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Integral-Based Memory Event-Triggered Controller Design for Uncertain Neural Networks with Control Input Missing

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Abstract: In this paper, the controller design problem for uncertain neural networks (NNs) with control input missing is addressed under an event-triggered (ET) scheme. First, under the zero-input method, the closed-loop system is modeled as a switched system which includes a stable subsystem and an unstable subsystem. Next, a novel integral-based memory event-triggered (IMET) scheme is designed, which can prevent Zeno behavior. The proposed IMET scheme is designed over a specified memory interval; thus, it can make full use of the historical state information, thereby reducing the adverse impact caused by packet dropouts. Then, with the analysis method of switched systems, a piecewise time-dependent Lyapunov functional is designed, and low conservative conditions are derived to ensure the exponential stability of the switched closed-loop system. Meanwhile, the constraints on the packet loss rate and the average dwell time are established. Moreover, the design of the controller gain is also given. Finally, the feasibility of IMET is verified using an example.

Keywords: control input missing; integral; memory event-triggered scheme; neural networks; switched systems; uncertainty

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1. Introduction

Due to their powerful adaptability, self-organization, and self-learning abilities, neural networks (NNs) have become a research hotspot for many scholars [1–4]. However, in the implementation of NNs, uncertainties are often encountered because of inaccurate modeling or environmental noise, which can degrade system performance and further lead to system instability [5–7]. In addition, on account of unreliable communication channels and limited bandwidth, the control signal may not reach the receiving terminal successfully. Hence, data packet dropout is an inevitable problem for the control of NNs. When packet dropout occurs from the controller to the actuator channel, it is referred ti as missing control input [8]. This phenomenon is inevitable due to actuator failure, intermittent controller unavailability, and other reasons. Generally, there are two methods to cope with this problem. One is the hold-input method [9,10]; that is, when the controller signal is lost, the latest control signal is taken as the input of the actuator. The other is the zero-input method [11–14]; that is, when the control signal is lost, the input of the actuator is set to zero, then the controlled system can be converted to a switched system. Promising results on systems with packet dropout have been achieved. For example, based on the zero-input method, robust synchronization for uncertainty delayed NNs with control packet dropout

was implemented under sampling control in [12]. For fuzzy system with packet dropouts, refs. [13,14] studied robust H_∞ control and exponential stabilization using the zero-input method under sampling control, respectively. It should be noted that although related research on neural networks incorporating these two network-induced phenomena has achieved certain results, there remains significant room for improvement.

On the other hand, networked control methods have attracted considerable attention in recent decades. As is well known, traditional time-triggered control methods will generate redundant data and therefore lead to over-occupation of limited communication bandwidth and blockage of information channels. It has been proved in [15] that the integration of an event-triggered scheme into the controller can effectively reduce the number of control task executions. Thereafter, ET control has attracted increasing attention from scholars [16–20]. The sampling of ET control is carried out only when a preset event is triggered; that is, the system will transmit information only as needed. In this way, the waste of network resources can be reduced while guaranteeing the expected performance. Among the existing ET schemes, the periodic event-triggered (PET) scheme is a classic one, in which the preset triggering condition is monitored periodically [21,22]. It can ensure that the interval between two adjacent triggers is greater than zero, so it can automatically avoid the emergence of Zeno phenomena. Based on the PET scheme, a novel ET scheme called the memory-based event-triggered (MET) scheme was devised in [23]. The MET scheme comprehensively utilizes the difference between historically transmitted data and the currently sampled data to design the triggering condition [24–27]. What needs to be pointed out is that most existing METs use the discrete mean value of a certain number of historically sampled or triggered data. However, if packet dropouts occur, some sampled data are partial, or all missing, then the effect of the MET scheme using a discrete mean value will be reduced. However, if the continuous mean value—that is, the integral over a past continuous interval—is employed to design the triggering condition, even if some sampled data are lost, the integral can still address the issue related to packet dropout due to the good property of the integral. In this way, both higher control performance and fewer triggering times can be achieved.

Enlightened by the above thoughts, this paper will investigate the stabilization of NNs with uncertainty and control input missing by designing an ET scheme. The contributions of this paper can be summarized as follows:

(1) To deal with the impact of packet dropout, a novel MET scheme, named IMET, is devised, which introduces an integral of the system state over a specified memory interval. The proposed IMET scheme can not only make use of the historical state information but also alleviate the effects of packet dropout and exclude the occurrence of Zeno phenomena.

(2) Under the proposed IMET scheme, the uncertain NN with control input missing is modeled by a switched system on the basis of the zero-input method. Then, a piecewise time-dependent Lyapunov functional consisting of a looped functional is designed. The exponential stability of the switched closed-loop system is analyzed and low conservative stability conditions and control gain design algorithms are developed.

The remainder of this paper is organized as follows. The IMET scheme is proposed and the closed-loop system is established in Section 1. The sufficient conditions for exponential stability and the co-design method of the control law are given in Section 2. The obtained results are verified using an example in Section 3. Section 4 concludes this paper.

Some special symbols are explained in Table 1.

Table 1. Notations and descriptions.

Notation	Description
$\mathbb{N}$	Set of non-negative integers
$\mathbb{R}^n$	Set of n-dimensional real vectors
$\mathbb{R}^{n\times m}$	Set of $n \times m$ real matrices
$\mathbb{R}_+^{n\times n}$	Set of symmetric positive-definite matrices
$M^T(M^{-1})$	Transposition (inverse) of matrix M
$\lambda_{\max}(M)(\lambda_{\min}(M))$	Maximum (minimum) eigenvalue of matrix M
$M > 0(< 0)$	Real symmetric and positive (negative) definite matrix M
col$\{\cdot\}$	Column vector
I_m	$m \times m$ identity matrix
0	Zero matrix with appropriate dimensions

2. Problem Formulation

Consider a NN with uncertainties modeled as follows:

$$\dot{x}(t) = (W_1 + \Delta W_1(t))x(t) + (W_2 + \Delta W_2(t))f(t, x(t)) + u(t), \tag{1}$$

where $x(t),\ u(t) \in \mathbb{R}^n$ denote the state vector and the control input, respectively; W_1 and W_2 are known real matrices, and $\Delta W_1(t)$ and $\Delta W_2(t)$ represent the parameter uncertainties. The system nonlinearity $f(t, x(t)) : \mathbb{R} \times \mathbb{R}^n \to \mathbb{R}^n$ is a piecewise-continuous function with $f(t, 0) = 0$ and satisfies

$$f^T(t, x(t))f(t, x(t)) \leq \beta^2 x^T(t)H^T Hx(t), \tag{2}$$

where $\beta > 0$ is a constant and H is a constant matrix.

