Event-triggered networked predictive control of system with data loss

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Abstract: This paper investigates the problem of event-triggered networked predictive control for systems with data loss. An event-triggered networked predictive control system is proposed. Based on predictive control model, a data loss compensation strategy is presented and an extended event-triggered transmission mechanism is developed. The closed-loop event-triggered predictive control system is described as a switched system and sufficient closed-loop stability conditions related to event-triggered mechanism are established. Under the event-triggered networked predictive control scheme, the consumption of the communication resources is reduced. Finally, an example is provided to illustrate the effectiveness of the proposed method.

1. Introduction

In recent years, with the development of computer science and network communication technique, networked control systems (NCSs), where the network is inserted in the feedback control loop, have received widespread attention. Compared with traditional control systems, NCSs have many advantages, such as easy installation and service, suitable for long-distance operation and control, and low cost. So they have been widely used in industrial automation, underwater detection, highway...
Despite the advantages, NCSs also have some inevitable disadvantages, such as data loss. When data are transmitted through the networks, it may be lost, and this phenomenon can deteriorate the control performance of NCSs. To compensate for the effect of data loss, model predictive control method has been proposed (Li & Shi, 2013; Liu, 2010; Song & Fang, 2014; Zou, Lam, Niu, & Li, 2015; Zou & Niu, 2013). In Zou and Niu (2013), the data loss was described as a Bernoulli process, and the predictive control with data loss compensation strategy was proposed to guarantee the closed-loop stability. In Zou et al. (2015), the data loss process was defined as a discrete-time homogeneous Markov chain, and the model predictive control synthesis approach for quantized systems was presented to guarantee the satisfaction of system constraints and the closed-loop stability. In Liu (2010), a networked predictive controller with data losses and network delays was designed, where the control prediction was adopted to compensate for the data losses and network delays actively. In Li and Shi (2013), the min–max model predictive control method was investigated for a constrained nonlinear networked control system, and the proposed method can effectively compensate for the data loss while guaranteeing the input-to-state practical stability. In Song and Fang (2014), a distributed model predictive control was proposed for a linear uncertain system with a polytopic description and subject to randomly occurring packet loss. It is worth noting that the time-triggered communication strategy is adopted in the aforementioned literatures, which may result in a waste of the communication resources.

In order to reduce the consumption of communication resources, the event-triggered strategy has been proposed (Åström & Bernhardsson, 1999). The main idea of the event-triggered strategy is to reduce the communication among the sensor, controller, and actuator by introducing an event-triggered condition, that is the data are transmitted only when the event-triggered condition is satisfied. Many results have been investigated in event-triggered control strategy (Dong, Wang, Alsaadi, & Ahmad, 2015; Li, & Shi, 2014; Liu, Wang, He, & Zhou, 2015; Peng, & Yang, 2013; Yin, Yue, & Hu, 2014). In Peng and Yang (2013), an event-triggered strategy and $H_\infty$ control method were designed for networked control systems, and the stability was analyzed using the Lyapunov–Krasovskii functional theory. In order to utilize the limited resources of wireless sensor networks efficiently, the event-based distributed filtering and state estimation problems were investigated in Liu et al. (2015) and Dong et al. (2015). In Yin et al. (2014), the problem of the model-based event-triggered predictive control was studied for networked systems with network delays, and the control gain and the parameter of the event-triggered condition were co-designed. In Li and Shi (2014), the event-triggered model predictive control for continuous-time nonlinear system was studied, and the computational efficiency of the proposed scheme has been proven to be higher than the conventional model predictive control. To the best of the authors’ knowledge, few works have investigated the problem of event-triggered networked predictive control for NCSs under the effect of data loss. How to design an event-triggered networked predictive controller to compensate for the data loss actively and reduce the consumption of communication resources while guaranteeing the closed-loop stability still remains challenging. This motivates the present study.

In this paper, an architecture of the event-triggered networked predictive control system is established, and the design of event-triggered mechanism and the compensation of data loss are considered simultaneously. In order to avoid an undesired performance degradation caused by data loss, a data loss compensation strategy is presented based on event-triggered predictive control model and an extended event-triggered mechanism is proposed using ACK. The closed-loop system is described as a switched system and the closed-loop stability conditions related to event-triggered parameters are established.

