Decentralized Event-Triggered Control for Large-Scale Networked Fuzzy Systems

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***Abstract*—This paper addresses event-triggered data transmission in a class of large-scale networked nonlinear systems with transmission delays and nonlinear interconnections. Each nonlinear subsystem in the considered large-scale system is represented by a Takagi–Sugeno model, and exchanges its information through a digital channel. We propose an event-triggering mechanism, which determines when the premise variables and system states should be transmitted to the controller. Our goal is to design a decentralized event-triggered state-feedback fuzzy controller, such that the resulting closed-loop fuzzy control system is asymptotically stable while the measured information is transmitted to the controller as little as possible. By using the input delay and perturbed system approaches, the closed-loop sampled-data fuzzy system with event-triggered control is first reformulated into a continuous-time system with time-varying delay and extra disturbance. Then, based on the new model, we introduce a Lyapunov–Krasovskii functional with virtue of Wirtinger's inequality, where not all of the Lyapunov matrices are required to be positive definite. The codesign result is derived to obtain simultaneously the controller gains, sampled period, network delay, and event-triggered parameter in terms of a set of linear matrix inequalities. Finally, two simulation examples are provided to validate the advantage of the proposed method.**

***Index Terms*—Codesign, decentralized control, event-triggered control, large-scale networked Takagi–Sugeno (T–S) fuzzy systems.**

I. Introduction

With the rapid development of digital technology, in the feedback loops communication networks are often applied instead of point-to-point connections due to their great advantages, such as low cost, simple installation and maintenance, reduced weight, and power requirements [1]. Unfortunately, the network-induced imperfections, such as quantization errors, packet dropouts, and time delays, can degrade significantly the performance of the closed-loop control system and may even lead to instability [2]. Recently, networked control systems (NCSs) have received considerable attention, and lots of results on studying combinations of these imperfections are available in the open literature, see [3]–[7], and references therein. It is worth mentioning that the design of an NCS often requires tradeoffs among the network-induced imperfections. More specifically, these features of sending larger control-packets and requiring time-stamping of messages will reduce quantization errors and packet dropouts but typically result in transmitting larger or more packets and inducing larger transmission delays [8]. In that case, an important issue arises in the implementation of NCSs as to how to identify methods such that the limited network bandwidth can be more effectively utilized.

In many digital implementations of NCSs, computers are often required to execute control tasks comprising of sampling, quantizing, transmitting the output of the plant, and computing, implementing the control input. In the execution of control tasks, the conventional principle is based on time-triggered control in the sense that the control task is executed in a periodic manner, and it will bring collision or channel congestion or larger time delays in the network due to the limited communication bandwidth. Recently, interest is shown in the event-triggered control aiming at reduction in data transmissions. The working principle based on event-triggered control is to decide whether or not to transmit control signals in term of a given threshold [9]–[14]. In other words, the control signals are not always implemented in every sampling period. The idea of event-based control has appeared under a variety of names, such as event-triggered feedback [9]–[11], interrupt-based feedback [12], self-triggered feedback [13], and state-triggered feedback [14].

On the other hand, strong nonlinearities of plants bring severe difficulties in the analysis and synthesis of nonlinear systems. Recently, the so-called Takagi–Sugeno (T–S) model-based method is introduced to overcome the difficulties induced by nonlinearities [15]. Once a smooth nonlinear system is represented by the T–S fuzzy model, its advantages are twofold: 1) The T–S fuzzy model is capable of approximating the nonlinear system at any preciseness. 2) Based on the T–S fuzzy model, powerful linear control methods can be developed for its control problems. Over the past few decades, lots of important results on the control of T–S fuzzy systems have been reported

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in the open literature, such as function approximation [16], [17], stability analysis [18], [19], controller, and filtering design [20]–[28]. More recently, the event-triggered scheme has been proposed to investigate networked T–S fuzzy systems. Some results on the state-feedback controller design with event-triggered scheme for T–S fuzzy systems were proposed in [29], [30]. The works in [31]–[33] studied the event-triggering filter problem for T–S fuzzy systems. The above mentioned works, however, adopted the parallel distributed compensation (PDC) fuzzy controller/filter to event-design. In that case, the premise variables between the system and controller/filter are synchronous. Such a requirement may be impractical due to network-induced imperfections. Under the event-triggered scheme, although a more reasonable scenario with the asynchronous premise variables was considered in [34]–[36], it less effectively uses the limited network bandwidth because the premise variables are transmitted under the conventional time-triggered method. It is noted that event-triggered scheme with sampled-data control can be investigated in the framework of time delay systems by using the input delay approach [37]. The works in [29], [32]–[36] performed stability analysis for the closed-loop fuzzy systems with event-triggered control based on Lyapunov–Krasovskii functional (LKF), where all Lyapunov matrices were required to be positive definite. The obtained results may be conservative. In addition, a special class of large-scale nonlinear systems with linear interconnection matrix $\bar{A}_{ij}$ were investigated in [38]–[40]. The restrictive condition with linear interconnection is not always suitable for practical implementations.

Motivated by the above considerations, this paper studies the event-triggered control problem for large-scale networked nonlinear systems with transmission delays and nonlinear interconnections. Each nonlinear subsystem in the considered large-scale system is represented by a T–S model and exchanges its information through a digital channel. Our considered scheme is decentralized event-triggered control in the sense that each subsystem is able to make broadcast decisions by using its locally sampled data when a prescribed event is triggered. We will propose an event-triggering mechanism (ETM), which determines when the premise variables and system states should be transmitted to the controller. By using the input delay and perturbed system approaches, the closed-loop sampled-data fuzzy system with event-triggered control is reformulated into a continuous-time system with time-varying delay and extra disturbance. Then, based on the new model, we introduce a LKF with virtue of Wirtinger's inequality, where not all of the Lyapunov matrices are required to be positive definite. The codesign problem consisting of the controller gains, sampled period, network delay, and event-triggered parameter can be solved in terms of a set of linear matrix inequalities (LMIs). Finally, two simulation examples are provided to validate the advantage of the proposed methods.

The main contributions of this paper are summarized as below:

1) The problem of decentralized event-triggered control for large-scale T–S fuzzy systems is studied for the first time.
2) We propose a novel event-triggered scheme, where the premise variables and system states are examined by an ETM, before they are transmitted to the controller. Compared with the method proposed in [30]–[36], the proposed triggered scheme significantly reduces data transmissions in communication networks, and can be easily extended to the event-triggered output feedback control for large-scale fuzzy systems.
3) We introduce a LKF with virtue of Wirtinger's inequality, where not all of the Lyapunov matrices are required to be positive definite. Compared with the method proposed in [38], [39], less conservative results to the event-triggered controller design of the large-scale fuzzy system are derived in terms of LMIs.
4) Instead of a special class of large-scale fuzzy systems with linear interconnection matrix $\bar{A}_{ij}$ in [38]–[40], we consider a general class of large-scale fuzzy systems, where nonlinearities appear in interconnections to other subsystems.

It is noted that control problems for the large-scale fuzzy systems with nonlinear interconnections are more complex and challenging than those with linear interconnections in [38]–[40].

Notations: $\Re^n$ is the n-dimensional Euclidean space and $\Re^{n\times m}$ is the set of $n \times m$ matrices. Matrix $P > 0\,(\geq 0)$ means that matrix P is positive definite (positive semidefinite). $\mathrm{Sym}\{A\}$ denotes $A + A^T$. $\mathbf{I}_n$ and $0_{m\times n}$ denote the $n \times n$ identity matrix and $m \times n$ zero matrix, respectively. $\mathbb{N}$ represents the set $[0, 1, \ldots]$. The subscripts n and $m \times n$ are omitted when the size is irrelevant or can be determined from the context. For a matrix $A \in \Re^{n\times n}$, A^{-1} and A^T denote the inverse and transpose of the matrix A, respectively. $\mathrm{diag}\{\cdots\}$ denotes a block-diagonal matrix. The notation $\|\cdot\|$ is the Euclidean vector norm. The notation $\star$ represents the terms induced by symmetry.

II. Model Description and Problem formulation

Consider a continuous-time large-scale nonlinear system containing N subsystems with interconnection, where the ith nonlinear subsystem is represented by the following T–S fuzzy model:

Plant Rule $\mathscr{R}_i^l$: **IF** $\zeta_{i1}(t)$ is $\mathscr{F}_{i1}^l$ and $\zeta_{i2}(t)$ is $\mathscr{F}_{i2}^l$ and $\cdots$ and $\zeta_{ig}(t)$ is $\mathscr{F}_{ig}^l$, **THEN**

$$\dot{x}_i(t) = A_{il}x_i(t) + B_{il}u_i(t) + \sum_{\substack{j=1\\ j\neq i}}^{N} \bar{A}_{ijl}x_j(t), \tag{1}$$

where $l \in \mathscr{L}_i := \{1, 2, \ldots, r_i\}$, $i \in \mathcal{N} := \{1, 2, \ldots, N\}$, N is the number of the subsystems. For the ith subsystem, $\mathscr{R}_i^l$ is the lth fuzzy inference rule; r_i is the number of inference rules; $\mathscr{F}_{i\phi}^l(\phi = 1, 2, \ldots, g)$ are fuzzy sets; $x_i(t) \in \Re^{n_{\mathrm{xi}}}$ and $u_i(t) \in \Re^{n_{\mathrm{ui}}}$ denote the system state and control input, respectively; $\zeta_i(t) := [\zeta_{i1}(t), \zeta_{i2}(t), \ldots, \zeta_{ig}(t)]$ are the measurable variables; A_{il} and B_{il} are the lth local model; $\bar{A}_{ijl}$ denotes the interconnected matrix of the ith and jth subsystems for the lth local model.

Define the inferred fuzzy set $\mathscr{F}_i^l := \prod_{\phi=1}^{g} \mathscr{F}_{i\phi}^l$ and normalized membership function $\mu_{il}\left[\zeta_i(t)\right]$, it yields

$$\begin{cases} \mu_{il}\left[\zeta_i(t)\right] := \dfrac{\prod_{\phi=1}^{g} \mu_{il\phi}\left[\zeta_{i\phi}(t)\right]}{\sum_{\varsigma=1}^{r_i}\prod_{\phi=1}^{g} \mu_{i\varsigma\phi}\left[\zeta_{i\phi}(t)\right]} \geq 0 \\ \sum_{l=1}^{r_i} \mu_{il}\left[\zeta_i(t)\right] = 1, \end{cases} \tag{2}$$

where $\mu_{il\phi}\left[\zeta_{i\phi}(t)\right]$ is the grade of membership of $\zeta_{i\phi}(t)$ in $\mathscr{F}_{i\phi}^l$. In the following, we will denote $\mu_{il} := \mu_{il}\left[\zeta_i(t)\right]$ for brevity.

