Performance-guaranteed Control for Discrete-time Systems Under Communication Constraints: An Event-triggered Mechanism and Quantized Data-based Protocol

Lanlan He, Xiaoqing Zhang, Xinrui Wang, and Jianping Zhou

***Abstract*—This paper deals with the issue of performance-guaranteed control for discrete-time systems under communication constraints. To alleviate communication burdens, an event-triggered mechanism and quantized data-based protocol is presented. The protocol integrates the advantages of the dual-threshold event-triggered mechanism and signal quantization, leading to a reduced channel occupancy rate compared to the normal weighted try-once-discard protocol and dual-threshold event-triggered protocol. Building upon this protocol, a state feedback controller relying on scheduling signals is proposed. A criterion on stability and energy-to-peak performance is established using the Lyapunov function method and some inequality approaches. Then, a numerically tractable method for determining the desired controller gain via solving linear matrix inequalities. Finally, a double-sided linear switched reluctance machine system is used as an example to illustrate the effectiveness of the designed protocol and the controller.**

***Index Terms*—Try-once-discard protocol, event-triggered mechanism, signal quantization, performance-guaranteed control, discrete-time system**

I. Introduction

WITH the continuous development and proliferation of mobile communication technologies, networked control systems (NCSs) have garnered widespread attention in the academic community, yielding substantial research outcomes [1–6]. Compared to conventional point-to-point connection systems, NCSs exhibit increased flexibility and scalability. However, it is important to note that NCSs often encounter challenges related to limited bandwidth in practical applications, which may result in packet disordering [7, 8], communication delays [9–11], and even packet dropouts [12, 13]. To conserve bandwidth resources and alleviate these transmission limitations, various scheduling protocols have been proposed, including the round-robin protocol [14, 15], stochastic communication protocol [16–18], and weighted try-once-discard protocol (WTODP) [19–21]. Among these, WTODP, which is based on the "maximum-error-first" principle [22], demonstrates active selection and often achieves higher efficiency.

However, as shown in [19–21], WTODP results in a single sensor node occupying the transmission channel at any given time, potentially leading to unnecessary resource wastage. In pursuit of more efficient utilization of network resources, Cheng et al. [23] proposed an event-triggered WTODP and applied it to address the observer-based asynchronous control problem of discrete-time nonlinear systems with communication constraints. Zhou et al. [24] further applied this protocol to study Markov jump systems under the influence of deception attacks, and proposed a filter design method. Different from [23] and [24], in the study of sliding-mode control for fuzzy systems, Yang et al. [25] introduced a novel dual-threshold event-triggered protocol (DTETP). This protocol dynamically adjusts the number of sensor nodes occupying transmission channels according to the relationship between thresholds and each sensor node, offering advantages over the event-triggered WTODP in [23, 24], which only allows a single node to transmit.

In addition to the event-triggered mechanism, signal quantization offers an effective means of alleviating the communication burden [26]. Consequently, protocols based on quantized data have found widespread application in NCSs. Using quantized data-based round-robin protocol, Li et al. [27] proposed a new distributed observer consensus method to address the quasi-consensus control problem for multi-agent systems with random external disturbances. Using quantized data-based stochastic communication protocol, Wu et al. [28] designed a dynamic feedback controller via the Takagi-Sugeno fuzzy model, addressing the H_∞ control problem for discrete-time nonlinear systems. Using quantized data-based WTODP, Wang et al. [29] investigated a class of fuzzy networked singularly perturbed systems by an observer-based method, while Li et al. [30] proposed a controller design scheme under lossy digital networks.

Motivated by the above discussion, we address the issue of performance-guaranteed control for discrete-time systems under communication constraints. The purpose is to design a state-feedback controller (SFC) dependent on the scheduling signal to ensure stability while satisfying energy-to-peak performance. To alleviate communication burdens, an event-triggered mechanism and quantized data-based protocol (ETQDP) is presented. The protocol combines the advantages of the DTET mechanism and signal quantization, leading to the reduction of the channel occupancy rate (COR)

Manuscript received April 12, 2024; revised September 9, 2024.

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compared to the normal WTODP [19–21] and DTETP [25]. A criterion on stability and energy-to-peak performance is established by using the Lyapunov function method and some inequality approaches. Then, a numerically tractable method for determining the desired controller gain via solving linear matrix inequalities (LMIs). Finally, a double-sided linear switched reluctance machine system is applied to verify the effectiveness of the ETQDP and the suitability of the proposed controller.

Notation. Throughout this paper, $\mathbb{R}^a$ denotes an a-dimensional real matrix. The notation $diag\{\cdot\}$ represents a block-diagonal matrix. For any matrix W, $W > 0$ indicates that W is symmetric and positive definite. The symbol '*' is used as a symmetry block in a square matrix. The function $arg \max_{\chi_1 \le \chi \le \chi_2} (f(\chi))$ determines the value of the independent variable $\chi \in [\chi_1, \chi_2]$ at which $f(\chi)$ reaches its maximum. Additionally, I and 0 denote the identity and zero matrices with suitable dimensions, respectively.

II. Preliminaries

Consider the following discrete-time linear system:

$$\begin{cases} x(h+1) = Ax(h) + Bu(h) + D\omega(h), \\ z(h) = Cx(h), \end{cases} \tag{1}$$

where $x(h) = [x_1(h), x_2(h), \cdots, x_n(h)]^T \in \mathbb{R}^n$, $u(h) \in \mathbb{R}^{n_u}$, $z(h) \in \mathbb{R}^{n_z}$, and $\omega(h) \in \mathbb{R}^{n_\omega}$ are the system state, control input, control output, and exterior disturbance input, respectively. A, B, C, and D are constant matrices with proper dimensions.

In the process of network communication, to mitigate communication congestion effectively, it is crucial to quantize signals before their transmission into the network space. Therefore, we suppose there exist n sensor nodes, and $x_i(h)(i \in N = \{1, 2, \cdots, n\})$ denotes the ith sensor node of the system state. Before being transmitted into the communication network, using a logarithmic quantizer $q(\cdot)$ to quantize the system state, expressed as follows:

$$q(x(h)) = [q_1(x_1(h)), q_2(x_2(h)), \cdots, q_n(x_n(h))]^T. \tag{2}$$

For each $q_i(\cdot)$, the quantization level is defined as

$$\Pi = \{\pm\pi_\iota : \pi_\iota = \rho^\iota \pi_0, \iota = 0, \pm1, \pm2, \cdots\} \cup \{\pm\pi_0\} \cup \{0\},$$

where $\pi_0 > 0$ denotes the initial value of $q_i(\cdot)$, ρ $(0 < \rho < 1)$ represents the quantization density. A higher quantization density results in more accurate quantization and better performance. Then, the logarithmic quantizer $q_i(\cdot)$ can be represented as:

$$q_i(x_i(h)) = \begin{cases} \pi_\iota, & x_i(h) \in \left(\frac{\pi_\iota}{1+\xi}, \frac{\pi_\iota}{1-\xi}\right], \\ 0, & x_i(h) = 0, \\ -q_i(-x_i(h)), & x_i(h) \le 0, \end{cases} \tag{3}$$

where $\xi = \frac{1-\rho}{1+\rho}$. Based on (3), utilizing the sector-bound method [31], the quantized state in (2) is redefined as:

$$q(x(h)) = (I + \Delta)x(h), \tag{4}$$

where $\Delta = diag\{\Delta_1, \cdots, \Delta_i\}$ with $\Delta_i \in [-\xi, \xi]$.

