IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 8 September 2023, accepted 7 October 2023, date of publication 24 October 2023, date of current version 30 October 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3324923

RESEARCH ARTICLE

Efficient Output Feedback MPC for NCS With Data Dropout and Bounded Disturbance via Adaptive Event-Triggered Control

MINGHONG SHE[1] AND WENBIN WU[1,2]
[1]Key Laboratory of IoT Security, Mianyang Teachers' College, Mianyang, Sichuan 621000, China
[2]School of Information Engineering, Southwest University of Science and Technology, Mianyang, Sichuan 621000, China

Corresponding author: Minghong She (mh_she@mtc.edu.cn)

This work was supported in part by the Mianyang Teachers' College 2020 Scientific Research Start-up Project under Grant QD2020A19; in part by the Sichuan Provincial ''Tianfu Scholars'' Special Expert Fund under Grant TFXZTPZJ01; in part by the Mianyang Teachers' College 2019 Scientific Research Start-up Project under Grant QD2019A27; and in part by the Industry-University-Research Innovation Fund for the China University-New Generation Information Technology Innovation Project under Grant 2022IT164.

ABSTRACT This paper studies efficient output feedback model predictive control (OFMPC) via adaptive event-triggered control (AETC) for the networked control system (NCS) with data dropout and bounded disturbance. First, we adopt AETC in NCS to save limited network resources and introduce a Bernoulli random variable to represent the occurrence of data dropout events. Subsequently, two sufficient conditions are presented to handle the gain matrix of the state observer and the estimation error bound. Then, by offline solving an elliptic invariant set satisfying the input constraint and online optimizing for additional perturbations, the initial feasible set is enlarged and the online computational burden is greatly reduced. Finally, the effectiveness of the proposed algorithm is verified by two simulation examples.

INDEX TERMS Efficient output feedback model predictive control (EOFMPC), the networked control system (NCS), adaptive event-triggered control (AETC).

I. INTRODUCTION

As a specific class of control, model predictive control (MPC) is able to efficiently handle multi-variable systems with various physical constraints in a systematic way [1] and is therefore widely used in academia and industry (see, e.g., [2], [3], [4], [5], [6], [7]). In [2], a synthesis approach for robust MPC was proposed that aimed to design a state feedback control law at each time to minimize the ''worst-case'' infinite-horizon objective function satisfying the control input and system output constraints. In [3] and [4], a multicell uncertain system was discussed, and parameter-dependent Lyapunov functions were designed based on multiple vertices of the polyhedron. In [5] and [6], free control motions were introduced to separate the first few control actions from the rest of the control actions governed by the feedback law. In [7], Ding et al. combined free control motions with parameter-dependent Lyapunov functions. The online MPC algorithms proposed in [2], [3], [4], [5], [6], and [7] are all designed to improve the control performance of the system. However, for systems that require fast control, the complexity of MPC may not meet the need for real-time system computation, so it is necessary to sacrifice the control performance of the system to reduce the complexity of online MPC computation. The core idea of [8], [9], and [10] was to offline compute a sequence of control laws for asymptotically stable elliptic invariant sets one after another and to select a suitable control law by online search. References [11], [12], [13], and [14] proposed an efficient MPC (EMPC) algorithm, whose main idea was to introduce additional perturbations in the design of the controller, to offline design an elliptic invariant set, and to online optimize the perturbations. The EMPC algorithm compared to the offline MPC algorithm in [8], [9], and [10] not only improves the control performance of the system but also enlarges the initial feasible set of the system, making it more applicable. In view of the advantages of the EMPC algorithm, it constitutes the motivation for the research in this paper.

The associate editor coordinating the review of this manuscript and approving it for publication was Mauro Gaggero.

The papers mentioned above were all done when the system state could be measured. Nonetheless, in practical applications, the state of most systems cannot be measured directly, so output feedback MPC (OFMPC) is often more applicable than state feedback MPC (SFMPC), but it is also more complex because of the need to refresh the estimation error set in real time. There are two common types of OFMPC: 1) dynamic OFMPC (see, e.g., [15] and [16]); 2) observer-based OFMPC (see, e.g., [17], [18], [19], [20]). In [17] and [18], the effect of external disturbances on the system control performance was not considered, and the estimation error eventually converged to the origin. In [15], [16], [19], and [20], external disturbances were taken into account, and it was verified that the estimation error eventually converged to around the origin as time evolved. Although [15], [16], [17], [18], [19], [20] made wonderful studies on OFMPC, their main purpose was still to improve the control performance of the system, which would result in a heavy online computational burden. In order to satisfy the real-time application of the system, [21] and [22] investigated the offline OFMPC and refreshed the estimation error set in real-time. Unfortunately, the algorithms proposed in [21] and [22] did not discuss the initial feasible set of the system adequately. Hence, in this paper, an efficient OFMPC (EOFMPC) algorithm is proposed, which not only reduces the online computational burden but also enlarges the initial feasible set of the system at the sacrifice of little control performance.

At another scientific frontier, as a closed-loop system connected by a communication network, the networked control system (NCS) has been widely used in industrial control due to its low cost and high reliability. On the one hand, due to the limited communication network bandwidth in NCS, some network-induced phenomena may occur, e.g., time delay [23], data quantization [24], and so on. Competing with the problems mentioned above, [25], [26], [27], [28], [29], [30] proposed an event-triggered control (ETC) that could save network resources. The idea in [25], [26], [27], [28], [29], and [30] was to determine whether signals needed to be released into the communication network based on a predetermined threshold. However, the trigger threshold cannot be flexibly adjusted when certain changes occur in the NCS. Therefore, the adaptive event-triggered control (AETC) proposed in [31], [32], and [33] combined the adaptive law with the trigger condition so that the trigger threshold could be dynamically adjusted and the network resources could be sufficiently utilized. On the other hand, most communication networks are prone to data dropout due to communication congestion, which has attracted widespread attention in academia as another challenge of NCS (see, e.g., [34], [35], [36], [37], [38], [39]). Both [40] and [41] provided an NCS framework for ETC for communication networks with data dropout. Reference [42] discussed the control problem of NCS with AETC and data dropout and guaranteed the stability of the system.

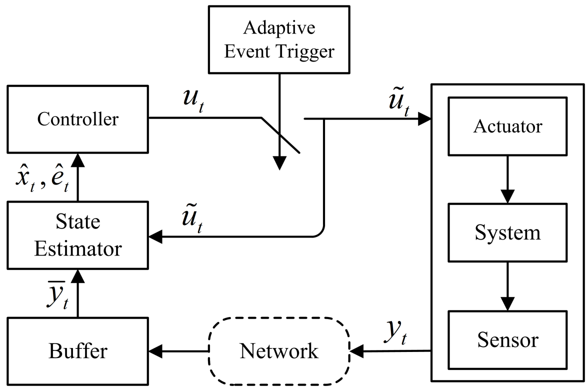

FIGURE 1. Structure of NCS.