By fuzzy blending, the ith global T–S fuzzy dynamic model is obtained by

$$\dot{x}_i(t) = A_i(\mu_i)x_i(t) + B_i(\mu_i)u_i(t) + \sum_{\substack{j=1 \\ j\neq i}}^{N} \bar{A}_{ij}(\mu_i)x_j(t) \tag{3}$$

where

$$\begin{cases} A_i(\mu_i) := \sum_{l=1}^{r_i} \mu_{il}A_{il}, B_i(\mu_i) := \sum_{l=1}^{r_i} \mu_{il}B_{il} \\ \bar{A}_{ij}(\mu_i) := \sum_{l=1}^{r_i} \mu_{il}\bar{A}_{ijl}. \end{cases} \tag{4}$$

Remark 2.1: Instead of a special class of large-scale fuzzy systems with linear interconnection matrix $\bar{A}_{ij}$ in [38]–[40], this paper considers a general class of large-scale fuzzy systems in (1), where nonlinearities appear in interconnections to other subsystems. It is noted that control problems for the large-scale fuzzy system (1) with nonlinear interconnections are more complex and challenging than those with linear interconnections in [38]–[40].

Before moving on, the following assumptions are firstly required.

Assumption 2.1: The sampler in each subsystem is clock-driven. Let h_i denote the upper bound of sampling intervals, we have

$$t_{k+1}^i - t_k^i \leq h_i, k \in \mathbb{N} \tag{5}$$

where $h_i > 0$.

Assumption 2.2: Assume that each subsystem in the large-scale system (1) is closed by a communication channel. The sampled signals at the instant t_k^i are transmitted over the communication network inducing a constant time delay $\tau_i \geq 0$.

Assumption 2.3: The zero-order-hold (ZOH) is event-driven, and it uses the latest sampled-data signals and holds them until the next transmitted data come.

It is noted that in the context of NCSs, the traditionally time-triggered implementation is undesirable due to the existence of the limit communication bandwidth. Here, in order to reduce data transmissions, inspired by [9], we will propose an ETM in the sense that it determines when information should be transmitted to the controller. Assume that the premise variable $\zeta_i(t)$ and the system state $x_i(t)$ are measurable, in that case both $\zeta_i(t)$ and $x_i(t)$ involve in the sampled-data measurement, event-triggered control, and network-induced delay. Now, without loss of generality, we further assume that both $\zeta_i(t)$ and $x_i(t)$ are packed, transmitted, and updated at the same time. Then, a decentralized event-triggered state-feedback fuzzy controller can be given by

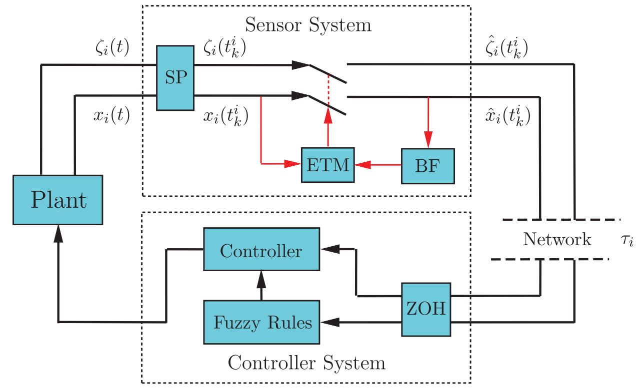

Fig. 1. Event-triggered state-feedback fuzzy controller.

Controller Rule $\mathscr{R}_i^s$: **IF** $\hat{\zeta}_{i1}(t_k^i - \tau_i)$ is $\mathscr{F}_{i1}^s$ and $\hat{\zeta}_{i2}(t_k^i - \tau_i)$ is $\mathscr{F}_{i2}^s$ and $\cdots$ and $\hat{\zeta}_{ig}(t_k^i - \tau_i)$ is $\mathscr{F}_{ig}^s$, **THEN**

$$u_i(t) = K_{is}\hat{x}_i(t_k^i - \tau_i), t \in [t_k^i, t_{k+1}^i) \tag{6}$$

where $K_{is} \in \Re^{n_u \times n_x}, s \in \mathscr{J}_i, i \in \mathcal{N}$ are controller gains to be determined; $\hat{\zeta}_i(t_k^i - \tau_i) := [\hat{\zeta}_{i1}(t_k^i - \tau_i), \hat{\zeta}_{i2}(t_k^i - \tau_i), \ldots, \hat{\zeta}_{ig}(t_k^i - \tau_i)]$; $\hat{\zeta}_i(t_k^i - \tau_i)$ and $\hat{x}_i(t_k^i - \tau_i)$ denote the updating signals in the fuzzy controller.

Similarly, the overall event-triggered state-feedback fuzzy controller is

$$u_i(t) = K_i(\hat{\mu}_i)\hat{x}_i(t_k^i - \tau_i), t \in [t_k^i, t_{k+1}^i) \tag{7}$$

where

$$\begin{cases} K_i(\hat{\mu}_i) := \sum_{s=1}^{r_i} \hat{\mu}_{is}\left[\hat{\zeta}_i(t_k^i - \tau_i)\right]K_{is} \\ \sum_{s=1}^{r_i} \hat{\mu}_{is}\left[\hat{\zeta}_i(t_k^i - \tau_i)\right] = 1, \\ \hat{\mu}_{is}\left[\hat{\zeta}_i(t_k^i - \tau_i)\right] := \dfrac{\prod_{\phi=1}^{g} \hat{\mu}_{is\phi}\left[\hat{\zeta}_{i\phi}(t_k^i - \tau_i)\right]}{\sum_{\varsigma=1}^{r_i}\prod_{\phi=1}^{g} \hat{\mu}_{i\varsigma\phi}\left[\hat{\zeta}_{i\phi}(t_k^i - \tau_i)\right]} \geq 0. \end{cases} \tag{8}$$

In the following, we will denote $\hat{\mu}_{is} := \hat{\mu}_{is}[\hat{\zeta}_i(t_k^i - \tau_i)]$ for brevity.

Remark 2.2: It is noted that the decentralized event-triggered fuzzy controller reduces to an PDC one when $\mu_{il} = \hat{\mu}_{il}$. However, the premise variables of the fuzzy controller (7) undergo sampled-data measurement, event-triggered control, and network-induced delay. In such circumstances, the asynchronous variables between μ_{il} and $\hat{\mu}_{il}$ are more realistic. As pointed out in [46], when the knowledge between μ_{il} and $\hat{\mu}_{il}$ is unavailable, the condition $\mu_{il} \neq \hat{\mu}_{il}$ generally leads to a linear controller instead of a fuzzy one, which degrades the stabilization ability of the controller. When the knowledge on μ_{il} and $\hat{\mu}_{il}$ is available, the design conservatism can be improved, and obtaining the corresponding fuzzy controller.

In order to implement the event-triggered fuzzy controller given by (7), we assume that each subsystem transmits its measurements through a networked channel, and propose a solution in Fig. 1, where SP, BF, and ETM are the sampler, buffer, and

ETM, respectively. For each subsystem, a smart sensor consists of an BF that is to store $\hat{x}_i\left(t_{k-1}^i\right)$, which represents the latest measurement datum transmitted successfully to the controller, and an ETM that determines whether or not to transmit both $x_i\left(t_k^i\right)$ and $\zeta_i(t_k^i)$ to the controller. Hence, in every sample period both $x_i\left(t\right)$ and $\zeta_i(t)$ are first sampled by the SP. Then, they are transmitted to the controller and are executed, only when a prescribed event is violated. This leads to a reduction of data transmissions.

To formalize the described solution, the ETM in the sensor can operate as

$$\begin{aligned}&\text{ETM: both } x_i\left(t_k^i\right) \text{ and } \zeta_i(t_k^i) \text{ are sent}\\ &\Leftrightarrow \left\|x_i\left(t_k^i\right)-\hat{x}_i\left(t_{k-1}^i\right)\right\| > \sigma_i\left\|x_i\left(t_k^i\right)\right\|\end{aligned} \tag{9}$$

where $\sigma_i \geq 0$ is a suitably chosen design parameter.

Based on the operating condition given in (9), an event-triggered strategy is formulated as follows:

$$\hat{x}_i\left(t_k^i\right) = \begin{cases} x_i\left(t_k^i\right), & \text{when } \left\|x_i\left(t_k^i\right)-\hat{x}_i\left(t_{k-1}^i\right)\right\| \\ & \quad > \sigma_i\left\|x_i\left(t_k^i\right)\right\| \\ \hat{x}_i\left(t_{k-1}^i\right), & \text{when } \left\|x_i\left(t_k^i\right)-\hat{x}_i\left(t_{k-1}^i\right)\right\| \\ & \quad \leq \sigma_i\left\|x_i\left(t_k^i\right)\right\| \end{cases} \tag{10}$$

$$\hat{\zeta}_i\left(t_k^i\right) = \begin{cases} \zeta_i\left(t_k^i\right), & \text{when } x_i\left(t_k^i\right) \text{ is sent} \\ \hat{\zeta}_i\left(t_{k-1}^i\right), & \text{when } x_i\left(t_k^i\right) \text{ is not sent.} \end{cases} \tag{11}$$

In the case, the ith closed-loop fuzzy control system is given by

$$\begin{aligned}\dot{x}_i(t) = &\ A_i(\mu_i)x_i\left(t\right) + B_i(\mu_i)K_i(\hat{\mu}_i)\hat{x}_i(t_k^i-\tau_i)\\ &+\sum_{\substack{j=1\\ j\neq i}}^{N}\bar{A}_{ij}(\mu_i)x_j(t), i\in\mathcal{N}.\end{aligned} \tag{12}$$

Remark 2.3: It is noted that the event-triggered strategy $\left\|x_i\left(t\right)-x_i\left(r_k^i\right)\right\| > \sigma_i\left\|x_i\left(r_k^i\right)\right\|$ proposed in [13] is required to examine the triggered condition, continuously. However, the event-triggered scheme given in (10) and (11) only verifies the triggered condition at each sampling instant.