In order to alleviate bandwidth pressure on the communication network, the communication protocol is employed to schedule the transmission sequence after quantization, thereby determining which sensor nodes can access the transmission channel.

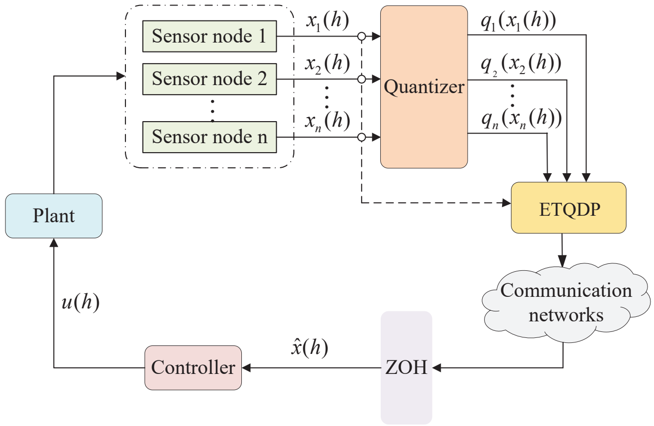

Fig. 1. Structure of the control system under ETQDP.

As illustrated in Fig. 1, we define $\hat{x}(h) = [\hat{x}_1(h), \hat{x}_2(h), \cdots, \hat{x}_n(h)]^T \in \mathbb{R}^n$, with $\hat{x}_i(h)$ as the actual data of the ith node received by the controller. For the ith sensor node, define $\phi_i(h)$ as:

$$\phi_i(h) = (\hat{x}_i(h-1) - x_i(h))^T \psi_i (\hat{x}_i(h-1) - x_i(h)), \tag{5}$$

where $\phi_i(h)$ represents the deviation between the current state and the signal received by the controller at the previous instant, and $\psi_i > 0$ is the specified weight. We set $\hat{x}_i(-1) = 0$ when $h = 0$.

The scheduling signal is defined as $\vartheta(h) \in N$, which represents the selected sensor node at instant h. According to the WTODP [19–21], $\vartheta(h)$ is defined as

$$\vartheta(h) = arg \max_{1 \le i \le n} (\phi_i(h)). \tag{6}$$

However, unlike WTODP [19–21] and DTETP [25], we adopt the following ETQDP to schedule the transmission data on any instant $h \in \{1, 2, \cdots\}$:

Given two positive threshold values f_{min} and f_{max}, satisfying $f_{min} < f_{max}$, along with a positive scalar θ_i, we consider the following cases:

Case 1. If there exists $i \in N$ such that

$$\phi_i(h) \ge f_{max} x_i^T(h) \theta_i x_i(h) \tag{7}$$

hold, the quantized data of these nodes will be transmitted. For the nodes that do not satisfy this condition, the compensation strategy is employed, in which their previously transmitted values are retained. Consequently, the actual signals received by the controller are given as follows:

$$\hat{x}_i(h) = \begin{cases} q_i(x_i(h)), & \text{if } x_i(h) \text{ satisfies (7)}, \\ \hat{x}_i(h-1), & \text{otherwise}. \end{cases} \tag{8}$$

Case 2. If case 1 does not hold, but there exists $i \in N$ such that

$$f_{max} x_i^T(h) \theta_i x_i(h) > \phi_i(h) \ge f_{min} x_i^T(h) \theta_i x_i(h), \tag{9}$$

hold, the quantized data of only one node which not only satisfies (9) but also satisfies (6) will be transmitted. In this case, utilizing the compensation strategy, the actual signals received by the controller are given as follows:

$$\hat{x}_i(h) = \begin{cases} q_i(x_i(h)), & \text{if } i = \vartheta(h), \\ \hat{x}_i(h-1), & \text{otherwise.} \end{cases}$$

Then, at the current instant h, the overall received data $\hat{x}(h)$ can be expressed as

$$\begin{aligned} \hat{x}(h) &= \Phi_{\vartheta(h)} q(x(h)) + \tilde{\Phi}_{\vartheta(h)} \hat{x}(h-1) \\ &= \Phi_{\vartheta(h)}((I+\Delta)x(h)) + \tilde{\Phi}_{\vartheta(h)} \hat{x}(h-1), \end{aligned} \quad (10)$$

where

$$\Phi_{\vartheta(h)} = diag\{\delta(\vartheta(h)-1), \delta(\vartheta(h)-2), \cdots, \delta(\vartheta(h)-n)\},$$
$$\tilde{\Phi}_{\vartheta(h)} = I - \Phi_{\vartheta(h)},$$

and $\delta(\cdot) \in \{0, 1\}$ is the Kronecker delta function, defined as

$$\delta(\cdot) = \begin{cases} 1, & \text{if } \vartheta(h) - i = 0, \\ 0, & \text{otherwise.} \end{cases}$$

Case 3. Cases 1 and 2 do not hold. In other words, for any $i \in N$ such that

$$\phi_i(h) < f_{min} x_i^T(h) \theta_i x_i(h),$$

hold, under this case, none of the sensor nodes are allowed to transmit their quantized data, the actual signals received by the controller can be given as

$$\hat{x}(h) = \hat{x}(h-1). \quad (11)$$

According to (8), (10), and (11), the SFC dependent on the scheduling signal is defined as

$$u(h) = K_{\nu(h)} \hat{x}(h), \quad (12)$$

where $K_{\nu(h)}$ is the control gain, and $\nu(h)$ represents the scheduling signal.

Combining (1) and (12), the closed-loop system (CLS) is formulated as follows:

$$\begin{cases} x(h+1) = Ax(h) + BK_{\nu(h)} \hat{x}(h) + D\omega(h), \\ z(h) = Cx(h). \end{cases} \quad (13)$$

Remark 1. It is worth noting that the control gain $K_{\nu(h)}$ will be affected by the scheduling signal $\nu(h)$. In Case 2, the scheduling signal $\nu(h)$ (i.e. $\vartheta(h)$ in (6).) can take values in the set N. Moreover, for Cases 1 and 3, we define the scheduling signal $\nu(h)$ as 0 and $n+1$, respectively. Thus, as mentioned in the above ETQDP, the scheduling signal $\nu(h)$ will take values in the set $\mathcal{I} \triangleq \{0, 1, 2, \cdots, n+1\}$ for different cases.