The organization of this paper is as follows. Section 2 introduces the basic setup of event-triggered networked predictive control system. In Section 3, the event-triggered predictive controller is designed, the data loss compensation strategy is proposed, and the closed-loop system is modeled. In
Section 4, the closed-loop stability is analyzed and stability conditions are derived. Simulation results are given to show the effectiveness of the proposed methods in Section 5, and conclusions are made in Section 6.

Notation. Throughout this paper, \( \mathbb{R}^m \) denotes the \( m \)-dimensional Euclidean space and \( \mathbb{R}^+ \) stands for the set of positive real numbers, respectively. Superscript \( T \) denotes matrix transposition and \( I \) is the identity matrix with appropriate dimension. In symmetric block matrices, \( * \) is used as an ellipsis for terms induced by symmetry. \( \text{diag}\{\cdot\} \) denotes the block diagonal matrix.

2. Problem formulation

We consider an event-triggered networked predictive control system shown in Figure 1, where the network exists between the event generator and predictive controller. The plant is given by the following discrete-time linear time-invariant (LTI) system

\[
    x(k+1) = Ax(k) + Bu(k),
\]

where \( x(k) \in \mathbb{R}^n \) is the state of the plant; \( u(k) \in \mathbb{R}^m \) is the control input; and \( A \in \mathbb{R}^{n \times n} \) and \( B \in \mathbb{R}^{n \times m} \) are known matrices with appropriate dimensions.

In order to reduce the communication resources consumption in the NCS, we introduce an event generator to limit the number of information transmission, that is the state information will be transmitted to the controller only when a certain event-triggered condition is satisfied. We denote the event-triggered instant as \( k_i (i = 0, 1, 2, \ldots) \). If the current state \( x(k_i) \) is transmitted to the controller at time \( k_i \), the next event-triggered instant \( k_{i+1} \) is decided by the following condition

\[
    k_{i+1} = k_i + \min_r \left\{ r \mid (\hat{x}(k_i + r) - x(k_i))^T \Phi (\hat{x}(k_i + r) - x(k_i)) > \mu \hat{x}(k_i + r)^T \Phi \hat{x}(k_i + r) \right\}.
\]

In (2), \( \hat{x}(k_i + r) \) is the estimated state at time \( k_i + r \), which will be derived from Section 3.2; \( r \) is a positive integer; \( \mu \in (0, 1) \) is a given parameter; and \( \Phi \) is a positive definite symmetric matrix to be designed in Section 4.

In practical NCS, data loss may happen when the data are transmitted over networks. At the event-triggered instant \( k_i \), when the state \( x(k_i) \) is transmitted to the controller, it may be lost, that is \( x(k_i) \) cannot arrive at the controller. In the sequel, the instant when the state is successfully transmitted to the controller is denoted as \( t_j (j = 0, 1, 2, \ldots) \).

Remark 1. According to the above description, not every sampling instant is event-triggered instant and the state may be lost when it is transmitted through the networks at the event-triggered instant. So we have \( \{t_0, t_1, t_2, \ldots\} \subset \{k_0, k_1, k_2, \ldots\} \subset \{0, 1, 2, \ldots\} \), and an example is shown in Figure 2.
The main objective of this paper is to design an event-triggered networked predictive control scheme with a data loss compensation strategy, such that the closed-loop stability is guaranteed and the communication burden of the networks is relieved.

3. Event-triggered networked predictive control with data loss compensation strategy

In the traditional time-triggered networked predictive control scheme, the state \( x(k) \) is sent to the controller at each sampling instant and the control law is updated periodically. In the event-triggered setup, the state is sent to the controller only when the event-triggered condition (2) is satisfied. Furthermore, in the process of event-triggered transmission, the presence of data loss results in the decrease of the control performance. In the following, the calculation of the event-triggered predictive control law and the data loss compensation strategy will be presented.

3.1. Event-triggered predictive control law

At time instant \( t_j \), the data are successfully transmitted to the controller and the following optimization problem of predictive control is solved:

\[
\min J(t_j) = \sum_{l=1}^{N_p} x(t_j + l | t_j)^T Q x(t_j + l | t_j) + \sum_{l=0}^{N_u-1} u(t_j + l | t_j)^T R u(t_j + l | t_j),
\]

s.t.

