Event-triggered communication scheme for stochastic systems in wireless sensor networks

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Abstract
With the development of sensors and network technology, wireless sensor networks are widely used in various scenes. However, in most applications, the energy of the sensor nodes cannot be supplemented. In addition, since the lifetime of the electronic switching element is measured by the number of trigger times, which makes the effective use of energy, extending the working life of the network becomes one of the key factors to be considered. This paper discusses an event-triggered control scheme for stochastic systems. The mechanism determines when the controller sends control data in order to balance system performance and drive frequency. In this paper, the control scheme is deduced by a class of quadratic performance index function. Then, the formula of performance index is designed based on state feedback and output feedback, and the upper bound of performance index is deduced and the conditions in the theorem can be constructed by solving a set of linear matrix inequalities, which can be easily tested with linear matrix inequality algorithms. Finally, a numerical example is given to illustrate the results.

Keywords
Wireless sensor networks, event-triggered, state feedback, output feedback, linear matrix inequality

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Introduction
Wireless sensor networks (WSNs) are wireless networks organized by wireless sensors. Sensor nodes can collaboratively monitor and sense a variety of environmental information within their network coverage area and transmit it to remote base stations for processing. WSNs have a wide range of application scenarios, which can be used in defense military, industrial control, environmental monitoring and traffic management, etc. Thus, WSNs have attracted the great attention of military, industry and academic institutions in various countries.\(^1\),\(^2\)

Typically, the battery energy of sensor nodes is limited and hard to replenish in most applications (e.g. deployed behind enemy lines or in harsh environments). When the battery power of a sensor node is exhausted, this node will lose its function. Moreover, the energy consumed by the data transmission of sensor nodes is generally much larger than that consumed by the nodes themselves.\(^3\) Since the lifetime of electronic switches depends on the number of triggers, utilizing energy effectively and prolonging the network lifetime are some of the key factors to be considered in the design of WSNs. Therefore, current researches on WSNs are mainly based on event-triggered control methods to study how to effectively use limited energy to extend the lifetime of sensor networks.\(^4\)–\(^6\)

In event-triggered control, the system control signal changes only when a specific event occurs, and the control signal takes effect only when the deviation exceeds the equilibrium state of the system. Therefore, event-triggered control is to give the system smaller control to balance system performance and trigger while maintaining system performance. Dynamic frequency can be used to reduce the number of transmission control and trigger times of electronic switching components, thus effectively utilizing energy and prolonging the working life of the network.

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In order to achieve the optimal controller performance, Reimann et al.\textsuperscript{7} presented an event-triggered state feedback controller. In Tallapragada and Chopra,\textsuperscript{8} an event-triggered-based output feedback controller was proposed to ensure the global stability of the system. A new stability criterion is established in Zhang and Han,\textsuperscript{9} and the discrete output-triggered transmission mechanism and the corresponding output/feedback controller were presented based on the criterion. In order to minimize the linear quadratic index under resource constraints, the optimal control law and the corresponding event-triggered mechanism are presented in Molin and Hirche.\textsuperscript{10} The design of optimal controller for networked control systems triggered by random events is discussed in Chaoqun and Guo.\textsuperscript{11} A novel method of optimal energy consumption management through event-triggered transmission was presented in Gatsis et al.,\textsuperscript{12} which designs the controllers using linear quadratic optimal control. A new event-triggered state feedback control method was presented in Lunze and Lehmann,\textsuperscript{13} which generates control inputs by simulating the feedback between two consecutive events. A calculation method for the upper bound of event-triggered control performance was presented in Cogill,\textsuperscript{14} in which an approximate value function based on Markov decision process is used. An event-triggered transmission scheme based on current battery energy level and queue length was presented in Cong and Zhou,\textsuperscript{15} and two performance indicators (i.e. transmission completion time and throughput) were considered.

The main contributions of this paper can be summarized as follows: we propose two event-triggered control mechanisms for stochastic system, derive the formulas of performance index of state feedback and output feedback using quadratic performance index functions. The upper bounds of the performance index are derived. The conditions in the theorem are transformed accordingly; thus, the LMI toolbox can be used.