To the best of the authors' knowledge, there is no existing literature on EOFMPC algorithms, let alone EOFMPC that considers AETC and data dropout simultaneously, which promotes the research work in this paper. The main contributions of this paper are presented below:

1) To reduce the bandwidth burden on the communication network, AETC is used, and the occurrence of data dropout is represented by a Bernoulli random variable.
2) In this article, we introduce the EOFMPC approach to NCS, which greatly reduces the online computational burden and enlarges the initial feasible set compared to the traditional online OFMPC approach.
3) The optimization problem of refreshing the estimation error bounds is obtained to guarantee that the error between the true and estimated states of the system is tighter.

Notation: All inequalities in vectors are expressed in an element-wise sense. $x_{h|t}$ represents, at the time t, the value of x, which predicts sampling instant $t+h$. $*$ in the matrix represents a symmetric term. The matrix inequality $\mathcal{A} > 0$ shows $\mathcal{A}$ is a positive-definite matrix, ε_Q means $\{x|x^TQx \leq 1\}$. I is the adaptive identity matrix.

II. PROBLEM STATEMENT

The framework of NCS with random data dropout and a state estimator is shown in FIGURE 1. The sampled data of the sensor may be lost when transmitting through the network, and the successful transmitted data $\bar{y}_t$ is the input of the state estimator. Based on the estimation state $\hat{x}_t$ obtained from the state estimator, u_t can be calculated by the controller. And $\tilde{u}_t$ is determined by the adaptive event-triggered law subsequently. What's more, the input of the system $\tilde{u}_t$ will also be the input of the state estimator.

A. LINEAR POLYTOPIC SYSTEM MODEL

Consider the uncertain discrete-time system in FIGURE 1, and it is described as

$$\begin{aligned} x_{t+1} &= A_t x_t + B_t \tilde{u}_t + D_t w_t \\ y_t &= C_t x_t + E_t w_t \end{aligned} \tag{1}$$

where $x \in \Re^{n_x}$, $u \in \Re^{n_u}$, $w \in \Re^{n_w}$ denote the system state, control input, and external disturbance, respectively. The disturbance w_t satisfies $\|w_t\|^2 \leq 1$ for all $t > 0$. Moreover, there exist h_t^l satisfies

$$[A_t|B_t|C_t|D_t|E_t] = \sum_{l=1}^{n_l} h_t^l [A_l|B_l|C_l|D_l|E_l] \tag{2}$$

where $h_t^l \geq 0$ and $\sum_{l=1}^{n_l} h_t^l = 1$. Assume that the polytope $Co\{[A_l|B_l|C_l|D_l|E_l]\}$, $l \in \{1, \ldots, n_l\}$, is exactly known, and at each sampling instant, h_t^l can be calculated.

B. NETWORK WITH DATA DROPOUT

In addition, due to the unreliable communication link between sensor and buffer, the data dropout is inevitable and may result in terrible consequences, which should be considered. Hence, the input of the state estimator $\bar{y}_t$ can be obtained as below:

$$\bar{y}_t = \beta_t y_t + (1 - \beta_t)\bar{y}_{t-1} \tag{3}$$

where β_t is a random variable satisfying the Bernoulli distribution. Furthermore, we can get the expectation and variance of the β_t

$$\begin{aligned} &\mathbb{E}\{\beta_t\} := \beta_E, \\ &\mathbb{D}\{\beta_t\} = \beta_E(1 - \beta_E) := \beta_D^2 \end{aligned} \tag{4}$$

Since the probability of β_t is known, β_E is a known scalar.

Remark 1: β_t denotes the Bernoulli random variable for data dropout. When $\beta_t = 1$, it means that the data was successfully transmitted, i.e., $\bar{y}_t = y_t$, and when $\beta_t = 0$, it means that data dropout occurred and $\bar{y}_t$ is still the data of the previous moment.

C. ADAPTIVE EVENT-TRIGGERED STRATEGY

In practical application, the communication resources of the network are limited. Therefore, an adaptive event-triggered strategy that can dynamically adjust the number of transmitted signals by choosing the appropriate threshold actively in view of the change in the system state is introduced to save limited communication resources.

In FIGURE 1, u_t and $\widetilde{u}_t$ are the output of the controller and the input of the system, respectively, and they satisfy

$$\widetilde{u}_t = \begin{cases} \widetilde{u}_{t-1} & \widetilde{e}_t^T P_u \widetilde{e}_t < \epsilon_t \widetilde{u}_{t-1}^T P_u \widetilde{u}_{t-1} \\ u_t & \widetilde{e}_t^T P_u \widetilde{e}_t \geq \epsilon_t \widetilde{u}_{t-1}^T P_u \widetilde{u}_{t-1} \end{cases} \tag{5}$$

where $\widetilde{e}_t := u_t - \widetilde{u}_{t-1}$, P_u is a weighting matrix determined by the optimization problem in the next section, and ϵ_t is the adaptive law. At time $t+1$, the adaptive law ϵ_{t+1} can be obtained, i.e.,

$$\epsilon_{t+1} = (\frac{1}{\epsilon_t} - \frac{1}{\check{\epsilon}})\widetilde{e}_t^T P_u \widetilde{e}_t + (1 - \sigma)\epsilon_t \tag{6}$$

where $\check{\epsilon} > 0$, ϵ_0 and $\sigma \in \{0, 1\}$ are pre-specify scalars.

Remark 2: We note that $\widetilde{u}_t$ will become the latest triggering data that is transmitted to the actuator by the controller when the sampling data $\widetilde{u}_t$ makes the AETC condition (5) to be established; otherwise, $\widetilde{u}_t$ will be maintained as the previous triggering data.

D. STATE ESTIMATOR

Since system state is unmeasurable in practice, let us construct the following estimator to estimate the system state:

$$\begin{aligned} \hat{x}_{t+1} &= A_t\hat{x}_t + B_t\widetilde{u}_t + L_p(\bar{y}_t - \hat{y}_t) \\ \hat{y}_t &= \beta_t C_t \hat{x}_t + (1 - \beta_t)\bar{y}_{t-1} \end{aligned} \tag{7}$$

where L_p is the estimator gain determined in the next section, and at time t, $\bar{y}_t$ is the estimator input.

The estimation error is defined as $\hat{e}_t := x_t - \hat{x}_t$. By subtracting (7) from (1), the estimation state and estimation error dynamics are obtained as

$$\begin{aligned} \hat{x}_{t+1} &= A_t\hat{x}_t + B_t u_t - B_t\widetilde{e}_t + \beta_t L_p C_t \hat{e}_t + \beta_t L_p E_t w_t \\ \hat{e}_{t+1} &= (A_t - \beta_t L_p C_t)\hat{e}_t + (D_t - \beta_t L_p E_t) w_t \end{aligned} \tag{8}$$

Based on the estimator, the system state can be described by the estimation state and the estimation error.

III. MAIN RESULTS

In this section, we will describe the main results in the subsections. The subsections A and B are about parameter determination and error analysis of the state estimator; In subsection C, the feedback gain and a weighting matrix of adaptive event-triggered are obtained. Based on subsections A, B, and C, subsection D introduces the EOFMPC algorithm.

