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Dynamic sum-based event-triggered H_∞ filtering for networked T-S fuzzy wind turbine systems with deception attacks

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ABSTRACT

This article is concerned with the dynamic sum-based event-triggered H_∞ filtering issue for networked wind turbine systems subject to deception attacks and communication delays. By considering the time-varying wind power case rather than the existing maximum power case, a more general T-S fuzzy system with two premise variables is modeled for nonlinear wind turbine system. In order to save the communication cost, a novel dynamic sum-based event-triggered scheme is proposed, which has the following three merits. First, some past sampled measurements are utilized to reduce redundant transmissions. Second, an auxiliary dynamic variable based on the past sampled measurements is introduced in the triggering condition to further enlarge the triggering intervals. Third, a dynamic triggering threshold is designed, which can be regulated adaptively along with the system evolution. With the help of Lyapunov method and linear matrix inequality technique, some sufficient co-design conditions of H_∞ filter and triggering matrices are derived for the T-S fuzzy filtering error system with deception attacks and communication delays. Lastly, some simulations are carried out to illustrate the advantages of the proposed strategy.

1. Introduction

In recent decades, the global energy landscape has been witnessing a profound shift towards sustainable and renewable sources of power generation. As a representative type of renewable energy, wind energy stands out as a vital player in the efforts to combat climate change and reduce greenhouse gas emissions. The growing urgency to transition from fossil fuels to clean energy sources has propelled substantial research into the optimization, efficiency enhancement, and cost reduction of wind turbine systems (WTSs). Recently, increasing attention has been devoted to analyze and design of WTSs to improve the power output and grid integration capability, and many research results and Overview papers about WTSs can be found in [1–5].

For practical WTSs, their inherent nonlinear and uncertain dynamics lead to challenge problems to control system design. There are two typical kinds of wind turbine generator: permanent magnetic synchronous generator (PMSG) and doubly-fed induction generator (DFIG). Regarding the DFIG-based WTSs integrating an energy store system considered in [6], a robust control strategy based on integral sliding mode control is developed to manage the powers of WTSs. In [7], an advanced backstepping integral action control method is proposed for the DFIG-based WTSs to monitor the rotor and the network side converters under normal network operations, while an improved protection scheme is added to the controller to overcome the negative effect caused by network fault. Compared

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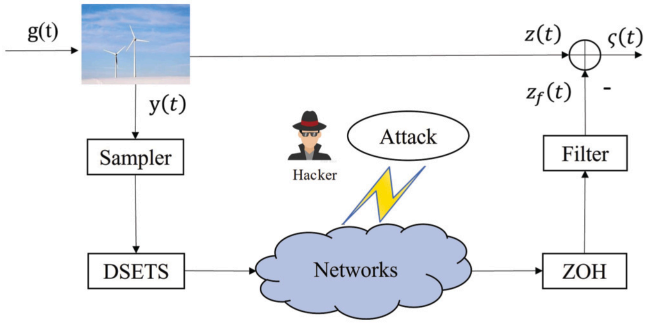

Fig. 1. The framework of H_∞ filtering for networked WTS against deception attacks under DSETS.

with DFIG, PMSG is more widely studied and used due to the features like direct drive, low rotational velocity and cheap maintenance fee. In order to handle the nonlinear dynamics, a T-S fuzzy modeling approach is utilized to establish a group of linear systems related to membership functions (MFs) for nonlinear switched systems [8]. Based on the T-S fuzzy model, various investigations about WTSs have been reported in [9–12]. To name a few, the sampled-data fuzzy controller is designed in [9] for T-S fuzzy PMSG-based WTSs affected by actuator faults. In [10], a disturbance observer is constructed to attenuate the negative effect of external disturbance and a sliding mode controller is designed to stabilize the T-S fuzzy PMSG-based WTSs. With the development of network technique, networked WTSs has attracted more and more attention [13–16]. The security of data communication is an important issue for networked systems [17,18]. If the exchanged signals are attacked in network channels, the expected performance, even stability, could be degraded. By considering cyber-attacks, many studies about secure control problems for WTSs can be found in [19,20,14]. Generally speaking, in [19], an adaptive resilient control strategy for the variable-speed WTSs working at low-speed area is proposed to deal with the deception attacks. A dual-triggered resilient torque control method for the variable-speed WTSs subject to denial-of-service (DoS) attacks is investigated in [20]. Considering DoSs and deception attacks simultaneously, the authors in [14] address the resilient control problem for WTSs.

On the other research line, as a high effective manner to mitigate network congestion and save limited network resource, event-triggered scheme (ETS) has been viewed as a replacement for the traditional time-triggered scheme [21–26]. In order to decrease the redundant transmissions, some control problems of a fuzzy WTS with back to back converter and a fuzzy WTS with actuator faults via ETSs are studied in [27] and [28], respectively. Note that the above outcomes are mostly based on the full measurable system states, which is difficult to be realized in engineering applications. It is known that H_∞ filtering is a powerful tool to estimate system states when the system disturbance is bounded. Meanwhile, the abrupt disturbances and noises in practical systems could result in unnecessary triggering events under the above ETSs [27,28], which only utilize the current sampled data. Recently, an improved integral ETS using some historical state information is proposed in [29] to further reduce communication burden. Although it has some advantages over some conventional ETSs, there exists the difficulty of analyzing Zeno behavior in the integral ETS [29]. In order to avoid Zeno behavior, a discrete version of the ETS using historical sampled data is addressed in [30] for the synchronization of delayed neural networks. In addition, the triggering thresholds of ETSs have significant effect on data releasing rate. However, the triggering thresholds in [27–30] are constant parameters and cannot be adjusted adaptively along with the system evolution.

Motivated by the previous observations, a dynamic sum-based event-triggered H_∞ fuzzy filter is designed for networked T-S fuzzy PMSG-based WTSs against deception attacks. The main contributions of this paper can be summarized as follows:

1) A new T-S fuzzy PMSG-based model is established by considering the time-varying wind power case, where an extra premise variable is introduced to handle the nonlinearity induced by time-varying wind power. Different from some existing results [4,10] considering a constant value at the maximum wind power case, our proposed model does not require that the generator always operates at the maximum power point.

2) A novel dynamic sum-based ETS (DSETS) is presented, which adopts the sum of some historical sampled outputs, a dynamic variable and some dynamic triggering thresholds. Compared with the traditional sampled-data ETS [21] only dependent on current sampled data, the network resource can be notably saved by the designed DSETS. In addition, the introduced dynamic variable in our DSETS is potential to generate larger triggering intervals than the existing integral ETS [30].

3) Some sufficient co-design conditions of fuzzy filter gains and triggering matrices are accomplished to ensure the stability of the filtering error WTS with given H_∞ index, where the proposed DSETS, deception attacks and communication delays are considered in a united framework.

Notation: In this article, $*$ is used to represent $[*]XY = Y^TXY$ or $\begin{bmatrix} X & Y \\ Y^T & X \end{bmatrix} = \begin{bmatrix} X & Y \\ * & X \end{bmatrix}$, where Y^T is the transpose of Y. $\mathbb{E}\{\cdot\}$ denotes the mathematical expectation operation.

2. Preliminaries

This section introduces the T–S fuzzy model of a nonlinear PMSG-based WTS. The framework of H_∞ filtering for networked WTS subject to deception attacks by using the proposed DSETS is drawn in Fig. 1.

The mechanical power output of the wind is formulated as:

$$\mathfrak{P}(t) = 0.5\mathfrak{I}\pi R^2 \Theta_p(\chi(t), \nu) v_1^3(t), \tag{1}$$

in which $v_1(t)$ and $v_2(t)$ are wind and rotor velocities, respectively, $\mathfrak{I}$ is air density, and the length of blade is represented by R. $\Theta_p(\chi(t), \nu)$ stands for power factor, $\chi(t) = v_2(t)R/v_1(t)$ denotes tip velocity ratio, ν means pitch angle.

According to [31], it yields

$$\Theta_p(\chi(t), \nu) = 0.22(\frac{116}{\chi_i} - 0.4\nu - 5)e^{-\frac{12.5}{\chi_i}}, \tag{2}$$

where $\frac{1}{\chi_i} = \frac{1}{\chi(t)+0.08\nu} - \frac{0.035}{\nu^3+1}$.

Then, the aerodynamic torque is given as:

$$\mathfrak{T}(t) = \frac{\mathfrak{P}(t)}{v_2(t)} = \frac{\mathfrak{I}\pi R^3 \Theta_p(\chi(t), \nu) v_1^2(t)}{2\chi(t)}. \tag{3}$$

The following dynamic equations of PMSG-based WTS are inferred as [32]:

$$\begin{cases} \mathfrak{F}_d(t) = \mathfrak{R}_s \mathfrak{I}_d(t) + \mathfrak{L}_d \frac{d\mathfrak{I}_d(t)}{dt} - w_e(t)\mathfrak{L}_q \mathfrak{I}_q(t) + b_1 g(t) \\ \mathfrak{F}_q(t) = \mathfrak{R}_s \mathfrak{I}_q(t) + \mathfrak{L}_q \frac{d\mathfrak{I}_q(t)}{dt} + w_e(t)\mathfrak{L}_d \mathfrak{I}_d(t) \\ \qquad + w_e(t) Y_f + b_2 g(t) \\ \dot{w}_g(t) = \frac{1}{J}(\mathfrak{T}_e(t) - \mathfrak{T}(t) - \epsilon w_g(t)) + b_3 g(t) \\ \mathfrak{T}_e(t) = \frac{3}{2} P_n \mathfrak{I}_q(t) Y_f \end{cases}, \tag{4}$$

in which $\mathfrak{F}_d(t)$ and $\mathfrak{I}_d(t)$ represent the voltage and current of d-axis, $\mathfrak{F}_q(t)$ and $\mathfrak{I}_q(t)$ are the voltage and current of q-axis, $\mathfrak{L}_d$ and $\mathfrak{L}_q$ denote the stator inductance on d axis and q axis, respectively, $g(t)$ is external disturbance in $\mathscr{L}_2[0, \infty)$, P_n, $w_g(t) = v_2(t)$ are the amount of poles and the rotor velocity, $\mathfrak{R}_s$ means the stator resistance, the permanent magnet flux is denoted by Y_f, $\mathfrak{T}_e(t)$ means the torque of generator, $w_e(t) = P_n w_g(t)$, J means the moment of inertia and ϵ represents the friction coefficient, respectively.