The remainder of this paper is organized as follows. The next section briefly introduces the background and lemmas of event-triggered control. The proposed event-triggered method can be found in the ‘Main results’ section. Simulation results are given in the penultimate section. Finally, the conclusions are presented.

Problem statement

Considering the discrete stochastic linear systems, the state space expressions are as follows

\begin{equation}
\begin{aligned}
x_{t+1} &= Ax_t + a_tBu_t + w_t \\
y_t &= Cx_t + v_t
\end{aligned}
\end{equation}

where $x_t \in \mathbb{R}^n$ denotes the state vector. $u_t \in \mathbb{R}^m$ is the control input. $w_t \in \mathbb{R}^r$ and $v_t \in \mathbb{R}^r$ are zero mean Gauss white noise vectors with covariance matrices $Q_w$ and $R$, respectively. $y_t \in \mathbb{R}^p$ is the sensor output and denotes event-triggered control variables. The system evolves from the initial state $x_0 = 0$. In order to use the limited number of activation times to maintain the control performance of the system, each sampling point needs to decide whether or not to send control signals.

In this paper, the model of networked control system is shown in Figure 1. The controller receives the states and outputs collected from the sensors and decides whether to send the control variables to the system by the event-triggered detector. If the system receives the control signal, feedback control should be adopted or the system will run automatically.

This work designs an event-triggered control scheme, which can lead to a smaller performance index of the system, i.e. formula (1), on the premise of balancing the system performance and trigger frequency. The event-triggered control scheme is designed for state feedback and output feedback, respectively, to minimize the upper bound of the corresponding closed-loop system performance index.

Terminology

- $\mathbb{R}^n$: $n$-dimensional Euclidean spaces defined on real fields.
- $\text{trace}(X)$: The trace of a matrix $X$.
- $E(v)$: Expectation of a random variable $v$.
- $A \succ 0$: The matrix $A$ is a symmetric positive definite matrix.
- The superscript “T” indicates the transposition of the matrix.
**Lemmas**

**Lemma 1.** (quadratic performance indices). Suppose the sequence \(z_0, z_1, \ldots\) satisfies the state space \(Z\). Suppose \(f: Z \rightarrow R\) and \(c: Z \rightarrow R\), then

\[
\bar{J} = \limsup_{T \to \infty} \frac{1}{T} \sum_{k=0}^{T-1} E(c(z_k))
\]

For all \(z \in Z\), if there is \(a \in R\) that satisfies \(f(z) \geq a\), then the performance index has the following upper bound

\[
\bar{J} \leq \sup_{z \in Z} (c(e) + E(f(z_{k+1})|z_k = e) - f(e))
\] (2)

**Lemma 2.** Suppose \(Y \succ 0\) and \(x \in R^n\), and \(w \sim (0, Q)\) is the white Gaussian noise column vector. Let \(f(x) = (x + w)^T Y (x + w)\), then

\[
E[f(x)] = x^T Y x + trace(Q Y)
\] (3)

**Main results**

In this section, a state feedback controller and an output feedback controller are presented for the system function (1). The feedback matrix can be obtained by solving a set of linear matrix inequalities.

**Design of the state feedback controller**

**Theorem 1.** For a given matrix \(Q\) and \(\lambda > 0\), if there exists matrix \(Y \succ 0\) and scalar \(\alpha > 0\) satisfies \(\lambda \geq \alpha\) that make the following matrix inequalities hold, i.e.

\[
(\lambda - \alpha) C^T \frac{\lambda}{trace\ C} C \leq Y - A_1^T Y A_1
\] (4)

\[
Q + A^T Y A - Y \leq \alpha C^T \frac{\lambda}{trace\ C} C
\] (5)

where \(A_1 = A + BK\). The trigger control scheme is

\[
\begin{cases}
  y^T \frac{\lambda}{trace\ Q} y_t \leq 1 + trace \left( \frac{\lambda}{trace\ Q} R \right) & a_t = 0 \\
  y^T \frac{\lambda}{trace\ Q} y_t > 1 + trace \left( \frac{\lambda}{trace\ Q} R \right) & a_t = 1
\end{cases}
\] (6)

Then, the quadratic performance index of the system is

\[
J = \begin{cases}
  x^T (Q + A^T Y A - Y) x_t + trace(Q_w Y) & a_t = 0 \\
  x^T (A_1^T Y A_1 - Y) x_t + \lambda + trace(Q_w Y) & a_t = 1
\end{cases}
\] (7)