A. OFF-LINE ESTIMATOR DESIGN

The estimator gain L_p will be obtained by following the following condition, which guarantees estimation error stability:

Define a quadratic $E(\hat{e}_t) = \|\hat{e}_t\|^2_{P_e^0}$ which is satisfied by the quadratic boundness condition, which yields

$$E(\hat{e}_t) \geq 1 \;\Rightarrow\; \mathbb{E}\{E(\hat{e}_{t+1})\} \leq E(\hat{e}_t) \tag{9}$$

Lemma 1: If there exist P_e^0 and Y_e^0 satisfying

$$\begin{bmatrix} (1-\lambda_1)P_e^0 & * & * & * \\ 0 & \lambda_1 I & * & * \\ P_e^0 A_j - \beta_E Y_e^0 C_j & P_e^0 D_j - \beta_E Y_e^0 E_j & P_e^0 & * \\ -\beta_D Y_e^0 C_j & -\beta_D Y_e^0 E_j & 0 & P_e^0 \end{bmatrix} \geq 0, \quad j \in \{1, \ldots, n_l\} \tag{10}$$

where $Y_e^0 = P_e^0 L_p$ and $0 \leq \lambda_1 \leq 1$ is a pre-specified scalar, the estimation error is ensured to stay within $\varepsilon_{P_e^0}$ for the sufficiently large t.

proof: According to (9), by applying the S-procedure, there exists a scalar $0 \leq \lambda_1 \leq 1$ satisfies

$$\hat{e}_t^T P_e^0 \hat{e}_t - \mathbb{E}\{\hat{e}_{t+1}^T P_e^0 \hat{e}_{t+1}\} - \lambda_1(\hat{e}_t^T P_e^0 \hat{e}_t - w_t^T w_t) \geq 0 \tag{11}$$

If the random variable $\beta_t = \hat{\beta}_t + \beta_E$, it can be obtained that

$$\mathbb{E}\{\hat{\beta}_t\} = 0,\ \mathbb{E}\{\hat{\beta}_t^2\} = \beta_D^2 \tag{12}$$

By using the Schur complement and considering the polytope $Co\{[A_l|B_l|C_l|D_l|E_l]\}$, $l \in \{1, \ldots, n_l\}$, (11) becomes (10). □

B. ERROR UPPER BOUND ANALYSIS OF ESTIMATOR

Since estimator error is uncertain, define a scalar η_t to describe the upper bound of estimator error, i.e.,

$$E(\hat{e}_t) \le \eta_t \tag{13}$$

For $t = 0$, assume that η_0 is a known scalar.

Lemma 2: At time t, the upper bound of estimator error η_{t+1} is obtained by following the optimization problem:

$$OP1: \min_{\lambda_2, \eta_{t+1}} \eta_{t+1} \quad s.t.\ (15) \tag{14}$$

$$\begin{bmatrix} \frac{\lambda_2 P_e^0}{\eta_t} & * & * & * \\ 0 & (1-\lambda_2)I & * & * \\ A_j - \beta_E L_p C_j & D_j - \beta_E L_p E_j & \eta_{t+1} P_e^{0^{-1}} & * \\ -\beta_D L_p C_j & -\beta_D L_p E_j & 0 & \eta_{t+1} P_e^{0^{-1}} \end{bmatrix} \ge 0, \quad j \in \{1, \ldots, n_l\} \tag{15}$$

where λ_2 is a scalar.

proof: At time t, according to (13), we have two inequalities, $E(\hat{e}_t)/\eta_t \le 1$ and $w_t^T w_t \le 1$. Based on the above inequalities, using the S-procedure, if there exist two scalars, $\lambda_2 \ge 0$ and $\lambda_3 \ge 0$ satisfy

$$1 - \frac{\mathbb{E}\{E(\hat{e}_{t+1})\}}{\eta_{t+1}} - \lambda_2\Big(1 - \frac{E(\hat{e}_t)}{\eta_t}\Big) - \lambda_3(1 - w_t^T w_t) \ge 0 \tag{16}$$

then $\mathbb{E}\{E(\hat{e}_{t+1})\}/\eta_{t+1} \le 1$ at time $t+1$ can be guaranteed. By taking inequality $1 - \lambda_2 - \lambda_3 \ge (1 - \lambda_2 - \lambda_3) w_t^T w_t$, (16) becomes

$$\lambda_2 \frac{E(\hat{e}_t)}{\eta_t} + (1 - \lambda_2) w_t^T w_t - \frac{\mathbb{E}\{E(\hat{e}_{t+1})\}}{\eta_{t+1}} \ge 0 \tag{17}$$

By using the Schur complement and considering the polytope $Co\{[A_l|B_l|C_l|D_l|E_l]\}$, $l \in \{1, \ldots, n_l\}$, (17) becomes (15). □

Based on the (14), we can get the upper bound of the estimator error at each time.

C. OFF-LINE OPTIMIZATION PROBLEM

The main aim of this subsection is to get the off-line feedback gain F and the weighting matrix of adaptive event-triggered P_u to guarantee the estimation state stability.

Firstly, define a feedback gain as $u_{h|t} = F\hat{x}_{h|t}$, and according to (8), the prediction of estimated state and estimated error are

$$\begin{aligned} \hat{x}_{h+1|t} &= (A_{h|t} + B_{h|t}F)\hat{x}_{h|t} - B_{h|t}\tilde{e}_{h|t} \\ &\quad + \beta_{h|t} L_p C_{h|t} \hat{e}_{h|t} + \beta_{h|t} L_p E_{h|t} w_{h|t} \end{aligned} \tag{18}$$

$$\begin{aligned} \hat{e}_{h+1|t} &= (A_{h|t} - \beta_{h|t} L_p C_{h|t})\hat{e}_{h|t} \\ &\quad + (D_{h|t} - \beta_{h|t} L_p E_{h|t}) w_{h|t} \end{aligned} \tag{19}$$

Secondly, define a quadratic function and a cost index as

$$V_{h|t} = \begin{bmatrix} \hat{x}_{h|t} \\ \hat{e}_{h|t} \end{bmatrix}^T \begin{bmatrix} P_x & 0 \\ 0 & P_e \end{bmatrix} \begin{bmatrix} \hat{x}_{h|t} \\ \hat{e}_{h|t} \end{bmatrix} + \epsilon_{h|t} \tag{20}$$

$$J_t^{0|\infty} = \sum_{h=0}^{\infty} \left(\begin{bmatrix} \hat{x}_{h|t} \\ u_{h|t} \end{bmatrix}^T \begin{bmatrix} L_x & 0 \\ 0 & L_u \end{bmatrix} \begin{bmatrix} \hat{x}_{h|t} \\ u_{h|t} \end{bmatrix} \right)$$

$$P_x > 0, P_e = \alpha P_e^0 > 0, L_x > 0, L_u > 0 \tag{21}$$

where P_x and α are determined by optimization problem (23) and L_x and L_u are determined by the user.