For the convenience of discussion, define the sets $\mathcal{T}_1$, $\mathcal{T}_2$, and $\mathcal{T}_3$ to represent the instants that satisfy Cases 1, 2, and 3, respectively.

Definition 1. The CLS (13) is said to have the energy-to-peak performance if the following conditions are satisfied:

1) For $\omega(h) = 0$, the CLS (13) is asymptotically stable in distinct instant sets $\mathcal{T}_1$, $\mathcal{T}_2$, and $\mathcal{T}_3$.

2) Under the zero-initial condition, and given a prescribed energy-to-peak performance index $\gamma > 0$, the following condition holds for all nonzero $\omega(h) \in L_2[0, +\infty)$:

$$\sup_{h \geq 0} z^T(h) z(h) \leq \gamma^2 \sum_{h=0}^{\infty} \omega^T(h) \omega(h). \quad (14)$$

Lemma 1. [32]. For any matrices $\mathcal{W}_1$, $\mathcal{W}_2$, and $\mathcal{W}_3$ with appropriate dimensions,

$$\begin{bmatrix} \mathcal{W}_1 & \mathcal{W}_2 \\ * & \mathcal{W}_3 \end{bmatrix} < 0$$
$$\mathcal{W}_3 < 0 \text{ and } \mathcal{W}_1 - \mathcal{W}_2 \mathcal{W}_3^{-1} \mathcal{W}_2^T < 0.$$

Lemma 2. [33]. For any matrices $\mathcal{S}_1$ and $\mathcal{S}_2$ of suitable dimensions, and for a constant $\upsilon > 0$, the following inequality is satisfied:

$$\mathcal{S}_1 \mathcal{S}_2^T + \mathcal{S}_2 \mathcal{S}_1^T \leq \upsilon^{-1} \mathcal{S}_1 \mathcal{S}_1^T + \upsilon \mathcal{S}_2 \mathcal{S}_2^T.$$

III. Main Results

In this section, we first study the asymptotic stability and energy-peak-performance analysis of CLS (13) under ETQDP and propose sufficient conditions as follows:

Theorem 1. For given scalars $\gamma > 0$, $\kappa > 0$, $f_{max} > f_{min} > 0$, and $\psi_i > 0$, suppose that there exist positive definite matrices $P > 0$ and $R > 0$, diagonal matrix $\Theta > 0$, gain matrices K_0, K_α and K_{n+1}, positive scalar $\lambda_{\alpha\beta} > 0$ with $\sum_{\beta=1}^{n} \lambda_{\alpha\beta} = 1$ $(\alpha \in N)$ such that

$$f_{max}\Theta - \Delta^2 \Psi \geq 0, \quad (15)$$

$$\begin{bmatrix} -P & C^T \\ * & -\gamma^2 I \end{bmatrix} < 0, \quad (16)$$

$$\Xi_0 = \begin{bmatrix} \Xi_0^{11} & \Xi_0^{12} & \Xi_0^{13} & 0 \\ * & \Xi_0^{22} & \Xi_0^{23} & 0 \\ * & * & \Xi_0^{33} & 0 \\ * & * & * & -R \end{bmatrix} < 0, \quad (17)$$

$$\Xi_\alpha = \begin{bmatrix} \Xi_\alpha^{11} & \Xi_\alpha^{12} & \Xi_\alpha^{13} \\ * & \Xi_\alpha^{22} & \Xi_\alpha^{23} \\ * & * & \Xi_\alpha^{33} \end{bmatrix} < 0, \quad (18)$$

$$\Xi_{n+1} = \begin{bmatrix} \Xi_{n+1}^{11} & \Xi_{n+1}^{12} & \Xi_{n+1}^{13} \\ * & \Xi_{n+1}^{22} & \Xi_{n+1}^{23} \\ * & * & \Xi_{n+1}^{33} \end{bmatrix} < 0 \quad (19)$$

hold, where

$$\begin{aligned}
\Xi_0^{11} &= A^T PA + A^T PBK_0 + K_0^T B^T PA + K_0^T B^T PB \\
&\quad \times K_0 + R - P + \kappa f_{max} \Theta, \\
\Xi_0^{12} &= A^T PBK_0 + K_0^T B^T PBK_0 + R, \\
\Xi_0^{13} &= A^T PD + K_0^T B^T PD, \\
\Xi_0^{22} &= K_0^T B^T PBK_0 + R - \kappa \Psi, \ \Xi_0^{23} = K_0^T B^T PD, \\
\Xi_0^{33} &= D^T PD - I, \\
\Xi_\alpha^{11} &= A^T PA + A^T PBK_\alpha \Phi_\alpha (I+\Delta) + (I+\Delta)^T \Phi_\alpha^T \\
&\quad \times K_\alpha^T B^T PA + (I+\Delta)^T \Phi_\alpha^T K_\alpha^T B^T PBK_\alpha \Phi_\alpha (I \\
&\quad + \Delta) + (I+\Delta)^T \Phi_\alpha^T R \Phi_\alpha (I+\Delta) - P + \Upsilon_\alpha, \\
\Xi_\alpha^{12} &= A^T PBK_\alpha \tilde{\Phi}_\alpha + (I+\Delta)^T \Phi_\alpha^T K_\alpha^T B^T PBK_\alpha \tilde{\Phi}_\alpha \\
&\quad + (I+\Delta)^T \Phi_\alpha^T R \tilde{\Phi}_\alpha - \Upsilon_\alpha, \\
\Xi_\alpha^{13} &= A^T PD + (I+\Delta)^T \Phi_\alpha^T K_\alpha^T B^T PD, \\
\Xi_\alpha^{22} &= \tilde{\Phi}_\alpha^T K_\alpha^T B^T PBK_\alpha \tilde{\Phi}_\alpha + \tilde{\Phi}_\alpha^T R \tilde{\Phi}_\alpha - R + \Upsilon_\alpha, \\
\Xi_\alpha^{23} &= \tilde{\Phi}_\alpha^T K_\alpha^T B^T PD, \ \Xi_\alpha^{33} = D^T PD - I, \\
\Xi_{n+1}^{11} &= A^T PA + A^T PBK_{n+1} + K_{n+1}^T B^T PA + K_{n+1}^T \\
&\quad \times B^T PBK_{n+1} - P + \kappa f_{min} \Theta, \\
\Xi_{n+1}^{12} &= A^T PBK_{n+1} + K_{n+1}^T B^T PBK_{n+1}, \\
\Xi_{n+1}^{13} &= A^T PD + K_{n+1}^T B^T PD,
\end{aligned}$$

$$\Xi_{n+1}^{22} = K_{n+1}^T B^T P B K_{n+1} - \kappa\Psi,$$
$$\Xi_{n+1}^{23} = K_{n+1}^T B^T P D,\ \Xi_{n+1}^{33} = D^T P D - I,$$
$$\Upsilon_\alpha = \Psi \sum_{\beta=1}^{n} \lambda_{\alpha\beta}(\Phi_\alpha - \Phi_\beta),\ \Theta = diag\{\theta_1, \theta_2, \cdots, \theta_n\},$$
$$\Psi = diag\{\psi_1, \psi_2, \cdots, \psi_n\}.$$

Then, the controller in (12) can make sure that CLS (13) in distinct instant sets $\mathcal{T}_1$, $\mathcal{T}_2$, and $\mathcal{T}_3$ is asymptotically stable with energy-to-peak performance γ.