Remark 2.4: It is also noted that a state-feedback fuzzy controller generally depends on premise variables and system states. The event-triggered scheme given in (10) and (11) shows that at the instant t_k^i both the premise variable $\zeta_i(t_k^i)$ and system state $x_i(t_k^i)$ are not always transmitted to the fuzzy controller only when a prescribed threshold based on the system state is violated. Thus, the proposed triggered scheme significantly reduces data transmissions.

Before ending this section, we give the following lemma, which will be used to obtain the main results.

Lemma 2.1: Given the interconnected matrix $\bar{A}_{ijl}$ in the system (1), and the symmetric positive definite matrix $W_i \in \Re^{n_{xi}\times n_{xi}}$, the following inequality holds:

$$\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\bar{A}_{ij}(\mu_i)W_i\bar{A}_{ij}^T(\mu_i) \leq \sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{l=1}^{r_i}\mu_{il}\bar{A}_{ijl}W_i\bar{A}_{ijl}^T. \tag{13}$$

Proof: Note that for $(i,j)\in\mathcal{N}, j\neq i, l\in\mathscr{L}_i$

$$\left[\bar{A}_{ijl}-\bar{A}_{ijf}\right]W_i\left[\bar{A}_{ijl}-\bar{A}_{ijf}\right]^T \geq 0 \tag{14}$$

which implies that

$$\bar{A}_{ijl}W_i\bar{A}_{ijl}^T+\bar{A}_{ijf}W_i\bar{A}_{ijf}^T \geq \bar{A}_{ijl}W_i\bar{A}_{ijf}^T+\bar{A}_{ijf}W_i\bar{A}_{ijl}^T. \tag{15}$$

By taking the relations in (4) and (15), we have

$$\begin{aligned}&\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\bar{A}_{ij}(\mu_i)W_i\bar{A}_{ij}^T(\mu_i)\\ &= \sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{l=1}^{r_i}\sum_{f=1}^{r_i}\mu_{il}\mu_{if}\bar{A}_{ijl}W_i\bar{A}_{ijf}^T\\ &= \frac{1}{2}\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{l=1}^{r_i}\sum_{f=1}^{r_i}\mu_{il}\mu_{if}\left[\bar{A}_{ijl}W_i\bar{A}_{ijf}^T+\bar{A}_{ijf}W_i\bar{A}_{ijl}^T\right]\\ &\leq \frac{1}{2}\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{l=1}^{r_i}\sum_{f=1}^{r_i}\mu_{il}\mu_{if}\left[\bar{A}_{ijl}W_i\bar{A}_{ijl}^T+\bar{A}_{ijf}W_i\bar{A}_{ijf}^T\right]\\ &= \frac{1}{2}\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{l=1}^{r_i}\mu_{il}\bar{A}_{ijl}W_i\bar{A}_{ijl}^T\\ &\quad+\frac{1}{2}\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{f=1}^{r_i}\mu_{is}\bar{A}_{ijf}W_i\bar{A}_{ijf}^T\\ &= \sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{l=1}^{r_i}\mu_{il}\bar{A}_{ijl}W_i\bar{A}_{ijl}^T.\end{aligned} \tag{16}$$

Thus, completing this proof. ■

III. Main Results

This section will firstly reformulate the closed-loop fuzzy control system (12) into a continuous-time system with time-varying delay and extra disturbance by using the input-delay and perturbed system approaches. Then, based on an LKF with virtue of Wirtinger's inequality, we will present stability analysis and controller synthesis for the large-scale networked fuzzy system in (3), respectively. It will be shown that the codesign result consisting of the controller gain, sampled period, network delay, and event-triggered parameter is derived in terms of a set of LMIs.

Based on the input delay approach [37], the sampled-data controller in (7) is reformulated as a delayed controller as follows:

$$u_i(t) = K_i(\hat{\mu}_i)\hat{x}_i(t-\eta_i(t)), t \in [t_k^i, t_{k+1}^i) \tag{17}$$

where $\eta_i(t) = t - t_k^i + \tau_i$. It follows from (17) and the Assumptions 2.1 and 2.3 that

$$\tau_i \le \eta_i(t) < \bar{\eta}_i, \bar{\eta}_i = \tau_i + h_i, t \in [t_k^i, t_{k+1}^i), k \in \mathbb{N}. \tag{18}$$

Combined with the large-scale fuzzy system in (3) and the delayed controller in (17), the closed-loop fuzzy event-triggered control system is given by

$$\begin{aligned}\dot{x}_i(t) = \; & A_i(\mu_i)x_i(t) + B_i(\mu_i)K_i(\hat{\mu}_i)\hat{x}_i(t-\eta_i(t)) \\ & + \sum_{\substack{j=1\\ j\neq i}}^{N} \bar{A}_{ij}(\mu_i)x_j(t), i \in \mathcal{N}.\end{aligned} \tag{19}$$

Here, we model the event-triggered counterpart as a disturbance [9], it yields

$$\begin{aligned} e_i(t-\eta_i(t)) &= \hat{x}_i(t-\eta_i(t)) - x_i(t-\eta_i(t)) \\ x_i(v) &= x_i(t-\eta_i(t)) - x_i(t-\tau_i), t \in [t_k^i, t_{k+1}^i).\end{aligned} \tag{20}$$

Then, by substituting (20) into (19), the closed-loop fuzzy control system in (19) can be rewritten as

$$\begin{aligned}\dot{x}_i(t) = \; & A_i(\mu_i)x_i(t) \\ & + B_i(\mu_i)K_i(\hat{\mu}_i)\left(x_i(t-\tau_i) + x_i(v) + e_i(t-\eta_i(t))\right) \\ & + \sum_{\substack{j=1\\ j\neq i}}^{N} \bar{A}_{ij}(\mu_i)x_j(t), i \in \mathcal{N}.\end{aligned} \tag{21}$$

Now, we introduce the following LKF with virtue of Wirtinger's inequality:

$$V(t) = \sum_{i=1}^{N}\left[V_{i1}(t) + V_{i2}(t)\right], t \in [t_k^i, t_{k+1}^i) \tag{22}$$

with

$$\begin{cases} V_{i1}(t) = x_i^T(t)P_ix_i(t) + \int_{t-\tau_i}^{t} x_i^T(\alpha)Q_ix_i(\alpha)d\alpha \\ \qquad + \tau_i\int_{-\tau_i}^{0}\int_{t+\beta}^{t}\dot{x}_i^T(\alpha)Z_i\dot{x}_i(\alpha)d\alpha d\beta \\ V_{i2}(t) = (\bar{\eta}_i - \tau_i)^2\int_{t_k^i-\tau_i}^{t}\dot{x}_i^T(\alpha)W_i\dot{x}_i(\alpha)d\alpha \\ \qquad - \frac{\pi^2}{4}\int_{t_k^i-\tau_i}^{t-\tau_i}\left[x_i(\alpha) - x_i\left(t_k^i-\tau_i\right)\right]^T \\ \qquad \times W_i\left[x_i(\alpha) - x_i\left(t_k^i - \tau_i\right)\right]d\alpha, \end{cases} \tag{23}$$

where $\{P_i, Q_i, Z_i, W_i\} \in \Re^{n_{\mathrm{x}i}\times n_{\mathrm{x}i}}, i \in \mathcal{N}$ are symmetric matrices, and $P_i > 0, Z_i > 0, W_i > 0$.

Inspired by [41], we do not require that the matrix Q_i in (23) is necessarily positive definite. To ensure the positive property of $V(t)$, we give the following lemma:

Lemma 3.1: Consider the Lyapunov–Krasovskii functional (LKF) in (22), then $V(t) \ge \epsilon\|x(t)\|^2$, where $\epsilon > 0$, $x(t) = \left[x_1^T(t)\; x_2^T(t)\; \cdots\; x_N^T(t)\right]^T$, if there exist the symmetric positive definite matrices $\{P_i, Z_i, W_i\} \in \Re^{n_{\mathrm{x}i}\times n_{\mathrm{x}i}}$, and symmetric matrix $Q_i \in \Re^{n_{\mathrm{x}i}\times n_{\mathrm{x}i}}$, such that for all $i \in \mathcal{N}$ the following inequalities hold:

$$\begin{bmatrix} \frac{1}{\tau_i}P_i + Z_i & -Z_i \\ \star & Q_i + Z_i \end{bmatrix} > 0. \tag{24}$$

Proof: First, by using Jensen's inequality (Lemma A1 in the Appendix A), we have

$$\begin{aligned} & \tau_i\int_{-\tau_i}^{0}\int_{t+\beta}^{t} x_i^T(\alpha)Z_ix_i(\alpha)d\alpha d\beta \\ & \ge \tau_i\int_{-\tau_i}^{0}\frac{-1}{\beta}\left[\int_{t+\beta}^{t}\dot{x}_i^T(\alpha)d\alpha\right] \\ & \quad \times Z_i\left[\int_{t+\beta}^{t}\dot{x}_i(\alpha)d\alpha\right]d\beta \\ & = \tau_i\int_{-\tau_i}^{0}\frac{-1}{\beta}\left[x_i(t) - x_i(t+\beta)\right]^T \\ & \quad \times Z_i\left[x_i(t) - x_i(t+\beta)\right]d\beta \\ & = \tau_i\int_{0}^{\tau_i}\frac{1}{\beta}\left[x_i(t) - x_i(t-\beta)\right]^T \\ & \quad \times Z_i\left[x_i(t) - x_i(t-\beta)\right]d\beta \\ & \ge \int_{0}^{\tau_i}\left[x_i(t) - x_i(t-\beta)\right]^T \\ & \quad \times Z_i\left[x_i(t) - x_i(t-\beta)\right]d\beta \\ & = \int_{t-\tau_i}^{t}\left[x_i(t) - x_i(\alpha)\right]^T \\ & \quad \times Z_i\left[x_i(t) - x_i(\alpha)\right]d\alpha. \end{aligned} \tag{25}$$

It follows from (22), (23), and (25) that

$$\begin{aligned} V_{i1}(t) &= x_i^T(t)P_ix_i(t) \\ & \quad + \int_{t-\tau_i}^{t} x_i^T(\alpha)Q_ix_i(\alpha)d\alpha \\ & \quad + \tau_i\int_{-\tau_i}^{0}\int_{t+\beta}^{t}\dot{x}_i^T(\alpha)Z_i\dot{x}_i(\alpha)d\alpha d\beta \\ & \ge \int_{t-\tau_i}^{t}\begin{bmatrix} x_i(t) \\ x_i(\alpha)\end{bmatrix}^T\begin{bmatrix} \frac{1}{\tau_i}P_i + Z_i & -Z_i \\ \star & Q_i + Z_i\end{bmatrix} \\ & \quad \times \begin{bmatrix} x_i(t) \\ x_i(\alpha)\end{bmatrix}d\alpha. \end{aligned} \tag{26}$$

For $V_{i2}(t)$ given in (23), we have $x_i(\alpha) - x_i\left(t_k^i - \tau_i\right) = 0$ when $\alpha = t_k^i - \tau_i$. By using Lemma A2 given in the Appendix A, it is easy to see that $V_{i2}(t) \ge 0$. Therefore, there always exists a positive scalar ϵ such that the inequality $V(t) \ge \epsilon\|x(t)\|^2$ holds if the inequality in (24) holds. Thus, completing this proof. ■

Based on the LKF in (22), a sufficient condition for the stability of the closed-loop fuzzy control system in (12) is given by the following theorem.