Assumption 1. *Suppose the parameter uncertainties $\Delta W_1(t)$ and $\Delta W_2(t)$ are of the following structure:*

$$[\Delta W_1(t)\ \Delta W_2(t)] = NF(t)[L_1\ L_2], \tag{3}$$

where $N \in \mathbb{R}^{n\times m}$, $L_1, L_2 \in \mathbb{R}^{m\times n}$ are known real matrices and the uncertain matrix $F(t) \in \mathbb{R}^{m\times m}$ is bounded by

$$F^T(t)F(t) \leq I_m,\ \ \forall t \geq 0. \tag{4}$$

We denote kh $(k \in \mathbb{N})$ as the sampling instants with sampling period $h > 0$, and $t_k h$ $(k \in \mathbb{N})$ with $t_0 h = 0$ as the triggering instants; that is, at $t_k h$, the sampled data packets are transmitted. We define $\widetilde{x}(t) = \frac{1}{\varpi}\int_{t-\varpi}^{t} x(s)ds$ with the integral period $\varpi > 0$. Then, the triggering condition of the IMET scheme is presented as follows:

$$\begin{aligned} t_{k+1}h &= t_k h + l_k h, \\ \text{with}\ \ l_k h &= \inf_{l\in\mathbb{N}}\Big\{lh|\ \widetilde{e}(t_k h + lh)^T \Omega \widetilde{e}(t_k h + lh) \geq \rho \widetilde{x}^T(t_k h)\Omega\widetilde{x}(t_k h)\Big\}, \end{aligned} \tag{5}$$

where $t_k h + lh$ is the current sampling instant, and $t_{k+1}h$ is the next triggering instant to be determined; $\widetilde{x}(t_k h) = \frac{1}{\varpi}\int_{t_k h-\varpi}^{t_k h} x(s)ds$ with the memory period $\varpi > 0$ and $\widetilde{e}(t_k h + lh) = x(t_k h + lh) - \widetilde{x}(t_k h)$; $\Omega \in \mathbb{R}_+^{n\times n}$ is the triggering matrix to be designed, and $0 < \rho < 1$ is a given constant.

Remark 1. *The existing MET (EMET) scheme is that proposed in [23].*

$$t_{k+1}h = t_kh + \inf_{l\in\mathbb{N}}\left\{ lh| \sum_{j=1}^{m} \mu_j e_j^T(t)\Omega e_j(t) \geq \rho\widehat{x}^T(t_kh)\Omega\widehat{x}(t_kh)\right\},$$

where m denotes the number of historically transmitted packets, $\widehat{x}(t_kh) = \frac{1}{m}\sum_{j=1}^{m} x(t_{k+1-j}h)$, $e_j(t) = x(t_kh+lh) - x(t_{k+1-j}h)$, and $0 \leq \mu_j \leq 1, \sum_{j=1}^{m}\mu_j = 1$. The distinction between EMET and IMET can be summarized in two points. First, the EMET scheme employs a discrete average of some historic data at t_kh, such as $\widehat{x}(t_kh) = \frac{1}{m}\sum_{j=1}^{m} x(t_{k+1-j}h)$ and $\sum_{j=1}^{m}\mu_j e_j^T(t)\Omega e_j(t) = \sum_{j=1}^{m}\mu_j[x(t_kh+lh) - x(t_{k+1-j}h]^T\Omega[x(t_kh+lh) - x(t_{k+1-j}h]$. However, the IMET scheme adopts the continuous mean of the system state over the interval $[t_kh-\varpi, t_kh)$, resulting in $\widetilde{x}(t_kh) = \frac{1}{\varpi}\int_{t_kh-\varpi}^{t_kh} x(s)ds$ and $\frac{1}{\varpi}\int_{t_kh-\varpi}^{t_kh} e^T(s)\Omega e(s)ds = \frac{1}{\varpi}\int_{t_kh-\varpi}^{t_kh}[x(t_kh+lh) - x(s)]^T\Omega[x(t_kh+lh) - x(s)]ds$. Second, IMET further incorporates the Jensen's inequality to derive a more stringent triggering condition. Using Jensen's inequality to $\frac{1}{\varpi}\int_{t_kh-\varpi}^{t_kh} e^T(s)\Omega e(s)ds$ yields

$$\begin{aligned}
&\tfrac{1}{\varpi}\int_{t_kh-\varpi}^{t_kh} e^T(s)\Omega e(s)ds\\
=&\tfrac{1}{\varpi}\int_{t_kh-\varpi}^{t_kh}[x(t_kh+lh) - x(s)]^T\Omega[x(t_kh+lh) - x(s)]ds\\
\geq&[x(t_kh+lh) - \widetilde{x}(t_kh)]^T\Omega[x(t_kh+lh) - \widetilde{x}(t_kh)],\\
=&\widetilde{e}(t_kh+lh)^T\Omega\widetilde{e}(t_kh+lh).
\end{aligned}$$

Finally, the proposed IMET scheme can be obtained. Furthermore, the IMET scheme can exclude Zeno behavior directly, because it is devised on the basis of the PET scheme and therefore can guarantee $t_{k+1}h - t_kh \geq h > 0$.

Remark 2. *It follows that the triggering condition of IMET is more stringent, which is beneficial for reducing redundant data transmission. Meanwhile, as is well known, the value of an integral over some time interval can not be affected by a finite number of discontinuous points. Therefore, for system (1), even if the sampled or triggered data at finite instants in $[t_kh-\varpi, t_kh)$ are missing, the introduction of the integral term can take full use of the historical information of the system state over this interval. In this way, it can better reflect the "memory" characteristic to reduce false triggers caused by fluctuations in signal measurements.*

In this paper, the state feedback controller is taken as

$$u(t) = K\widetilde{x}(t_kh),\ t \in [t_kh, t_{k+1}h), \tag{6}$$

where K is the control gain. By combining it with (3), the closed-loop system can be described as follows:

$$\dot{x}(t) = W_1x(t) + W_2f(t,x(t)) + NF(t)[L_1x(t) + L_2f(t,x(t))] + K\widetilde{x}(t_kh),\ t \in [t_kh, t_{k+1}h). \tag{7}$$

From a practical point of view, it is assumed that packet losses happen in the controller–actuator channel; that is to say, if some triggering instants t_kh may be lost, then $u(t_kh) = 0$, $t \in [t_kh, t_{k+1}h)$. In this case, the closed-loop system with control packet loss has the following description:

$$\dot{x}(t) = W_1x(t) + W_2f(t,x(t)) + NF(t)[L_1x + L_2f(t,x(t))]. \tag{8}$$

If we introduce a switching signal $\sigma(t) : [0, \infty) \to \mathbb{S} = \{s, u\}$ with $K_s = K$ and $K_u = 0$ to distinguish whether the triggering instant is lost, then a switched system can be organized as follows:

$$\dot{x}(t) = W_1 x(t) + W_2 f(t, x(t)) + NF(t)[L_1 x(t) + L_2 f(t, x(t))] + K_{\sigma(t)} \widetilde{x}(t_k h),\ t \in [t_k h,\ t_{k+1} h). \tag{9}$$

Obviously, system (9) switches between the stable subsystem (7) and the unstable subsystem (8).