By choosing the state vector $\zeta(t) = \begin{bmatrix} \zeta_1(t) & \zeta_2(t) & \zeta_3(t) \end{bmatrix}^T = \begin{bmatrix} w_g(t) & \mathfrak{I}_q(t) & \mathfrak{I}_d(t) \end{bmatrix}^T$, control input $u(t) = \begin{bmatrix} \mathfrak{F}_q(t) & \mathfrak{F}_d(t) \end{bmatrix}^T$ and using (1)-(4), the nonlinear state space of PMSG-based WTS can be expressed as follows:

$$\dot{\zeta}(t) = \mathscr{A}_0 \zeta(t) + \mathscr{B}_0 u(t) + B g(t), \tag{5}$$

where $\zeta(t)$ and $u(t)$ denote the state and control input, and

$$\mathscr{A}_0 = \begin{bmatrix} -\frac{\epsilon + T_0(t) w_g(t)}{J} & \frac{3P_n Y_f}{2J} & 0 \\ -\frac{P_n Y_f}{\mathfrak{L}_q} & -\frac{\mathfrak{R}_s}{\mathfrak{L}_q} & -\frac{P_n w_g(t)\mathfrak{L}_d}{\mathfrak{L}_q} \\ 0 & \frac{P_n w_g(t)\mathfrak{L}_q}{\mathfrak{L}_d} & -\frac{\mathfrak{R}_s}{\mathfrak{L}_d} \end{bmatrix}, \quad \mathscr{B}_0 = \begin{bmatrix} 0 & 0 \\ \frac{1}{\mathfrak{L}_q} & 0 \\ 0 & \frac{1}{\mathfrak{L}_d} \end{bmatrix}, \quad B = \begin{bmatrix} b_3 \\ -\frac{b_2}{\mathfrak{L}_q} \\ -\frac{b_1}{\mathfrak{L}_d} \end{bmatrix}, \quad T_0(t) = \frac{\Theta_p(\chi(t), \nu)\mathfrak{I}\pi R^5}{2\chi^3(t)}.$$

In order to construct the T-S fuzzy model of wind turbine system with PMSG, two premise variables $\vartheta_1(t) = w_g(t)$ and $\vartheta_2(t) = T_0(t) w_g(t)$ are selected. It is assumed that $\vartheta_1(t) \in [\vartheta_{1\min} \quad \vartheta_{1\max}] = [M_1 \quad M_2]$ and $\vartheta_2(t) \in [\vartheta_{2\min} \quad \vartheta_{2\max}] = [M_3 \quad M_4]$. Then, one can derive:

Plant rule i: IF $\vartheta_1(t)$ is x_i^1, $\vartheta_2(t)$ is x_i^2, THEN

$$\dot{\zeta}(t) = \mathscr{A}_i \zeta(t) + \mathscr{B}_0 u(t) + B_i g(t), \tag{6}$$

where $B_i = B$, $x_i^s (s = 1, ..., m)$ means the fuzzy set for the ith rule $(i = 1, ..., r)$, $m = 2$ and $r = 4$ are the amount of premise variables and fuzzy rules, and

$$\mathscr{A}_1 = \begin{bmatrix} -\frac{\epsilon + M_3}{J} & \frac{3P_n Y_f}{2J} & 0 \\ -\frac{P_n Y_f}{\mathfrak{L}_q} & -\frac{\mathfrak{R}_s}{\mathfrak{L}_q} & -\frac{P_n M_1 \mathfrak{L}_d}{\mathfrak{L}_q} \\ 0 & \frac{P_n M_1 \mathfrak{L}_q}{L_d} & -\frac{\mathfrak{R}_s}{\mathfrak{L}_d} \end{bmatrix}, \quad \mathscr{A}_2 = \begin{bmatrix} -\frac{\epsilon + M_4}{J} & \frac{3P_n Y_f}{2J} & 0 \\ -\frac{P_n Y_f}{\mathfrak{L}_q} & -\frac{\mathfrak{R}_s}{\mathfrak{L}_q} & -\frac{P_n M_1 \mathfrak{L}_d}{\mathfrak{L}_q} \\ 0 & \frac{P_n M_1 \mathfrak{L}_q}{L_d} & -\frac{\mathfrak{R}_s}{\mathfrak{L}_d} \end{bmatrix},$$

$$\mathscr{A}_3 = \begin{bmatrix} -\frac{\epsilon + M_3}{J} & \frac{3P_n Y_f}{2J} & 0 \\ -\frac{P_n Y_f}{\mathfrak{L}_q} & -\frac{\mathfrak{R}_s}{\mathfrak{L}_q} & -\frac{P_n M_2 \mathfrak{L}_d}{\mathfrak{L}_q} \\ 0 & \frac{P_n M_2 \mathfrak{L}_q}{\mathfrak{L}_d} & -\frac{\mathfrak{R}_s}{\mathfrak{L}_d} \end{bmatrix}, \quad \mathscr{A}_4 = \begin{bmatrix} -\frac{\epsilon + M_4}{J} & \frac{3P_n Y_f}{2J} & 0 \\ -\frac{P_n Y_f}{\mathfrak{L}_q} & -\frac{\mathfrak{R}_s}{\mathfrak{L}_q} & -\frac{P_n M_2 \mathfrak{L}_d}{\mathfrak{L}_q} \\ 0 & \frac{P_n M_2 \mathfrak{L}_q}{\mathfrak{L}_d} & -\frac{\mathfrak{R}_s}{\mathfrak{L}_d} \end{bmatrix}.$$

By choosing a state feedback controller $u(t) = \mathscr{K}\zeta(t)$ to stabilize the WTS, the closed-loop T-S fuzzy WTS is given as:

$$\begin{cases} \dot{\zeta}(t) = \sum_{i=1}^{r} \mu_i(t)(A_i\zeta(t) + B_i g(t)) \\ y(t) = C\zeta(t) \\ z(t) = L\zeta(t) \end{cases}, \tag{7}$$

where $y(t) \in \mathbb{R}^p$ is the measured output, $z(t) \in \mathbb{R}^q$ is the signal to be estimated, $A_i = \mathscr{A}_i + \mathscr{B}_0\mathscr{K}$, B_i, C and L are known parameter matrices with appropriate dimensions, $\mu_i(t)$ is the normalized membership function satisfying

$$\begin{aligned} &\sum_{i=1}^{4} \mu_i(t) = 1,\ \ \theta_{1\min}(t) = \frac{\vartheta_1(t) - M_1}{M_2 - M_1},\ \ \theta_{1\max}(t) = 1 - \theta_{1\min}(t), \\ &\theta_{2\min}(t) = \frac{\vartheta_2(t) - M_3}{M_4 - M_3},\ \ \theta_{2\max}(t) = 1 - \theta_{2\min}(t), \\ &\mu_1(t) = \theta_{1\min}(t)\theta_{2\min}(t),\ \ \mu_2(t) = \theta_{1\min}(t)\theta_{2\max}(t), \\ &\mu_3(t) = \theta_{1\max}(t)\theta_{2\min}(t),\ \ \mu_4(t) = \theta_{1\max}(t)\theta_{2\max}(t). \end{aligned} \tag{8}$$

Remark 1. In some existing results [4,10], the T-S fuzzy PMSG-based WTS model is usually established by assuming the maximum wind power case with a constant value of $T_0(t)$. However, in this paper, a new T-S fuzzy model is derived as (7), where the time-varying wind power case is considered and a premise variable $\vartheta_2(t) = T_0(t)w_g(t)$ is added. Compared with [4,10], it is not necessary for the presented model that the generator is always maintained at the maximum power point with higher control cost.

By considering the limited capacity of the communication channel, an event generator is established between the sensor and the filtering to determine whether the current sampled output $y(l_k h)$ is released to the filtering or not. When the last triggering time is $t_k h$, the next triggering time $t_{k+1}h$ is determined by the following DSETS:

$$t_{k+1}h = t_k h + \min_{l\geq 1} \left\{ lh | \sum_{n=0}^{N} \psi_n(t) \geq \lambda\phi(t) \right\}, \tag{9}$$

where

$$\begin{aligned} &\psi_n(t) = [*]\Phi_n e_n(t) - \delta_n(lh)[*]\Phi_n y(l_k h - nh), \\ &e_n(t) = y(t_k h - nh) - y(l_k h - nh),\ n = 0, 1, \cdots, N, \\ &\dot{\phi}(t) = -\rho\phi(t) - \sum_{n=0}^{N} \psi_n(t), \end{aligned}$$

and h is the sampling period, $l_k h = t_k h + lh, l \in \mathbb{N}$, Φ_n are positive weighting matrices to be determined, $\phi(t)$ is an auxiliary dynamic variable, λ and ρ are positive scalars, $\delta_n(lh) \in [\delta_{nm},\ \delta_{nM}](0 < \delta_{nm} \leq \delta_{nM} < 1)$ are dynamic triggering thresholds, which are adjusted by

$$\delta_n(lh) = \delta_{nM} - (\delta_{nM} - \delta_{nm})\frac{2}{\pi}\tanh(\|y(l_k h)\|). \tag{10}$$

Remark 2. If we choose $\delta_{nm} = \delta_{nM} = \delta_n$ and $\lambda = 0$, the proposed DSETS reduces to the existing ETS developed in [30]:

$$t_{k+1}h = t_k h + \min_{l\geq 1} \left\{ lh | \sum_{n=0}^{N} \psi_n(t) \geq 0 \right\}. \tag{11}$$

In addition, if $N = 0$, $\delta_{0m} = \delta_{0M} = \delta_0$ and $\lambda = 0$ are considered, our DSETS is further reduced to the conventional normal ETS studied in [21]:

$$t_{k+1}h = t_k h + \min_{l\geq 1} \left\{ lh | \psi_0(t) \geq 0 \right\}. \tag{12}$$

Note that our proposed DSETS covers the existing ETSs [21,30] as the special cases, which means it is more general and practical. Moreover, compared with the existing ETSs in [21,30], the proposed DSETS utilizes not only the historical sampled outputs but also an auxiliary dynamic variable, which is potential to decrease the data triggering frequency and save more limited network resources.