Theorem 3.1: Given the large-scale T–S fuzzy system in (3) and a decentralized event-triggered fuzzy controller in the form of (7), the closed-loop fuzzy control system in (12) is asymptotically stable, if there exist the symmetric positive definite matrices $\{P_i, Z_i, W_i, M_i, U_i\} \in \Re^{n_{\mathrm{xi}} \times n_{\mathrm{xi}}}$, and symmetric matrix $Q_i \in \Re^{n_{\mathrm{xi}} \times n_{\mathrm{xi}}}$, matrix multipliers $\mathcal{G}_i \in \Re^{5n_{\mathrm{xi}} \times n_{\mathrm{xi}}}$, and positive scalars $\{\bar{\eta}_i, \tau_i, \sigma_i\}$, such that for all $i \in \mathcal{N}$ the following matrix inequalities hold:

$$\begin{bmatrix} \frac{1}{\tau_i} P_i + Z_i & -Z_i \\ \star & Q_i + Z_i \end{bmatrix} > 0 \tag{27}$$

$$\begin{bmatrix} \Theta_i + \mathrm{Sym}\{\mathcal{G}_i \mathbb{A}_i(\mu_i, \hat{\mu}_i)\} & \mathcal{G}_i \mathscr{A}_{ij}(\mu_i) \\ \star & -\mathscr{M}_i \end{bmatrix} < 0 \tag{28}$$

where

$$\Theta_i = \begin{bmatrix} \Theta_i^{(1)} & P_i & 0 & 0 & 0 \\ \star & \Theta_i^{(2)} & Z_i & 0 & 0 \\ \star & \star & \Theta_i^{(3)} & \sigma_i^2 U_i & 0 \\ \star & \star & \star & \Theta_i^{(4)} & 0 \\ \star & \star & \star & \star & -U_i \end{bmatrix},$$

$$\Theta_i^{(1)} = \tau_i^2 Z_i + (\bar{\eta}_i - \tau_i)^2 W_i, \Theta_i^{(2)} = Q_i - Z_i + \sum_{\substack{j=1 \\ j \neq i}}^{N} M_j,$$

$$\Theta_i^{(3)} = -Q_i - Z_i + \sigma_i^2 U_i, \Theta_i^{(4)} = -\frac{\pi^2}{4} W_i + \sigma_i^2 U_i,$$

$$\mathbb{A}_i(\mu_i, \hat{\mu}_i) = \begin{bmatrix} -\mathbf{I} & A_i(\mu_i) & B_i(\mu_i)K_i(\hat{\mu}_i) & B_i(\mu_i)K_i(\hat{\mu}_i) & B_i(\mu_i)K_i(\hat{\mu}_i) \end{bmatrix}$$

$$\mathscr{A}_{ij}(\mu_i) = \underbrace{\left[\bar{A}_{i1}(\mu_i) \cdots \bar{A}_{ij, j\neq i}(\mu_i) \cdots \bar{A}_{i\mathrm{N}}(\mu_i)\right]}_{N-1},$$

$$\mathscr{M}_i = \mathrm{diag}\underbrace{\{M_i \cdots M_i \cdots M_i\}}_{N-1}. \tag{29}$$

Proof: By taking the time derivative of $V(t)$ along the trajectory of the system in (21), one has

$$\begin{aligned} \dot{V}_{i1}(t) \leq\; & 2x_i^T(t) P_i \dot{x}_i(t) + x_i^T(t) Q_i x_i(t) \\ & - x_i^T(t - \tau_i) Q_i x_i(t - \tau_i) \\ & + \tau_i^2 \dot{x}_i^T(t) Z_i \dot{x}_i(t) \\ & - \tau_i \int_{t-\tau_i}^{t} \dot{x}_i^T(\alpha) Z_i \dot{x}_i(\alpha) d\alpha, \end{aligned} \tag{30}$$

$$\dot{V}_{i2}(t) \leq (\bar{\eta}_i - \tau_i)^2 \dot{x}_i^T(t) W_i \dot{x}_i(t) - \frac{\pi^2}{4} x_i^T(v) W_i x_i(v). \tag{31}$$

Based on Jensen's inequality (Lemma A1 given in the Appendix A), we have

$$\begin{aligned} & -\tau_i \int_{t-\tau_i}^{t} \dot{x}_i^T(\alpha) Z_i \dot{x}_i(\alpha) d\alpha \\ & \leq -\left[\int_{t-\tau_i}^{t} \dot{x}_i(\alpha) d\alpha\right]^T Z_i \left[\int_{t-\tau_i}^{t} \dot{x}_i(\alpha) d\alpha\right] \\ & = -(x_i(t) - x_i(t-\tau_i))^T Z_i (x_i(t) - x_i(t-\tau_i)). \end{aligned} \tag{32}$$

Define the matrix multipliers $\mathcal{G}_i \in \Re^{5n_{\mathrm{xi}} \times n_{\mathrm{xi}}}, i \in \mathcal{N}$, and it follows from (21) that

$$\begin{aligned} 0 = & \sum_{i=1}^{N} 2\chi_i^T(t) \mathcal{G}_i \mathbb{A}_i(\mu_i, \hat{\mu}_i) \chi_i(t) \\ & + \sum_{i=1}^{N} 2\chi_i^T(t) \mathcal{G}_i \sum_{\substack{j=1 \\ j\neq i}}^{N} \bar{A}_{ij}(\mu_i) x_j(t) \end{aligned} \tag{33}$$

where

$$\begin{aligned} \chi_i(t) = & \begin{bmatrix} \dot{x}_i^T(t) & x_i^T(t) & x_i^T(t-\tau_i) & x_i^T(v) & e_i^T(t - \eta_i(t)) \end{bmatrix}^T \\ \mathbb{A}_i(\mu_i, \hat{\mu}_i) = & \begin{bmatrix} -\mathbf{I} & A_i(\mu_i) & B_i(\mu_i)K_i(\hat{\mu}_i) & B_i(\mu_i)K_i(\hat{\mu}_i) & B_i(\mu_i)K_i(\hat{\mu}_i) \end{bmatrix}. \end{aligned} \tag{34}$$

Note that

$$2\bar{x}^T \bar{y} \leq \bar{x}^T M^{-1} \bar{x} + \bar{y}^T M \bar{y} \tag{35}$$

where $\bar{x}, \bar{y} \in \Re^n$ and symmetric matrix $M > 0$.

Define $M_i = M_i^T > 0$, and by using the relation of (35), we have

$$\begin{aligned} & \sum_{i=1}^{N} 2\chi_i^T(t) \mathcal{G}_i \sum_{\substack{j=1 \\ j\neq i}}^{N} \bar{A}_{ij}(\mu_i) x_j(t) \\ & \leq \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j\neq i}}^{N} \chi_i^T(t) \mathcal{G}_i \bar{A}_{ij}(\mu_i) M_i^{-1} \bar{A}_{ij}^T(\mu_i) \mathcal{G}_i^T \chi_i(t) \\ & \quad + \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j\neq i}}^{N} x_j^T(t) M_i x_j(t) \\ & \leq \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j\neq i}}^{N} \chi_i^T(t) \mathcal{G}_i \bar{A}_{ij}(\mu_i) M_i^{-1} \bar{A}_{ij}^T(\mu_i) \mathcal{G}_i^T \chi_i(t) \\ & \quad + \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j\neq i}}^{N} x_i^T(t) M_j x_i(t). \end{aligned} \tag{36}$$

In addition, it follows from (9), (10), and (20) that

$$\begin{aligned}\|e_i(t-\eta_i(t))\| &= \|\hat{x}_i(t-\eta_i(t)) - x_i(t-\eta_i(t))\| \\ &\leq \sigma_i \|x_i(t-\eta_i(t))\| \\ &= \sigma_i \|x_i(t-\tau_i) + x_i(v)\|. \end{aligned} \quad (37)$$

Based on the relation in (37), and define the symmetric positive definite matrices U_i, we have

$$e_i^T(t-\eta_i(t)) U_i e_i(t-\eta_i(t)) \leq \sigma_i^2 \begin{bmatrix} x_i(t-\tau_i) \\ x_i(v) \end{bmatrix}^T \begin{bmatrix} U_i & U_i \\ \star & U_i \end{bmatrix} \begin{bmatrix} x_i(t-\tau_i) \\ x_i(v) \end{bmatrix}. \quad (38)$$

It follows from (30)–(38) that

$$\begin{aligned}\dot{V}(t) \leq & \sum_{i=1}^{N} \left[2x_i^T(t) P_i \dot{x}_i(t) + x_i^T(t) Q_i x_i(t)\right] \\ & - \sum_{i=1}^{N} x_i^T(t-\tau_i) Q_i x_i(t-\tau_i) \\ & + \sum_{i=1}^{N} \tau_i^2 \dot{x}_i^T(t) Z_i \dot{x}_i(t) \\ & - \sum_{i=1}^{N} (x_i(t) - x_i(t-\tau_i))^T Z_i (x_i(t) - x_i(t-\tau_i)) \\ & + \sum_{i=1}^{N} (\bar{\eta}_i - \tau_i)^2 \dot{x}_i^T(t) W_i \dot{x}_i(t) \\ & - \sum_{i=1}^{N} \frac{\pi^2}{4} x_i^T(v) W_i x_i(v) \\ & + \sum_{i=1}^{N} 2\chi_i^T(t) \mathcal{G}_i \mathbb{A}_i(\mu_i, \hat{\mu}_i) \chi_i(t) \\ & + \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j\neq i}}^{N} \chi_i^T(t) \mathcal{G}_i \bar{A}_{ij}(\mu_i) M_i^{-1} \bar{A}_{ij}^T(\mu_i) \mathcal{G}_i^T \chi_i(t) \\ & + \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j\neq i}}^{N} x_i^T(t) M_j x_i(t) \\ & + \sum_{i=1}^{N} \sigma_i^2 \begin{bmatrix} x_i(t-\tau_i) \\ x_i(v) \end{bmatrix}^T \begin{bmatrix} U_i & U_i \\ \star & U_i \end{bmatrix} \begin{bmatrix} x_i(t-\tau_i) \\ x_i(v) \end{bmatrix} \\ & - \sum_{i=1}^{N} \left\{e_i^T(t-\eta_i(t)) U_i e_i(t-\eta_i(t))\right\} \\ = & \sum_{i=1}^{N} \chi_i^T(t) \left[\Theta_i + \mathrm{Sym}\left\{\mathcal{G}_i \mathbb{A}_i(\mu_i, \hat{\mu}_i)\right\}\right] \chi_i(t) \\ & + \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j\neq i}}^{N} \chi_i^T(t) \mathcal{G}_i \bar{A}_{ij}(\mu_i) M_i^{-1} \bar{A}_{ij}^T(\mu_i) \mathcal{G}_i^T \chi_i(t), \end{aligned} \quad (39)$$

where Θ_i and $\mathbb{A}_i(\mu_i, \hat{\mu}_i)$ are defined in (29).

