D^T I + M_1\|_2^2\right], \quad \alpha_2 = \lambda_{\max}[1/\epsilon_5 P^T P], \quad q_0 = (\prod_{i=1}^{N_1} 1/\delta_i \prod_{j=1}^{N_2} \eta_j)^{N_0}, \quad \text{then system (40) is exponentially ISS.}

In particular, when \( \delta_i = 1 \), the stabilizing impulse strength and destabilizing impulse strength are reduced to be \( \delta_i \) and \( \eta_i \), respectively. Moreover, similar to Remark 2, let max \( \{\tilde{t}_{ik} - \tilde{t}_{ik-1}\} = \lambda_i \) and \( \inf \{\tilde{t}_{ik} - \tilde{t}_{ik-1}\} = \mu_i \). It is equivalent to \( \chi_{11}(T, t) \geq T - t/\lambda_i - 1, \quad \chi_{21}(T, t) \leq T - t/\mu_i + 1 \), which leads to the following corollary.

**Corollary 2.** Suppose that two constants \( \delta_i \) and \( \eta_i \) satisfy \( 0 < \delta_i < 1, \eta_i > 1 \). \( \beta_2 = 2\gamma_{1k} \) denotes the impulsive strengths, which can be chosen by the set \( \{\delta_i, \eta_i\} \). Under Assumptions 1, 2, and 3, if

\[
\alpha_0 - q_0 \alpha_2 - q_0 \alpha_3 r_0 > 0,
\]

(42) 

where \( \alpha_0 = -[\ln \delta/\lambda + \ln \eta/\mu + \alpha_1], \quad \alpha_1 = \lambda_{\max} \left[-(\alpha + \alpha^T) + B^T B + I^T L + C^T C + D^T D + I + M_1\right], \quad \alpha_2 = \lambda_{\max}[P^T P + M_1], \quad \alpha_3 = \lambda_{\max}[\tau_0 Q^T Q], \quad q_0 = \prod_{i=1}^{N_1} 1/\delta_i \prod_{j=1}^{N_2} \eta_j, \quad \text{then system (1) is MEISS.}

When external input \( u(t) = 0 \), according to the above results, the following assertions might be derived immediately.

**Theorem 2.** Let \( \beta_2 = 2\gamma_{1k} \) denote the impulsive strengths, which take values from two finite sets \( \{\delta_i, 0 < \delta_i < 1, i = 1, 2, \ldots, 1\} \) and \( \{\eta_j, |\eta_j| > 1, j = 1, 2, \ldots, 1\} \). Suppose that all the other conditions in Theorem 1 are on hold. If external input \( u(t) = 0, \) then system (1) is MES.

**Corollary 3.** Let \( \beta_2 = 2\gamma_{1k} \) represent the impulsive strengths, which take values from two finite sets \( \{\delta_i, 0 < \delta_i < 1, i = 1, 2, \ldots, 1\} \) and \( \{\eta_j, |\eta_j| > 1, j = 1, 2, \ldots, 1\} \). Suppose that all the other conditions in Corollary 1 are on hold. If external input \( u(t) = 0, \) then system (40) is exponentially stable.

**Remark 5.** In [11], the exponential stability of delayed neural networks with hybrid impulses was discussed. This paper further explores the MEISS of mixed delayed neural networks with stochastic disturbances and hybrid impulses. Particularly, when stochastic terms, distributed delays and external input are removed, the addressed system is reduced to the system in [11]. In light of Remark 2, when \( \max \{\tilde{t}_{ik} - \tilde{t}_{ik-1}\} = \lambda_i \) and \( \inf \{\tilde{t}_{ik} - \tilde{t}_{ik-1}\} = \mu_i \), we can choose flexible constant \( N_0 = 1 \) in Assumption 3. Let \( \epsilon_1 = \epsilon_2 = 1 \). Applying Corollary 3 to this case, if \( \alpha_0 = -[\sum_{i=1}^{N_1} \ln \delta_i/\lambda_i + \sum_{j=1}^{N_2} \ln \eta_j/\mu_j + \alpha_1], \quad \alpha_1 = \lambda_{\max} \left[-(\alpha + \alpha^T) + B^T B + I^T L + C^T C + D^T D + I + M_1\right], \quad \alpha_2 = \lambda_{\max}[P^T P], \quad \text{and} \quad q_0 = \prod_{i=1}^{N_1} 1/\delta_i \prod_{j=1}^{N_2} \eta_j, \quad \text{then the considered system is exponentially stable, which accords with the result in [11].}

**Remark 6.** Recently, different control strategies have been developed to deal with some nonlinear systems. For instance, in [27], a stochastic integral sliding mode control strategy for singularly perturbed Markov jump descriptor systems subject to nonlinear perturbation was proposed and a novel mode and switch-dependent integral switching surface were introduced. In [28], the problem of path following for the underactuated unmanned surface vehicles (USVs) subject to state constraints has been tackled, where one control scheme was presented by combining the backstepping technique, adaptive dynamic programming, and the event-triggered mechanism. In [29], quantized nonstationary filtering for networked Markov switching repeated scalar nonlinear systems was investigated based on a multiple hierarchical structure strategy. Moreover, these control strategies can be applied to many applicable systems in the real world. Actually, impulsive control is also one of the significant control strategies. In this paper, we establish some MEISS criteria about stochastic neural networks with hybrid impulses. In the future, we could further explore the control problems of some applicable systems combined with input-to-state stability theory.
4. Numerical Example