Remark 3. In terms of the adaptive law in (10), the dynamic triggering thresholds are related to the sampled output $y(l_k h)$. The idea behind the regulation rule is that more data need to be triggered to improve the filtering performance when $y(l_k h)$ is away from the steady state. On the other hand, if $y(l_k h)$ converges to the equilibrium point, the triggered signals can be reduced to mitigate communication burden.

Given the function of a zero-order-holder (ZOH), the latest triggered signal $y(t_k h)$ will be maintained as the input of filter until a new data is accepted, that is

$$\tilde{y}(t) = y(t_k h), \quad t \in [t_k h + d_k, \quad t_{k+1} h + d_{k+1}), \tag{13}$$

where d_k means the transmission delay induced by communication network at time $t_k h$. Similar to [33], the interval $t \in [t_k h + d_k, t_{k+1} h + d_{k+1})$ is divided into $t_{k+1} - t_k + 1$ segments, and each segment is denoted by $\varpi_l = [t_k h + lh + d_k^l, t_k h + lh + h + d_{k+1}^{l+1})$. Obviously, $t \in [t_k h + d_k, t_{k+1} h + d_{k+1}) = \cup_{l=0}^{t_{k+1}-t_k+1} \varpi_l$ with $d_k^0 = d_k$, $d_k^{t_{k+1}-t_k+1} = d_{k+1}$. By defining $d_n(t) = t - t_k h - lh + nh$, it yields

$$nh = d_{nm} \le d_n(t) \le (n+1)h + \bar{d} = d_{nM}, \tag{14}$$

where delay upper bound is $\bar{d} = \max\left\{d_k\right\}$. And we can rewrite $y(t_k h - nh)$ as

$$y(t_k h - nh) = e_n(t) + y(t - d_n(t)). \tag{15}$$

In addition, it is critical to consider the impact of cyber-attacks since the triggered data packets are vulnerable to malicious attacks and change while being transported via the communication network. This work considers the deception attacks which intends to change the data packets by injecting a false signal. In this manner, the actual input to the filter can be described as

$$\hat{y}(t) = \tilde{y}(t) + \alpha(t) f(t), \tag{16}$$

where $\alpha(t)$ is a Bernoulli distributed variable, $f(t)$ is the deception signal and meets the following constraint

$$\| f(t) \|_2 \le \| F y(t) \|_2, \tag{17}$$

with a constant matrix F. The feature of deception attacks is described by the stochastic variable $\alpha(t)$, whose probabilities are $Prob\{\alpha(t) = 1\} = \mathbb{E}\{\alpha(t)\} \triangleq \bar{\alpha}_1$, $Prob\{\alpha(t) = 0\} = 1 - \bar{\alpha}_1 = \bar{\alpha}_2$.

Based on the DSETS, the T-S fuzzy filter is constructed as

$$\begin{cases} \dot{\zeta}_f(t) = \sum\limits_{j=1}^{r} \mu_j(t_k h)(A_{fj}\zeta_f(t) + B_{fj}\hat{y}(t)) \\ z_f(t) = C_f \zeta_f(t) \end{cases}, \tag{18}$$

in which A_{fj}, B_{fj}, C_f are filter gains going to be designed.

Define $\tilde{\zeta}(t) = [\zeta^T(t) \quad \zeta_f^T(t)]^T$ and $\varsigma(t) = z(t) - z_f(t)$. By combining (7), (16) and (18), the filtering error system is deduced as

$$\begin{cases} \dot{\tilde{\zeta}}(t) = \sum\limits_{i=1}^{r} \sum\limits_{j=1}^{r} \mu_i \mu_j^k \left(\mathscr{A}_{ij}\tilde{\zeta}(t) + \mathscr{B}_j \hat{y}(t) + \mathscr{B}_{gi} g(t)\right) \\ \varsigma(t) = \mathscr{L}_0 \tilde{\zeta}(t) \end{cases}, \tag{19}$$

where μ_i, μ_j^k are the abbreviations of $\mu_i(t)$ and $\mu_j^k(t_k h)$, and

$$\mathscr{A}_{ij} = \begin{bmatrix} A_i & 0 \\ 0 & A_{fj} \end{bmatrix}, \quad \mathscr{B}_j = \begin{bmatrix} 0 \\ B_{fj} \end{bmatrix}, \quad \mathscr{B}_{gi} = \begin{bmatrix} B_i \\ 0 \end{bmatrix}, \quad \mathscr{L}_0 = \begin{bmatrix} L & -C_f \end{bmatrix}.$$

To deal with the asynchronous MFs μ_i and μ_j^k, the assumption $\mu_j^k \ge \rho_j \mu_j$ with $\rho_j (0 < \rho_j \le 1)$ borrowing the method in [33] is utilized.

Substituting (15) and (16) into (19), we establish the filtering error system as the following delay model:

$$\begin{cases} \dot{\tilde{\zeta}}(t) = \sum\limits_{i=1}^{r} \sum\limits_{j=1}^{r} \mu_i \mu_j^k \left(\mathscr{A}_{ij}\tilde{\zeta}(t) + \mathscr{B}_{dj}\tilde{\zeta}(t - d_0(t)) + \mathscr{B}_j e_0(t) + \mathscr{B}_{gi} g(t) + \alpha(t)\mathscr{B}_j f(t)\right) \\ \varsigma(t) = \mathscr{L}_0 \tilde{\zeta}(t) \end{cases}, \tag{20}$$

where

$$\mathscr{B}_{dj} = \begin{bmatrix} 0 & 0 \\ B_{fj} C & 0 \end{bmatrix}.$$

To end this section, a helpful lemma is introduced as below.

Lemma 1. *[34]For given positive scalars p, q, $\varepsilon \in (0,1)$, matrix $\mathscr{W} \in \mathbb{R}^p > 0$, matrices $\mathscr{J}_1 \in \mathbb{R}^{p\times q}$ and $\mathscr{J}_2 \in \mathbb{R}^{p\times q}$. For all vector $\varkappa \in \mathbb{R}^q$, define:*

$$\mathscr{F}(\varepsilon, \mathscr{W}) = \frac{1}{\varepsilon} \; \varkappa^T \mathscr{J}_1^T \mathscr{W} \mathscr{J}_1 \varkappa + \frac{1}{1-\varepsilon} \; \varkappa^T \mathscr{J}_2^T \mathscr{W} \mathscr{J}_2 \varkappa. \tag{21}$$

Then, if there exists a matrix $\mathscr{U} \in \mathbb{R}^{p\times p}$ *such that* $\begin{bmatrix} \mathscr{W} & \mathscr{U}^T \\ * & \mathscr{W} \end{bmatrix} > 0$, *one has*

$$\min_{\varepsilon\in(0,1)} \mathscr{F}(\varepsilon,\mathscr{W}) \geqslant \begin{bmatrix} \mathscr{J}_1\varkappa \\ \mathscr{J}_2 \end{bmatrix}^T \begin{bmatrix} \mathscr{W} & \mathscr{U}^T \\ * & \mathscr{W} \end{bmatrix} \begin{bmatrix} \mathscr{J}_1\varkappa \\ \mathscr{J}_2 \end{bmatrix}. \tag{22}$$

3. Main results

In this section, sufficient conditions to ensure the stability of the filtering error system with given H_∞ index in the presence of deception attacks are provided Theorem 1. Furthermore, the co-design conditions of triggering matrices and filter gains are produced in Theorem 2.

Theorem 1. *For given scalars* h, $\bar{d}$, d_{0m}, d_{0M}, d_{1m}, d_{1M}, d_{2m}, d_{2M}, $\bar{\alpha}_1$, β, γ, δ_{0M}, δ_{1M}, δ_{2M}, *under the DSETS (9), the filtering error system (20) is stable in mean square sense with prescribed* H_∞ *performance index* γ *if there exist symmetric matrices* $P>0$, $R_{1n}>0$, $R_{2n}>0$, $R_{3n}>0$, $R_{4n}>0$, $\Phi_n>0$, $\begin{bmatrix} R_{4n} & X_n \\ * & R_{4n} \end{bmatrix}>0$ *and matrices* Γ_i $(i=1,2,3,4)$, X_n, $n=0,1,2$, G *with appropriate dimensions such that:*

$$\Xi^{ij} - \Gamma_i < 0, \tag{23}$$

$$\rho_i\Xi^{ii} - \rho_i\Gamma_i + \Gamma_i < 0 (i=j), \tag{24}$$

$$\rho_j\Xi^{ij} + \rho_i\Xi^{ji} - \rho_j\Gamma_i - \rho_i\Gamma_j + \Gamma_i + \Gamma_j \leq 0 \ (i<j), \tag{25}$$

where

$$\Xi^{ij} = \begin{bmatrix} \Xi_1^{ij} & * \\ \Xi_2^{ij} & \Xi_3 \end{bmatrix}, \ \Psi = \begin{bmatrix} -\Phi_0 & * & * \\ 0 & -\Phi_1 & * \\ 0 & 0 & -\Phi_2 \end{bmatrix},$$