The switched system based on the zero-input method is shown in Figure 1. From Figure 1, it can be observed that the occurrence of packet loss generates a switching signal $\sigma(t)$, which subsequently determines the value of the feedback controller and activates the corresponding subsystem.

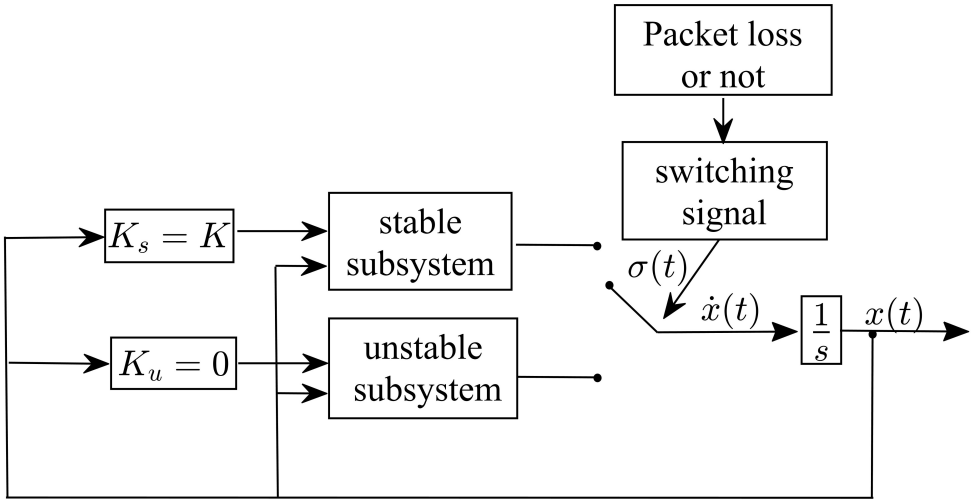


Figure 1. Overall block diagram of the switched system based on the zero-input method.

Assumption 2. *In this paper, it is assumed that missing packets only occur in the controller–actuator channel, and δ is employed to represent the loss rate of control packets.*

According to the triggering condition in (5), there are $l_k - 1$ sampling instants within the triggering interval $(t_k h, t_{k+1} h)$. Next, using the partition method, the triggering interval $[t_k h, t_{k+1} h)$ can be written as follows:

$$[t_k h,\ t_{k+1} h) = \bigcup_{l=0}^{l_k - 1} \Big[t_k h + lh,\ t_k h + (l+1)h\Big) = \bigcup_{l=0}^{l_k - 1} J_l. \tag{10}$$

We define the time-varying delay $\theta_1(t) = t - (t_k h + lh),\ t \in J_l$, then $\theta_1(t) \in [0, h)$. Thus, one can have the following:

$$\tilde{x}(t_k h) = x(t_k h + lh) - \tilde{e}(t_k h + lh) = x(t - \theta_1(t)) - \tilde{e}(t_k h + lh),\ t \in J_l. \tag{11}$$

Therefore, the closed-loop system (9) can finally be expressed as follows:

$$\dot{x}(t) = W_1 x(t) + W_2 f(t, x(t)) + NF(t)[L_1 x(t) + L_2 f(t, x(t))] + K_{\sigma(t)}[x(t - \theta_1(t)) - \tilde{e}(t_k h + lh)],\ t \in J_l. \tag{12}$$

Definition 1 ([28]). *If there exist $c_1, c_2 > 0$ satisfying*

$$\|x(t)\|^2 \le c_1 e^{-c_2(t - t_0)} \cdot \sup_{-\varpi \le s \le 0} \|x(t_0 + s)\|^2,\ \forall t > t_0.$$

then the closed-loop system (1) is said to be exponentially stable.

Definition 2. *For a switching signal $\sigma(t)$, if there exists a constant $\tau_a > 0$, such that*

$$N_{\sigma(t)}(t_1, t_2) \leq N_0 + \frac{t_1 - t_2}{\tau_a}, \ \forall t_1 > t_2 \geq 0,$$

holds for $N_0 \geq 1$, where $N_{\sigma(t)}(t_1, t_2)$ stands for the number of switching events on (t_2, t_1), then τ_a is called the average dwell time (ADT) of $\sigma(t)$.

Lemma 1 ([29])**.** *For any continuously differentiable function $x : [a_1, a_2] \to \mathbb{R}$, the following inequality holds for a given matrix $H > 0$:*

$$\int_{a_1}^{a_2} \dot{x}^T(t) H \dot{x}(t) dt \geq \frac{1}{a_2 - a_1} (x(a_2) - x(a_1))^T H (x(a_2) - x(a_1)) + \frac{3}{a_2 - a_1} X^T H X, \quad (13)$$

where $X = x(a_2) + x(a_1) - \frac{2}{a_2 - a_1} \int_{a_1}^{a_2} x(t) dt$.

3. Main Results

The stability criterion and the controller design for the resulting system (12) will be proposed in this section.

Theorem 1. *For given scalars $\beta > 0$, $\nu > 0$, $\rho > 0$, $\varphi_1 > 0$, $\varphi_2 > 0$, $\varpi > 0$, $\lambda_s > 0$, $\lambda_u < 0$, $\mu > 1$ and feedback gain matrix K, the closed-loop system in (12) is exponentially stable if there exist matrices $P_s,\ P_u,\ Q_s,\ Q_u,\ S,\ \Omega, \in \mathbb{R}_+^{n \times n}$, $R = \begin{bmatrix} R_{11} & R_{12} \\ * & R_{22} \end{bmatrix} \in \mathbb{R}_+^{2n \times 2n}$ and matrices $M_1,\ M_2 \in \mathbb{R}^{n \times n}$, such that the following LMIs hold:*

$$\begin{bmatrix} \Sigma_1 & \nu \Gamma^T \\ * & -\nu I_m \end{bmatrix} < 0, \quad (14)$$

$$\begin{bmatrix} \Sigma_2 & \nu \Gamma^T \\ * & -\nu I_m \end{bmatrix} < 0, \quad (15)$$

$$\begin{bmatrix} \Pi & \nu \Lambda^T \\ * & -\nu I_m \end{bmatrix} < 0, \quad (16)$$

$$P_u \leq \mu P_s,\ Q_u \leq \mu e^{-(\lambda_s - \lambda_u) \cdot \varpi} Q_s, \quad (17)$$