The upper bound of performance index is

\[
\bar{J} \leq \alpha + trace(Q_w Y)
\] (8)

**Proof.** Given the state feedback formula \(u_t = K x_t\), the system function (1) can be rewritten as

\[
x_{t+1} = \begin{cases}
  A x_t + w_t & a_t = 0 \\
  (A + BK)x_t + w_t & a_t = 1
\end{cases}
\] (9)

Let \(f(x) = x^T Y x\) denote quadratic performance index function of states, then

\[
f(x_{t+1}) = \begin{cases}
  (A x_t + w_t)^T Y (A x_t + w_t) & a_t = 0 \\
  (A_1 x_t + w_t)^T Y (A_1 x_t + w_t) & a_t = 1
\end{cases}
\] (10)

where \(A_1 = A + BK\). According to lemma 2, the expectation is

\[
E[f(x_{t+1})] = \begin{cases}
  x^T A^T Y A x_t + trace(Q_w Y) & a_t = 0 \\
  x^T A_1^T Y A_1 x_t + trace(Q_w Y) & a_t = 1
\end{cases}
\] (11)

Suppose

\[
c(x) = (1 - a_t) x^T Q x_t + \lambda a_t
\] (12)

then the right part of formula (2) can be rewritten as

\[
J = c(x) + E[f(x_{t+1})] - f(x)
\] (13)

combining equations (1) and (12) with equation (13), formula (7) is proved.

According to equation (6), and supposing that \(a_t = 1\), the event-triggered control scheme is as follows

\[
y^T \frac{\lambda}{trace\ Q} y_t > 1 + trace \left( \frac{\lambda}{trace\ Q} R \right)
\] (14)

Expectation of formula (14) is

\[
E \left( y^T \frac{\lambda}{trace\ Q} y_t \right) > E \left[ 1 + trace \left( \frac{\lambda}{trace\ Q} R \right) \right]
\] (15)

Combining \(y_t = C x_t + v_t\) with equation (15), we get

\[
E \left[ (C x_t + v_t)^T \frac{\lambda}{trace\ Q} (C x_t + v_t) \right] > E \left[ 1 + trace \left( \frac{\lambda}{trace\ Q} R \right) \right].
\]

Using the method for finding polynomial expectation of random variable in lemma 2, the above formula can
be simplified as $x_i^T C^T \frac{\lambda}{\text{tr}(Q)} C x_i + \text{trace}\left(\frac{\lambda}{\text{tr}(Q)} R\right) > 1 + \text{trace}\left(\frac{\lambda}{\text{tr}(Q)} R\right)$ i.e.

$$x_i^T \left(C^T \frac{\lambda}{\text{tr}(Q)} C x_i\right) > 1$$ (16)

Multiplying $x_i^T$ and its transpose by equation (4), we get

$$(\lambda - x) x_i^T \left(C^T \frac{\lambda}{\text{tr}(Q)} C\right) x_i \leq x_i^T (Y - A_i^T Y A_i) x_i$$ (17)

According to equations (16) and (17), we get

$$(\lambda - x) \leq x_i^T (Y - A_i^T Y A_i) x_i$$ (18)

According to equation (7), when $a_i = 1$, the formula becomes

$$J = x_i^T (A_i^T Y A_i - Y) x_i + \lambda + \text{trace}(Q_n Y) \leq x - \lambda + \lambda + \text{trace}(Q_n Y) = x + \text{trace}(Q_n Y)$$ (19)

When $a_i = 0$, similar to the derivation process of equation (15), we get

$$x_i^T C^T \frac{\lambda}{\text{tr}(Q)} C x_i \leq 1$$ (20)

Multiplying $x_i^T$ and its transpose by equation (5), we get

$$x_i^T (Q + A^T Y A - Y) x_i \leq 2x_i^T \left(C^T \frac{\lambda}{\text{tr}(Q)} C\right) x_i$$ (21)

According to equations (20) and (21), the inequality is given by

$$x_i^T (Q + A^T Y A - Y) x_i \leq x$$ (22)