$$\Xi_1^{ij} = \begin{bmatrix} \Xi_{11} & * & * & * & * & * & * & * \\ \Xi_{21}^{ij} & \Xi_{22} & * & * & * & * & * & * \\ 0 & R_{30} & \Xi_{33} & * & * & * & * & * \\ \Xi_{41}^{ij} & \Xi_{42}^{ij} & \Xi_{43} & \Xi_{44} & * & * & * & * \\ 0 & 0 & X_0^T & \Xi_{54} & \Xi_{55} & * & * & * \\ \Xi_{61}^{ij} & \Xi_{62}^{ij} & 0 & 0 & 0 & -\gamma^2 I & * & * \\ 0 & R_{31} & 0 & 0 & 0 & 0 & \Xi_{77} & * \\ 0 & 0 & 0 & 0 & 0 & 0 & \Xi_{87} & \Xi_{88} \end{bmatrix},$$

$$\Xi_2^{ij} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & X_1^T & \Xi_{98} \\ 0 & R_{32} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \mathscr{B}_j^T G^T & \beta\mathscr{B}_j^T G^T & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \mathscr{L}_0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \bar{\alpha}_1\mathscr{B}_j^T G^T & \beta\bar{\alpha}_1\mathscr{B}_j^T G^T & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$\Xi_3 = \begin{bmatrix} \Xi_{99} & * & * & * & * & * & * \\ 0 & \Xi_{1010} & * & * & * & * & * \\ 0 & \Xi_{1110} & \Xi_{1111} & * & * & * & * \\ 0 & X_2^T & \Xi_{1211} & \Xi_{1212} & * & * & * \\ 0 & 0 & 0 & 0 & -(\rho+\lambda)\Psi & * & * \\ 0 & 0 & 0 & 0 & 0 & -I & * \\ 0 & 0 & 0 & 0 & 0 & 0 & -I \end{bmatrix},$$

$$\begin{aligned} \Xi_{11} =& -G^T - G + d_{0m}^2 R_{30} + (d_{0M}-d_{0m})^2 R_{40} + d_{1m}^2 R_{31} \\ &+ (d_{1M}-d_{1m})^2 R_{41} + d_{2m}^2 R_{31} + (d_{2M}-d_{2m})^2 R_{42}, \\ \Xi_{21}^{ij} =& \mathscr{A}_{ij}^T G^T - \beta G + P, \ \ \Xi_{33} = -R_{10} - R_{30} - R_{40}, \\ \Xi_{22} =& R_{10} + R_{11} + R_{12} + R_{20} + R_{21} + R_{22} - R_{30} - R_{31} \\ &- R_{32} + \beta\mathscr{A}_{ij}^T G^T + \beta G\mathscr{A}_{ij} + H^T C^T F^T F C H, \\ \Xi_{41}^{ij} =& \mathscr{B}_{dj}^T G^T, \Xi_{42}^{ij} = \beta\mathscr{B}_{dj}^T G^T, \Xi_{61}^{ij} = \mathscr{B}_{gj}^T G^T, \Xi_{62}^{ij} = \beta\mathscr{B}_{gj}^T G^T, \end{aligned}$$

$$
\begin{aligned}
&\Xi_{43} = R_{40} - X_0^T, \Xi_{54} = -X_0^T + R_{40}, \Xi_{55} = -R_{20} - R_{40},\\
&\Xi_{44} = -2R_{40} + X_0^T + X_0 + \delta_{0M}(\rho+\lambda)H^T C^T \Phi_0 CH,\\
&\Xi_{77} = -R_{11} - R_{31} - R_{41},\ \Xi_{87} = R_{41} - X_1^T,\\
&\Xi_{88} = -2R_{41} + X_1^T + X_1 + \delta_{1M}(\rho+\lambda)H^T C^T \Phi_1 CH,\\
&\Xi_{98} = -X_1^T + R_{41},\ \Xi_{99} = -R_{21} - R_{41},\\
&\Xi_{1010} = -R_{12} - R_{32} - R_{42},\ \Xi_{1110} = R_{42} - X_2^T\\
&\Xi_{1111} = -2R_{42} + X_2^T + X_2 + \delta_{2M}(\rho+\lambda)H^T C^T \Phi_2 CH,\\
&\Xi_{1211} = -X_2^T + R_{42},\ \Xi_{1212} = -R_{22} - R_{42},\ H = \begin{bmatrix} I & 0 \end{bmatrix}.
\end{aligned}
$$

Proof. Select the Lyapunov-Krasovskii functional as

$$
V(t) = \tilde{\zeta}^T(t)P\tilde{\zeta}(t) + \sum_{n=0}^{n=2} V_n(t) + \lambda\phi(t), \tag{26}
$$

where

$$
\begin{aligned}
V_0(t) = &\int_{t-d_{0m}}^{t} \tilde{\zeta}^T(s)R_{10}\tilde{\zeta}(s)ds + \int_{t-d_{0M}}^{t} \tilde{\zeta}^T(s)R_{20}\tilde{\zeta}(s)ds\\
&+ (d_{0M} - d_{om})\int_{-d_{0M}}^{-d_{om}}\int_{t+s}^{t} \dot{\tilde{\zeta}}^T(v)R_{40}\dot{\tilde{\zeta}}(v)dvds + d_{0m}\int_{-d_{0m}}^{0}\int_{t+s}^{t} \dot{\tilde{\zeta}}^T(v)R_{30}\dot{\tilde{\zeta}}(v)dvds,\\
V_1(t) = &\int_{t-d_{1m}}^{t} \tilde{\zeta}^T(s)R_{11}\tilde{\zeta}(s)ds + \int_{t-d_{1M}}^{t} \tilde{\zeta}^T(s)R_{21}\tilde{\zeta}(s)ds\\
&+ (d_{1M} - d_{1m})\int_{-d_{1M}}^{-d_{1m}}\int_{t+s}^{t} \dot{\tilde{\zeta}}^T(v)R_{41}\dot{\tilde{\zeta}}(v)dvds + d_{1m}\int_{-d_{1m}}^{0}\int_{t+s}^{t} \dot{\tilde{\zeta}}^T(v)R_{31}\dot{\tilde{\zeta}}(v)dvds,\\
V_2(t) = &\int_{t-d_{2m}}^{t} \tilde{\zeta}^T(s)R_{12}\tilde{\zeta}(s)ds + \int_{t-d_{2M}}^{t} \tilde{\zeta}^T(s)R_{22}\tilde{\zeta}(s)ds\\
&+ (d_{2M} - d_{2m})\int_{-d_{2M}}^{-d_{2m}}\int_{t+s}^{t} \dot{\tilde{\zeta}}^T(v)R_{42}\dot{\tilde{\zeta}}(v)dvds + d_{2m}\int_{-d_{2m}}^{0}\int_{t+s}^{t} \dot{\tilde{\zeta}}^T(v)R_{32}\dot{\tilde{\zeta}}(v)dvds.
\end{aligned}
$$

By following the similar proof process in Lemma 2.2 in [25], the positiveness of $\phi(t)$ can be derived. Then, it is easy to ensure $V(t) > 0$.

Computing the derivative of $V(t)$, one can obtain

$$
\begin{aligned}
\dot{V}(t) &= \dot{\tilde{\zeta}}^T(t)P\tilde{\zeta}(t) + \tilde{\zeta}^T(t)P\dot{\tilde{\zeta}}(t) + \sum_{n=0}^{2}\dot{V}_n(t) + \lambda\dot{\phi}(t)\\
&= \dot{\tilde{\zeta}}^T(t)P\tilde{\zeta}(t) + \tilde{\zeta}^T(t)P\dot{\tilde{\zeta}}(t) + \sum_{n=0}^{2}\dot{V}_n(t) + \lambda\left(-\rho\phi(t) - \sum_{n=0}^{N}\psi_n(t)\right),
\end{aligned} \tag{27}
$$

where

$$
\begin{aligned}
\dot{V}_0(t) = &\tilde{\zeta}^T(t)R_{10}\tilde{\zeta}(t) + \tilde{\zeta}^T(t)R_{20}\tilde{\zeta}(t) + d_{0m}^2\dot{\tilde{\zeta}}^T(t)R_{30}\dot{\tilde{\zeta}}(t) - d_{0m}\int_{t-d_{0m}}^{t} \dot{\tilde{\zeta}}^T(s)R_{30}\dot{\tilde{\zeta}}(s)ds - (d_{0M} - d_{0m})\int_{t-d_{0M}}^{t-d_{0m}} \dot{\tilde{\zeta}}^T(s)R_{40}\dot{\tilde{\zeta}}(s)ds\\
&- \tilde{\zeta}^T(t-d_{0m})R_{10}\tilde{\zeta}(t-d_{0m}) - \tilde{\zeta}^T(t-d_{0M})R_{20}\tilde{\zeta}(t-d_{0M}) + (d_{0M} - d_{0m})^2\dot{\tilde{\zeta}}^T(t)R_{40}\dot{\tilde{\zeta}}(t),\\
\dot{V}_1(t) = &\tilde{\zeta}^T(t)R_{11}\tilde{\zeta}(t) + \tilde{\zeta}^T(t)R_{21}\tilde{\zeta}(t) + d_{1m}^2\dot{\tilde{\zeta}}^T(t)R_{31}\dot{\tilde{\zeta}}(t) - d_{1m}\int_{t-d_{1m}}^{t} \dot{\tilde{\zeta}}^T(s)R_{31}\dot{\tilde{\zeta}}(s)ds - (d_{1M} - d_{1m})\int_{t-d_{1M}}^{t-d_{1m}} \dot{\tilde{\zeta}}^T(s)R_{41}\dot{\tilde{\zeta}}(s)ds
\end{aligned}
$$

$$-\tilde{\zeta}^T(t-d_{1m})R_{11}\tilde{\zeta}(t-d_{1m})-\tilde{\zeta}^T(t-d_{1M})R_{21}\tilde{\zeta}(t-d_{1M})+(d_{1M}-d_{1m})^2\dot{\tilde{\zeta}}^T(t)R_{41}\dot{\tilde{\zeta}}(t),$$

$$\dot{V}_2(t)=\tilde{\zeta}^T(t)R_{12}\tilde{\zeta}(t)+\tilde{\zeta}^T(t)R_{22}\tilde{\zeta}(t)+d_{2m}^2\dot{\tilde{\zeta}}^T(t)R_{32}\dot{\tilde{\zeta}}(t)-d_{2m}\int_{t-d_{2m}}^{t}\dot{\tilde{\zeta}}^T(s)R_{32}\dot{\tilde{\zeta}}(s)ds-(d_{2M}-d_{2m})\int_{t-d_{2M}}^{t-d_{1m}}\dot{\tilde{\zeta}}^T(s)R_{42}\dot{\tilde{\zeta}}(s)ds$$

$$-\tilde{\zeta}^T(t-d_{2m})R_{12}\tilde{\zeta}(t-d_{2m})-\tilde{\zeta}^T(t-d_{2M})R_{22}\tilde{\zeta}(t-d_{2M})+(d_{2M}-d_{2m})^2\dot{\tilde{\zeta}}^T(t)R_{42}\dot{\tilde{\zeta}}(t).$$