Lemma 3: For $h \ge 0$, $V_{h|t}$ satisfies the quadratic boundness condition, i.e.,

$$V_{h|t} \ge \gamma \Rightarrow V_{h|t} - \mathbb{E}\{V_{h+1|t}\} - J_t^{h|h} \ge 0 \tag{22}$$

and it is guaranteed by the following condition, that is

$$OP2: \min_{\alpha, Q_x, \gamma, Y, P_u, Q_u} trace(P_u Q_u) \quad s.t.\ (24), (25) \tag{23}$$

$$\begin{bmatrix} P_u & * \\ I & Q_u \end{bmatrix} \ge 0, \tag{24}$$

$$\begin{bmatrix} (1-\sigma)Q_x & * & * & * & * \\ 0 & \Delta_{22} & * & * & * \\ \Delta_{31} & \Delta_{32} & \Delta_{33} & * & * \\ \Delta_{41} & \Delta_{42} & 0 & \Delta_{44} & * \\ \Delta_{51} & 0 & 0 & 0 & \Delta_{55} \end{bmatrix} \ge 0, \quad j \in \{1, \ldots, n_l\} \tag{25}$$

where σ is a pre-specified scalar, $Q_x = P_x^{-1}$, $Y = FQ_x$,

$$\Delta_{22} = \begin{bmatrix} S_{11} & * & * \\ 0 & S_{22} & * \\ S_{31} & 0 & S_{33} \end{bmatrix}, \quad S_{22} = \frac{P_u}{\check{\epsilon}},$$

$$\begin{aligned} S_{11} &= \alpha[(1-\sigma)P_e^0 - (A_j - \beta_E L_p C_j)^T P_e^0 (A_j - \beta_E L_p C_j) \\ &\quad - (\beta_D L_p C_j)^T P_e^0 (\beta_D L_p C_j)], \\ S_{31} &= -\alpha[(D_j - \beta_E L_p E_j)^T P_e^0 (A_j - \beta_E L_p C_j) \\ &\quad + (\beta_D L_p E_j)^T P_e^0 (\beta_D L_p C_j)], \\ S_{33} &= \sigma I \gamma - \alpha[(D_j - \beta_E L_p E_j)^T P_e^0 (D_j - \beta_E L_p E_j) \\ &\quad + (\beta_D L_p E_j)^T P_e^0 (\beta_D L_p E_j)], \end{aligned}$$

$$\Delta_{31} = \begin{bmatrix} A_j Q_x + B_j Y \\ 0 \end{bmatrix},$$

$$\Delta_{32} = \begin{bmatrix} \beta_E L_p C_j & -B_j & \beta_E L_p E_j \\ \beta_D L_p C_j & 0 & \beta_D L_p E_j \end{bmatrix},$$

$$\Delta_{33} = \begin{bmatrix} Q_x & * \\ 0 & Q_x \end{bmatrix},$$

$$\Delta_{41} = Y, \Delta_{42} = \begin{bmatrix} 0 & -I & 0 \end{bmatrix}, \quad \Delta_{44} = Q_u,$$

$$\Delta_{51} = \begin{bmatrix} Q_x \\ Y \end{bmatrix}, \quad \Delta_{55} = \begin{bmatrix} L_x^{-1} & * \\ 0 & L_u^{-1} \end{bmatrix}.$$

proof: According to the S-procedure method, (22) holds if there exists a non-negative scalar σ satisfying $V_{h|t} - \mathbb{E}\{V_{h+1|t}\} - J_t^{h|h} - \sigma(V_{h|t} - \gamma\|w_t\|^2) \ge 0$. The detailed proof procedure is similar to the reference paper [20]. □

D. EFFICIENT OUTPUT FEEDBACK MPC

1) PREVIOUS WORK

We introduce the augmented state c and get maximum initial feasible set.

Firstly, define the input of system $u_{h|t}$ as

$$u_{h|t} = F\hat{x}_{h|t} + c_{h|t} \tag{26}$$

where $c_{h|t} = Gf_{h|t}, f_{h|t} \in \Re^N$, $G = [I_{n_u}, 0, \ldots, 0]$, N is determined by th user (see the reference paper [11]). $f_{h|t}$ can be denoted as $f_{h|t} = [c_{0|t}^T, c_{1|t}^T, c_{2|t}^T, \ldots, c_{N-1|t}^T]^T$.

Secondly, the prediction of f is defined as $f_{h+1|t} = Mf_{h|t}$, where M is a variable matrix with an appropriate dimension and $f_{0|t}$ is a variable in the following online optimization problem.

With (18), we can get

$$\begin{aligned}\begin{bmatrix}\hat{x}_{h+1|t}\\ f_{h+1|t}\end{bmatrix} &= \begin{bmatrix}A_{h|t}+B_{h|t}F & B_{h|t}G\\ 0 & M\end{bmatrix}\begin{bmatrix}\hat{x}_{h|t}\\ f_{h|t}\end{bmatrix}\\ &\quad + \begin{bmatrix}-B_{h|t}\\ 0\end{bmatrix}\tilde{e}_{h|t} + \begin{bmatrix}\beta_{h|t}L_pC_{h|t}\\ 0\end{bmatrix}\hat{e}_{h|t}\\ &\quad + \begin{bmatrix}\beta_{h|t}L_pE_{h|t}\\ 0\end{bmatrix}w_{h|t}\end{aligned} \tag{27}$$

According to (26), we redefine the $V_{h|t}$ and $J_t^{0|\infty}$ as

$$V_{h|t} = \begin{bmatrix}z_{h|t}\\ \hat{e}_{h|t}\end{bmatrix}^T\begin{bmatrix}P_z & 0\\ 0 & P_e\end{bmatrix}\begin{bmatrix}z_{h|t}\\ \hat{e}_{h|t}\end{bmatrix} + \epsilon_{h|t} \tag{28}$$

$$\begin{aligned}J_t^{0|\infty} &= \sum_{h=0}^{\infty}\left(\hat{x}_{h|t}^TL_x\hat{x}_{h|t} + u_{h|t}^TL_uu_{h|t} + f_{h|t}^TL_ff_{h|t}\right)\\ &= \sum_{h=0}^{\infty}\left(z_{h|t}^TL_zz_{h|t}\right)\end{aligned} \tag{29}$$

where $P_z > 0, P_e = \alpha P_e^0 > 0$, $z_{h|t} = [\hat{x}_{h|t}^T, f_{h|t}^T]^T$, L_f is a pre-specified weighing matrix and

$$L_z = \begin{bmatrix}L_x + F^TL_uF & F^TL_uG\\ G^TL_uF & G^TL_uG + L_f\end{bmatrix}.$$