When $a_i = 0$, formula (7) becomes

$$J = x_i^T (Q + A^T Y A - Y) x_i + \text{trace}(Q_n Y) \leq x + \text{trace}(Q_n Y)$$ (23)

According to equations (19) and (23), formula (2) becomes

$$\tilde{J} \leq J \leq x + \text{trace}(Q_n Y)$$ (24)

According to equation (7), the performance index and $K$ are uncorrelated when $a_i = 1$. In order to make the performance index smaller, let

$$A_1 = A + BK = 0$$ (25)

Solving the formula (25), we get

$$K = -(B^T Y B)^{-1} B^T Y A$$ (26)

As a result

$$A_1 = A + BK = A + B \left[-(B^T Y B)^{-1} B^T Y A\right] = A - BB^{-1} Y^{-1} (B^T)^{-1} B^T Y A = 0$$

According to equation (4), theorem 1 is nonlinear because it contains the product terms of matrix variables $K$ and $Y$. Therefore, the LMI toolbox cannot be used. However, theorem 1 can be transformed into the linear matrix inequalities for variables $Y$ and $x$ by using equation (26).

**Corollary 1.** Given the matrix $Q$ and $\lambda > 0$, and using the method of solving the following linear matrix inequality optimization

$$\min [x + \text{trace}(Q_n Y)]$$

$$\begin{aligned}
Y &> 0 \\
x &> 0 \\
x - \lambda &< 0 \\
(\lambda - x) C^T \frac{\lambda}{\text{tr}(Q)} C - Y &< 0 \\
Q + A^T Y A - Y - x C^T \frac{\lambda}{\text{tr}(Q)} C &\leq 0
\end{aligned}$$ (27)

the performance index of theorem 1 can be minimum, when $K = -(B^T Y B)^{-1} B^T Y A$.

**Remark 1.** In theorem 1, $Q$ is error weight and $\lambda$ is communication weight, which are given according to the actual environment.

**Design of output feedback controller**

**Theorem 1.** Given matrix $Q$ and $\lambda > 0$, if there exists matrix $Y > 0$, scalar $x > 0$ and $\tilde{\lambda} = \lambda + \text{trace}(K^T B^T Y B K R)$ make the following linear matrix inequalities holds, i.e.

$$\tilde{\lambda} - x \geq 0$$ (28)

$$\text{(}\tilde{\lambda} - x) C^T \frac{\lambda}{\text{tr}(Q)} C \leq Y - A_i^T Y A_i$$ (29)
\[ Q + A^T YA - Y \leq x C^T \frac{\lambda}{\text{trace} Q} C \]  

(30)

where \( A_1 = A + BKC \). The trigger control scheme is

\[
\begin{cases}
    y_t^T \frac{\lambda}{\text{trace} Q} y_t \leq 1 + \text{trace} \left( \frac{\lambda}{\text{trace} Q} R \right) & a_t = 0 \\
    y_t^T \frac{\lambda}{\text{trace} Q} y_t > 1 + \text{trace} \left( \frac{\lambda}{\text{trace} Q} R \right) & a_t = 1
\end{cases}
\]

(31)

Then, the quadratic performance index of the system is

\[
J = \begin{cases}
    x_t^T (Q + A^T YA - Y) x_t + \text{trace}(Q_w Y) & a_t = 0 \\
    x_t^T (A_1^T YA_1 - Y) x_t + \tilde{\lambda} + \text{trace}(Q_w Y) & a_t = 1
\end{cases}
\]

(32)

The upper bound of performance index is

\[
f(x) \leq x + \text{trace}(Q_w Y)
\]

(33)

**Proof.** Given the output feedback formula \( u_t = K y_t \), the system function (1) can be rewritten as

\[
x_{t+1} = Ax_t + a_t BK y_t + w_t = Ax_t + a_t BK (C x_t + v_t) + w_t = (A + a_t BK C) x_t + a_t BK v_t + w_t
\]

(34)

Using the event-triggered method, \( x_{t+1} \) can be given by

\[
x_{t+1} = \begin{cases}
    Ax_t + w_t & a_t = 0 \\
    A_1 x_t + BK v_t + w_t & a_t = 1
\end{cases}
\]

(35)