\[
x(t_j + l + 1 | t_j) = A x(t_j + l | t_j) + B u(t_j + l | t_j),
\]

where \( Q \) and \( R \) are symmetrical positive-definite weighting matrices; \( N_p \) and \( N_u \) are predictive horizon and control horizon, respectively; and \( x(t_j + l | t_j) \) and \( u(t_j + l | t_j) \) are the state and control inputs predicted at time \( t_j + l \) based on the measurement at time \( t_j \). According to (4), the predictive equation of the plant can be described as

\[
X(t_j + 1) = A_p x(t_j) + B_p U(t_j),
\]

where

\[
X(t_j + 1) = [x(t_j + 1 | t_j)^T \cdots x(t_j + N_p | t_j)^T]^T,
\]

\[
U(t_j) = [u(t_j | t_j)^T \cdots u(t_j + N_u - 1 | t_j)^T]^T,
\]

\[
A_p = [A^T (A^2)^T \cdots (A^{N_u})^T]^T,
\]

\[
B_p = \begin{bmatrix}
B & 0 & \cdots & 0 & 0 \\
AB & B & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
A^{N_u-1} B & A^{N_u-2} B & \cdots & AB & B \\
\vdots & \vdots & \cdots & \vdots & \vdots \\
A^{N_p-1} B & A^{N_p-2} B & \cdots & A^{N_p-N_u+1} B & \sum_{i=0}^{N_u-N_p} A^i B
\end{bmatrix}
\]

Further, the performance objective (3) can be written as

\[
J(t_j) = X(t_j + 1)^T \bar{Q} X(t_j + 1) + U(t_j)^T \bar{R} U(t_j),
\]

where \( \bar{Q} = \text{diag}(Q, \ldots, Q) \) and \( \bar{R} = \text{diag}(R, \ldots, R) \). Then, the predictive control optimization problem (3 and 4) can be reformulated as

\[
\min_{U(t_j)} J(t_j)
\]

subject to (5). According to \( \partial J(t_j)/\partial U(t_j) = 0 \), the optimal solution can be obtained as follows:
Then, the control law at event-triggered time instant $t_j$ is $u(t_j) = u(t_j|t_{j-1}) = Fx(t_j)$, where the predictive control feedback gain is $F = -(I\ 0\ \ldots\ 0)(B_p^TQB_p + R)^{-1}B_p^TQA_p$.

### 3.2. Data loss compensation strategy under event-triggered transmission mechanism

Assume that the state $x(k_j)$ is transmitted successfully at time $k_j$, that is we have $t_j = k_j$. Between the two successfully transmitted instants $[t_j, t_{j+1})$ (see Figure 3), the data loss compensation strategy is proposed as follows: at the event-triggered time instant $k_{i+s}$ ($s = 1, 2, \ldots, d$), the following control law is used

$$u(k_{i+s}) = F\hat{x}(k_{i+s}),$$

and between the two event-triggered instants $[k_{i+s}, k_{i+s+1})$, the control law remains constant, i.e.

$$u(k) = F\hat{x}(k_{i+s}), \ k \in [k_{i+s}, k_{i+s+1}) \subset [t_j, t_{j+1}).$$

Then, the corresponding states between the two successfully transmitted instants $[t_j, t_{j+1})$ can be estimated:

$$x(k_j) = x(t_j)$$

$$\dot{x}(k_j + 1) = Ax(k_j) + BFx(k_j)$$

$$\dot{x}(k_j + j + 1) = A\dot{x}(k_j + j) + BFx(k_j)$$

$$j = 1, 2, \ldots, k_{i+s} - k_j - 1$$

$$\dot{x}(k_{i+s} + j + 1) = A\dot{x}(k_{i+s} + j) + BFx(k_{i+s})$$

$$j = 0, 1, 2, \ldots, k_{i+s+1} - k_{i+s} - 1, \ s = 1, 2, \ldots, d,$$

where $k_{i+s}$ ($s = 1, 2, \ldots, d$) denotes the event-triggered instant triggered by the condition (2), and the data may be lost at these instants; $d$ denotes the maximal allowable number of successive data losses; and $\hat{x}(k)$, $k \in [t_j, t_{j+1})$ denotes the estimated state at time $k$ under the action of the control laws (9) and (10).