Lemma 4: For $h \geq 0$, $V_{h|t}$ satisfied, the quadratic boundness condition is guaranteed, i.e.,

$$V_{h|t} \geq \gamma \ \Rightarrow\ V_{h|t} - \mathbb{E}\{V_{h+1|t}\} - J_t^{h|h} \geq 0 \tag{30}$$

and the maximum initial feasible set τ_3 will be obtained if the following optimization problem is solved as follows:

$$OP3: \underset{\alpha,\gamma,M',\tau_1,\tau_3,\tau_4}{maximize}\ \log det(\tau_3) \quad s.t.\ (32) \tag{31}$$

$$\begin{bmatrix}\Phi_{11} & * & * & * & *\\ 0 & \Phi_{22} & * & * & *\\ \Phi_{31} & \Phi_{32} & \Phi_{33} & * & *\\ \Phi_{41} & \Phi_{42} & 0 & \Phi_{44} & *\\ \Phi_{51} & 0 & 0 & 0 & \Phi_{55}\end{bmatrix} \geq 0, \quad j \in \{1,\ldots,n_l\} \tag{32}$$

where $\tau_1 \in \Re^{n_x\times n_x}$, $\tau_3 \in \Re^{n_x\times n_x}$, $\tau_4 \in \Re^{Nn_u\times n_x}$,

$$\Phi_{11} = (1-\sigma)\begin{bmatrix}\tau_3 & *\\ \tau_1 & \tau_1\end{bmatrix}, \quad \Phi_{22} = \Delta_{22},$$

$$\Phi_{31} = \begin{bmatrix}(A_j+B_jF)\tau_3 + B_jG\tau_4 & (A_j+B_jF)\tau_1\\ (A_j+B_jF)\tau_3 + B_jG\tau_4 + M' & (A_j+B_jF)\tau_1\\ 0 & 0\\ 0 & 0\end{bmatrix},$$

$$\Phi_{32} = \begin{bmatrix}\beta_EL_pC_j & -B_j & \beta_EL_pE_j\\ \beta_EL_pC_j & -B_j & \beta_EL_pE_j\\ \beta_DL_pC_j & 0 & \beta_DL_pE_j\\ \beta_DL_pC_j & 0 & \beta_DL_pE_j\end{bmatrix},$$

$$\Phi_{33} = \begin{bmatrix}\tau_3 & * & * & *\\ \tau_1 & \tau_1 & * & *\\ 0 & 0 & \tau_3 & *\\ 0 & 0 & \tau_1 & \tau_1\end{bmatrix}, \quad \Phi_{41} = \begin{bmatrix}F\tau_3 + G\tau_4 & F\tau_1\end{bmatrix},$$

$$\Phi_{42} = \begin{bmatrix}0 & -I & 0\end{bmatrix}, \quad \Phi_{44} = P_u^{-1},$$

$$\Phi_{51} = \begin{bmatrix}\tau_3 & \tau_1\\ \tau_4 & 0\end{bmatrix}, \quad \Phi_{55} = L_z^{-1},$$

α in Φ_{22} is a variable and M' in Φ_{31} defined as $M' := \tau_2^TM\tau_4$.

proof: By using S-procedure, (30) becomes

$$V_{h|t} - \mathbb{E}\{V_{h+1|t}\} - J_t^{0|0} - \sigma(V_{h|t} - \gamma w_{h|t}^Tw_{h|t}) \geq 0 \tag{33}$$

According to (6) (19), (27), (28) and (29), by taking the Schur complement and the polytope $Co\{[A_l|B_l|C_l|D_l|E_l]\}$, $l \in \{1,\ldots,n_l\}$, (33) becomes

$$\begin{bmatrix}(1-\sigma)P_z & * & * & * & *\\ 0 & \Phi_{22} & * & * & *\\ \Psi_{31} & \Psi_{32} & \Psi_{33} & * & *\\ \Psi_{41} & \Phi_{42} & 0 & \Phi_{44} & *\\ I & 0 & 0 & 0 & \Phi_{55}\end{bmatrix} \geq 0, \quad j \in \{1,\ldots,n_l\} \tag{34}$$

where $\Psi_{31} = \begin{bmatrix}A_j+B_jF & B_jG\\ 0 & M\end{bmatrix}$, $\Psi_{41} = [F\ 0]$, $\Psi_{32} = \begin{bmatrix}\beta_{h|t}L_pC_j & -B_j & \beta_{h|t}L_pE_j\\ 0 & 0 & 0\end{bmatrix}$, $\Psi_{33} = P_z^{-1}$.

Then, the variable substitution is used to linearize the above LMI. Let us define

$$P_z = \begin{bmatrix}\tau_1^{-1} & \tau_1^{-1}\tau_2^T\\ \tau_2\tau_1^{-1} & \xi_1\end{bmatrix}, \quad P_z^{-1} = \begin{bmatrix}\tau_3 & \tau_4^T\\ \tau_4 & \xi_2\end{bmatrix} \tag{35}$$

By taking the congruence transformation diag$\{\Phi_{51}, I, P_z\Phi_{51}, I, I\}$ and (4), (34) becomes (32). □

2) ON-LINE OPTIMIZATION PROBLEM

In the previous subsection, γ, α and P_z^{-1} are obtained. In the following introduction of approaches, they will be used as known. At each time t, consider the following optimization problem

$$OP4: \min_{f_{0|t}} f_{0|t}^TL_ff_{0|t} \quad s.t.\ V_{0|t} \leq \gamma_t \tag{36}$$

which can ensure the stability of the estimation state. $V_{0|t} \leq \gamma_t$ is guaranteed by

$$\begin{bmatrix} \gamma_t - \alpha\eta_t - \epsilon_t & * & * \\ \hat{x}_{0|t} & \tau_3 & * \\ f_{0|t} & \tau_4 & \xi_2 \end{bmatrix} \geq 0 \tag{37}$$

where $\xi_2 = \tau_4(\tau_3 - \tau_1)^{-1}\tau_4^T$.

proof: According (13) and (28), we can get

$$\gamma_t - z_{0|t}^T P_z z_{0|t} - \hat{e}_{0|t}^T P_e \hat{e}_{0|t} - \epsilon_t \geq 0 \tag{38}$$

$$\hat{e}_{0|t}^T P_e \hat{e}_{0|t} \leq \alpha\eta_t \tag{39}$$

By using Schur complement, (37) can be obtained. □

In order to guarantee feasible and closed-loop stability for (36), at time $t = 0$, let us define $\gamma_0 = \gamma$, and according to (30), set γ_{t+1} as

$$\gamma_{t+1} = \gamma_t - J_t^{0|0} \tag{40}$$

IV. NUMERICAL EXAMPLE

Example 1: We introduce a continuous stirred tank reactor (CSTR) system and its parameters, which has been investigated in [43]. Then, the proposed algorithm parameters will be set based on the CSTR system. Finally, assume different situations about data dropout rate β_E, disturbance w_t and the initial state of the estimator and CSTR system.