$$P_s \leq \mu P_u,\ Q_s \leq \mu Q_u, \quad (18)$$

where $\Sigma_1,\ \Sigma_2 \in \mathbb{R}^{(7n+m) \times (7n+m)}$ and $\Pi \in \mathbb{R}^{(3n+m) \times (3n+m)}$ are symmetric matrices, and $\Sigma_1(1,1) = \lambda_s P_s - \frac{4e^{-\lambda_s h}}{h} R_{11} + \varphi_1 M_1 W_1 + \varphi_1 W_1^T M_1^T + Q_s + \beta^2 H^T H + (\frac{\lambda_s}{4} h^2 - h) S$, $\Sigma_1(1,2) = \Sigma_2(1,2) = P_s - \varphi_1 M_1 + \varphi_2 W_1^T M_2^T + \frac{h^2}{4} S$, $\Sigma_1(1,3) = \Sigma_2(1,3) = \varphi_1 M_1 W_2$, $\Sigma_1(1,4) = \Sigma_2(1,4) = \varphi_1 M_1 N$, $\Sigma_1(1,5) = \Sigma_2(1,5) = \frac{-2e^{-\lambda_s h}}{h} R_{11} - e^{-\lambda_s h} R_{12} + \varphi_1 M_1 K$, $\Sigma_1(1,6) = \Sigma_2(1,6) = -\varphi_1 M_1 K$, $\Sigma_1(1,7) = \Sigma_2(1,7) = \frac{6e^{-\lambda_s h}}{h} R_{11}$, $\Sigma_1(2,2) = -\varphi_2(M_2 + M_2^T)$, $\Sigma_1(2,3) = \Sigma_2(2,3) = \varphi_2 M_2 W_2$, $\Sigma_1(2,4) = \Sigma_2(2,4) = \varphi_2 M_2 N$, $\Sigma_1(2,5) = \varphi_2 M_2 K$, $\Sigma_1(2,6) = \Sigma_2(2,6) = -\varphi_2 M_2 K$, $\Sigma_1(3,3) = \Sigma_2(3,3) = -I_m$, $\Sigma_1(4,4) = \Sigma_2(4,4) = -\nu I_m$, $\Sigma_1(5,5) = \Sigma_2(5,5) = \frac{-4e^{-\lambda_s h}}{h} R_{11} + 2e^{-\lambda_s h} R_{12} + \rho\Omega - h e^{-\lambda_s h} R_{22}$, $\Sigma_1(5,6) = \Sigma_2(5,6) = -\rho\Omega$, $\Sigma_1(5,7) = \Sigma_2(5,7) = \frac{6e^{-\lambda_s h}}{h} R_{11}$, $\Sigma_1(6,6) = \Sigma_2(6,6) = (\rho - 1)\Omega$, $\Sigma_1(7,7) = \Sigma_2(7,7) = \frac{-12e^{-\lambda_s h}}{h} R_{11}$, $\Sigma_1(8,8) = \Sigma_2(8,8) = -e^{-\lambda_s \varpi} Q_s$, $\Sigma_2(1,1) = \lambda_s P_s - \frac{4e^{-\lambda_s h}}{h} R_{11} + \varphi_1 M_1 W_1 + \varphi_1 W_1^T M_1^T + Q_s + \beta^2 H^T H + (\frac{\lambda_s}{4} h^2 + h) S$, $\Sigma_2(2,2) = -\varphi_2(M_2 + M_2^T) + h R_{11}$, $\Sigma_2(2,5) = \varphi_2 M_2 K + h R_{12}$, $\Sigma_2(5,5) = \frac{-4e^{-\lambda_s h}}{h} R_{11} + 2e^{-\lambda_s h} R_{12} + \rho\Omega + h R_{22}$, $\Pi(1,1) = P_u W_1 + W_1^T P_u^T + \lambda_u P_u + \beta^2 H^T H + Q_u$, $\Pi(1,2) = P_u W_2$, $\Pi(1,3) = P_u N$, $\Pi(2,2) = -I_m$, $\Pi(3,3) = -\nu I_m$, $\Pi(4,4) = -Q_u$, $\Gamma = [L_1\ 0_{m \times n}\ L_2\ 0_{m \times m}\ 0_{m \times n}\ 0_{m \times n}\ 0_{m \times n}]$, $\Lambda = [L_1\ L_2\ 0_{m \times m}\ 0_{m \times n}]$. The ADT τ_a and the pocket loss rate δ satisfy the following constraints:

$$\tau_a > \frac{\ln \mu}{\lambda_s(1-\delta)+\lambda_u\delta}, \ \ \delta < \frac{\lambda_s}{\lambda_s-\lambda_u}. \tag{19}$$

Proof. Consider a Lyapunov functional $V(t)$ as follows, where $V_s(t)$ is for the stable subsystem (7) and $V_u(t)$ is for the unstable subsystem (8):

$$V(t) = V_{\sigma(t)}(t) = \begin{cases} V_s(t), & \text{for } \sigma(t) = s \\ V_u(t), & \text{for } \sigma(t) = u \end{cases}, \ \ t \in J_l,$$

with

$$\begin{aligned} V_s(t) =& \textstyle\sum_{i=1}^{4} V_{si}(t), \\ =& x(t)^T P_s x(t) + \tfrac{1}{\varpi}\int_{-\varpi}^{0}\int_{t+v}^{t} e^{\lambda_s(s-t)} x(s)^T Q_s x(s) ds dv \\ &+ \theta_2(t)\int_{t-\theta_1(t)}^{t} e^{\lambda_s(s-t)} \begin{bmatrix} \dot{x}(s) \\ x(t-\theta_1(t)) \end{bmatrix}^T R \begin{bmatrix} \dot{x}(s) \\ x(t-\theta_1(t)) \end{bmatrix} ds + \theta_1(t)\theta_2(t) x(t)^T S x(t), \end{aligned} \tag{20}$$

$$\begin{aligned} V_u(t) =& \textstyle\sum_{i=1}^{2} V_{ui}(t), \\ =& x(t)^T P_u x(t) + \tfrac{1}{\varpi}\int_{-\varpi}^{0}\int_{t+v}^{t} e^{\lambda_u(s-t)} x(s)^T Q_u x(s) ds dv, \end{aligned} \tag{21}$$

in which $\theta_1(t) = t - (t_k h + lh)$, $\theta_2(t) = t_k h + (l+1)h - t$, and $\lambda_s > 0$, $\lambda_u < 0$ are given constants.

Case 1: When the closed-loop system (12) is in the stable subsystem, the derivative of $V_s(t)$ along the trajectory of the stable subsystem (7) is as follows:

$$\begin{aligned} &\dot{V}_s(t) + \lambda_s V_s(t) \\ \le\ & 2x(t)^T P_s \dot{x}(t) + \lambda_s x(t)^T P_s x(t) + x(t)^T Q_s x(t) - \tfrac{1}{\varpi}\int_{-\varpi}^{0} e^{\lambda_s v} x(t+v)^T Q_s x(t+v) dv \\ &- \int_{t-\theta_1(t)}^{t} e^{-\lambda_s h} \dot{x}^T(s) R_{11} \dot{x}(s) ds - 2e^{-\lambda_s h}\Big[x(t) - x(t-\theta_1(t))\Big]^T R_{12} x(t-\theta_1(t)) \\ &- \theta_1(t) e^{-\lambda_s h} x^T(t-\theta_1(t)) R_{22} x(t-\theta_1(t)) + \theta_2(t) \begin{bmatrix} \dot{x}(t) \\ x(t-\theta_1(t)) \end{bmatrix}^T R \begin{bmatrix} \dot{x}(t) \\ x(t-\theta_1(t)) \end{bmatrix} \\ &+ [\theta_2(t) - \theta_1(t)] x(t)^T S x(t) + 2\theta_1(t)\theta_2(t) x(t)^T S \dot{x}(t) + \lambda_s \theta_1(t)\theta_2(t) x(t)^T S x(t). \end{aligned} \tag{22}$$