By applying Schur complement lemma to (28), it can be seen from (39) that the inequality in (28) implies the stability of the large-scale fuzzy control system, thus, completing this proof. ■

It is noted that the conditions given in (28) are non-LMIs when the controller gains are unknown. It is also noted that when the knowledge between μ_{il} and $\hat{\mu}_{il}$ is unavailable, the condition $\mu_{il} \neq \hat{\mu}_{il}$ generally leads to a linear controller instead of a fuzzy one, which induces the design conservatism. From a practical perspective, it is possible to obtain a prior knowledge between μ_{il} and $\hat{\mu}_{il}$. Thus, we assume

$$\underline{\rho}_{il} \leq \frac{\hat{\mu}_{il}}{\mu_{il}} \leq \bar{\rho}_{il} \quad (40)$$

where $\underline{\rho}_{il}$ and $\bar{\rho}_{il}$ are known positive scalars.

Based on Theorem 3.1 and (40), we will present the codesign result consisting of the fuzzy controller gains, sampled period, network delay, and event-triggered parameter in terms of a set of LMIs, the result is summarized as follows:

Theorem 3.2: Consider the large-scale T–S fuzzy system in (3). A decentralized event-triggered fuzzy controller in the form of (7) exists, such that the closed-loop fuzzy control system in (12) is asymptotically stable, if there exist the symmetric positive definite matrices $\{\bar{P}_i, \bar{W}_i, \bar{Z}_i, \bar{U}_i, V_i, V_0\} \in \Re^{n_{xi} \times n_{xi}}$, $V_0 \leq V_i$, and symmetric matrices $\bar{Q}_i \in \Re^{n_{xi} \times n_{xi}}$ and matrices $X_{ils} = X_{isl}^T, G_i \in \Re^{n_{xi} \times n_{xi}}$, $\bar{K}_{is} \in \Re^{n_{ui} \times n_{xi}}$, and positive scalars $\{\bar{\eta}_i, \tau_i, \sigma_i, \bar{\rho}_{il}, \underline{\rho}_{il}\}$, such that for all $(l, s) \in \mathscr{L}_i, i \in \mathcal{N}$ the following LMIs hold:

$$\begin{bmatrix} \frac{1}{\tau_i}\bar{P}_i + \bar{Z}_i & -\bar{Z}_i \\ \star & \bar{Q}_i + \bar{Z}_i \end{bmatrix} > 0 \quad (41)$$

$$\bar{\rho}_{il} \Sigma_{ill} + X_{ill} < 0, \quad (42)$$

$$\underline{\rho}_{il} \Sigma_{ill} + X_{ill} < 0, \quad (43)$$

$$\bar{\rho}_{is} \Sigma_{ils} + \bar{\rho}_{il} \Sigma_{\mathrm{isl}} + X_{ils} + X_{\mathrm{isl}} < 0 \quad (44)$$

$$\underline{\rho}_{is} \Sigma_{ils} + \underline{\rho}_{il} \Sigma_{\mathrm{isl}} + X_{ils} + X_{\mathrm{isl}} < 0 \quad (45)$$

$$\underline{\rho}_{is} \Sigma_{ils} + \bar{\rho}_{il} \Sigma_{\mathrm{isl}} + X_{ils} + X_{\mathrm{isl}} < 0 \quad (46)$$

$$\bar{\rho}_{is} \Sigma_{ils} + \underline{\rho}_{il} \Sigma_{\mathrm{isl}} + X_{ils} + X_{\mathrm{isl}} < 0 \quad (47)$$

$$\begin{bmatrix} X_{i11} & \cdots & X_{i1r_i} \\ \vdots & \ddots & \vdots \\ X_{ir_i1} & \cdots & X_{\mathrm{ir}_i r_i} \end{bmatrix} > 0 \quad (48)$$

where

$$\Sigma_{ils} = \begin{bmatrix} \Sigma_{ils}^{(1)} & \mathcal{E}_{(1)} G_i^T \\ \star & -(N-1)^{-1} V_0 \end{bmatrix}$$

$$\Sigma_{ils}^{(1)} = \bar{\Theta}_i + \mathrm{Sym}\left\{\mathcal{E}_{(2)} \bar{\mathbb{A}}_{ils}\right\} + \sum_{\substack{j=1 \\ j\neq i}}^{N} \mathcal{E}_{(2)} \bar{A}_{ijl} V_i \bar{A}_{ijl}^T \mathcal{E}_{(2)}^T$$

$$\bar{\Theta}_i = \begin{bmatrix} \bar{\Theta}_i^{(1)} & \bar{P}_i & 0 & 0 & 0 \\ \star & \bar{Q}_i - \bar{Z}_i & \bar{Z}_i & 0 & 0 \\ \star & \star & \bar{\Theta}_i^{(3)} & \sigma_i^2 \bar{U}_i & 0 \\ \star & \star & \star & -\frac{\pi^2}{4}\bar{W}_i + \sigma_i^2 \bar{U}_i & 0 \\ \star & \star & \star & \star & -\bar{U}_i \end{bmatrix}$$

$$\bar{\Theta}_i^{(1)} = \tau_i^2 \bar{Z}_i + (\bar{\eta}_i - \tau_i)^2 \bar{W}_i, \bar{\Theta}_i^{(3)} = -\bar{Q}_i - \bar{Z}_i + \sigma_i^2 \bar{U}_i$$

$$\bar{\mathbb{A}}_{ils} = \begin{bmatrix} -G_i & A_{il} G_i & B_{il}\bar{K}_{is} & B_{il}\bar{K}_{is} & B_{il}\bar{K}_{is} \end{bmatrix}$$

$$\mathcal{E}_{(1)} = \begin{bmatrix} 0 & \mathbf{I} & 0 & 0 & 0 \end{bmatrix}^T, \mathcal{E}_{(2)} = \begin{bmatrix} \mathbf{I} & \mathbf{I} & 0 & 0 & 0 \end{bmatrix}^T. \quad (49)$$

Furthermore, a decentralized event-triggered fuzzy controller in the form of (7) is given by

$$K_{is} = \bar{K}_{is} G_i^{-1}, s \in \mathscr{L}_i, i \in \mathcal{N}. \quad (50)$$

Proof: For matrix inequality linearization purpose, define $M_i = V_i^{-1}, V_0 \leq V_i, i \in \mathcal{N}$, it yields

$$\sum_{\substack{j=1 \\ j \neq i}}^{N} M_j \leq (N-1) V_0^{-1}. \quad (51)$$

Now, by substituting (51) into (28), and applying Schur complement lemma, the following inequality implies (28):

$$\begin{bmatrix} \Sigma_{ils}^{(1)} & \mathcal{E}_{(1)} \\ \star & -(N-1)^{-1} V_0 \end{bmatrix} < 0 \quad (52)$$

where

$$\Sigma_{ils}^{(1)} = \bar{\Theta}_i + \text{Sym}\left\{\mathcal{G}_i \mathbb{A}_i(\mu_i, \hat{\mu}_i)\right\} + \sum_{\substack{j=1 \\ j \neq i}}^{N} \mathcal{G}_i \bar{A}_{ij}(\mu_i) V_i \bar{A}_{ij}^T(\mu_i) \mathcal{G}_i^T$$

$$\bar{\Theta}_i = \begin{bmatrix} \Theta_i^{(1)} & P_i & 0 & 0 & 0 \\ \star & Q_i - Z_i & Z_i & 0 & 0 \\ \star & \star & \Theta_i^{(3)} & \sigma_i^2 U_i & 0 \\ \star & \star & \star & \Theta_i^{(4)} & 0 \\ \star & \star & \star & \star & -U_i \end{bmatrix}$$

$$\Theta_i^{(1)} = \tau_i^2 Z_i + (\bar{\eta}_i - \tau_i)^2 W_i, \Theta_i^{(3)} = -Q_i - Z_i + \sigma_i^2 U_i$$

$$\Theta_i^{(4)} = -\frac{\pi^2}{4} W_i + \sigma_i^2 U_i, \mathcal{E}_{(1)} = \begin{bmatrix} 0 & \mathbf{I} & 0 & 0 & 0 \end{bmatrix}^T$$

$$\mathbb{A}_i(\mu_i, \hat{\mu}_i) = \big[-\mathbf{I} \quad A_i(\mu_i) \quad B_i(\mu_i) K_i(\hat{\mu}_i) \quad B_i(\mu_i) K_i(\hat{\mu}_i) \quad B_i(\mu_i) K_i(\hat{\mu}_i) \big]. \quad (53)$$

It follows from (42) and (48) that

$$\tau_i^2 \bar{Z}_i + (\bar{\eta}_i - \tau_i)^2 \bar{W}_i - \text{Sym}\{G_i\} < 0, i \in \mathcal{N} \quad (54)$$

which implies that $G_i, i \in \mathcal{N}$ are nonsingular matrices.