1) The parameters of the CSTR system are shown as follows:

The number of polyhedral vertices $n_l = 4$ and the state space matrices of the system are

$$A_1 = \begin{bmatrix} 0.823 & -0.002 \\ 6.123 & 0.937 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 0.965 & -0.002 \\ -0.676 & 0.943 \end{bmatrix},$$

$$A_3 = \begin{bmatrix} 0.890 & -0.003 \\ 2.945 & 0.997 \end{bmatrix}, \quad A_4 = \begin{bmatrix} 0.893 & -0.001 \\ 2.774 & 0.886 \end{bmatrix},$$

$$B_1 = \begin{bmatrix} -0.092 \\ 0.1014 \end{bmatrix}, \quad B_2 = \begin{bmatrix} -0.097 \\ 0.1016 \end{bmatrix},$$

$$B_3 = \begin{bmatrix} -0.157 \\ 0.1045 \end{bmatrix}, \quad B_4 = \begin{bmatrix} -0.034 \\ 0.0968 \end{bmatrix},$$

$$C_1 = C_2 = C_3 = C_4 = \begin{bmatrix} 0 & 1 \end{bmatrix},$$

$$D_1 = D_2 = D_3 = D_4 = \begin{bmatrix} 0.008 \\ 0.023 \end{bmatrix},$$

$$E_1 = E_2 = E_3 = E_4 = 0.04,$$

$$h_t^1 = \frac{1}{2}\frac{\bar{y}_t - 0.5703}{1.7891}, \quad h_t^2 = \frac{1}{2}\frac{-\bar{y}_t + 2.3594}{1.7891},$$

$$h_t^3 = \frac{1}{2}\frac{\bar{y}_t - 0.0307}{0.0281}, \quad h_t^4 = \frac{1}{2}\frac{-\bar{y}_t + 0.0588}{0.0281}.$$

2) The parameters of the adaptive event-triggered are set as $\epsilon_0 = 1.2$, $\check{\epsilon} = 1.3$ and $\sigma = 0.01$. The scalar λ_1 in (10) is set to 0.1, 0.15, and 0.19. The dimension of f_t, $N = 3$. The weight matrices are

$$L_f = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad L_x = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad L_u = 1.$$

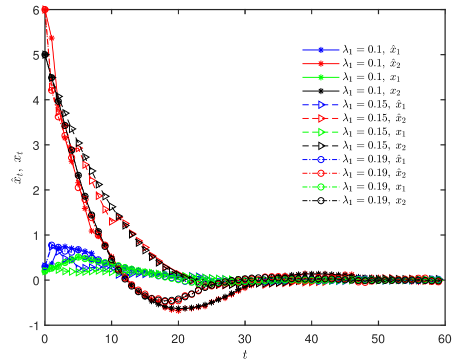

FIGURE 2. x_t **and** $\hat{x}_t$ **for standard situation under different** λ_1 **in Example 1.**

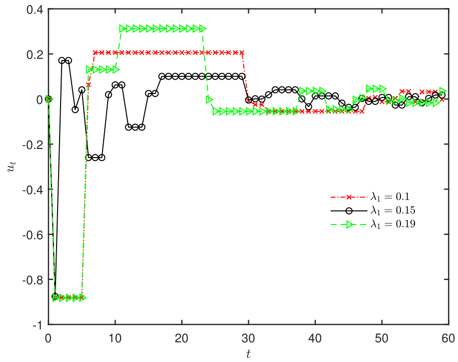

FIGURE 3. **Control intput of the system under different** λ_1 **in Example 1.**

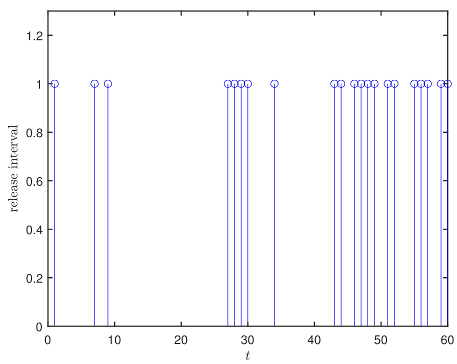

FIGURE 4. **Trigger times of the system under AETC in Example 1.**

3) Set the data dropout rate to $\beta_E = 0.6$ and the disturbance to $w_t \in (-1, 1)$. The initial states are $\hat{x}_0 = [0.2; 5]$ and $x_0 = [0.3; 6]$.

Record the above settings as standard situations, and the simulation results of standard situations are presented as

In FIGURE 2, it is observed that with disturbance w, the state of the estimator and system finally approaches 0. FIGURES 3 and 4 show the control input u_t of the system. FIGURE 4 indicates the trigger time point and release interval under AETC. It can be determined that only 35% of the communication resource has been occupied. FIGURE 5 can verify that $\beta_E = 0.6$. In FIGURE 6, we can see that the

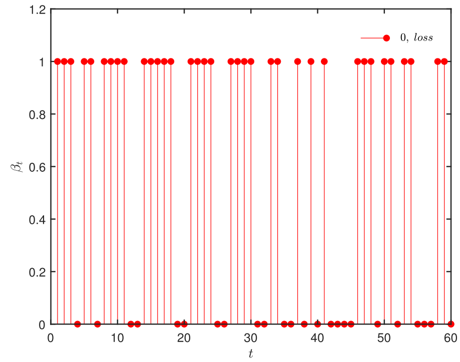

FIGURE 5. Data dropout time points in Example 1.

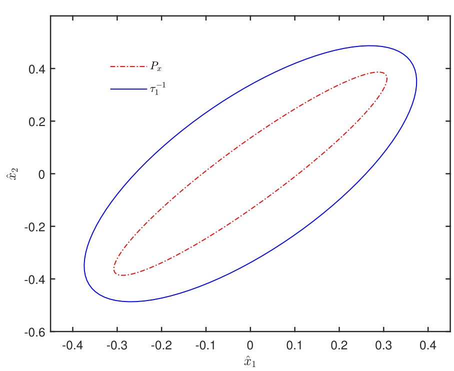

FIGURE 6. The ellipsoidal set for standard situation in Example 1.

area of $\{x|x^T P_x x \leq 1\}$ less than $\{x|x^T \tau^{-1} x \leq 1\}$ ($\tau^{-1} = [I_{n_x}, 0]P_z[I_{n_x}; 0]$), and it shows that the addition of augmented state $f_{0|t}$ enlarges the initial feasible set of the algorithm.

Example 2: The corresponding matrices for the system with polyhedral vertices $n_l = 2$ are given as follows, which has been studied in [44]:

$$A_1 = A_2 = \begin{bmatrix} 0.9617 & 0 & 0 \\ 0 & 0.9872 & 0 \\ 0 & 0 & 0.6564 \end{bmatrix},$$

$$B_1 = B_2 = \begin{bmatrix} 45.4498 \\ 0 \\ 119.097 \end{bmatrix},$$

$$C_1 = 21.0606\Psi_{c1}, \quad C_2 = 21.0606\Psi_{c2},$$

$$\Psi_{c1} = \begin{bmatrix} 10.9952 & -0.6717 & 5.6465 \end{bmatrix},$$

$$\Psi_{c2} = \begin{bmatrix} 10.9952 & -0.6717 & 2.4199 \end{bmatrix},$$

$$D_1 = D_2 = \begin{bmatrix} -0.0004525 \\ 0.0004525 \\ -0.0006790 \end{bmatrix},$$

$$E_1 = E_2 = 0,$$

$$h_t^1 = \frac{\bar{y}_t - 5.05}{4.95}, \; h_t^2 = 1 - \frac{\bar{y}_t - 5.05}{4.95}.$$

In addition, the data dropout rate is $\beta_E = 0.9$. The initial states are $\hat{x}_0 = [0.03; -0.1; 0.03]$ and $x_0 = [0.0001; 0.0001; 0.038]$. The rest of the parameters are the same as in Example 1.