According to the well-known Jensen inequality, for $n=0,1,2$, it leads to

$$-d_{nm}\int_{t-d_{nm}}^{t}\dot{\tilde{\zeta}}^T(s)R_{3n}\dot{\tilde{\zeta}}(s)ds\le-[*]R_{3n}[\tilde{\zeta}(t)-\tilde{\zeta}(t-d_{nm})]. \tag{28}$$

With the aid of Lemma 1, for $n=0,1,2$, we have

$$-(d_{nM}-d_{nm})\int_{t-d_{nM}}^{t-d_{nm}}\dot{\tilde{\zeta}}^T(s)R_{4n}\dot{\tilde{\zeta}}(s)ds\le-\iota_n^T(t)\Omega_n\iota_n(t), \tag{29}$$

where

$$\iota_n(t)=\begin{bmatrix}\tilde{\zeta}^T(t-d_{nm}) & \tilde{\zeta}^T(t-d_n(t)) & \tilde{\zeta}^T(t-d_{nM})\end{bmatrix}^T,$$

$$\Omega_n=\begin{bmatrix}R_{4n} & * & * \\ -R_{4n}+X_n^T & 2R_{4n}-X_n^T-X_n & * \\ -X_n^T & X_n^T-R_{4n} & R_{4n}\end{bmatrix}.$$

According to the presented DSETS (9), it leads to

$$\sum_{n=0}^{2}\psi_n(t)<\lambda\phi(t). \tag{30}$$

By combining (30) and (27), it gives

$$\dot{V}(t)\le\dot{\tilde{\zeta}}^T(t)P\tilde{\zeta}(t)+\tilde{\zeta}^T(t)P\dot{\tilde{\zeta}}(t)+\sum_{n=0}^{2}\dot{V}_n(t)-(\rho+\lambda)\sum_{n=0}^{N}\psi_n(t), \tag{31}$$

which further yields

$$\dot{V}(t)\le\dot{\tilde{\zeta}}^T(t)P\tilde{\zeta}(t)+\tilde{\zeta}^T(t)P\dot{\tilde{\zeta}}(t)+\sum_{n=0}^{2}\dot{V}_n(t)+(\rho+\lambda)\sum_{n=0}^{2}\left(\delta_{nM}[*]\Phi_ny(l_kh-nh)-[*]\Phi_ne_n(t)\right) \tag{32}$$

for $\delta_n(lh)\le\delta_{nM}$.

Define the following augmented vector

$$\begin{aligned}\xi(t)=&[\dot{\tilde{\zeta}}^T(t),\tilde{\zeta}^T(t),\tilde{\zeta}^T(t-d_{0m}),\tilde{\zeta}^T(t-d_0(t)),\tilde{\zeta}^T(t-d_{0M}),g^T(t),\tilde{\zeta}^T(t-d_{1m}),\tilde{\zeta}^T(t-d_1(t)),\\&\tilde{\zeta}^T(t-d_{1M}),\tilde{\zeta}^T(t-d_{2m}),\tilde{\zeta}^T(t-d_2(t)),\tilde{\zeta}^T(t-d_{2M}),e_0^T(t),e_1^T(t),e_2^T(t),\varsigma^T(t),f^T(t)]^T.\end{aligned} \tag{33}$$

For the filtering error system (19) and the constructed relax matrix $\mathscr{G}$, it yields

$$\sum_{i=1}^{r}\sum_{j=1}^{r}\mu_i\mu_j^k\xi^T(t)(\mathscr{G}S_{ij}+S_{ij}^T\mathscr{G}^T)\xi(t)=0, \tag{34}$$

where

$$S_{ij}=\big[-I,\ \mathscr{A}_{ij},\ 0,\ \mathscr{B}_{dj},\ 0,\ \mathscr{B}_{gi},$$
$$0,\ 0,\ 0,\ 0,\ 0,\ 0,\ \mathscr{B}_j,\ 0,\ 0,\ 0,\ \alpha(t)\mathscr{B}_j\big],$$
$$\mathscr{G}=\left[G^T,\beta G^T,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0\right]^T.$$

Taking the mathematical expectation of (34) results in

$$\mathbb{E}\left\{\sum_{i=1}^{r}\sum_{j=1}^{r}\mu_i\mu_j^k\xi^T(t)(\mathscr{G}S_{ij}+S_{ij}^T\mathscr{G}^T)\xi(t)\right\}$$

$$= \mathbb{E}\left\{ \sum_{i=1}^{r}\sum_{j=1}^{r} \mu_i \mu_j^k \xi^T(t)(\mathscr{G}\mathscr{S}_{ij} + \mathscr{S}_{ij}^T \mathscr{G}^T)\xi(t) \right\} = 0, \tag{35}$$

where

$$\mathscr{S}_{ij} = \big[-I,\ \mathscr{A}_{ij},\ 0,\ \mathscr{B}_{dj},\ 0,\ \mathscr{B}_{gi},$$
$$0,\ 0,\ 0,\ 0,\ 0,\ 0,\ \mathscr{B}_j,\ 0,\ 0,\ 0,\ \bar{\alpha}_1\mathscr{B}_j \big].$$

From (32) and (35), we have

$$\mathbb{E}\left\{ \dot{V}(t) + \varsigma^T(t)\varsigma(t) - \gamma^2 g^T(t)g(t) \right\} \le \mathbb{E}\left\{ \sum_{i=1}^{r}\sum_{j=1}^{r} \mu_i \mu_j^k \xi^T(t)\Xi^{ij}\xi(t) \right\}. \tag{36}$$

In terms of $\sum_{j=1}^{r} \mu_j = \sum_{j=1}^{r} \mu_j^k = 1$, it yields

$$\sum_{i=1}^{r}\sum_{j=1}^{r} \mu_i(\mu_j - \mu_j^k)\Gamma_i = \sum_{i=1}^{r} \mu_i(\sum_{j=1}^{r} \mu_j - \sum_{j=1}^{r} \mu_j^k)\Gamma_i = 0. \tag{37}$$

By combining (36) and (37), one gets

$$\begin{aligned}
\mathbb{E}\left\{ \sum_{i=1}^{r}\sum_{j=1}^{r} \mu_i \mu_j^k \xi^T(t)\Xi^{ij}\xi(t) \right\} &= \mathbb{E}\left\{ \sum_{i=1}^{r}\sum_{j=1}^{r} [\mu_i \mu_j^k \xi^T(t)\Xi^{ij}\xi(t) + \mu_i(\mu_j - \mu_j^k)\xi^T(t)\Gamma_i\xi(t)] \right\} \\
&= \mathbb{E}\left\{ \sum_{i=1}^{r}\sum_{j=1}^{r} [\mu_i \mu_j^k \xi^T(t)(\Xi^{ij} - \Gamma_i)\xi(t) + \mu_i\mu_j \xi^T(t)\Gamma_i\xi(t)] \right\}.
\end{aligned} \tag{38}$$

By considering $\mu_j^k \ge \rho_j \mu_j$ and $\Xi^{ij} - \Gamma_i < 0$, it gives

$$\begin{aligned}
\mathbb{E}\left\{ \sum_{i=1}^{r}\sum_{j=1}^{r} \mu_i \mu_j^k \xi^T(t)\Xi^{ij}\xi(t) \right\} &= \mathbb{E}\left\{ \sum_{i=1}^{r}\sum_{j=1}^{r} [\mu_i \mu_j^k \xi^T(t)\Xi^{ij}\xi(t) + \mu_i(\mu_j - \mu_j^k + \rho_j\mu_j - \rho_j\mu_j)\xi^T(t)\Gamma_i\xi(t)] \right\} \\
&= \mathbb{E}\left\{ \sum_{i=1}^{r}\sum_{j=1}^{r} [\mu_i\mu_j \xi^T(t)(\Gamma_i - \rho_j\Gamma_i + \rho_j\Xi^{ij})\xi(t) \right. \\
&\quad \left. + (-\mu_i\mu_j^k + \mu_i\mu_j\rho_j)\xi^T(t)\Gamma_i\xi(t) + (\mu_i\mu_j^k - \mu_i\mu_j\rho_j)\xi^T(t)\Xi^{ij}\xi(t)] \right\} \\
&= \mathbb{E}\left\{ \sum_{i=1}^{r}\sum_{j=1}^{r} [\mu_i\mu_j \xi^T(t)(\Gamma_i - \rho_j\Gamma_i + \rho_j\Xi^{ij})\xi(t) + \mu_i(\mu_j^k - \rho_j\mu_j)\xi^T(t)(\Xi^{ij} - \Gamma_i)\xi(t)] \right\} \\
&\le \mathbb{E}\left\{ \sum_{i=1}^{r} \mu_i^2 \xi^T(t)(\rho_i\Xi^{ii} - \rho_i\Gamma_i + \Gamma_i)\xi(t) + \sum_{i=1}^{r} \mu_i(\mu_j^k - \rho_j\mu_j)\xi^T(t)(\Xi^{ij} - \Gamma_i)\xi(t) \right. \\
&\quad \left. + \sum_{i=1}^{r}\sum_{i<j}^{r} \xi^T(t)(\rho_j\Xi^{ij} + \rho_i\Xi^{ji} - \rho_j\Gamma_i - \rho_i\Gamma_j + \Gamma_i + \Gamma_j)\xi(t) \right\}.
\end{aligned} \tag{39}$$

According to the conditions (23)-(25), it leads to

$$\mathbb{E}\left\{ \dot{V}(t) + \varsigma^T(t)\varsigma(t) - \gamma^2 g^T(t)g(t) \right\} < 0, \tag{40}$$

which ensures $\mathbb{E}\{\dot{V}(t)\} < 0$ for $g(t) = 0$.