We further define

$$\begin{cases} \mathcal{G}_i = \begin{bmatrix} G_i^{-1} & G_i^{-1} & 0 & 0 & 0 \end{bmatrix}^T \\ \Gamma_1 := \text{diag}\left\{ G_i \quad G_i \quad G_i \quad G_i \quad G_i \quad \mathbf{I} \right\} \\ \bar{P}_i = G_i^T P_i G_i, \bar{Q}_i = G_i^T Q_i G_i \\ \bar{Z}_i = G_i^T Z_i G_i, \bar{U}_i = G_i^T U_i G_i, \bar{W}_i = G_i^T W_i G_i. \end{cases} \quad (55)$$

By substituting (55) into (52), and performing a congruence transformation by Γ_1, and extracting the fuzzy membership functions, we have

$$\sum_{l=1}^{r_i}\sum_{f=1}^{r_i}\sum_{s=1}^{r_i} \mu_{il}\mu_{\text{if}}\hat{\mu}_{is}\Sigma_{ilfs} < 0 \quad (56)$$

where

$$\Sigma_{ilfs} = \begin{bmatrix} \Sigma_{ilfs}^{(1)} & \mathcal{E}_{(1)} G_i^T \\ \star & -(N-1)^{-1} V_0 \end{bmatrix} \quad (57)$$

and $\Sigma_{ilfs}^{(1)}, \bar{\Theta}_i, \mathcal{E}_{(2)}$ and $\bar{\mathbb{A}}_{ils}$ are define in (49).

Then, by using Lemma 2.1, the following inequality implies (56):

$$\sum_{l=1}^{r_i}\sum_{s=1}^{r_i} \mu_{il}\hat{\mu}_{is}\Sigma_{ils} < 0 \quad (58)$$

where Σ_{ils} is defined in (49).

By taking the relation in (40) and using Lemma A3 given in the Appendix A, the inequality in (58) holds if the inequalities (42)–(48) hold. Then, by performing congruence transformations to (27) by Γ_2, where $\Gamma_2 := \text{diag}\{G_i, G_i\}$, the inequalities in (41) can be obtained. Thus, completing this proof. ■

For the case where the information between μ_{il} and $\hat{\mu}_{il}$ is unavailable, the corresponding result on decentralized event-triggered linear controller design can be obtained as follows:

Corollary 3.1: Consider the large-scale T–S fuzzy system in (3). A decentralized event-triggered linear controller exists, such that the closed-loop fuzzy control system in (12) is asymptotically stable, if there exist the symmetric positive definite matrices $\{\bar{P}_i, \bar{W}_i, \bar{Z}_i, \bar{U}_i, V_i, V_0\} \in \Re^{n_{xi}\times n_{xi}}$, $V_0 \leq V_i$, and symmetric matrices $\bar{Q}_i \in \Re^{n_{xi}\times n_{xi}}$, and matrices $G_i \in \Re^{n_{xi}\times n_{xi}}$, $\bar{K}_i \in \Re^{n_{ui}\times n_{xi}}$, and positive scalars $\{\bar{\eta}_i, \tau_i, \sigma_i\}$, such that for all $l \in \mathscr{L}_i, i \in \mathcal{N}$ the following LMIs hold:

$$\begin{bmatrix} \frac{1}{\tau_i}\bar{P}_i + \bar{Z}_i & -\bar{Z}_i \\ \star & \bar{Q}_i + \bar{Z}_i \end{bmatrix} > 0 \quad (59)$$

$$\begin{bmatrix} \Sigma_{\text{ilfs}}^{(1)} & \mathcal{E}_{(1)} G_i^T \\ \star & -(N-1)^{-1} V_0 \end{bmatrix} < 0 \quad (60)$$

where

$$\Sigma_{\text{ilfs}}^{(1)} = \bar{\Theta}_i + \text{Sym}\left\{\mathcal{E}_{(2)}\bar{\mathbb{A}}_{il}\right\} + \sum_{\substack{j=1\\j\neq i}}^{N} \mathcal{E}_{(2)}\bar{A}_{ijl} V_i \bar{A}_{ijl}^T \mathcal{E}_{(2)}^T$$

$$\bar{\Theta}_i = \begin{bmatrix} \bar{\Theta}_i^{(1)} & \bar{P}_i & 0 & 0 & 0 \\ \star & \bar{Q}_i - \bar{Z}_i & \bar{Z}_i & 0 & 0 \\ \star & \star & \bar{\Theta}_i^{(3)} & \sigma_i^2 \bar{U}_i & 0 \\ \star & \star & \star & \bar{\Theta}_i^{(4)} & 0 \\ \star & \star & \star & \star & -\bar{U}_i \end{bmatrix}$$

$$\bar{\Theta}_i^{(1)} = \tau_i^2 \bar{Z}_i + (\bar{\eta}_i - \tau_i)^2 \bar{W}_i$$

$$\bar{\Theta}_i^{(3)} = -\bar{Q}_i - \bar{Z}_i + \sigma_i^2 \bar{U}_i, \bar{\Theta}_i^{(4)} = -\frac{\pi^2}{4}\bar{W}_i + \sigma_i^2 \bar{U}_i$$

$$\bar{\mathbb{A}}_{il} = \begin{bmatrix} -G_i & A_{il}G_i & B_{il}\bar{K}_i & B_{il}\bar{K}_i & B_{il}\bar{K}_i \end{bmatrix}$$

$$\mathcal{E}_{(1)} = \begin{bmatrix} 0 & \mathbf{I} & 0 & 0 & 0 \end{bmatrix}^T, \mathcal{E}_{(2)} = \begin{bmatrix} \mathbf{I} & \mathbf{I} & 0 & 0 & 0 \end{bmatrix}^T. \quad (61)$$

Remark 3.1: It is noted that when designing an event-triggered linear controller in (62), the premise variables are no longer required to transmit through communication networks. Compared with the event-triggered fuzzy controller in (7), the linear one reduces the requirements for extra hardware and software but raising the design conservatism.

IV. Simulation Examples

In this section, two examples will be used to validated the effectiveness of the decentralized event-triggered controller design method proposed in this paper.

Example 4.1: Consider a continuous-time large-scale T–S fuzzy system in the form of (1) with three interconnected subsystems as follows:

Plant Rule $\mathscr{R}_i^l$: **IF** $x_{i1}(t)$ is $\mathscr{F}_{i1}^l$ and $x_{i2}(t)$ is $\mathscr{F}_{i2}^l$, **THEN**

$$\dot{x}_i(t) = A_{il}x_i(t) + B_{il}u_i(t) + \sum_{\substack{j=1\\j\neq i}}^{3} \bar{A}_{ijl}x_j(t), i = \{1,2,3\}$$

where $\mathscr{F}_{i1}^l \in [2,4,6], \mathscr{F}_{i2}^l \in [0,2]$, $\{A_{il}, B_{il}, \bar{A}_{ijl}\}$ is listed in Appendix B.

It is noted that the open-loop large-scale fuzzy system is unstable, as shown in Fig. 2 for the initial conditions $x_1(0) = [1.1, 0]^T, x_2(0) = [1.2, 0]^T$, and $x_3(0) = [1.3, 0]^T$. Here, our aim is to design a decentralized event-triggered controller in the form of (7) such that the resulting closed-loop fuzzy control system is asymptotically stable with less data transmissions. It is noted that there are no existing results on decentralized event-triggered control for large-scale fuzzy systems. It is also noted that the delay-dependent method can be developed for sampled-data control systems by using input-delay approach [37]. Assume that $\tau_i = 0.3$, $\bar{\eta}_i = 0.32$, it has been found that there are no feasible solutions based on the design method proposed in [38], [39]. However, by applying Corollary 3.1 with $\bar{Q}_i > 0$, we indeed obtain a feasible solution with the maximum triggered parameter $\sigma_{\text{imax}} = 0.03$. Now, we consider the condition that $\bar{Q}_i$ may be negative definite. By using Corollary 3.1, the maximum triggered parameter can be further improved to $\sigma_{\text{imax}} = 0.06$, and the corresponding linear controller gains are

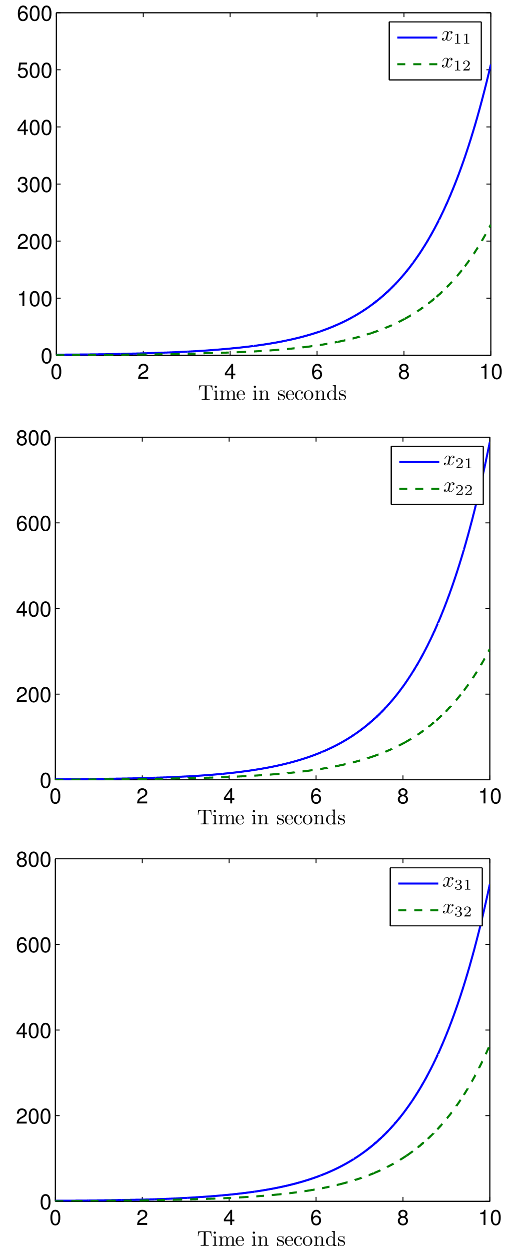

Fig. 2. State responses for open-loop large-scale fuzzy system in Example 4.1.

$$K_1 = [-5.2584 \quad -2.9934]$$
$$K_2 = [-4.9395 \quad -3.6419]$$
$$K_3 = [-5.3985 \quad -3.1262].$$