In this section, two examples have been provided to exhibit the validity of the theoretical results in Theorem 1 and Theorem 2, in which hybrid impulsive effects are introduced.

\begin{align*}
\mathcal{A} &= \begin{pmatrix} 2.7 & 0 \\ 0 & 3 \end{pmatrix}; \quad \mathcal{B} = \begin{pmatrix} 0.3 & 0.5 \\ 0.8 & 0.9 \end{pmatrix}; \quad \mathcal{C} = \begin{pmatrix} 0.4 & 0.2 \\ 0.1 & 0.3 \end{pmatrix}; \\
\mathcal{D} &= \begin{pmatrix} 0.7 & 0.8 \\ 0.9 & 0.5 \end{pmatrix}; \quad \varphi(t, x(t), x(t - \tau(t))) = \begin{pmatrix} 0.4x_1(t) & 0.3x_1(t - \tau(t)) \\ 0.5x_1(t) & 0.2x_2(t - \tau(t)) \end{pmatrix}, \\
f(x(t)) &= \begin{pmatrix} 0.8\tanh(x_1(t)) \\ 0.9\tanh(x_2(t)) \end{pmatrix}; \\
g(x(t)) &= \begin{pmatrix} 0.24\tanh(x_1(t)) \\ 0.2\tanh(x_2(t)) \end{pmatrix}; \\
h(x(t)) &= \begin{pmatrix} 0.9\tanh(x_1(t)) \\ 0.85\tanh(x_2(t)) \end{pmatrix}; \\
u(t) &= \begin{pmatrix} 1.8\sin t \\ 1.8\cos t \end{pmatrix}; \\
\gamma_{ik} &= \begin{cases} 0.5, k = 2j - 1, \\ 0.8, k = 2j, j \in \mathbb{Z} \end{cases}; \\
ym_{2k} &= 0.8, k \in \mathbb{Z}.
\end{align*}

Therefore, all the conditions are satisfied in Theorem 1, then system (9) is MESS (See Figure 1). While \( u(t) = 0 \), according to Theorem 2, the system is MES (Figure 2).

**Example 2.** Assume that parameters of the neural network (9) meet that

\begin{align*}
\mathcal{A} &= \begin{pmatrix} 2.1 & 0 \\ 0 & 2.4 \end{pmatrix}; \quad \mathcal{B} = \begin{pmatrix} 0.2 & -0.15 \\ 0.32 & 0.1 \end{pmatrix}; \quad \mathcal{C} = \begin{pmatrix} 0.65 & 0.25 \\ -0.18 & 0.4 \end{pmatrix}; \\
\mathcal{D} &= \begin{pmatrix} 0.12 & 0.16 \\ 0.35 & -0.3 \end{pmatrix}; \\
f(x(t)) &= \begin{pmatrix} 0.36\sin(x_1(t)) \\ 0.24\sin(x_2(t)) \end{pmatrix}; \\
g(x(t)) &= \begin{pmatrix} 0.12\sin(x_1(t)) \\ 0.15\sin(x_2(t)) \end{pmatrix}; \\
u(t) &= \begin{pmatrix} 5\sin t \\ 2\cos t \end{pmatrix}; \\
\gamma_{ik} &= \begin{cases} 0.9, k = 2j - 1, \\ 0.6, k = 2j, \end{cases} \quad \gamma_{2k} = 0.7.
\end{align*}

**Remark 7.** From the above two examples, it could be seen that stabilizing impulses and destabilizing impulses coexist simultaneously. In Example 1, the stabilizing impulses are dominant, which plays an important role in stabilizing systems. While in Example 2, the destabilizing impulses are dominant, which could be seen as impulsive perturbations. Under this circumstance, the original system can tolerate the impulsive perturbations and maintain input-to-state stability. Different from the theoretical results in [26], the sufficient conditions on MEISS criteria are more easily verified by virtue of the average impulsive interval approach.
Figure 1: 2nd moment of the system states $x_1(t), x_2(t)$ in Example 1 with input $u(t) = (1.8 \sin t, 1.8 \cos t)^T$, and initial value $(-40, 36)^T$.

Figure 2: 2nd moment of the system states $x_1(t), x_2(t)$ in Example 1 input $u(t) = 0$, and initial value $(-40, 36)^T$.

Figure 3: 2nd moment of the system states $x_1(t), x_2(t)$ in Example 2 with input $u(t) = (5 \sin t, 2 \cos t)^T$ and initial value $(18, 26)^T$. 
Acknowledgments

The authors declare that they have no conflicts of interest.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Data Availability

All data, models, and code generated or used during the study appear in the submitted article.

Conclusions

This article investigates the issues of MEISS for stochastic neural networks with hybrid impulses. A generalized comparison principle is introduced and a new inequality about the solution of the impulsive differential equation is derived. Moreover, combining the impulsive differential inequality and average impulsive interval approach based on different kinds of impulsive sequences, some novel criteria are constructed to guarantee that the system is MEISS. When external input $u(t) = 0$, the addressed system is MES. Since hybrid impulses and external input at each impulsive moment are incorporated, our model becomes more general. Consequently, our theoretical achievements also improve the previous results. In the future, we will further explore some control problems of applicable systems by virtue of ISS theory.

5. Conclusions

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