Let \( f(x) = x^T Y x \) denote the quadratic performance index function of states, then

\[
f(x_{t+1}) = \begin{cases}
    (Ax_t + w_t)^T Y (Ax_t + w_t) & a_t = 0 \\
    (A_1 x_t + BK v_t + w_t)^T Y (A_1 x_t + BK v_t + w_t) & a_t = 1
\end{cases}
\]

(36)

where \( A_1 = A + BKC \). According to lemma 2, the expectation is

\[
E[f(x_{t+1})] = \begin{cases}
    x_t^T A^T YA x_t + \text{trace}(Q_w Y) & a_t = 0 \\
    x_t^T A_1^T YA_1 x_t + \text{trace}(Q_w Y) + \text{trace}(M) & a_t = 1
\end{cases}
\]

(37)

where \( M = K^T B^T Y B K R \).

Suppose

\[
c(x) = (1 - a_t) x_t^T Q x_t + \lambda a_t
\]

(38)

then formula (32) can be obtained by using the proof process of theorem 1.

According to equation (31), and supposing that \( a_t = 1 \), the event-triggered control scheme is as follows

\[
y_t^T \frac{\lambda}{\text{trace} Q} y_t > 1 + \text{trace} \left( \frac{\lambda}{\text{trace} Q} R \right)
\]

(39)

Expectation of formula (39) is

\[
E \left( y_t^T \frac{\lambda}{\text{trace} Q} y_t \right) > E \left[ 1 + \text{trace} \left( \frac{\lambda}{\text{trace} Q} R \right) \right]
\]

(40)

Combining \( y_t = C x_t + v_t \) with equation (40), we get

\[
E \left[ (C x_t + v_t)^T \frac{\lambda}{\text{trace} Q} (C x_t + v_t) \right] > E \left[ 1 + \text{trace} \left( \frac{\lambda}{\text{trace} Q} R \right) \right].
\]

Using the method for finding polynomial expectation of random variable in lemma 2, the above formula can be simplified as

\[
x_t^T C^T \frac{\lambda}{\text{trace} Q} C x_t > 1 + \text{trace} \left( \frac{\lambda}{\text{trace} Q} R \right), \text{i.e.}
\]

\[
x_t^T C^T \frac{\lambda}{\text{trace} Q} C x_t > 1
\]

(41)

Multiplying \( x_t^T \) and its transpose by equation (29), we get

\[
(\tilde{\lambda} - z) x_t^T \left( C^T \frac{\lambda}{\text{trace} Q} C \right) x_t \leq x_t^T (Y - A_1^T YA_1) x_t
\]

(42)

According to equations (41) and (42), the inequality is given by

\[
(\tilde{\lambda} - z) \leq x_t^T (Y - A_1^T YA_1) x_t
\]

(43)

When \( a_t = 1 \), formula (32) becomes

\[
J = x_t^T (A_1^T YA_1 - Y) x_t + \tilde{\lambda} + \text{trace}(Q_w Y)
\]

\[
\leq z - \tilde{\lambda} + \text{trace}(Q_w Y) = z + \text{trace}(Q_w Y)
\]

(44)

When \( a_t = 0 \), similar to the derivation process of equation (41), we get

\[
x_t^T C^T \frac{\lambda}{\text{trace} Q} C x_t \leq 1
\]

(45)
Multiplying \( x_i^T \) and its transpose by equation (30), we get
\[
x_i^T(Q + A^T YA - Y)x_i \leq x x_i^T \left( C^T \frac{\lambda}{\text{trace} Q} C \right) x_i \tag{46}
\]
According to equations (45) and (46), the inequality is given by
\[
x_i^T(Q + A^T YA - Y)x_i \leq x \tag{47}
\]
When \( a_i = 0 \), formula (32) becomes
\[
J = x_i^T(Q + A^T YA - Y)x_i + \text{trace}(Q_u Y) \leq x + \text{trace}(Q_u Y) \tag{48}
\]
Combining equations (44) and (48) with equation (2), we get
\[
\tilde{J} \leq J \leq x + \text{trace}(Q_u Y) \tag{49}
\]
Theorem 2 is proved.