Proof: Consider the Lyapunov function as

$$\mathcal{V}(h) = x^T(h)Px(h) + \hat{x}^T(h-1)R\hat{x}(h-1). \tag{20}$$

Subsequently, we will analyze the $\Delta\mathcal{V}(h)$ under different transmission cases.

For $h \in \mathcal{T}_1$, we obtain

$$\begin{aligned}\Delta\mathcal{V}(h) &= \mathcal{V}(h+1) - \mathcal{V}(h)\\ &= x^T(h+1)Px(h+1) + \hat{x}^T(h)R\hat{x}(h) - x^T(h)P\\ &\quad \times x(h) - \hat{x}^T(h-1)R\hat{x}(h-1)\\ &= \big[Ax(h) + BK_{\nu(h)}\hat{x}(h) + D\omega(h)\big]^T P\big[Ax(h)\\ &\quad + BK_{\nu(h)}\hat{x}(h) + D\omega(h)\big] + \hat{x}^T(h)R\hat{x}(h)\\ &\quad - x^T(h)Px(h) - \hat{x}^T(h-1)R\hat{x}(h-1). \end{aligned} \tag{21}$$

Define $e_i(h) = \hat{x}_i(h) - x_i(h) (i \in N)$. When $x_i(h)$ satisfies (7), according to (8), we have $e_i(h) = (1+\Delta_i)x_i(h) - x_i(h)$, then $e_i^T(h)\psi_i e_i(h) = x_i^T(h)\Delta_i^2\psi_i x_i(h)$. Thus, from (15), we obtain:

$$f_{max}x_i^T(h)\theta_i x_i(h) - e_i^T(h)\psi_i e_i(h) \geq 0.$$

When $x_i(h)$ does not satisfy (7), we have $\hat{x}_i(h) = \hat{x}_i(h-1)$, then $e_i^T(h)\psi_i e_i(h) = \phi_i(h)$, which implies $f_{max}x_i^T(h)\theta_i x_i(h) > e_i^T(h)\psi_i e_i(h)$. It is not difficult to deduce that

$$\begin{aligned}&\sum_{i=1}^{n}\big[f_{max}x_i^T(h)\theta_i x_i(h) - e_i^T(h)\psi_i e_i(h)\big]\\ =&f_{max}x^T(h)\Theta x(h) - e^T(h)\Psi e(h) \geq 0,\end{aligned} \tag{22}$$

where $e(h) = [e_1^T(h), e_2^T(h), \cdots, e_n^T(h)]^T$. To simplify the expression, define the scheduling signal $\nu(h) = 0$. Then, from (21) and (22), for scalar $\kappa > 0$, we can derive that

$$\begin{aligned}\Delta\mathcal{V}(h) &\leq \big[Ax(h) + BK_0x(h) + BK_0e(h) + D\omega(h)\big]^T P\\ &\quad \times \big[Ax(h) + BK_0x(h) + BK_0e(h) + D\omega(h)\big]\\ &\quad + \big[x(h) + e(h)\big]^T R\big[x(h) + e(h)\big] - x^T(h)P\\ &\quad \times x(h) - \hat{x}^T(h-1)R\hat{x}(h-1) + \kappa\big[f_{max}x^T(h)\\ &\quad \times \Theta x(h) - e^T(h)\Psi e(h)\big]\\ &= \eta_1^T(h)\Xi_0\eta_1(h) + \omega^T(h)\omega(h),\end{aligned}$$

where $\eta_1(h) = [x^T(h)\ e^T(h)\ \omega^T(h)\ \hat{x}^T(h-1)]^T$. According to (17), we have

$$\Delta\mathcal{V}(h) \leq \omega^T(h)\omega(h). \tag{23}$$

When $\omega(h) = 0$, we can obtain $\Delta\mathcal{V}(h) \leq 0$. Therefore, according to Lyapunov stability theory, it can be concluded that CLS (13) is asymptotically stable.

When $\omega(h) \neq 0$, we define a performance index function as follows:

$$\mathcal{J}(h) \triangleq \mathcal{V}(h) - \sum_{\mu=0}^{h-1}\omega^T(\mu)\omega(\mu). \tag{24}$$

Then, under the zero initial condition, we obtain

$$\begin{aligned}\mathcal{J}(h) &= \mathcal{V}(h) - \mathcal{V}(0) - \sum_{\mu=0}^{h-1}\omega^T(\mu)\omega(\mu)\\ &= \sum_{\mu=0}^{h-1}\{\Delta\mathcal{V}(\mu) - \omega^T(\mu)\omega(\mu)\}\end{aligned}$$

which, in conjunction with (23), results in $\mathcal{J}(h) \leq 0$. It follows that

$$\mathcal{V}(h) \leq \sum_{\mu=0}^{h}\omega^T(\mu)\omega(\mu). \tag{25}$$

Utilizing Lemma 1 to (16), we can abtain

$$C^TC < \gamma^2 P. \tag{26}$$

By means of (13), (20), (25), and (26), we have

$$\begin{aligned}z^T(h)z(h) &= x^T(h)C^TCx(h)\\ &\leq \gamma^2 x^T(h)Px(h)\\ &\leq \gamma^2\mathcal{V}(h)\\ &\leq \gamma^2\sum_{\mu=0}^{h}\omega^T(\mu)\omega(\mu)\\ &\leq \gamma^2\sum_{h=0}^{\infty}\omega^T(h)\omega(h),\end{aligned}$$

which implies the energy-to-peak performance.