By applying Jensen's inequality to the first integral term in (22), one obtains the following:

$$\begin{aligned} -\tfrac{1}{\varpi}\int_{-\varpi}^{0} e^{\lambda_s v} x(t+v)^T Q_s x(t+v) dv &= -\tfrac{1}{\varpi}\int_{t-\varpi}^{t} e^{\lambda_s(s-t)} x^T(s) Q_s x(s) ds, \\ &\le -\tfrac{1}{\varpi}\int_{t-\varpi}^{t} e^{-\lambda_s \varpi} x^T(s) Q_s x(s) ds, \\ &\le -e^{-\lambda_s \varpi}\Big[\tfrac{1}{\varpi}\int_{t-\varpi}^{t} x(s) ds\Big]^T Q_s \Big[\tfrac{1}{\varpi}\int_{t-\varpi}^{t} x(s) ds\Big], \\ &= -e^{-\lambda_s \varpi} \widetilde{x}^T(t) Q_s \widetilde{x}(t), \end{aligned} \tag{23}$$

with $\widetilde{x}(t) = \frac{1}{\varpi}\int_{t-\varpi}^{t} x(s) ds$.

In terms of Lemma 1, the second integral term in (22) can be estimated as follows:

$$-\int_{t-\theta_1(t)}^{t} e^{-\lambda_s h}\dot{x}^T(s)R_{11}\dot{x}(s)ds < -\frac{e^{-\lambda_s h}}{h}\begin{bmatrix} x(t) \\ x(t-\theta_1(t)) \\ \varepsilon(t) \end{bmatrix}^T \begin{bmatrix} 4R_{11} & 2R_{11} & -6R_{11} \\ * & 4R_{11} & -6R_{11} \\ * & * & 12R_{11} \end{bmatrix} \begin{bmatrix} x(t) \\ x(t-\theta_1(t)) \\ \varepsilon(t) \end{bmatrix}, \tag{24}$$

where $\varepsilon(t) = \frac{1}{\theta_1(t)}\int_{t-\theta_1(t)}^{t} x(s)ds$.

Utilizing the free-weighing matrix method, the following equation holds for constants $\varphi_1 > 0$, $\varphi_2 > 0$ and appropriate dimension matrices M_1, M_2:

$$\begin{aligned} &\left[2\varphi_1 x^T(t)M_1 + 2\varphi_2\dot{x}^T(t)M_2\right] \\ &\times\left[-\dot{x}(t) + W_1x(t) + W_2f(t,x(t)) + Nq(t) + K\big(x(t-\theta_1(t)) - \widetilde{e}(t_kh+lh)\big)\right] = 0, \end{aligned} \tag{25}$$

in which $q(t) = F(t)p(t)$ and $p(t) = L_1x + L_2f(t,x(t))$.

Meanwhile, based on (4), one obtains $q^T(t)q(t) \le p^T(t)p(t)$; then, for constant $\nu > 0$, it follows that

$$\nu\left[\varsigma^T(t)\Gamma^T\Gamma\varsigma(t) - q^T(t)q(t)\right] \ge 0, \tag{26}$$

where $\varsigma(t) = \mathrm{col}\{x(t), \dot{x}(t), f(t,x(t)), q(t), x(t-\theta_1(t)), \widetilde{e}(t_kh+lh), \varepsilon(t), \widetilde{x}(t)\}$, $\Gamma = [L_1\ 0_{m\times n}\ L_2\ 0_{m\times m} 0_{m\times n}\ 0_{m\times n}\ 0_{m\times n}\ 0_{m\times n}]$.

Substituting (2), (5), (23)–(26) into (22), and considering the fact that

$$\theta_1(t)\theta_2(t) \le \frac{(\theta_1(t)+\theta_2(t))^2}{4} = \frac{h(\theta_1(t)+\theta_2(t))}{4},$$

we can have

$$\dot{V}_s(t) + \lambda_sV_s(t) \le \varsigma^T(t)\Big\{\frac{\theta_1(t)}{h}(\Sigma_1 + \nu\Gamma^T\Gamma) + \frac{\theta_2(t)}{h}(\Sigma_2 + \nu\Gamma^T\Gamma)\Big\}\varsigma(t),$$

where Σ_1, Σ_2 are defined in Theorem 1. Next, according to LMIs (14) and (15), one can finally obtain the following:

$$\dot{V}_s(t) + \lambda_sV_s(t) < 0. \tag{27}$$

Case 2: When the closed-loop system (12) is in the unstable subsystem, taking the derivation of $V_u(t)$ yields the following:

$$\begin{aligned} &\dot{V}_u(t) + \lambda_uV_u(t) \\ =&2x(t)^TP_u\dot{x}(t) + \lambda_sx(t)^TP_ux(t) + x(t)^TQ_ux(t) - \tfrac{1}{\varpi}\int_{-\varpi}^{0} e^{\lambda_uv}x(t+v)^TQ_ux(t+v)dv. \end{aligned} \tag{28}$$

With the same operation, we give the estimation of the integral term in (28) as follows:

$$-\tfrac{1}{\varpi}\int_{-\varpi}^{0} e^{\lambda_uv}x(t+v)^TQ_ux(t+v)dv \le -\widetilde{x}^T(t)Q_u\widetilde{x}(t), \tag{29}$$

in which $\widetilde{x}(t) = \frac{1}{\varpi}\int_{t-\varpi}^{t} x(s)ds$.

Simultaneously, we have the following identical equation and inequality:

$$\nu\left[\eta^T(t)\Lambda^T\Lambda\eta(t) - q^T(t)q(t)\right] \ge 0, \tag{30}$$

where $\eta(t) = \mathrm{col}\{x(t), f(t,x(t)), q(t), \widetilde{x}(t)\}$ and $\Lambda = [L_1\ L_2\ 0_{m\times m}\ 0_{m\times n}]$.

Combining with (2), (28)–(30), one has the following:

$$\dot{V}_u(t) + \lambda_u V_u(t) \leq \eta^T(t)\big(\Pi + \nu\Lambda^T\Lambda\big)\eta(t). \tag{31}$$

Based on (16), one can conclude the following:

$$\dot{V}_u(t) + \lambda_u V_u(t) < 0. \tag{32}$$

Furthermore, synthesizing (27) and (32), one can now obtain that

$$\dot{V}(t) + \lambda V(t) < 0, \tag{33}$$

in which $\lambda = \lambda_{\sigma(t)} = \begin{cases} \lambda_s, & \text{for } \sigma(t) = s, \\ \lambda_u, & \text{for } \sigma(t) = u. \end{cases}$

Moreover, we denote $\{\tau_l\}$ as the switching series between the stable subsystem and the unstable subsystem during $(0, t)$. Then, the triggering instant τ_l may be transmitted or lost. In what follows, these two cases will be discussed in detail.