### 3.3. Closed-loop model of the event-triggered networked predictive control with data loss

If there is no restriction on the number of successive data losses, the measurement difference $x(k_{i+s} + r) - x(k_{i+s})$ can be arbitrarily large. In order to avoid an undesired performance degradation in the event-triggered NCS, we propose an extended event-triggered strategy using acknowledgment signals (ACKs). The transmission mechanism is described as follows: at the event-triggered instant $k_{i+s}$ the data $\hat{x}(k_{i+s})$ are sent from the event generator to the controller. If $\hat{x}(k_{i+s})$ is successfully transmitted to the controller, the controller sends an ACK to the event generator over a reliable channel. If $\hat{x}(k_{i+s})$ is lost, the controller will not send the ACK to the event generator. After a predefined waiting time $T_w \in \mathbb{R}^+$, if the event generator does not get any ACK, it resends the data $\hat{x}(k_{i+s} + T_w)$ to the controller at time $k_{i+s} + T_w$, which is considered as the new event-triggered instant $k_{i+s+1}$. $\hat{x}(k_{i+s} + T_w)$ can be obtained from the predictive state (14), i.e.

$$\hat{x}(k_{i+s} + T_w) = A^T\hat{x}(k_{i+s}) + \sum_{j=1}^{T_w} A^{T-s-j}BF\hat{x}(k_{i+s}).$$
The extended event-triggered mechanism becomes

\[
\begin{cases}
    k_{i+1} = k_i + T_w, & \text{if the transmission has failed at time } k_i, \\
    k_{i+1} = k_i + \min \{ r | [\hat{x}(k_i + r) - x(k)]^T \Phi [\hat{x}(k_i + r) - x(k)] \} > \mu \hat{x}(k_i + r)^T \Phi \hat{x}(k_i + r), & \text{else.}
\end{cases}
\]

(15)

(16)

At the next event-triggered instant \( k_{i+1} \), the state \( x(k_{i+1}) \) is updated according to

\[
x(k_{i+1}) = \begin{cases}
    \hat{x}(k_i + r), & \text{if } [\hat{x}(k_i + r) - x(k)]^T \Phi [\hat{x}(k_i + r) - x(k)] \\
    > \mu \hat{x}(k_i + r)^T \Phi \hat{x}(k_i + r), \\
    \hat{x}(k_i + T_w), & \text{else}
\end{cases}
\]

(17)

where \( \hat{x}(k_i + r) \) and \( \hat{x}(k_i + T_w) \) can be obtained from the predictive state (14), and then the data are transmitted toward the predictive controller.

Under the event-triggered mechanism (15–16), system (1) with data loss compensation (9–10) can be described as the following closed-loop system:

\[
x(k + 1) = Ax(k) + Bu(k_i) = Ax(k) + BF\hat{x}(k_i)
\]

\[
k \in [k_i, k_{i+1}) \subset [t_j, t_{j+1}).
\]

(18)

According to the event-triggered predictive states (11–14), we have

\[
\hat{x}(k_i) = [A^{k_i-k} + \sum_{j=1}^{k_i-k} A^{k_i-k-j}BF]x(k).
\]

(19)

So the closed-loop system can be rewritten as:

\[
x(k + 1) = Ax(k) + BF[A^{k-k} + \sum_{j=1}^{k-k} A^{k-k-j}BF]x(k)
\]

\[
k \in [k_i, k_{i+1}) \subset [t_j, t_{j+1}), \quad s = 0, 1, 2, \ldots d.
\]

(20)

Define the state measurement difference \( e(k) = \hat{x}(k) - x(k) \) for \( k \in [k_i, k_{i+1}) \subset [t_j, t_{j+1}), s = 0, 1, 2, \ldots d. \) Then, the closed-loop system can be further described as the following switched system:

\[
x(k + 1) = \Pi_{\sigma_s} x(k) - \Xi_{\sigma_s} e(k),
\]

\[
\sigma_s \in S = \{ \sigma_0, \sigma_1, \ldots, \sigma_d \}
\]

(21)

where

\[
\Pi_{\sigma_s} = A + BF[A^{\sigma_s} + \sum_{j=1}^{\sigma_s} A^{\sigma_s-j}BF], \quad \Xi_{\sigma_s} = BF[A^{\sigma_s} + \sum_{j=1}^{\sigma_s} A^{\sigma_s-j}BF],
\]

\[
\sigma_s = k_{i+1} - k_i, \quad k \in [k_i, k_{i+1}) \subset [t_j, t_{j+1}), \quad s = 0, 1, 2, \ldots d.
\]