For $h \in \mathcal{T}_2$, we can obtain

$$\begin{aligned}\Delta\mathcal{V}(h) &= \mathcal{V}(h+1) - \mathcal{V}(h)\\ &= \big[Ax(h) + BK_{\nu(h)}\hat{x}(h) + D\omega(h)\big]^T P\big[Ax(h)\\ &\quad + BK_{\nu(h)}\hat{x}(h) + D\omega(h)\big] + \hat{x}^T(h)R\hat{x}(h)\\ &\quad - x^T(h)Px(h) - \hat{x}^T(h-1)R\hat{x}(h-1).\end{aligned} \tag{27}$$

To simplify the expression, define the scheduling signal $\nu(h) = \alpha \in N$. Then, according to the selection principle of the WTODP [19–21], we derive that

$$(\hat{x}(h-1) - x(h))^T\Psi(\Phi_\alpha - \Phi_\beta)(\hat{x}(h-1) - x(h)) \geq 0, \tag{28}$$

holds for all $\beta \in N$. Combining (10), (27), and (28) yields

$$\begin{aligned}\Delta\mathcal{V}(h) &\leq \big[Ax(h) + BK_\alpha\big[\Phi_\alpha(I+\Delta)x(h) + \tilde{\Phi}_\alpha\hat{x}(h-1)\big]\\ &\quad + D\omega(h)\big]^T P\big[Ax(h) + BK_\alpha\big[\Phi_\alpha(I+\Delta)x(h)\\ &\quad + \tilde{\Phi}_\alpha\hat{x}(h-1)\big] + D\omega(h)\big] + \big[\Phi_\alpha(I+\Delta)x(h)\\ &\quad + \tilde{\Phi}_\alpha\hat{x}(h-1)\big]^T R\big[\Phi_\alpha(I+\Delta)x(h) + \tilde{\Phi}_\alpha\\ &\quad \times \hat{x}(h-1)\big] - x^T(h)Px(h) - \hat{x}^T(h-1)\\ &\quad \times R\hat{x}(h-1) + (\hat{x}(h-1) - x(h))^T\Upsilon_\alpha\\ &\quad \times (\hat{x}(h-1) - x(h))\\ &= \eta_2^T(h)\Xi_\alpha\eta_2(h) + \omega^T(h)\omega(h),\end{aligned} \tag{29}$$

where $\eta_2(h) = [x^T(h)\ \hat{x}^T(h-1)\ \omega^T(h)]^T$. From (18), we can obtain $\Delta\mathcal{V}(h) \leq \omega^T(h)\omega(h)$. Following a similar line of reasoning as above $h \in \mathcal{T}_1$, we can subsequently conclude that CLS (13) is asymptotically stable and with the energy-to-peak performance.

For $h \in \mathcal{T}_3$, in this case, $\hat{x}(h) = \hat{x}(h-1)$, we have

$$\begin{aligned}\Delta\mathcal{V}(h) &= x^T(h+1)Px(h+1) - x^T(h)Px(h) \\ &= \big[Ax(h) + BK_{\nu(h)}\hat{x}(h) + D\omega(h)\big]^T P\big[Ax(h) \\ &\quad + BK_{\nu(h)}\hat{x}(h) + D\omega(h)\big] - x^T(h)Px(h). \quad (30)\end{aligned}$$

Owing to $\phi_i(h) < f_{min}x_i^T(h)\theta_i x_i(h)$ for all $i \in N$, and $e_i(h) = \hat{x}_i(h-1) - x_i(h)$, we can get

$$\sum_{i=1}^{n}\big[f_{min}x_i^T(h)\theta_i x_i(h) - e_i^T(h)\psi_i e_i(h)\big] > 0.$$

It is not difficult to deduce that

$$f_{min}x^T(h)\Theta x(h) - e^T(h)\Psi e(h) > 0. \quad (31)$$

To simplify the expression, define the scheduling signal $\nu(h) = n+1$. Then, for scalar $\kappa > 0$, we can derive from (30) and (31) that

$$\begin{aligned}\Delta\mathcal{V}(h) &\le \big[Ax(h) + BK_{n+1}x(h) + BK_{n+1}e(h) + D \\ &\quad \times \omega(h)\big]^T P\big[Ax(h) + BK_{n+1}x(h) + BK_{n+1} \\ &\quad \times e(h) + D\omega(h)\big] - x^T(h)Px(h) + \kappa\big[f_{min} \\ &\quad \times x^T(h)\Theta x(h) - e^T(h)\Psi e(h)\big] \\ &= \eta_3^T(h)\Xi_{n+1}\eta_3(h) + \omega^T(h)\omega(h), \quad (32)\end{aligned}$$

where $\eta_3(h) = [x^T(h)\ e^T(h)\ \omega^T(h)]^T$. From (19) we can obtain $\Delta\mathcal{V}(h) \le \omega^T(h)\omega(h)$. Following a similar line of reasoning as above $h \in \mathcal{T}_1$, we can subsequently conclude that CLS (13) is asymptotically stable with the energy-to-peak performance. The proof is completed. ∎

Remark 2. Since the quantized state signal reaches the controller through ET-WTODP in distinct instant sets, $\mathcal{T}_1$, $\mathcal{T}_2$, and $\mathcal{T}_3$ have different forms. Therefore, to achieve stability and satisfy the desired performance index, we analyzed the sufficient conditions required under different transmission cases.

Next, we provide a feasible solution based on some inequality approaches to ensure the stability conditions (15)-(19) in Theorem 1.

Theorem 2. For given scalars $\gamma > 0$, $\kappa > 0$, $f_{max} > f_{min} > 0$, and $\psi_i > 0$, suppose that there exist positive definite matrices $P > 0$ and $R > 0$, diagonal matrix $\Theta > 0$, gain matrices K_0, K_α, and K_{n+1}, positive scalar $\upsilon > 0$ and $\lambda_{\alpha\beta} > 0$ with $\sum_{\beta=1}^{n}\lambda_{\alpha\beta} = 1$ $(\alpha \in N)$ such that

$$f_{max}\Theta - \xi^2\Psi \ge 0, \quad (33)$$

$$\begin{bmatrix} -P & C^T \\ * & -\gamma^2 I\end{bmatrix} < 0, \quad (34)$$

$$\Xi_0 = \begin{bmatrix} \Xi_0^{11} & R & 0 & A^T + K_0^T B^T & 0 \\ * & R - \kappa\Psi & 0 & K_0^T B^T & 0 \\ * & * & -I & D^T & 0 \\ * & * & * & P - 2I & 0 \\ * & * & * & * & -R \end{bmatrix} < 0, \quad (35)$$

$$\Xi_\alpha = \begin{bmatrix} \Xi_\alpha^{11} & -\Upsilon_\alpha & 0 & \Xi_\alpha^{14} & \Phi_\alpha^T R & 0 \\ * & \Xi_\alpha^{22} & 0 & \Xi_\alpha^{24} & \tilde{\Phi}_\alpha^T R & 0 \\ * & * & -I & D^T & 0 & 0 \\ * & * & * & \Xi_\alpha^{44} & 0 & BK_\alpha\Phi_\alpha \\ * & * & * & * & -R & R\Phi_\alpha \\ * & * & * & * & * & -\frac{\upsilon}{\xi^2}I \end{bmatrix} < 0, \quad (36)$$

$$\Xi_{n+1} = \begin{bmatrix} \Xi_{n+1}^{11} & 0 & 0 & A^T + K_{n+1}^T B^T \\ * & -\kappa\Psi & 0 & K_{n+1}^T B^T \\ * & * & -I & D^T \\ * & * & * & P - 2I \end{bmatrix} < 0 \quad (37)$$

hold, where

$$\begin{aligned}&\Xi_0^{11} = R - P + \kappa f_{max}\Theta,\ \Xi_\alpha^{11} = -P + \Upsilon_\alpha + \upsilon I, \\ &\Xi_\alpha^{14} = A^T + \Phi_\alpha^T K_\alpha^T B^T,\ \Xi_\alpha^{22} = -R + \Upsilon_\alpha, \\ &\Xi_\alpha^{24} = \tilde{\Phi}_\alpha^T K_\alpha^T B^T,\ \Xi_\alpha^{44} = P - 2I, \\ &\Xi_{n+1}^{11} = -P + \kappa f_{min}\Theta,\ \Theta = diag\{\theta_1, \theta_2, \cdots, \theta_n\}, \\ &\Upsilon_\alpha = \Psi\sum_{\beta=1}^{n}\lambda_{\alpha\beta}(\Phi_\alpha - \Phi_\beta),\ \Psi = diag\{\psi_1, \psi_2, \cdots, \psi_n\}.\end{aligned}$$