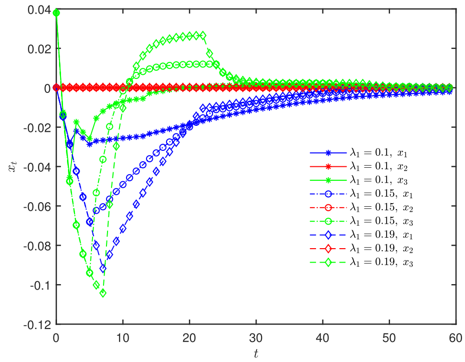

FIGURE 7. x_t for standard situation under different λ_1 in Example 2.

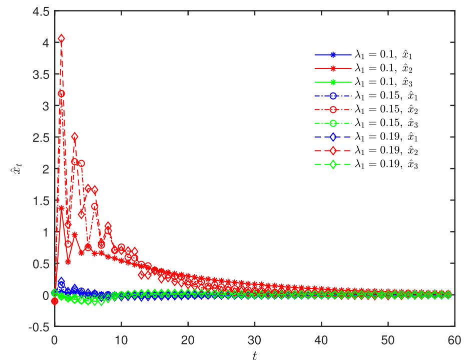

FIGURE 8. $\hat{x}_t$ for standard situation under different λ_1 in Example 2.

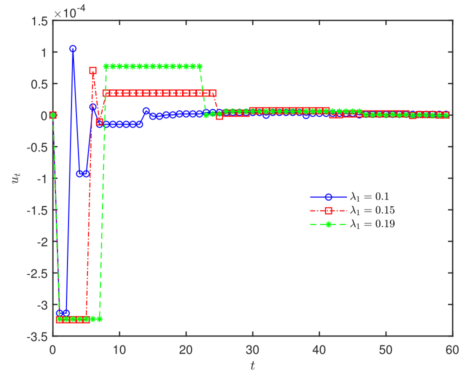

FIGURE 9. Control intput of the system under different λ_1 in Example 2.

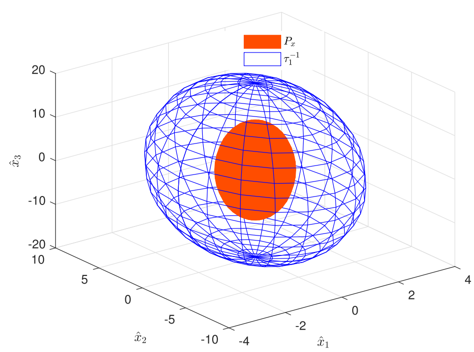

FIGURE 10. The ellipsoidal set for standard situation in Example 2.

FIGURE 7 and FIGURE 8 represent the true and estimated states of the system, and FIGURE 9 represents the control input under data dropout, and it can be clearly seen that the system gradually stabilizes as time evolves. From FIGURE 10, it can be observed that our proposed method can enlarge the initial feasible set of the system.

It can be concluded that the proposed EOFMPC method for NCS is feasible and shows satisfactory performance.

V. CONCLUSION

For NCS with data dropout and bounded disturbance, the synthesis approach of EOFMPC has been investigated. According to the linear polytopic uncertain system, the online optimization problem was provided, which was based on offline estimator design, the rule of estimator error upper bound updating, an offline optimization problem for state feedback gain, and an offline optimization problem for augmented state. On account of the EOFMPC with AETC, the optimality of the system and the initial feasible set have been significantly improved with the increasing dimension of the augmented state. In the future, we plan to investigate the efficient dynamic OFMPC (EDOFMPC) approach in NCS and consider other possible events in the communication channel.

REFERENCES

[1] D. Q. Mayne, "Model predictive control: Recent developments and future promise," *Automatica*, vol. 50, no. 12, pp. 2967–2986, Dec. 2014.

[2] M. V. Kothare, V. Balakrishnan, and M. Morari, "Robust constrained model predictive control using linear matrix inequalities," *Automatica*, vol. 32, no. 10, pp. 1361–1379, Oct. 1996.

[3] F. A. Cuzzola, J. C. Geromel, and M. Morari, "An improved approach for constrained robust model predictive control," *Automatica*, vol. 38, no. 7, pp. 1183–1189, Jul. 2002.

[4] W.-J. Mao, "Robust stabilization of uncertain time-varying discrete systems and comments on 'an improved approach for constrained robust model predictive control,"' *Automatica*, vol. 39, no. 6, pp. 1109–1112, Jun. 2003.

[5] Y. Lu and Y. Arkun, "Quasi-min-max MPC algorithms for LPV systems," *Automatica*, vol. 36, no. 4, pp. 527–540, Apr. 2000.

[6] H. H. J. Bloemen, T. J. J. van den Boom, and H. B. Verbruggen, "Optimizing the end-point state-weighting matrix in model-based predictive control," *Automatica*, vol. 38, no. 6, pp. 1061–1068, Jun. 2002.

[7] B. Ding, Y. Xi, and S. Li, "A synthesis approach of on-line constrained robust model predictive control," *Automatica*, vol. 40, no. 1, pp. 163–167, Jan. 2004.

[8] Z. Wan and M. V. Kothare, "An efficient off-line formulation of robust model predictive control using linear matrix inequalities," *Automatica*, vol. 39, no. 5, pp. 837–846, May 2003.

[9] D. Angeli, A. Casavola, G. Franzè, and E. Mosca, "An ellipsoidal off-line MPC scheme for uncertain polytopic discrete-time systems," *Automatica*, vol. 44, no. 12, pp. 3113–3119, Dec. 2008.

[10] B. Ding, Y. Xi, M. T. Cychowski, and T. O'Mahony, "Improving off-line approach to robust MPC based-on nominal performance cost," *Automatica*, vol. 43, no. 1, pp. 158–163, Jan. 2007.

[11] B. Kouvaritakis, J. A. Rossiter, and J. Schuurmans, "Efficient robust predictive control," *IEEE Trans. Autom. Control*, vol. 45, no. 8, pp. 1545–1549, 2000.

[12] M. Cannon and B. Kouvaritakis, "Optimizing prediction dynamics for robust MPC," *IEEE Trans. Autom. Control*, vol. 50, no. 11, pp. 1892–1897, Nov. 2005.

[13] L. Imsland, N. Bar, and B. A. Foss, "More efficient predictive control," *Automatica*, vol. 41, no. 8, pp. 1395–1403, Aug. 2005.

[14] Y. Dong, Y. Song, and G. Wei, "Efficient model-predictive control for networked interval type-2 T–S fuzzy system with stochastic communication protocol," *IEEE Trans. Fuzzy Syst.*, vol. 29, no. 2, pp. 286–297, Feb. 2021.

[15] X. Tang and L. Deng, "Multi-step output feedback predictive control for uncertain discrete-time T–S fuzzy system via event-triggered scheme," *Automatica*, vol. 107, pp. 362–370, Sep. 2019.

[16] X. Tang, L. Deng, and H. Qu, "Predictive control for networked interval type-2 T–S fuzzy system via an event-triggered dynamic output feedback scheme," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 8, pp. 1573–1586, Aug. 2019.