Remark 2 In this paper, it can be seen that \( x(k) = \hat{x}(k) \) for \( k \in [t_j, t_{j+1}), j = 0, 1, 2, \ldots \) It can be proved by means of the mathematical induction. For the successfully transmitted state \( x(t) = x(k) \), according to (1) and (12), we have \( x(k+1) = Ax(k) + BF\hat{x}(k) \) and \( \hat{x}(k+1) = Ax(k) + BF\hat{x}(k) \), so \( x(k+1) = \hat{x}(k+1) \). For \( \forall k \in (t_j, t_{j+1}) \), we assume \( x(k) = \hat{x}(k) \). Then, we just need to prove that \( x(k+1) = \hat{x}(k+1) \). For \( k \in [k_i, k_{i+1}) \subset (t_j, t_{j+1}), s = 0, 1, 2, \ldots d, \) we have \( x(k+1) = Ax(k) + BF\hat{x}(k) \). According to (11)-(14), it can be concluded that \( \hat{x}(k+1) = Ax(k) + BF\hat{x}(k) \). So, we have \( x(k+1) = \hat{x}(k+1) \).
Remark 3 The switching modes $\sigma_i$, $\sigma_j$, ..., $\sigma_d$ are related to the number of successive data losses, and the closed-loop system is switched among the $d+1$ subsystems according to the number of successive data losses.

Remark 4 According to the event-triggered conditions (15–16), no event is triggered at time $k \in [k_i, k_i + 1) \subset [t_i, t_{i+1})$. So we have

$$e(k)^T \Phi e(k) \leq \mu x(k)^T \Phi x(k), \ k \in (k_i, k_i + 1) \subset [t_i, t_{i+1}).$$

(22)

4. Stability analysis

In this section, based on the closed-loop system (21), we discuss the design of the event-triggered parameter $\Phi$ using the Lyapunov stability theory and the LMI technique. The stability condition is provided in the following theorem.

**Theorem 1** Consider the proposed event-triggered networked control system with data loss. For given system matrices $A$ and $B$, the constant parameter $\mu \in (0, 1)$, and the predictive control feedback gain $F$ if there exist matrices $P > 0$ and $\Phi > 0$ with appropriate dimensions such that the following LMIs hold for all $\sigma_i \in S$:

$$
\begin{bmatrix}
-P + \mu \Phi & * & * \\
0 & -\Phi & * \\
\Pi_{\theta_i} & -P \Xi_{\theta_i} & -P
\end{bmatrix} < 0,
\quad \sigma_i = k_i + 1 - k_i, \ i = 0, 1, 2, \ldots, d
$$

(23)

then the closed-loop switched system in (21) is asymptotically stable.

**Proof** Choose the Lyapunov function of the closed-loop switched system as

$$V(x(k)) = x(k)^T Px(k),$$

(24)

where $P$ is a positive definite symmetric matrix. For $k \in [k_i, k_i + 1) \subset [t_i, t_{i+1})$, calculating the difference of the Lyapunov function according to the closed-loop system (21) and taking the inequality (22) into account, we have

$$\Delta V = V(x(k + 1)) - V(x(k))$$

$$= x(k + 1)^T Px(k + 1) - x(k)^T Px(k)$$

$$\leq x(k + 1)^T Px(k + 1) - x(k)^T Px(k) - e(k)^T \Phi e(k) + \mu x(k)^T \Phi x(k)$$

$$= [\Pi_{\theta_i} x(k) - \Xi_{\theta_i} e(k)]^T P [\Pi_{\theta_i} x(k) - \Xi_{\theta_i} e(k)] - x(k)^T Px(k) - e(k)^T \Phi e(k) + \mu x(k)^T \Phi x(k)$$

$$= \begin{bmatrix} x(k) \\ e(k) \end{bmatrix}^T \Omega \begin{bmatrix} x(k) \\ e(k) \end{bmatrix}$$

where

$$\Omega = \begin{bmatrix} \Pi_{\theta_i}^T P \Pi_{\theta_i} - P + \mu \Phi & * \\
-\Xi_{\theta_i}^T P \Xi_{\theta_i} & -\Xi_{\theta_i}^T P \Xi_{\theta_i} - \Phi \end{bmatrix}.$$  

\[\Omega\]

\[\Omega\] can be decomposed as

$$\Omega = \begin{bmatrix} -P + \mu \Phi & * \\
0 & -\Phi \end{bmatrix} + \begin{bmatrix} \Pi_{\theta_i}^T P & * \\
-\Xi_{\theta_i}^T P & -\Xi_{\theta_i}^T P \Xi_{\theta_i} \end{bmatrix} P^{-1} \begin{bmatrix} \Pi_{\theta_i} & -P \Xi_{\theta_i} \end{bmatrix}.$$  