Then, the controller in (12) can make sure that CLS (13) in distinct instant sets $\mathcal{T}_1$, $\mathcal{T}_2$, and $\mathcal{T}_3$ is asymptotically stable with energy-to-peak performance γ.

Proof: Firstly, applying Lemma 1 to (36), we have

$$\Xi_\alpha = \bar{\Xi}_\alpha + \frac{\xi^2}{\upsilon}\mathcal{S}_1^T\mathcal{S}_1 < 0, \quad (38)$$

where

$$\bar{\Xi}_\alpha = \begin{bmatrix} \bar{\Xi}_\alpha^{11} & -\Upsilon_\alpha & 0 & A^T + \Phi_\alpha^T K_\alpha^T B^T & \Phi_\alpha^T R \\ * & -R + \Upsilon_\alpha & 0 & \tilde{\Phi}_\alpha^T K_\alpha^T B^T & \tilde{\Phi}_\alpha^T R \\ * & * & -I & D^T & 0 \\ * & * & * & P - 2I & 0 \\ * & * & * & * & -R \end{bmatrix},$$

$$\bar{\Xi}_\alpha^{11} = -P + \Upsilon_\alpha + \upsilon I,$$

$$\mathcal{S}_1 = \begin{bmatrix} 0 & 0 & 0 & \Phi_\alpha^T K_\alpha^T B^T & \Phi_\alpha^T R^T \end{bmatrix}.$$

Because of $\Delta^2 \le \xi^2$, we can deduce from (38) that

$$\bar{\Xi}_\alpha + \upsilon^{-1}\mathcal{S}_1^T\Delta^2\mathcal{S}_1 < 0. \quad (39)$$

Utilizing Lemma 2 to (39), we get

$$\tilde{\Xi}_\alpha \le \hat{\Xi}_\alpha + \upsilon^{-1}\mathcal{S}_1^T\Delta^2\mathcal{S}_1 + \upsilon\mathcal{S}_2^T\mathcal{S}_2, \quad (40)$$

where

$$\tilde{\Xi}_\alpha = \begin{bmatrix} -P + \Upsilon_\alpha & -\Upsilon_\alpha & 0 & \tilde{\Xi}_\alpha^{14} & \tilde{\Xi}_\alpha^{15} \\ * & -R + \Upsilon_\alpha & 0 & \tilde{\Phi}_\alpha^T K_\alpha^T B^T & \tilde{\Phi}_\alpha^T R \\ * & * & -I & D^T & 0 \\ * & * & * & P - 2I & 0 \\ * & * & * & * & -R \end{bmatrix},$$

$$\hat{\Xi}_\alpha = \begin{bmatrix} -P + \Upsilon_\alpha & -\Upsilon_\alpha & 0 & \hat{\Xi}_\alpha^{14} & \Phi_\alpha^T R \\ * & -R + \Upsilon_\alpha & 0 & \tilde{\Phi}_\alpha^T K_\alpha^T B^T & \tilde{\Phi}_\alpha^T R \\ * & * & -I & D^T & 0 \\ * & * & * & P - 2I & 0 \\ * & * & * & * & -R \end{bmatrix},$$

$$\mathcal{S}_2 = \begin{bmatrix} I & 0 & 0 & 0 & 0 \end{bmatrix},\ \tilde{\Xi}_\alpha^{14} = A^T + \Phi_\alpha^T K_\alpha^T B^T,$$

$$\tilde{\Xi}_\alpha^{15} = (I + \Delta)^T\Phi_\alpha^T R,\ \hat{\Xi}_\alpha^{14} = A^T + \Phi_\alpha^T K_\alpha^T B^T.$$

For any matrix $P > 0$, the following inequality holds:

$$(I - P)P^{-1}(I - P)^T \ge 0,$$

which implies $P - 2I \geq -P^{-1}$. Therefore, by utilizing Lemma 1, it is easy to prove that (18) can be ensured by (36). Similarly, according to (35) and (37), it can be concluded that (17) and (19). The proof is completed. ■

If the signal quantization is not considered, the protocol will degenerate into the DTETP. Subsequently, the following stability criterion can be derived:

Corollary 1. For given scalars $\gamma > 0$, $\kappa > 0$, $f_{max} > f_{min} > 0$, and $\psi_i > 0$, suppose that there exist positive definite matrices $P > 0$ and $R > 0$, diagonal matrix $\Theta > 0$, gain matrices K_0, K_α, and K_{n+1}, positive scalar $\lambda_{\alpha\beta} > 0$ with $\sum_{\beta=1}^{n} \lambda_{\alpha\beta} = 1$ $(\alpha \in N)$ such that

$$\begin{bmatrix} -P & C^T \\ * & -\gamma^2 I \end{bmatrix} < 0, \quad (41)$$

$$\Xi_0 = \begin{bmatrix} \Xi_0^{11} & R & 0 & A^T + K_0^T B^T & 0 \\ * & R - \kappa\Psi & 0 & K_0^T B^T & 0 \\ * & * & -I & D^T & 0 \\ * & * & * & P-2I & 0 \\ * & * & * & * & -R \end{bmatrix} < 0, \quad (42)$$

$$\Xi_\alpha = \begin{bmatrix} \Xi_\alpha^{11} & -\Upsilon_\alpha & 0 & \Xi_\alpha^{14} & \Phi_\alpha^T R \\ * & -R+\Upsilon_\alpha & 0 & \tilde{\Phi}_\alpha^T K_\alpha^T B^T & \tilde{\Phi}_\alpha^T R \\ * & * & -I & D^T & 0 \\ * & * & * & P-2I & 0 \\ * & * & * & * & -R \end{bmatrix} < 0, \quad (43)$$

$$\Xi_{n+1} = \begin{bmatrix} \Xi_{n+1}^{11} & 0 & 0 & A^T + K_{n+1}^T B^T \\ * & -\kappa\Psi & 0 & K_{n+1}^T B^T \\ * & * & -I & D^T \\ * & * & * & P-2I \end{bmatrix} < 0 \quad (44)$$

hold, where

$$\begin{aligned} \Xi_0^{11} &= R - P + \kappa f_{max}\Theta, \ \Xi_\alpha^{11} = -P + \Upsilon_\alpha, \\ \Xi_\alpha^{14} &= A^T + \Phi_\alpha^T K_\alpha^T B^T, \ \Xi_{n+1}^{11} = -P + \kappa f_{min}\Theta, \\ \Upsilon_\alpha &= \Psi \sum_{\beta=1}^{n} \lambda_{\alpha\beta}(\Phi_\alpha - \Phi_\beta), \\ \Theta &= diag\{\theta_1, \theta_2, \cdots, \theta_n\}, \\ \Psi &= diag\{\psi_1, \psi_2, \cdots, \psi_n\}. \end{aligned}$$