If τ_l is the lost triggering instant, then one has the following:

$$\begin{aligned} V(\tau_l^-) &= V_s(\tau_l^-) = V_{s1}(\tau_l) + V_{s2}(\tau_l), \\ V(\tau_l) &= V_u(\tau_l) = V_{u1}(\tau_l) + V_{u2}(\tau_l). \end{aligned}$$

In terms of the condition in (17), one further has

$$V(\tau_l) \leq \mu V(\tau_l^-). \tag{34}$$

If τ_l is the transmitted triggering instant, then based on (18), the same result $V(\tau_l) \leq \mu V(\tau_l^-)$ can still be obtained.

During the interval $(0, t)$, we denote $T_s(0, t)$ and $T_u(0, t)$ as the total length of all stable intervals and the total length of all unstable intervals, respectively. Obviously, the loss rate of control packet δ can be represented as follows:

$$\delta = \frac{T_u(t)}{t}. \tag{35}$$

Let τ_q be the switching instant nearest to t. Due to the condition (27), (32), and (34)–(35), the following holds:

$$\begin{aligned} V(t) &\leq e^{-\lambda_{\sigma(\tau_q)}(t-\tau_q)} V_{\sigma(\tau_q)}(\tau_q), \\ &\leq \mu e^{-\lambda_{\sigma(\tau_q)}(t-\tau_q)} V_{\sigma(\tau_q^-)}(\tau_q^-), \\ &\vdots \\ &\leq \mu^{N_{\sigma(t)}(t,0)} e^{-\lambda_s T_s(0,t)} e^{-\lambda_u T_u(0,t)} V(0), \\ &\leq \mu^{N_0 + \frac{t}{\tau_a}} e^{-\lambda_s(t-\delta t) - \lambda_u \delta t} V(0), \\ &= \epsilon_1 e^{-\epsilon_2 t} V(0), \end{aligned} \tag{36}$$

with $\epsilon_1 = e^{N_0 \ln \mu}$, $\epsilon_2 = \lambda_s(1-\delta) + \lambda_u \delta - \frac{\ln \mu}{\tau_a}$.

In line with (20) and (21), one can obtain

$$V(t) \geq \lambda_1 \|x(t)\|^2,$$

and

$$V(0) \leq \lambda_2 \|x(0)\|^2 + \varpi \cdot \lambda_3 \sup_{-\varpi \leq s \leq 0} \|x(s)\|^2 \leq \epsilon_3 \sup_{-\varpi \leq s \leq 0} \|x(s)\|^2,$$

in which $\lambda_1 = \min\{\lambda_{\min}\{P_s\}, \lambda_{\min}\{P_u\}\}$, $\lambda_2 = \max\{\lambda_{\max}\{P_s\}, \lambda_{\max}\{P_u\}\}$, $\lambda_3 = \max\{\lambda_{\max}\{Q_s\}, \lambda_{\max}\{Q_u\}\}$ and $\epsilon_3 = \lambda_2 + \varpi \cdot \lambda_3$.

Considering (36), the following inequality can be deduced:

$$\|x(t)\|^2 \leq \epsilon_4 e^{-\epsilon_2 t} \sup_{-\varpi \leq s \leq 0} \|x(s)\|^2,$$

where $\epsilon_4 = \frac{\epsilon_1 \epsilon_3}{\lambda_1}$. Thus, based on Definition 1, the system (12) is exponentially stable. □

Remark 3. *Looped functionals $V_{s3}(t)$ and $V_{s4}(t)$ can result in $V_{s3}(t_k h + lh) = V_{s3}(t_k h + (l+1)h) = 0$ and $V_{s4}(t_k h + lh) = V_{s4}(t_k h + (l+1)h) = 0$, in which $t_k h + lh$ and $t_k h + (l+1)h$ are sampling instants. Given that the switching instant τ_l comes from the set of sampling instants, it follows that $V_{s3}(\tau_l) = 0$ and $V_{s4}(\tau_l) = 0$. As a result, $V_{s3}(t)$ and $V_{s4}(t)$ will not appear during the analysis of $V(\tau_l) \leq \mu V(\tau_l^-)$. This enables LMIs for system stability to be simplified, consequently enlarging the feasible region of the LMIs. Additionally, looped functionals $V_{s3}(t)$ and $V_{s4}(t)$ can fully utilize the system information over $[x(t_k h + lh), x(t))$ and $[x(t), x(t_k h + (l+1)h))$, which contributes to obtaining results with reduced conservatism.*

Next, the controller design for the system (1) based on the aforementioned analysis will be given by employing the matrix decoupling method.

Theorem 2. *For given positive scalars β, ν, ρ, ϖ, λ_s, κ, φ_1, φ_2, $\mu > 1$ and negative scalar λ_u, the closed-loop system (1) is exponentially stable under the design of control gain matrix $K = M_1^{-1}\widehat{K}$ if there exist matrices P_s, P_u, Q_s, Q_u, S, $\Omega \in \mathbb{R}_+^{n\times n}$, $R \in \mathbb{R}_+^{2n\times 2n}$, arbitrary matrices $M_1, \widehat{K}$, such that the following LMIs hold:*

$$\begin{bmatrix} \widehat{\Sigma}_1 & \nu\Gamma^T \\ * & -\nu I_m \end{bmatrix} < 0, \tag{37}$$

$$\begin{bmatrix} \widehat{\Sigma}_2 & \nu\Gamma^T \\ * & -\nu I_m \end{bmatrix} < 0, \tag{38}$$

$$\begin{bmatrix} \Pi & \nu\Lambda^T \\ * & -\nu I_m \end{bmatrix} < 0, \tag{39}$$

$$P_u \leq \mu P_s,\ Q_u \leq \mu e^{-(\lambda_s - \lambda_u)\cdot\varpi} Q_s, \tag{40}$$