By integrating (40) over $[0, +\infty)$, one has

$$\mathbb{E}\{V(\infty) - V(0)\} < \mathbb{E}\left\{ \int_0^\infty (\gamma^2 g^T(t)g(t) - \varsigma^T(t)\varsigma(t))dt \right\}. \tag{41}$$

In addition, for $g(t) \neq 0$ and zero initial state, it yields $\mathbb{E}\left\{ \int_0^\infty \varsigma^T(t)\varsigma(t)dt \right\} \le \mathbb{E}\left\{ \int_0^\infty \gamma^2 g^T(t)g(t) \right\}$ based on (41). Then, the filtering error system is stable in mean square sense with given H_∞ index γ. □

Remark 4. It is noted that the complexity of the conditions in the above theorem are related to the number of historical sampled outputs N. In order to simplify the derivations, $N = 2$ is considered in this work to show the effectiveness of the proposed DSETS. Meanwhile, the similar results for different N can be obtained easily based on the above theorem.

Based on the results of Theorem 1, we are in position to design the filter gains and triggering matrices.

Theorem 2. *For given scalars h, $\bar{d}$, d_{0m}, d_{0M}, d_{1m}, d_{1M}, d_{2m}, d_{2M}, κ, $\bar{\alpha}_1$, β, γ, δ_{0M}, δ_{1M}, δ_{2M}, under the DSETS (9), the filtering error system (20) is stable in mean square sense with prescribed H_∞ performance index γ if there exist symmetric matrices $P > 0$, $R_{1n} > 0$, $R_{2n} > 0$, $R_{3n} > 0$, $R_{4n} > 0$, $\Phi_n > 0$, $\begin{bmatrix} R_{4n} & X_n \\ * & R_{4n} \end{bmatrix} > 0$ and matrices $\tilde{\Gamma}_i$ $(i = 1, 2, ..., r)$, X_n, $n = 0, 1, 2$, G_1, G_2 and G_3 such that*

$$\tilde{\Xi}^{ij} - \tilde{\Gamma}_i < 0, \tag{42}$$

$$\rho_i \tilde{\Xi}^{ii} - \rho_i \tilde{\Gamma}_i + \tilde{\Gamma}_i < 0 \; (i = j), \tag{43}$$

$$\rho_j \tilde{\Xi}^{ij} + \rho_i \tilde{\Xi}^{ji} - \rho_j \tilde{\Gamma}_i - \rho_i \tilde{\Gamma}_j + \tilde{\Gamma}_i + \tilde{\Gamma}_j \le 0 \; (i < j), \tag{44}$$

where

$$\tilde{\Xi}^{ij} = \begin{bmatrix} \tilde{\Xi}_1^{ij} & * \\ \tilde{\Xi}_2^{ij} & \Xi_3 \end{bmatrix},$$

$$\tilde{\Xi}_1^{ij} = \begin{bmatrix} \Xi_{11} & * & * & * & * & * & * & * \\ \tilde{\Xi}_{21}^{ij} & \tilde{\Xi}_{22} & * & * & * & * & * & * \\ 0 & R_{30} & \Xi_{33} & * & * & * & * & * \\ \ni_2^T & \beta \ni_2^T & \Xi_{43} & \Xi_{44} & * & * & * & * \\ 0 & 0 & X_0^T & \Xi_{54} & \Xi_{55} & * & * & * \\ \ni_3^T & \beta \ni_3^T & 0 & 0 & 0 & -\gamma^2 I & * & * \\ 0 & R_{31} & 0 & 0 & 0 & 0 & \Xi_{77} & * \\ 0 & 0 & 0 & 0 & 0 & 0 & \Xi_{87} & \Xi_{88} \end{bmatrix},$$

$$\tilde{\Xi}_{21}^{ij} = \ni_1^T - \beta G + P,$$

$$\begin{aligned} \tilde{\Xi}_{22} = & R_{10} + R_{11} + R_{12} + R_{20} + R_{21} + R_{22} - R_{30} - R_{31} \\ & - R_{32} + \beta \ni_1^T + \beta \ni_1 + H^T C^T F^T F C H, \end{aligned}$$

$$\tilde{\Xi}_2^{ij} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & X_1^T & \Xi_{98} \\ 0 & R_{32} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \ni_4^T & \beta \ni_4^T & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \mathscr{L}_0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \bar{\alpha}_1 \ni_4^T & \beta \bar{\alpha}_1 \ni_4^T & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$\ni_1 = \begin{bmatrix} G_1 A_i & \mathscr{G}_{Aj} \\ G_3 A_i & \kappa \mathscr{G}_{Aj} \end{bmatrix}, \quad \ni_2 = \begin{bmatrix} \mathscr{G}_{Bj} C & 0 \\ \kappa \mathscr{G}_{Bj} C & 0 \end{bmatrix}, \quad \ni_3 = \begin{bmatrix} G_1 B_i \\ G_3 B_i \end{bmatrix}, \quad \ni_4 = \begin{bmatrix} \mathscr{G}_{Bj} \\ \kappa \mathscr{G}_{Bj} \end{bmatrix}.$$

Then, the filter gains are computed as $A_{fj} = G_2^{-1} \mathscr{G}_{Aj}$, $B_{fj} = G_2^{-1} \mathscr{G}_{Bj}$, $C_f = \mathscr{C}_f$.

Proof. On the basis of Theorem 1, the matrix G is constructed as

$$G = \begin{bmatrix} G_1 & G_2 \\ G_3 & \kappa G_2 \end{bmatrix}. \tag{45}$$

Define two new variables $\mathscr{G}_{Aj} = G_2 A_{fj}$ and $\mathscr{G}_{Bj} = G_2 B_{fj}$. Then, some matrices in the conditions in Theorem 1 are rewritten as

$$\begin{aligned} G \mathscr{A}_{ij} &= \begin{bmatrix} G_1 A_i & \mathscr{G}_{Aj} \\ G_3 A_i & \kappa \mathscr{G}_{Aj} \end{bmatrix}, \; G \mathscr{B}_{dj} = \begin{bmatrix} \mathscr{G}_{Bj} C & 0 \\ \kappa \mathscr{G}_{Bj} C & 0 \end{bmatrix}, \\ G \mathscr{B}_{gi} &= \begin{bmatrix} G_1 B_i \\ G_3 B_i \end{bmatrix}, \; G \mathscr{B}_j = \begin{bmatrix} \mathscr{G}_{Bj} \\ \kappa \mathscr{G}_{Bj} \end{bmatrix}. \end{aligned} \tag{46}$$

Substituting the above matrices (46) into the conditions (23)-(25), one can obtain the conditions (42)-(44). Moreover, the filtering gains are calculated by

Table 1
WTS Parameters.

Parameter	Value	Parameter	Value
J	$5\times10^{-3} N\cdot m$	R	0.5m
$\mathfrak{J}$	$1.2kg/m^2$	Y_f	0.16Wb
ϵ	$6^{-3} N\cdot m\cdot s/rad$	$\mathfrak{R}_s$	1.13Ω
$\mathfrak{L}_d=\mathfrak{L}_q$	2.7×10^{-3}H	M_1	-10
P_n	8	M_2	10

$$A_{fj}=G_2^{-1}\mathscr{G}_{Aj},\quad B_{fj}=G_2^{-1}\mathscr{G}_{Bj},\quad C_f=\mathscr{C}_f.\quad \square \tag{47}$$

4. Simulation example

In the simulation, the system parameters are chosen the same with [4] and shown in Table 1.

In addition, different from the existing T-S fuzzy WTSs modeled under the maximum power case of generator, the time-varying power output related to $\Theta_p(\chi(t),\nu)$ and $\chi(t)$ is considered. According to relationship between $\Theta_p(\chi(t),\nu)$ and $\chi(t)$ shown in [35], their values belong to $\Theta_p(\chi(t),\nu)\in[0.14,\ 0.48]$ and $\chi(t)\in[5.5,\ 8.1]$. Therefore, the bounds of $\vartheta_2(t)=T_0(t)w_g(t)$ can be computed as $M_3=-1.55\times10^{-4}$ and $M_4=1.7\times10^{-3}$.