Then, the controller in (12) can make sure that CLS (13) in distinct instant sets $\mathcal{T}_1$, $\mathcal{T}_2$, and $\mathcal{T}_3$ is asymptotically stable with energy-to-peak performance γ.

If the signal quantization and ET mechanism are not considered, the protocol will degenerate into the conventional WTODP. Subsequently, the following stability criterion can be derived:

Corollary 2. For given scalars $\gamma > 0$, and $\psi_i > 0$, suppose that there exist positive definite matrices $P > 0$ and $R > 0$, gain matrices K_α, positive scalar $\lambda_{\alpha\beta} > 0$ with $\sum_{\beta=1}^{n} \lambda_{\alpha\beta} = 1$ $(\alpha \in N)$ such that

$$\begin{bmatrix} -P & C^T \\ * & -\gamma^2 I \end{bmatrix} < 0, \quad (45)$$

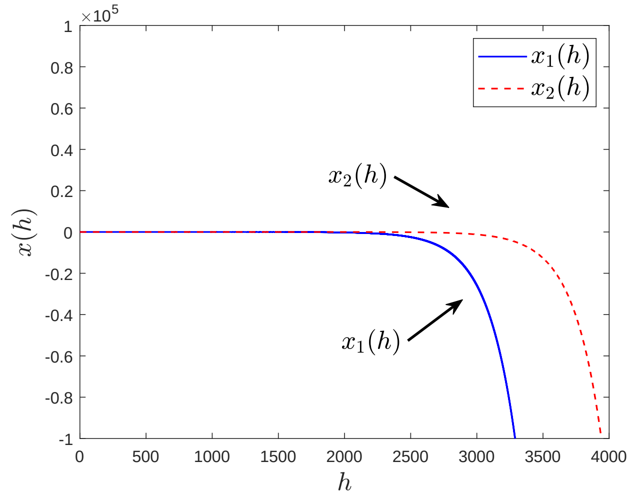

Fig. 2. State trajectories without control.

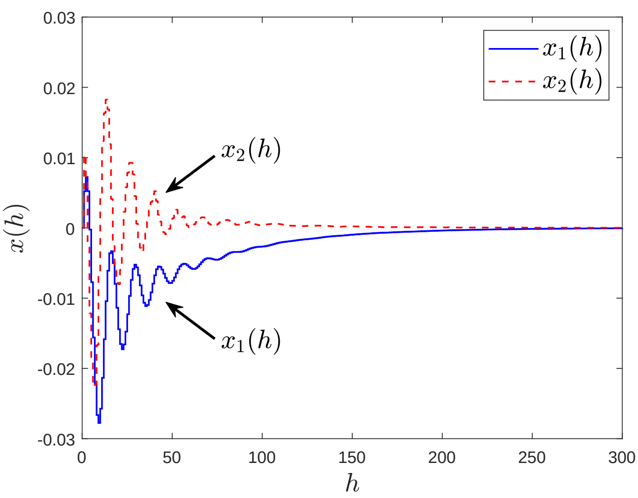

Fig. 3. State trajectories of CLS under ETQDP.

$$\Xi_\alpha = \begin{bmatrix} \Xi_\alpha^{11} & -\Upsilon_\alpha & 0 & \Xi_\alpha^{14} & \Phi_\alpha^T R \\ * & -R+\Upsilon_\alpha & 0 & \tilde{\Phi}_\alpha^T K_\alpha^T B^T & \tilde{\Phi}_\alpha^T R \\ * & * & -I & D^T & 0 \\ * & * & * & P-2I & 0 \\ * & * & * & * & -R \end{bmatrix} < 0 \quad (46)$$

hold, where

$$\begin{aligned} \Xi_\alpha^{11} &= -P + \Upsilon_\alpha, \ \Xi_\alpha^{14} = A^T + \Phi_\alpha^T K_\alpha^T B^T, \\ \Upsilon_\alpha &= \Psi \sum_{\beta=1}^{n} \lambda_{\alpha\beta}(\Phi_\alpha - \Phi_\beta), \\ \Psi &= diag\{\psi_1, \psi_2, \cdots, \psi_n\}. \end{aligned}$$

Then, the controller in (12) can make sure that CLS (13) is asymptotically stable with energy-to-peak performance γ.

IV. Numerical Example

In this section, the proposed energy-to-peak control based on the ETQDP design is applied to the double-sided linear switched reluctance machine system as in [34]. Using the online least squares identification method, at the sampling time of $T = 0.001s$, we obtain the system parameters as

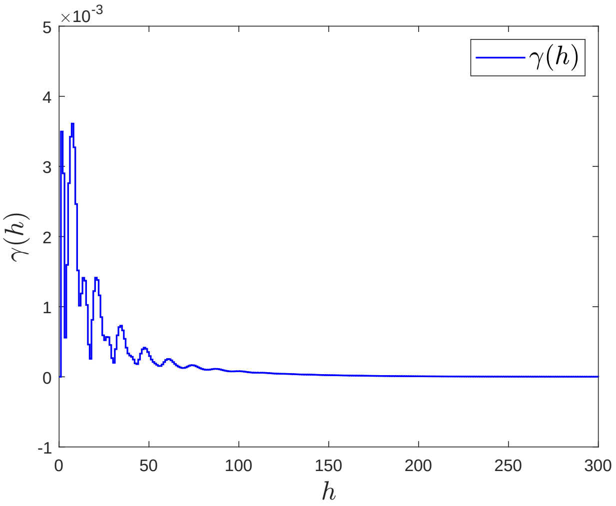

Fig. 4. Trajectory of $\gamma(h)$.

TABLE I
γ_{min} FOR VARIOUS ρ.