Using the Schur complement, $\Omega < 0$ is equivalent to the LMIs (23). Thus, if the LMIs (23) hold, then $\Delta V < 0$. According to the Lyapunov stability theory, we can conclude that the closed-loop system is asymptotically stable. This completes the proof.\[\Box\]
The algorithm of the event-triggered networked predictive control with data loss is given as follows:

**Offline:**

**Step 1.1** Given $x(t_0) = x(k_0) = x(0)$, $N_p$, $N_u$, $Q$, $R$, compute the predictive control feedback gain $F$.

**Step 1.2** Given $\mu$, solve the LMIs (23) to get the parameter $\Phi$ in the event-triggered condition (16).

**Online:**

**Step 2.1** Compute the predictive control law $u(0) = Fx(0)$. Set $i = i + 1$.

**Step 2.2** At time instant $k > 0$, measure the system state $x(k)$. Check the event-triggered condition (16), if (16) is satisfied, go to **Step 2.3**. Otherwise, go to **Step 2.8**.

**Step 2.3** Set $x(k_i) = x(k)$. Transmit the state $x(k_i)$ to the controller over the networks. If the data are successfully transmitted, go to **Step 2.4**. Otherwise, go to **Step 2.5**.

**Step 2.4** The controller sends an ACK to the event generator, and set $j = j + 1$. Compute the control law $u(k) = F\hat{x}(k_i)$. Set $k = k + 1$, $i = i + 1$, and repeat **Step 2.2**.

**Step 2.5** The event generator does not get any ACK, then feed $u(k) = F\hat{x}(k_i)$ to the plant. Set $k = k + 1$, and go to **Step 2.6**.

**Step 2.6** If the event-triggered condition (15) is satisfied, that is $k = k_i + T_w$, set $i = i + 1$, and go to **Step 2.7**. Otherwise, go to **Step 2.5**.

**Step 2.7** Set $x(k_i) = x(k)$. Transmit the state $x(k_i)$ to the controller over the networks. If the data are successfully transmitted, go to **Step 2.4**. Otherwise, go to **Step 2.5**.

**Step 2.8** Feed $u(k) = F\hat{x}(k_i)$ to the plant. Set $k = k + 1$, and repeat **Step 2.2**.

5. **Simulation example**

In this section, an example is given to illustrate the effectiveness of the proposed algorithm of the event-triggered networked predictive control with data loss for NCS. Consider the following discrete-time system matrices:

$$
A = \begin{bmatrix}
1 & 0.1 & -0.0124 & -0.0004 \\
0 & 1 & -0.25 & -0.0124 \\
0 & 0 & 0.0619 & 0.1021 \\
0 & 0 & 1.2502 & 0.0619
\end{bmatrix},
B = \begin{bmatrix}
0.0013 \\
0.0251 \\
-0.0013 \\
-0.0255
\end{bmatrix}.
$$

The initial state is $x_0 = [0.05, -0.1, 0, 0.02]^T$; the predictive control parameters are $Q = 4 \times I_{4 \times 4}$, $R = 0.01, N_p = 5$, and $N_u = 3$ and the parameter of the event-triggered condition provided by (16) is $\mu = 0.1$; the waiting time $T_w = 2$; and the maximal allowable number of successive data losses is $d = 2$. According to Equation (8), the predictive control feedback gain matrix is $F = [-4.3617 \ -14.3952 \ 10.1882 \ 0.5811]$. The state trajectories and control input of the closed-loop system are depicted in Figures 4 and 5, respectively, by which we can see that the closed-loop system with data loss is stable. Under the event-triggered conditions (15–16), the event-triggered instants of the system (1) with data loss are
described in Figure 6. In this figure, the value 0.3 represents that the event is triggered by the condition (16), the value 0.2 represents that the event is triggered by the condition (15), and the value 0 represents that no event is triggered. The instants that the event is triggered but the data are lost are denoted by the symbol of red “×.” It can be shown that the proposed algorithm of the event-triggered
networked predictive control with data loss can reduce the communication resources’ consumption and guarantee the closed-loop stability.

6. Conclusion

In this paper, the event-triggered networked predictive control for NCS with data loss has been studied. The data loss compensation strategy and the extended event-triggered mechanism have been proposed. The stability conditions of the closed-loop switched system have been given based on the Lyapunov stability theory.

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