According to the system parameters, and the stabilization controller $\mathscr{K}=\begin{bmatrix}0.1 & -0.2 & 0.3\\ -0.1 & -0.1 & 0.1\end{bmatrix}$, the resulting closed-loop system parameters are derived and selected as:

$$A_1=\begin{bmatrix}-1.1690 & 384 & 0\\ -437.037 & -492.5926 & 191.1111\\ -37.037 & 42.963 & -381.4815\end{bmatrix}, B_1=\begin{bmatrix}10\\ 5\\ 0\end{bmatrix},$$
$$A_2=\begin{bmatrix}-0.8601 & 384 & 0\\ -437.037 & -492.5926 & 191.1111\\ -37.037 & 42.9630 & -381.4815\end{bmatrix}, B_2=B_1,$$
$$A_3=\begin{bmatrix}-1.2310 & 384 & 0\\ -437.037 & -492.5926 & 31.1111\\ -37.037 & -117.037 & -381.4815\end{bmatrix}, B_3=B_1,$$
$$A_4=\begin{bmatrix}-1.5399 & 384 & 0\\ -437.037 & -492.5926 & 31.1111\\ -37.037 & -117.037 & -381.4815\end{bmatrix}, B_4=B_1,$$
$$C=\begin{bmatrix}1 & 0 & 0\end{bmatrix},\ \ L=\begin{bmatrix}1 & 0 & 0\end{bmatrix}.$$

The upper bound of communication delay $d(t)$ is $\bar{d}=0.01s$, and then we have $d_{0m}=0$, $d_{0M}=0.01$, $d_{1m}=0.01$, $d_{1M}=0.02$, $d_{2m}=0.02$, $d_{2M}=0.03$. The deception attack is considered as $f(t)=0.4\tanh(y(t))$ with the upper bound $F=0.4$ and the attack probability $\bar{\alpha}_1=0.4$. By selecting the H_∞ performance index $\gamma=0.5$, the sampling period $h=0.001s$, $\rho_1=\rho_2=0.9$, $\rho_3=\rho_4=0.8$, $\kappa=0.8$, $\beta=100$, $\delta_{0M}=0.2$, $\delta_{1M}=0.25$, $\delta_{2M}=0.3$, $\delta_{0m}=\delta_{1m}=\delta_{2m}=0.01$, $\rho=10$ and $\lambda=1$, the filter gains and triggering matrices are solved by the conditions in Theorem 2 as:

$$A_{f1}=\begin{bmatrix}-81.7118 & 382.2605 & 45.9453\\ -276.8115 & -470.0202 & 118.4243\\ -21.3586 & -33.6373 & -229.1419\end{bmatrix},\ B_{f1}=\begin{bmatrix}-0.1217\\ 0.0807\\ 0.0220\end{bmatrix},$$
$$A_{f2}=\begin{bmatrix}-81.4213 & 382.8825 & 43.9002\\ -277.1802 & -471.2154 & 114.9926\\ -21.2805 & -34.1347 & -230.6150\end{bmatrix},\ B_{f2}=\begin{bmatrix}-0.1195\\ 0.0697\\ 0.0150\end{bmatrix},$$
$$A_{f3}=\begin{bmatrix}-79.3965 & 382.8308 & 24.8882\\ -276.3782 & -468.5242 & 91.9536\\ -21.8027 & -36.7193 & -230.6663\end{bmatrix},\ B_{f3}=\begin{bmatrix}-0.1521\\ 0.0585\\ -0.0002\end{bmatrix},$$
$$A_{f4}=\begin{bmatrix}-80.6052 & 383.9292 & 28.5569\\ -275.9081 & -469.2693 & 85.6995\\ -21.8062 & -37.2931 & -232.7477\end{bmatrix},\ B_{f4}=\begin{bmatrix}-0.1309\\ 0.0285\\ -0.0091\end{bmatrix},$$
$$C_f=\begin{bmatrix}-0.4263 & 0.2481 & -0.0280\end{bmatrix},\ \ \Phi_0=0.0080,\ \ \Phi_1=0.1496,\ \ \Phi_2=0.1247.$$

The external disturbance is considered as $g(t)=\begin{cases}\mathscr{U}(t), & 0<t<0.2s\\ 0, & t\geq 0.2s\end{cases}$, and $\mathscr{U}(t)$ is a random variable obeying $|\mathscr{U}(t)|\leq 10$. The initial state of the system is $\zeta(0)=\begin{bmatrix}5 & -2 & 3\end{bmatrix}^T$, and the initial state of filter is $\zeta_f(0)=\begin{bmatrix}4 & -1 & 2\end{bmatrix}^T$. In the case where deception

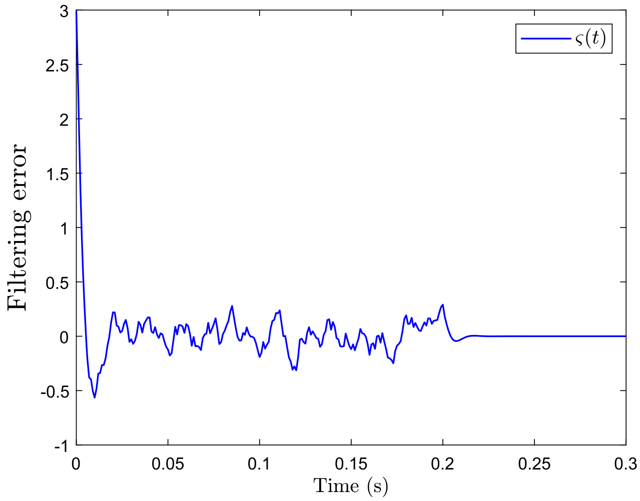

Fig. 2. The filtering error under DSETS.

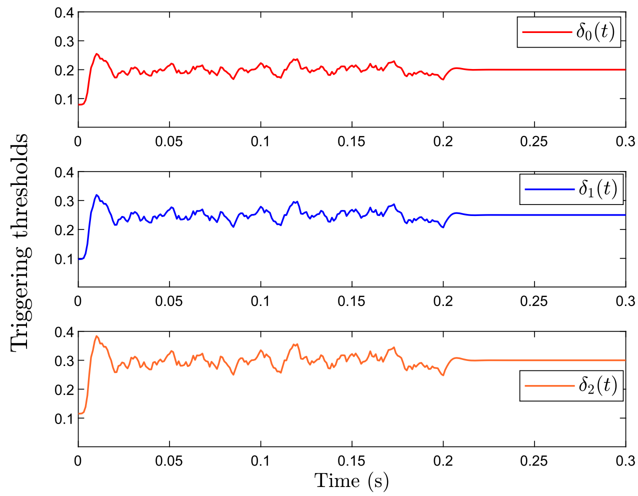

Fig. 3. The dynamic triggering thresholds $\delta_n(t)$ under DSETS. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

Table 2
The amount of triggering times.

Methods	Amount
Our DSETS	39
Existing ETS [30]	109
Normal ETS [21]	120

attacks happening, the curve of filtering error is depicted in the Fig. 2, and the dynamic triggering thresholds, the triggering instants are drawn in Fig. 3 and Fig. 4, respectively. These results denote that the proposed event-triggered filtering method is effective to stabilize the filtering error WTS once the system is invaded by deception attacks.

In the following, the advantage of the presented DSETS over the existing ETSs [30,21] is illustrated. According to the above chosen parameters and derived filter gains, the filtering errors and triggering instants obtained by three ETSs are shown in Fig. 5, Fig. 6 and Table 2, respectively.

It is observed from Fig. 5 and Fig. 6 that the responses of filtering error under three different ETSs are very similar, while the triggering times generated by our DSETS are decreased significantly. As shown in Table 2, the proposed DSETS decreases 64.2% and 67.5% transmissions compared to the existing ETS [30] and normal ETS [21], respectively. This indicates that the presented DSETS utilizing an auxiliary dynamic variable and some past measured outputs has better ability to decrease unnecessary triggering events and save more network resources than some existing ETSs.

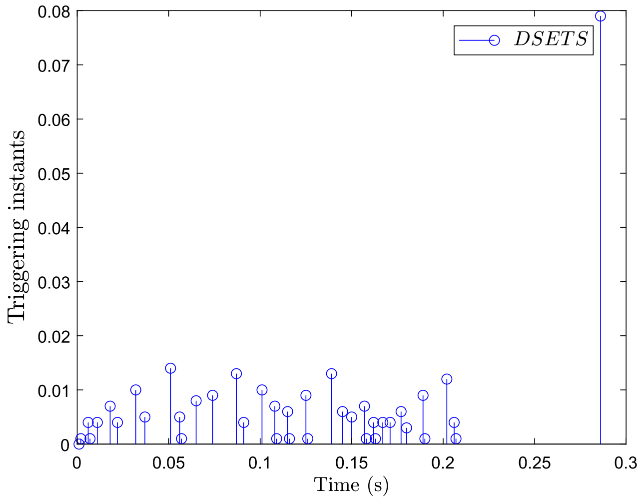

Fig. 4. The triggering intervals under DSETS.

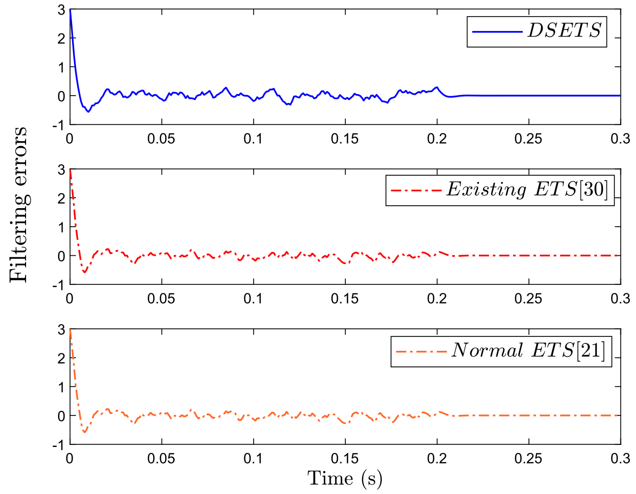

Fig. 5. The filtering error under different ETSs.

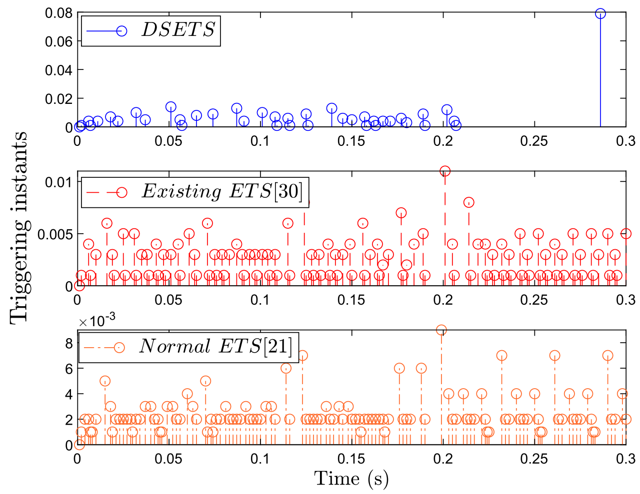

Fig. 6. The triggering intervals under different ETSs.