Similar to Theorem 1, in order to make the performance index smaller, let
\[
A_1 = A + BK C = 0 \tag{50}
\]
Solving formula (35), we get
\[
K = -(B^T Y B)^{-1} B^T Y A C^T (C C^T)^{-1} \tag{51}
\]
As a result
\[
A_1 = A + BK C = A + B \left[ -(B^T Y B)^{-1} B^T Y A C^T (C C^T)^{-1} \right] C
= A - BB^{-1} Y^{-1} (B^T)^{-1} B^T Y A (C C^T)^{-1} C^{-1} C = 0
\]
Since \( \tilde{\lambda} \) in theorem 2 contains \( K \) and \( Y \), it cannot be simply transformed into LMI like state feedback. However, it can be assumed that \( \tilde{\lambda} \) is a given value; thus, it is transformed into linear matrix inequality optimization problems similar to state feedback, i.e. firstly calculating the values of \( K \) and \( Y \), and then verifying whether \( \lambda \) satisfies the conditions (if not, Adjust \( \tilde{\lambda} \) until the conditions are met).

**Remark 2.** Unlike theorem 1, the controller and event-driven mechanism in theorem 2 are output-based and subject to double noise.

**Simulation**

In order to verify the performance of the proposed method, the corresponding simulation results are given in this section. The parameters of system function (1) are given by
\[
A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 2 \end{bmatrix}
\]
\[
Q_u = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}, \quad R = 0.05
\]
\[
Q = \begin{bmatrix} 0.1 & -0.03 \\ -0.03 & 3 \end{bmatrix}, \quad \lambda = 0.29
\]
Solving the LMI optimization problem of corollary 1, we get
\[
Y = \begin{bmatrix} 0.2663 & -0.0421 \\ -0.0421 & 0.6300 \end{bmatrix}, \quad x = 0.1673
\]
\[
K = [-0.2761 - 1.00]
\]

Figure 2 shows the results of periodic and proposed event-triggered control methods when state feedback control scheme is used. Figure 2(a) shows the results of the state component \( x_1 \), Figure 2(b) shows the results of the state component \( x_2 \), and Figure 2(c) shows the results of the control amount \( u \). Figure 2(a) shows the results of the state component \( x_1 \), Figure 2(b) shows the results of the state component \( x_2 \), and Figure 2(c) shows the results of the control amount \( u \).

The output feedback event-triggered control scheme is designed by using the same parameters of state feedback, i.e. the solution of LMI is
\[
Y = \begin{bmatrix} 0.2722 & -0.0382 \\ -0.0382 & 0.6443 \end{bmatrix}, \quad x = 0.1719
\]
\[
K = -0.4557 \tilde{\lambda} = 0.2987
\]

Figure 2 shows the results of periodic and proposed event-triggered control methods when output feedback control scheme is used. Figure 2(a) shows the results of the state component \( x_1 \), Figure 2(b) shows the results of the state component \( x_2 \), and Figure 2(c) shows the results of the control amount \( u \), respectively. Figure 2(a) shows the results of state component \( x_1 \), Figure 2(b) shows the results of state component \( x_2 \), and Figure 2(c) shows the results of control amount \( u \).

As can be seen from Figures 2 and 3, the stability of the system is better when periodic transmission is used, but the control times are larger and each control amount is smaller. When the proposed event-triggered transmission is used, the amplitude of the
Figure 2. State trajectories and control signals for state feedback. (a) $x_1$, (b) $x_2$ and (c) $u$. 
Figure 3. Output trajectories and control signals for state feedback. (a) $x_1$, (b) $x_2$ and (c) $u$. 
system state is larger, but the control times are fewer and each control amount is larger. Therefore, on the premise of maintaining system performance, the proposed event-triggered control methods can reduce control frequency, which lead to the effect of balancing system performance and control frequency. The upper bound index and the scalar \( a \) corresponding to output feedback and state feedback are given in Table 1.

### Table 1. The results of state feedback and output feedback.

|                | State feedback | Output feedback |
|----------------|----------------|-----------------|
| Upper bound    | 0.2569         | 0.2636          |
| \( x \)        | 0.1673         | 0.1719          |

### Conclusion

In this article, two output-based event-driven control strategies are proposed, which can effectively reduce the transmission of the control quantity and reduce the network load. The corresponding theorems of the two strategies are converted into LMI form, which can be solved conveniently. In the future, we will study the event-driven control strategy for time-delay stochastic systems.

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