ρ	0.95	0.96	0.97	0.98	0.99
γ_{min}	0.1350	0.1348	0.1345	0.1343	0.1341

follows:

$$A = \begin{bmatrix} 1.0004 & 0.0909 \\ 0.0085 & 0.8247 \end{bmatrix}, B = \begin{bmatrix} 0.0047 \\ 0.0909 \end{bmatrix}.$$

The other system parameters are given by

$$C = \begin{bmatrix} 0.1 & 0.1 \\ 0 & -0.1 \end{bmatrix}, \ D = \begin{bmatrix} 0.01 \\ 0.02 \end{bmatrix}.$$

Assuming there are two sensor nodes, choose $\kappa = 0.8$, $f_{max} = 1.98$, $f_{min} = 1.71$, $\rho = 0.99$, and the weight matrix $\Psi = diag\{0.1, 1\}$. We initialize the system state $x(0) = [0 \ 0]^T$. The exogenous disturbance input is assumed to be $w(h) = cos(0.15\pi h)exp(-0.06h)$. The state trajectories without control are shown in Fig. 2. By utilizing the MOSEK and YALMIP toolboxes to solve the LMIs in Theorem 2, we can obtain the minimum energy-to-peak performance index $\gamma_{min} = 0.1317$ and the control gains as

$$K_0 = \begin{bmatrix} -1.1648 & -2.9507 \end{bmatrix}, K_1 = \begin{bmatrix} -1.1781 & -0.0562 \end{bmatrix},$$
$$K_2 = \begin{bmatrix} -1.1746 & -7.6679 \end{bmatrix}, K_3 = \begin{bmatrix} -1.1651 & -2.9517 \end{bmatrix}.$$

Fig. 3 depicts the state trajectories of CLS under ETQDP. Define

$$\gamma(h) = \frac{\sqrt{\sup_{h\geq 0} z^T(h)z(h)}}{\sqrt{\sum_{h=0}^{\infty} \omega^T(h)\omega(h)}},$$

$$\text{COR} = \frac{\textit{The total occupied channel moments}}{\textit{The total moments}} \times 100\%.$$

Then, the trajectory of $\gamma(h)$ is illustrated in Fig. 4. Furthermore, for various values of the quantization density ρ, different values of γ_{min} can be obtained, as shown in Table I. It is evident that as the value of ρ increases, γ_{min} gradually decreases.

When setting $\gamma = 2.1$ and $\rho = 0.98$, with the other parameters remaining the same, the selection of the sensor nodes under ETQDP, DTETP, and WTODP are displayed in

TABLE II
COR FOR DIFFERENT PROTOCOL.

protocol	WTODP [19–21]	DTETP [25]	ETQDP
COR	100%	47.33%	35.67%

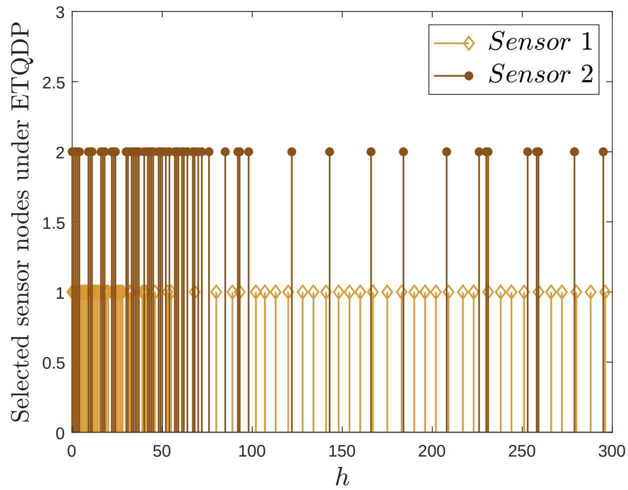

Fig. 5. Selected sensor nodes under ETQDP.

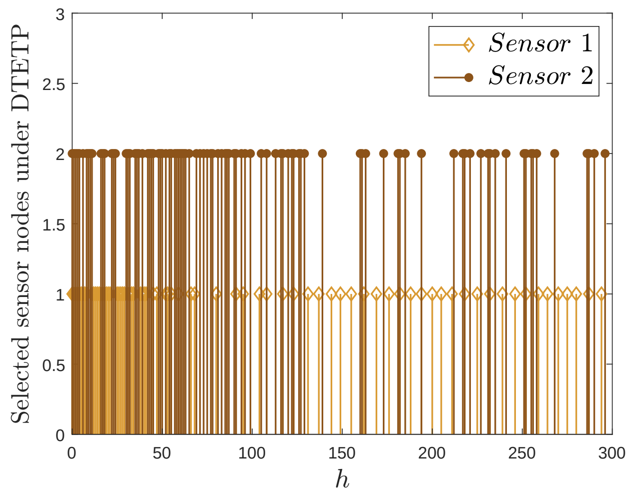

Fig. 6. Selected sensor nodes under DTETP.

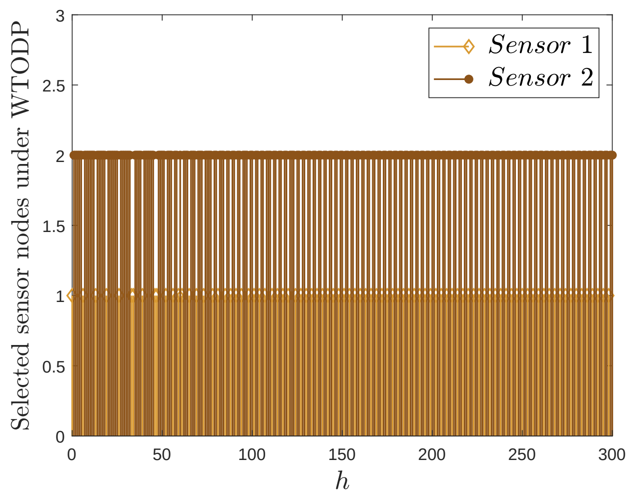

Fig. 7. Selected sensor nodes under WTODP.

Figs. 5, 6, and 7, respectively. It can be seen that the number of sensor nodes occupying the transmission channel in Figs. 5 and 6 changes with time, and there are some instants when no node occupies the transmission channel, while in Fig. 7, there is one sensor node occupies the transmission channel at each moment. Moreover, Table II presents a statistical evaluation that shows the COR of the DTETP stands at $142/300 = 47.33\%$, representing a reduction of 52.67% compared to that of the conventional WTODP. The COR of ETQDP is $107/300 = 35.67\%$, which is reduced by 11.66% based on DTETP.

V. Conclusion

This paper addressed the issue of performance-guaranteed control for discrete-time systems under communication constraints. To alleviate communication burdens, an ETQDP was presented. The protocol combined the advantages of both the DTET mechanism and signal quantization, resulting in a decrease in the COR compared to the conventional WTODP and DTETP. Additionally, a SFC relying on scheduling signals was proposed based on this protocol. A criterion of stability and energy-to-peak performance was established by employing the Lyapunov function method and various inequality approaches. Subsequently, a numerically tractable method was developed for determining the desired controller gain by solving LMIs. Finally, a double-sided linear switched reluctance machine system was used to verify the effectiveness of the ETQDP and the suitability of the controller.

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