[17] B. Ding and X. Ping, "Output feedback predictive control with one free control move for nonlinear systems represented by a Takagi–Sugeno model," *IEEE Trans. Fuzzy Syst.*, vol. 22, no. 2, pp. 249–263, Apr. 2014.

[18] X. Tang, L. Deng, J. Yu, and H. Qu, "Output feedback predictive control of interval type-2 T–S fuzzy systems with Markovian packet loss," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 4, pp. 2450–2459, Aug. 2018.

[19] X. Ping and W. Pedrycz, "Output feedback model predictive control of interval type-2 T–S fuzzy system with bounded disturbance," *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 1, pp. 148–162, Jan. 2020.

[20] X. Tang, L. Deng, N. Liu, S. Yang, "Observer-based output feedback MPC for T-S fuzzy system with data loss and bounded disturbance," *IEEE Trans. Cybern.*, vol. 49, no. 6, pp. 2119–2132, 2019.

[21] X. Ping and B. Ding, "Off-line approach to dynamic output feedback robust model predictive control," *Syst. Control Lett.*, vol. 62, no. 11, pp. 1038–1048, Nov. 2013.

[22] J. Hu and B. Ding, "An efficient offline implementation for output feedback min-max MPC," *Int. J. Robust Nonlinear Control*, vol. 29, no. 2, pp. 492–506, Jan. 2019.

[23] C.-K. Zhang, K.-Y. Xie, Y. He, J. She, and M. Wu, "Matrix-injection-based transformation method for discrete-time systems with time-varying delay," *Sci. China Inf. Sci.*, vol. 66, no. 5, May 2023, Art. no. 159201.

[24] Q. Zheng, S. Xu, and B. Du, "Quantized guaranteed cost output feedback control for nonlinear networked control systems and its applications," *IEEE Trans. Fuzzy Syst.*, vol. 30, no. 7, pp. 2402–2411, Jul. 2022.

[25] D. Yue, E. Tian, and Q.-L. Han, "A delay system method for designing event-triggered controllers of networked control systems," *IEEE Trans. Autom. Control*, vol. 58, no. 2, pp. 475–481, Feb. 2013.

[26] P. Shi, H. Wang, and C.-C. Lim, "Network-based event-triggered control for singular systems with quantizations," *IEEE Trans. Ind. Electron.*, vol. 63, no. 2, pp. 1230–1238, Feb. 2016.

[27] M. Ghodrat and H. J. Marquez, "On the event-triggered controller design," *IEEE Trans. Autom. Control*, vol. 65, no. 10, pp. 4122–4137, Oct. 2020.

[28] S. Luo and F. Deng, "On event-triggered control of nonlinear stochastic systems," *IEEE Trans. Autom. Control*, vol. 65, no. 1, pp. 369–375, Jan. 2020.

[29] T. Feng, Y.-E. Wang, L. Liu, and B. Wu, "Observer-based event-triggered control for uncertain fractional-order systems," *J. Franklin Inst.*, vol. 357, no. 14, pp. 9423–9441, Sep. 2020.

[30] J. Lian and C. Li, "Event-triggered control for a class of switched uncertain nonlinear systems," *Syst. Control Lett.*, vol. 135, Jan. 2020, Art. no. 104592.

[31] R. Zhang, D. Zeng, J. H. Park, Y. Liu, and X. Xie, "Adaptive event-triggered synchronization of reaction–diffusion neural networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 8, pp. 3723–3735, Aug. 2021.

[32] T. Gao, J. Huang, R. Ling, and Y. Zhou, "Adaptive event-triggered control of a class of series elastic actuator system," *Int. J. Control, Autom. Syst.*, vol. 19, no. 7, pp. 2536–2543, Jul. 2021.

[33] Y. Sun, H. Xiao, D. Ding, and S. Liu, "Secure filtering under adaptive event-triggering protocols with memory mechanisms," *ISA Trans.*, vol. 127, pp. 13–21, Aug. 2022.

[34] J. Xiong and J. Lam, "Stabilization of linear systems over networks with bounded packet loss," *Automatica*, vol. 43, no. 1, pp. 80–87, 2007.

[35] K. You and L. Xie, "Minimum data rate for mean square stabilizability of linear systems with Markovian packet losses," *IEEE Trans. Autom. Control*, vol. 56, no. 4, pp. 772–785, Apr. 2011.

[36] K. Tsumura, H. Ishii, and H. Hoshina, "Tradeoffs between quantization and packet loss in networked control of linear systems," *Automatica*, vol. 45, no. 12, pp. 2963–2970, Dec. 2009.

[37] H. Lin and S. Sun, "Estimation for networked random sampling systems with packet losses," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 51, no. 9, pp. 5511–5521, Sep. 2021.

[38] M. Xue, Y. Tang, L. Wu, W. Zhong, and F. Qian, "Switching stabilization for type-2 fuzzy systems with network-induced packet losses," *IEEE Trans. Cybern.*, vol. 49, no. 7, pp. 2591–2604, Jul. 2019.

[39] H. Yang, Y. Xu, and J. Zhang, "Event-driven control for networked control systems with quantization and Markov packet losses," *IEEE Trans. Cybern.*, vol. 47, no. 8, pp. 2235–2243, Aug. 2017.
[40] V. Dolk and M. Heemels, "Event-triggered control systems under packet losses," *Automatica*, vol. 80, pp. 143–155, Jun. 2017.
[41] M. Kooshkbaghi and H. J. Marquez, "Event-triggered discrete-time cubature Kalman filter for nonlinear dynamical systems with packet dropout," *IEEE Trans. Autom. Control*, vol. 65, no. 5, pp. 2278–2285, May 2020.
[42] Z. Zhang, H. Liang, C. Wu, and C. K. Ahn, "Adaptive event-triggered output feedback fuzzy control for nonlinear networked systems with packet dropouts and actuator failure," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 9, pp. 1793–1806, Sep. 2019.
[43] Z. Wan and M. V. Kothare, "Efficient scheduled stabilizing output feedback model predictive control for constrained nonlinear systems," *IEEE Trans. Autom. Control*, vol. 49, no. 7, pp. 1172–1177, Jul. 2004.
[44] J. Hu and B. Ding, "A periodic approach to dynamic output feedback MPC for quasi-LPV model," *IEEE Trans. Autom. Control*, vol. 66, no. 5, pp. 2257–2264, May 2021.

MINGHONG SHE was born in Sichuan, China. He received the B.Eng. degree from Southwest University, Chongqing, China, in 2007, and the M.Eng. degree in computer science and the Ph.D. degree in control theory and control engineering from Chongqing University, Chongqing, in 2010, and 2019, respectively. He is currently an Associate Professor with the Mianyang Teachers' College. His current research interests include system identification, modeling, and intelligent control.

WENBIN WU was born in Sichuan, China. He received the B.Eng. degree from the Nanjing University of Science and Technology, Nanjing, China, in 2004, and the M.Eng. degree in electronic and communication from the Southwest University of Science and Technology, Mianyan, China, in 2014. He is currently an Associate Professor with the Mianyang Teachers' College. His current research interests include complex networking control and the IoT Security.