$$P_s \leq \mu P_u,\ Q_s \leq \mu Q_u, \tag{41}$$

where $\widehat{\Sigma}_1$, $\widehat{\Sigma}_2 \in \mathbb{R}^{(7n+m)\times(7n+m)}$ and $\Pi \in \mathbb{R}^{(3n+m)\times(3n+m)}$ are symmetric matrices, and $\widehat{\Sigma}_1(1,2) = \widehat{\Sigma}_2(1,2) = P_s - \varphi_1 M_1 + \kappa\varphi_2 W_1^T M_1^T + \frac{h^2}{4} S$, $\widehat{\Sigma}_1(1,5) = \widehat{\Sigma}_2(1,5) = \frac{-2e^{-\lambda_s h}}{h} R_{11} - e^{-\lambda_s h} R_{12} + \varphi_1 \widehat{K}$, $\widehat{\Sigma}_1(1,6) = \widehat{\Sigma}_2(1,6) = -\varphi_1 \widehat{K}$, $\widehat{\Sigma}_1(2,2) = -\kappa\varphi_2(M_1 + M_1^T)$, $\widehat{\Sigma}_2(2,2) = -\kappa\varphi_2(M_1 + M_1^T) + hR_{11}$, $\widehat{\Sigma}_1(2,3) = \widehat{\Sigma}_2(2,3) = \kappa\varphi_2 M_1 W_2$, $\widehat{\Sigma}_1(2,4) = \widehat{\Sigma}_2(2,4) = \kappa\varphi_2 M_1 N$, $\widehat{\Sigma}_1(2,5) = \kappa\varphi_2 \widehat{K}$, $\widehat{\Sigma}_2(2,5) = \kappa\varphi_2 \widehat{K} + hR_{12}$, $\widehat{\Sigma}_1(2,6) = \widehat{\Sigma}_2(2,6) = -\kappa\varphi_2 \widehat{K}$, the other blocks of $\widehat{\Sigma}_1$, $\widehat{\Sigma}_2$ have the same definition as those of Σ_1, Σ_2 in Theorem 1, and the ADT and the pocket loss rate satisfy $\tau_a > \frac{\ln \mu}{\lambda_s(1-\delta)+\lambda_u \delta}$ and $\delta < \frac{\lambda_s}{\lambda_s - \lambda_u}$.

Proof. We define $M_2 = \kappa M_1$, $\widehat{K} = M_1 K$. Then, LMIs (14)–(18) can be represented as (37)–(41). Based on (37)–(41), one can calculate the gain matrix $K = M_1^{-1}\widehat{K}$, which achieve the proof. □

4. Numerical Simulation

In this section, a numerical example will be employed to demonstrate the effectiveness of the proposed IMET scheme.

Example 1. *Consider the following NN with the following uncertainties:*

$$W_1 = \begin{bmatrix} -1.8 & 0 \\ 0 & -1.9 \end{bmatrix},\ W_2 = \begin{bmatrix} 2.79 & 1 \\ -1 & 2.5 \end{bmatrix},\ N = \begin{bmatrix} 0.02 \\ 0.01 \end{bmatrix},\ f(t,x(t)) = \begin{bmatrix} 0.5\sin(x_1(t)) \\ 0.5\sin(x_2(t)) \end{bmatrix},$$
$$L_1 = \begin{bmatrix} -0.01 & 0.01 \end{bmatrix},\ L_2 = \begin{bmatrix} -0.02 & -0.01 \end{bmatrix},\ F(t) = 0.6 + 0.3\sin t.$$

The initial condition is chosen as $x(0) = (0.2, -0.1)^T$. *We select* $\lambda_s = 0.2$, $\lambda_u = -0.1$, *then the loss rate is calculated as* $\delta < 0.667$ *based on Condition (19) in Theorem 1. Then, we set* $\delta = 0.1$ *and* $\mu = 1.1$, *and the ADT is calculated as* $\tau_a > 0.561$. *We take* $\kappa = 1.1$, $\rho = 0.3$, $\varpi = 0.2$, $\beta = 0.6$ *and constant matrix* $H = I_2$; *then, the control gain matrix and the triggering parameter* Ω *are calculated based on Theorem 2 as follows:*

$$K = \begin{bmatrix} -0.418 & 0.141 \\ 0.098 & -0.498 \end{bmatrix},\ \Omega = \begin{bmatrix} 5.667 & -2.746 \\ -2.746 & 8.824 \end{bmatrix}.$$

The state responses under the EMET and the IMET are shown in Figure 2. It is clear that the system trajectories obtained via the IMET scheme are gentler and can converge to zero much faster than the ones obtained by the EMET. This means that the IMET can ensure better system performance. Figures 3 and 4 present the execution interval and the cumulative triggering times for the EMET scheme and the IMET scheme, respectively. One can determine that the triggering interval of the IMET is larger that of the EMET. Meanwhile, the total triggering number for the IMET scheme is 33, which is less than 52 obtained via the EMET scheme. Combining Figures 2–4, one can conclude that the proposed IMET scheme can reduce the network burden on the premise of ensuring good system performance.

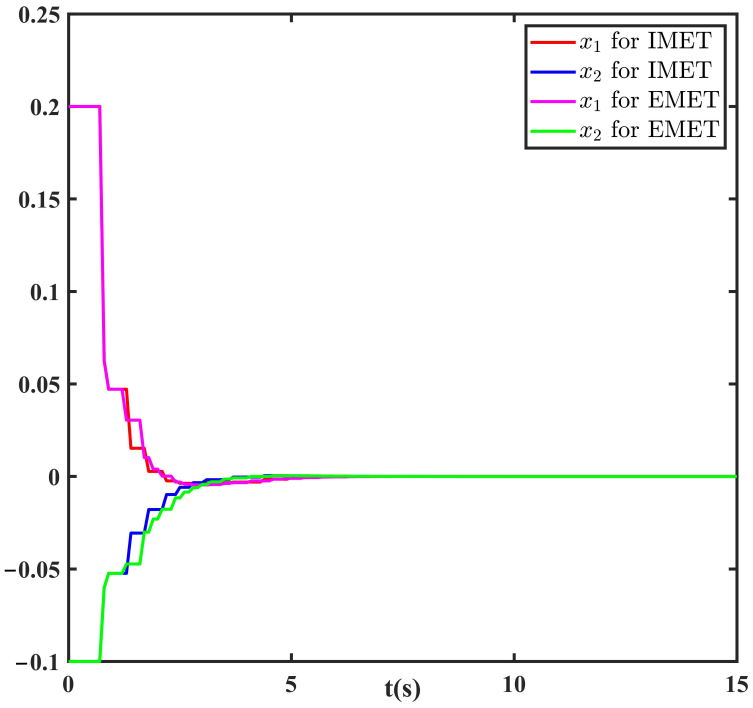


Figure 2. The trajectories of $x_i(t)$ under EMET and IMET.

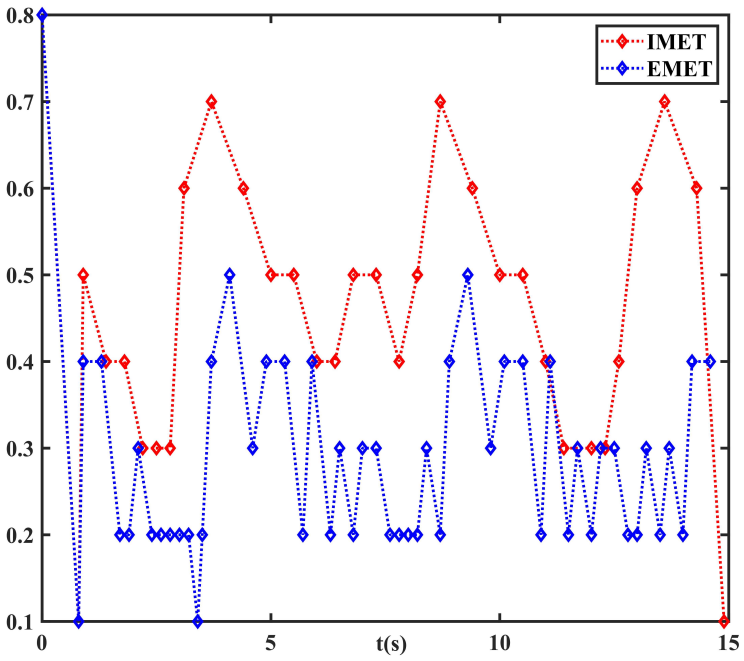


Figure 3. The execution interval.