Then, let us assume that the information in the asynchronous variables μ_{il} and $\hat{\mu}_{il}$ is known and satisfies that $\underline{\rho}_{il} = 0.5$ and $\bar{\rho}_{il} = 2$. By applying Theorem 3.2, the maximum triggered parameter $\sigma_{\text{imax}} = 0.11$ is obtained, and the corresponding fuzzy controller gains are

$$K_{11} = [-4.4937 \quad -3.4164\,]$$
$$K_{12} = [-5.2133 \quad -2.5383\,]$$
$$K_{13} = [-4.5973 \quad -3.0479\,]$$
$$K_{14} = [-4.4937 \quad -3.4164\,]$$
$$K_{15} = [-5.2133 \quad -2.5383\,]$$
$$K_{16} = [-4.5973 \quad -3.0479\,]$$

for the first subsystem, and

$$K_{21} = [-4.9570 \quad -4.5588\,]$$
$$K_{22} = [-3.9601 \quad -1.8918\,]$$
$$K_{23} = [-4.7000 \quad -4.5020\,]$$
$$K_{24} = [-4.9570 \quad -4.5588\,]$$
$$K_{25} = [-3.9601 \quad -1.8918\,]$$
$$K_{26} = [-4.7000 \quad -4.5020\,]$$

for the second subsystem, and

$$K_{31} = [-4.1337 \quad -3.1060\,]$$
$$K_{32} = [-4.3532 \quad -1.6762\,]$$
$$K_{33} = [-4.4272 \quad -3.5038\,]$$
$$K_{34} = [-4.1337 \quad -3.1060\,]$$
$$K_{35} = [-4.3532 \quad -1.6762\,]$$
$$K_{36} = [-4.4272 \quad -3.5038\,]$$

for the third subsystem.

Based on the above solutions in Theorem 3.2, it can be seen from Fig. 3 that the state responses for the large-scale fuzzy system converge to zero. Fig. 4 shows that when using event-triggered control, the number of transmissions reduces from 200 to 25 in subsystem 1, and from 200 to 20 in subsystem 2, and from 200 to 21 in subsystem 3, respectively.

In this example, we calculate the number of transmitted packets by applying the methods developed in [38], [39], and by using Corollary 3.1, and by using Theorem 3.2, respectively. Table I lists the detailed comparison. Clearly, the communication resource is significantly saved by using the event-triggered scheme proposed in this paper.

Example 4.2: Consider a solar photovoltaic (PV) power systems using dc/dc converter, and a permanent-magnet synchronous generator (PMSG) using ac/dc converter. Their dynamic models are respectively described by the following differential equationsvs [42]:

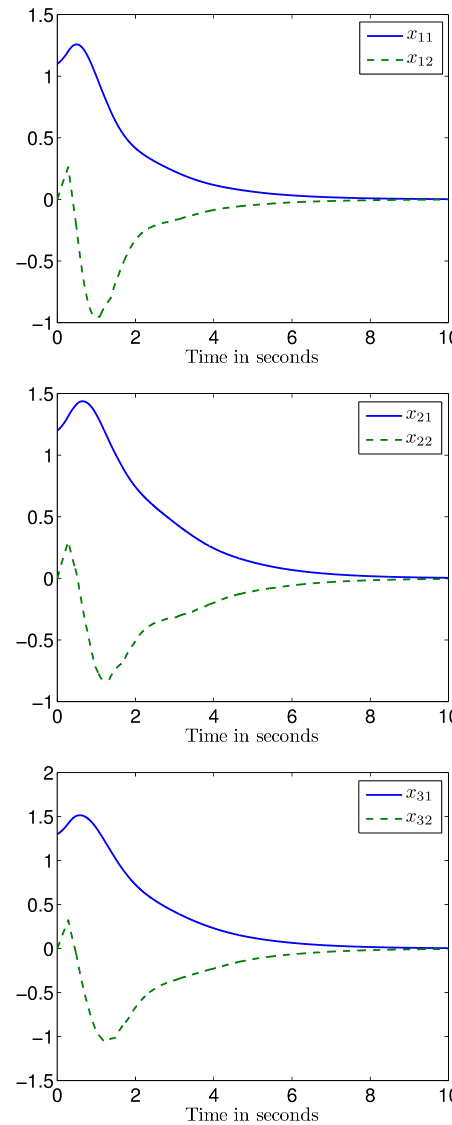

Fig. 3. State responses for closed-loop large-scale fuzzy control system in Example 4.1.

$$\begin{cases} \dot{v}_{\text{PV}} = \dfrac{1}{C_{\text{PV}}}\left(\phi_{\text{PV}} - \phi_L u\right) \\ \dot{\phi}_L = \dfrac{1}{L}\left(R_0\left(\phi_0 - \phi_L\right) - R_L\phi_L - v_0\right) \\ \qquad + \dfrac{1}{L}\left(V_D + v_{\text{PV}} - R_M\phi_L\right)u - \dfrac{V_D}{L} \\ \dot{v}_0 = \dfrac{1}{C_0}\left(\phi_L - \phi_0\right) \end{cases}$$

and [43]

$$\begin{cases} L_d\dot{\phi}_{ds} = -R_s\phi_{ds} + \omega L_q\left(i_{qs}\right)\phi_{qs} + v_d \\ L_q\left(i_{qs}\right)\dot{\phi}_{qs} = -R_s\phi_{qs} - 0.5\omega_g P_n L_d\phi_{ds} - \omega\psi_m + v_q \\ C_s\dot{v}_{\text{dc}} = \dfrac{3}{2}\left(d_s\phi_{ds} + d_q\phi_{qs}\right) - \phi_0 \end{cases}$$

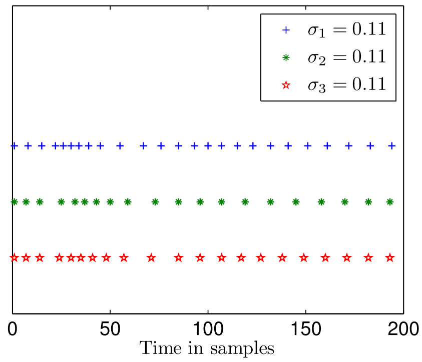

Fig. 4. Event-triggered times for $\sigma_i = 0.11$ in Example 4.1.

TABLE I
COMPARISON OF NUMBER OF TRANSMITTED PACKETS FOR DIFFERENT METHODS WITH $\tau_i = 0.3, \bar{\eta}_i = 0.32, \underline{\rho}_{il} = 0.5, \bar{\rho}_{il} = 2$ IN EXAMPLE 4.1

Methods		[38]	[39]	Corollary 3.1	Theorem 3.2
σ_i		0.03	0.03	0.06	0.11
100 sampling times	Subystem 1	–	–	29	12
	Subystem 2	–	–	24	12
	Subystem 3	–	–	28	12
500 sampling times	Subystem 1	–	–	98	52
	Subystem 2	–	–	91	55
	Subystem 3	–	–	93	54

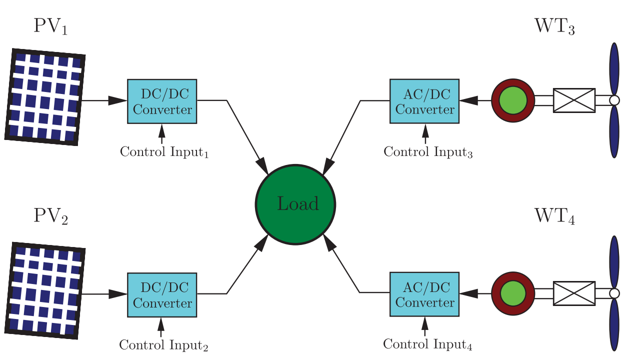

Fig. 5. DC microgrid with two solar PV powers and two PMSGs in Example 4.2.

where in the solar PV system, $v_{\rm PV}, \phi_L$, and v_0 are the PV array voltage, the current on the inductance L, and the voltage of the capacitance C_0, respectively; R_0, R_L, and R_M are the internal resistance on the capacitance C_0, the inductance L, and the power MOSFET, respectively; V_D is the forward voltage of the power diode; ϕ_0 is the measurable load current. In the PMSG system, ψ_m and R_s denote the magnet flux linkage and stator resistance, respectively; ϕ_{ds}, v_d, L_d, and $\phi_{qs}, v_q, L_q\left(i_{qs}\right)$ are the current, voltage, inductance in d-axis and in q-axis, respectively; P_n and ω_g are the number of poles and the rotor speed, respectively; d_s and d_q are the duty-ratio signals, ω is the electrical angular velocity, $v_{\rm dc}$ is the voltage of the capacitance C_s.

Now, let us consider a DC microgrid with two solar PV subsystems and two PMSGs as shown in Fig 5. The dynamic model can be given by

$$\begin{cases} \dot{v}_{\mathrm{PV}(i)} = \dfrac{1}{C_{\mathrm{PV}(i)}}\dfrac{\phi_{\mathrm{PV}(i)}}{v_{\mathrm{PV}(i)}}v_{\mathrm{PV}(i)} - \dfrac{1}{C_{\mathrm{PV}(i)}}\phi_{L(i)}u_{(i)} \\ \dot{\phi}_{L(i)} = \left(-\dfrac{1}{L_{(i)}}R_{0(i)} - \dfrac{1}{L_{(i)}}R_{L(i)} - \dfrac{V_{D(i)}}{L_{(i)}\phi_{L(i)}}\right)\phi_{L(i)} \\ \qquad + \left(\dfrac{R_{0(i)}}{L_{(i)}\left(R_{\mathrm{line}(i)}+R_{\mathrm{load}}\right)} - \dfrac{1}{L_{(i)}}\right)v_{0(i)} \\ \qquad - \sum_{j=1, j\neq i}^{N}\dfrac{R_{0(i)}R_{\mathrm{load}}}{L_{(i)}\left(R_{\mathrm{line}(i)}+R_{\mathrm{load}}\right)}\phi_{0(j)} \\ \qquad + \dfrac{1}{L_{(i)}}\left(V_{D(i)} + v_{\mathrm{PV}(i)} - R_{M(i)}\phi_{L(i)}\right)u_{(i)} \\ \dot{v}_{0(i)} = \dfrac{1}{C_{0(i)}}\phi_{L(i)} - \dfrac{1}{C_{0(i)}\left(R_{\mathrm{line}(i)}+R_{\mathrm{load}}\right)}v_{0(i)} \\ \qquad + \sum_{j=1, j\neq i}^{N}\dfrac{R_{\mathrm{load}}}{C_{0(i)}\left(R_{\mathrm{line}(i)}+R_{\mathrm{load}}\right)}\phi_{0(j)}, i=\{1,2\} \end{cases}$$