5. Conclusion

This paper concentrates on the event-triggered H_∞ filter design for T-S fuzzy WTS against deception attacks and communication delays. In order to reduce communication and computation load, an innovative DSETS has been presented whose triggering rule is constructed by using some previous sampled measurements and an auxiliary dynamic variable. Meanwhile, compared with some ETSs with constant triggering thresholds, our DSETS includes dynamic triggering thresholds, which can be adjusted along with system outputs adaptively. Resorting to the Lyapunov–Krasovskii method, some novel co-design conditions for solving H_∞ filter gains and triggering matrices are deduced. The merits of the provided theory are demonstrated via some simulations.

CRediT authorship contribution statement

Shen Yan: Writing – review & editing, Writing – original draft, Supervision, Investigation, Funding acquisition, Conceptualization. **Xinyi Yang:** Writing – original draft, Methodology, Investigation. **Zhou Gu:** Writing – review & editing, Methodology, Investigation. **Xiangpeng Xie:** Writing – review & editing, Investigation, Formal analysis. **Fan Yang:** Writing – review & editing, Software, Investigation.

Declaration of competing interest

The authors declare that no conflicts of interest exist in the submission of this manuscript.

Data availability

No data was used for the research described in the article.

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References

[1] N.A. Orlando, M. Liserre, R.A. Mastromauro, A. Dell'Aquila, A survey of control issues in PMSG-based small wind-turbine systems, IEEE Trans. Ind. Inform. 9 (3) (2013) 1211–1221.
[2] M. Yessef, B. Bossoufi, M. Taoussi, A. Lagrioui, H. Chojaa, S. Lee, B.G. Kang, M. Abouhawwash, Improving the maximum power extraction from wind turbines using a second-generation CRONE controller, Energies 15 (10) (2022) 3644.
[3] M. Sun, Y. Sun, L. Chen, Z. Zou, Y. Min, R. Liu, F. Xu, Y. Wu, Novel temporary frequency support control strategy of wind turbine generator considering coordination with synchronous generator, IEEE Trans. Sustain. Energy 13 (2) (2022) 1011–1020.
[4] S. Yan, Z. Gu, J.H. Park, X. Xie, Adaptive memory-event-triggered static output control of T–S fuzzy wind turbine systems, IEEE Trans. Fuzzy Syst. 30 (9) (2021) 3894–3904.
[5] M. Yessef, B. Bossoufi, M. Taoussi, A. Lagrioui, H. Chojaa, Overview of control strategies for wind turbines: ANNC, FLC, SMC, BSC, and PI controllers, Wind Eng. 46 (6) (2022) 1820–1837.
[6] H. Chojaa, A. Derouich, O. Zamzoum, A. Watil, M. Taoussi, A.Y. Abdelaziz, Z.M.S. Elbarbary, M.A. Mossa, Robust control of DFIG-based WECS integrating an energy storage system with intelligent MPPT under a real wind profile, IEEE Access 11 (2023) 90065–90083.
[7] A. Loulijat, H. Chojaa, M.E. marghichi, N. Ettalabi, A. Hilali, A. Mouradi, A.Y. Abdelaziz, Z.M.S. Elbarbary, M.A. Mossa, Enhancement of LVRT ability of DFIG wind turbine by an improved protection scheme with a modified advanced nonlinear control loop, Processes 11 (5) (2023) 1417.
[8] G. Zong, X. Sun, D. Yang, S. Su, K. Shi, Finite-time H_∞ control for switched fuzzy systems: a dynamic adaptive event-triggered control approach, Fuzzy Sets Syst. 464 (2023) 108475.
[9] V. Gandhi, Y.H. Joo, T–S fuzzy sampled-data control for nonlinear systems with actuator faults and its application to wind energy system, IEEE Trans. Fuzzy Syst. 30 (2) (2020) 462–474.
[10] S. Hwang, J.B. Park, Y.H. Joo, Disturbance observer-based integral fuzzy sliding-mode control and its application to wind turbine system, IET Control Theory Appl. 13 (12) (2019) 1891–1900.
[11] H. Badihi, Y. Zhang, P. Pillay, S. Rakheja, Fault-tolerant individual pitch control for load mitigation in wind turbines with actuator faults, IEEE Trans. Ind. Electron. 68 (1) (2020) 532–543.
[12] S. Yan, Z. Gu, J.H. Park, X. Xie, Sampled memory-event-triggered fuzzy load frequency control for wind power systems subject to outliers and transmission delays, IEEE Trans. Cybern. 53 (6) (2022) 4043–4053.
[13] A. Honarbari, S. Najafi-Shad, M. Saffari Pour, S.S.M. Ajarostaghi, A. Hassannia, MPPT improvement for PMSG-based wind turbines using extended Kalman filter and fuzzy control system, Energies 14 (22) (2021) 7503.
[14] A. Amini, M. Ghafouri, A. Mohammadi, M. Hou, A. Asif, K. Plataniotis, Secure sampled-data observer-based control for wind turbine oscillation under cyber attacks, IEEE Trans. Smart Grid 13 (4) (2022) 3188–3202.
[15] Z. Hu, S. Liu, W. Luo, L. Wu, Resilient distributed fuzzy load frequency regulation for power systems under cross-layer random denial-of-service attacks, IEEE Trans. Cybern. 52 (4) (2020) 2396–2406.
[16] H. Badihi, S. Jadidi, Z. Yu, Y. Zhang, N. Lu, Smart cyber-attack diagnosis and mitigation in a wind farm network operator, IEEE Trans. Ind. Inform. 19 (9) (2023) 9468–9478.
[17] Y. Tan, Y. Yuan, X. Xie, B. Niu, Dynamic event-triggered security control for networked TS fuzzy system with non-uniform sampling, Fuzzy Sets Syst. 452 (2023) 91–109.

[18] S. Yan, Z. Gu, J.H. Park, X. Xie, A delay-kernel-dependent approach to saturated control of linear systems with mixed delays, Automatica 152 (2023) 110984.
[19] S. Zhao, Q. Yang, P. Cheng, R. Deng, J. Xia, Adaptive resilient control for variable-speed wind turbines against false data injection attacks, IEEE Trans. Sustain. Energy 13 (2) (2022) 971–985.
[20] S. Zhao, J. Xia, R. Deng, P. Cheng, Q. Yang, X. Jiao, Dual-triggered adaptive torque control strategy for variable-speed wind turbine against denial-of-service attacks, IEEE Trans. Smart Grid 14 (4) (2023) 3072–3084.
[21] X. Zhang, Q.-L. Han, Event-based H_∞ filtering for sampled-data systems, Automatica 51 (2015) 55–69.
[22] Y. Liu, X. Zhao, J.H. Park, F. Fang, Fault-tolerant control for TS fuzzy systems with an aperiodic adaptive event-triggered sampling, Fuzzy Sets Syst. 452 (2023) 23–41.
[23] Z. Gu, X. Huang, X. Sun, X. Xie, J.H. Park, Memory-event-triggered tracking control for intelligent vehicle transportation systems: a leader-following approach, IEEE Trans. Intell. Transp. Syst. 25 (5) (2024) 4021–4031.
[24] G. Liu, Y. Pan, H.K. Lam, H. Liang, Event-triggered fuzzy adaptive quantized control for nonlinear multi-agent systems in nonaffine pure-feedback form, Fuzzy Sets Syst. 416 (2021) 27–46.
[25] S. Yan, Z. Gu, X. Xie, Adaptive critic learning control of nonlinear wind turbine systems via integral event-triggered scheme, IEEE Trans. Circuits Syst. II, Express Briefs (2024), https://doi.org/10.1109/TCSII.2024.3393982.
[26] L. An, G. Yang, C. Deng, C. Wen, Event-triggered reference governors for collisions-free leader-following coordination under unreliable communication topologies, IEEE Trans. Autom. Control 69 (4) (2024) 2116–2130, https://doi.org/10.1109/TAC.2023.3291654.
[27] P. Mani, Y.H. Joo, Fuzzy event-triggered control for back-to-back converter involved PMSG-based wind turbine systems, IEEE Trans. Fuzzy Syst. 30 (5) (2021) 1409–1420.
[28] G. Nagamani, Y.H. Joo, G. Soundararajan, R. Mohajerpoor, Robust event-triggered reliable control for TS fuzzy uncertain systems via weighted based inequality, Inf. Sci. 512 (2020) 31–49.
[29] S. Yan, M. Shen, S.K. Nguang, G. Zhang, L. Zhang, A distributed delay method for event-triggered control of T–S fuzzy networked systems with transmission delay, IEEE Trans. Fuzzy Syst. 27 (10) (2019) 1963–1973.
[30] L. Zhang, D. Zhang, S.K. Nguang, A.K. Swain, Z. Yu, Event-triggered output-feedback control for synchronization of delayed neural networks, IEEE Trans. Cybern. 53 (9) (2023) 5618–5630.
[31] M. Rosyadi, R. Takahashi, S.M. Muyeen, J. Tamura, Stabilization of fixed speed wind generator by using variable speed PM wind generator in multi-machine power system, J. Int. Conf. Electr. Mach. Syst. 2 (1) (2013) 111–119.
[32] K. Tan, S. Islam, Optimum control strategies in energy conversion of PMSG wind turbine system without mechanical sensors, IEEE Trans. Energy Convers. 19 (2) (2004) 392–399.
[33] C. Peng, M. Wu, X. Xie, Y. Wang, Event-triggered predictive control for networked nonlinear systems with imperfect premise matching, IEEE Trans. Fuzzy Syst. 26 (5) (2018) 2797–2806.
[34] P.G. Park, J.W. Ko, C. Jeong, Reciprocally convex approach to stability of systems with time-varying delays, Automatica 47 (1) (2011) 235–238.
[35] M. Rosyadi, S.M. Muyeen, R. Takahashi, J. Tamura, Stabilization of fixed speed wind generator by using variable speed PM wind generator in multi-machine power system, in: 2012 15th International Conference on Electrical Machines and Systems (ICEMS), 2012, pp. 1–6.