Figure 5 displays the trajectories of the control input under the IMET scheme with packet loss rate $\delta = 0.1$. The intervals corresponding to $u = 0$ suggest that the system is under the unstable subsystem. The starting points of these intervals are the moments when the packets are lost, and the end points are the moments when the system is under the controller again. Meanwhile, the switching signal $\sigma(t)$ is shown in Figure 6.

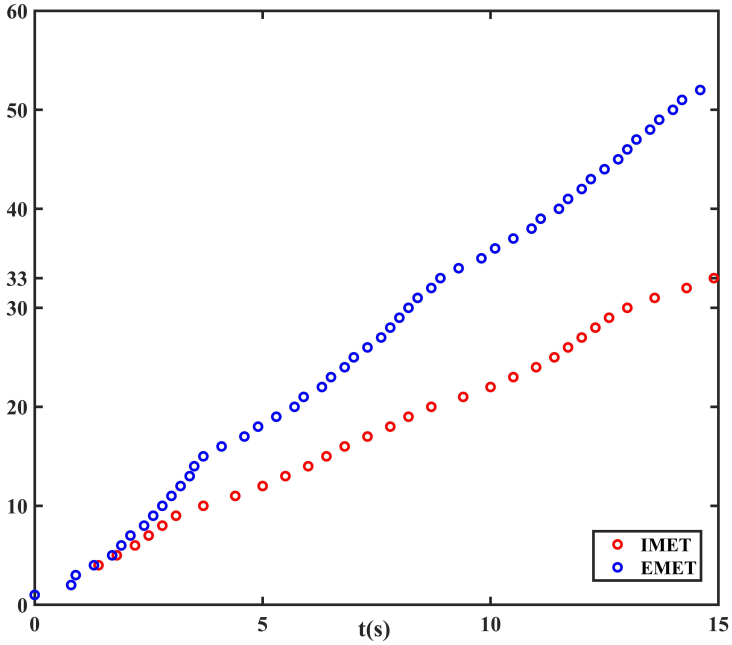


Figure 4. The cumulative triggering times.

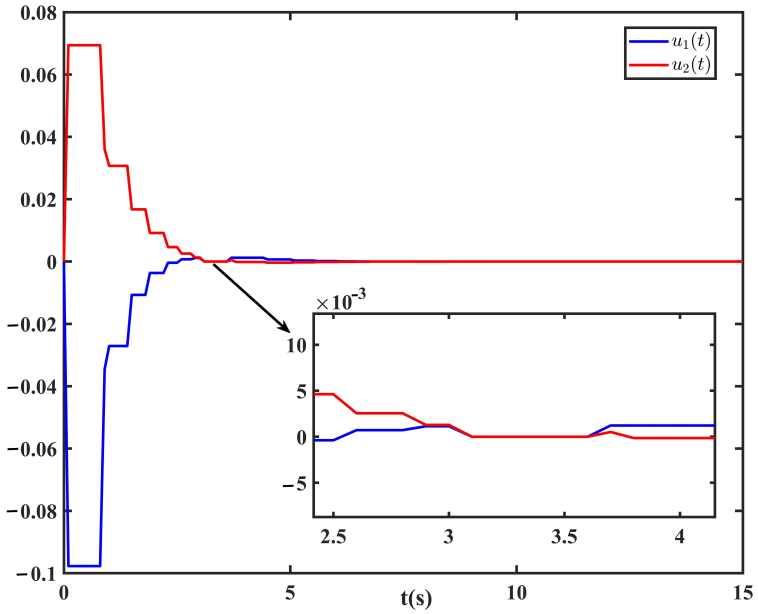


Figure 5. The trend of the control input $u_i(t)$.

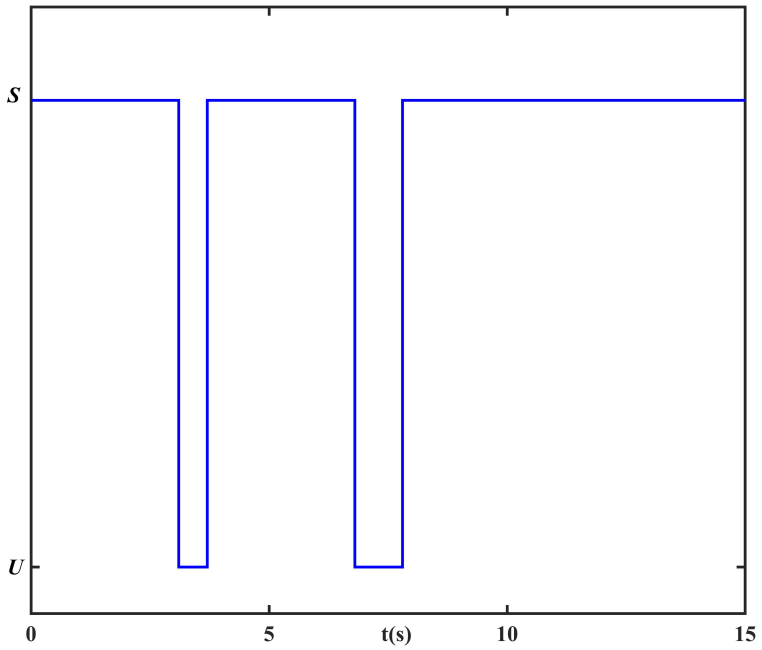


Figure 6. The switched signal.

5. Conclusions

In this paper, by employing the zero-input method, the stabilization problem of an uncertain NN with missing input is converted into the stability problem of a switched system and then is addressed by developing an IMET scheme. Compared with the EMET scheme, the proposed IMET scheme is based on the PET scheme and therefore can prevent Zeno behavior naturally. Moreover, it introduces an integral over a past time interval of the latest triggering instant to construct the triggering condition. Therefore, even if the packets close to the current trigger are missing, it can still employ the integral to cover the information of the system with packet loss. To study the switched closed-loop system, a new piecewise Lyapunov functional is designed, which not only contains a looped functional to fully use the state information but also contains a Lyapunov functional involving the memory period of the IMET scheme. Then, by using this functional and combining with

some inequalities, we establish sufficient conditions that guarantee the exponential stability of the resulting closed-loop system. Finally, an example is provided to analyze the validity of the obtained results.

Author Contributions: P.W. studied the stability and the control of the networked systems. Z.W. was in charge of the calculus theory and the simulation. H.X. provided recommendations for research; and, lastly, P.W. contributed to the contents and writing of the manuscript. All authors have read and approved the final manuscript.

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