and

$$\begin{cases} \dot{\phi}_{\mathrm{ds}(i)} = \dfrac{-R_{s(i)}}{L_{d(i)}}\phi_{\mathrm{ds}(i)} + \dfrac{0.5\omega_{g(i)}P_{n(i)}L_{q(i)}\left(i_{qs(i)}\right)}{L_{d(i)}}\phi_{qs(i)} \\ \dot{\phi}_{\mathrm{qs}(i)} = \dfrac{-R_{s(i)}}{L_{q(i)}\left(i_{\mathrm{qs}(i)}\right)}\phi_{\mathrm{qs}(i)} - \dfrac{0.5\omega_{g(i)}P_{n(i)}L_{d(i)}}{L_{q(i)}\left(i_{qs(i)}\right)}\phi_{\mathrm{ds}(i)} \\ \dot{v}_{\mathrm{dc}(i)} = -\dfrac{1}{C_{s(i)}\left(R_{\mathrm{load}}+R_{\mathrm{line}(i)}\right)}v_{\mathrm{dc}(i)} \\ \qquad + \sum_{j=1, j\neq i}^{N}\dfrac{R_{\mathrm{load}}}{C_{s(i)}\left(R_{\mathrm{load}}+R_{\mathrm{line}(i)}\right)}\phi_{0(j)} \\ \qquad + \dfrac{3}{2C_{s(i)}}u_{(i)}, i=\{3,4\} \end{cases}$$

where $R_{\mathrm{line}(i)}$ denotes the line resistance on the ith subsystem, R_{load} is the consumer load.

In this simulation, the values of the parameters are $V_{D(1)} = 9.1$ V, $C_{\mathrm{PV}(1)} = 0.0101$ F, $C_{0(1)} = 0.0472$ F, $L_{(1)} = 0.0516$ H, $R_{L(1)} = 1.7\ \Omega$, $R_{0(1)} = 1.2\ \Omega$, $R_{M(1)} = 0.8\ \Omega$; $V_{D(2)} = 9.2$ V, $C_{\mathrm{PV}(2)} = 0.0108$ F, $C_{0(2)} = 0.0411$ F, $L_{(2)} = 0.0514$ H, $R_{L(2)} = 1.8\ \Omega, R_{0(2)} = 1.1\ \Omega$, $R_{M(2)} = 0.85\ \Omega$; $R_{s(3)} = 8.9\ \Omega, L_{d(3)} = 0.0629$ H, $P_{n(3)} = 12, C_{s(3)} = 0.0418$ F; $R_{s(4)} = 9\ \Omega, L_{d(4)} = 0.0684$ H, $P_{n(4)} = 12, C_{s(4)} = 0.0431$ F, $R_{\mathrm{load}} = 18\ \Omega$, $R_{\mathrm{line}(i)} = 1.3\ \Omega$. Assume that $\phi_{L(i)} = 0.25\phi_{0(i)}, i=\{1,2\}$, and $\phi_{\mathrm{qs}(i)} = 0.25\phi_{0(i)}, i=\{3,4\}$, we can approximate the dc microgird by the following T–S model with four fuzzy rules:

Plant Rule $\mathscr{R}_i^1$: **IF** $\left(v_{\mathrm{PV}(i)}, \phi_{\mathrm{PV}(i)}\right)$ is $(9.5, 0.36)$ and $\phi_{L(i)}$ is 0.25, **THEN**

$$\dot{x}_i\left(t\right) = A_{i1}x_i\left(t\right) + B_{i1}u_i\left(t\right) + \sum_{\substack{j=1\\ j\neq i}}^{4}\bar{A}_{ij}x_j(t), i=\{1,2\}$$

Plant Rule $\mathscr{R}_i^2$**: IF** $\left(v_{\mathrm{PV}(i)}, \phi_{\mathrm{PV}(i)}\right)$ is $(9.5, 0.36)$ and $\phi_{L(i)}$ is 0.29, **THEN**

$$\dot{x}_i(t) = A_{i2}x_i(t) + B_{i2}u_i(t) + \sum_{\substack{j=1\\ j\neq i}}^{4} \bar{A}_{ij}x_j(t), i = \{1, 2\}$$

Plant Rule $\mathscr{R}_i^3$**: IF** $\left(v_{\mathrm{PV}(i)}, \phi_{\mathrm{PV}(i)}\right)$ is $(12.3, 0.42)$ and $\phi_{L(i)}$ is 0.25, **THEN**

$$\dot{x}_i(t) = A_{i3}x_i(t) + B_{i3}u_i(t) + \sum_{\substack{j=1\\ j\neq i}}^{4} \bar{A}_{ij}x_j(t), i = \{1, 2\}$$

Plant Rule $\mathscr{R}_i^4$**: IF** $\left(v_{\mathrm{PV}(i)}, \phi_{\mathrm{PV}(i)}\right)$ is $(12.3, 0.42)$ and $\phi_{L(i)}$ is 0.29, **THEN**

$$\dot{x}_i(t) = A_{i4}x_i(t) + B_{i4}u_i(t) + \sum_{\substack{j=1\\ j\neq i}}^{4} \bar{A}_{ij}x_j(t), i = \{1, 2\}$$

Plant Rule $\mathscr{R}_i^1$**: IF** $\omega_{g(i)}$ is 74 and $L_{q(i)}$ is 0.0515, **THEN**

$$\dot{x}_i(t) = A_{i1}x_i(t) + B_{i1}u_i(t) + \sum_{\substack{j=1\\ j\neq i}}^{4} \bar{A}_{ij}x_j(t), i = \{3, 4\}$$

Plant Rule $\mathscr{R}_i^2$**: IF** $\omega_{g(i)}$ is 74 and $L_{q(i)}$ is 0.0541, **THEN**

$$\dot{x}_i(t) = A_{i2}x_i(t) + B_{i2}u_i(t) + \sum_{\substack{j=1\\ j\neq i}}^{4} \bar{A}_{ij}x_j(t), i = \{3, 4\}$$

Plant Rule $\mathscr{R}_i^3$**: IF** $\omega_{g(i)}$ is 80 and $L_{q(i)}$ is 0.0515, **THEN**

$$\dot{x}_i(t) = A_{i3}x_i(t) + B_{i3}u_i(t) + \sum_{\substack{j=1\\ j\neq i}}^{4} \bar{A}_{ij}x_j(t), i = \{3, 4\}$$

Plant Rule $\mathscr{R}_i^4$**: IF** $\omega_{g(i)}$ is 80 and $L_{q(i)}$ is 0.0541, **THEN**

$$\dot{x}_i(t) = A_{i4}x_i(t) + B_{i4}u_i(t) + \sum_{\substack{j=1\\ j\neq i}}^{4} \bar{A}_{ij}x_j(t), i = \{3, 4\}$$

where $\left\{A_{il}, B_{il}, \bar{A}_{ij}\right\}, l = \{1, 2, 3, 4\}$ is listed in Appendix C.

Fig. 6 shows that the open-loop dc microgrid is unstable under the initial conditions $x_1(0) = [2, 2, 4]^T$, $x_2(0) = [2.5, 1.9, 4.5]^T$, $x_3(0) = [3, 1.8, 5]^T$, and $x_4(0) = [3.5, 1.7, 4.5]^T$. Our aim is to design a decentralized event-triggered controller in the form of (7) such that the resulting closed-loop fuzzy control system is asymptotically stable with less data transmissions. It is noted that there are no existing results on decentralized event-triggered control for large-scale fuzzy systems. It is also noted that the delay-dependent method can be developed for sampled-data control systems by using input-delay approach [37]. Assume that $\tau_i = 0.17$, $\bar{\eta}_i = 0.18$, it has been found that there are no feasible solutions based on the design method proposed in [38], [39]. However, by applying Corollary 3.1 with $\bar{Q}_i > 0$, we indeed obtain a feasible solution with the maximum triggered parameter $\sigma_{i\max} = 0.032$. Consider the condition that $\bar{Q}_i$ may be negative definite, and by

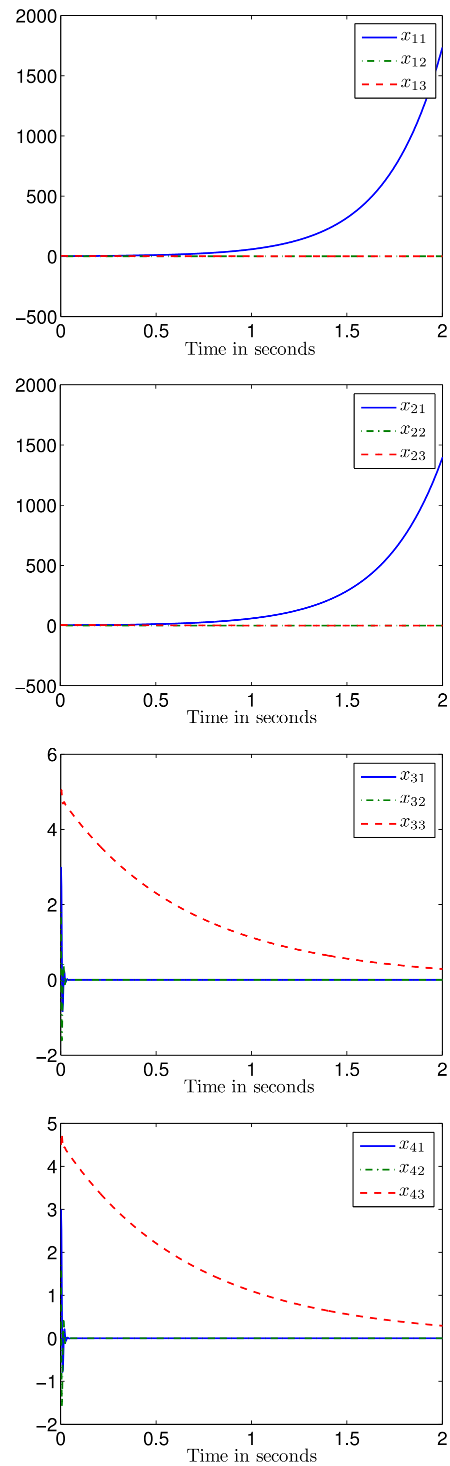

Fig. 6. State responses for open-loop dc microgrid in Example 4.2.

using Corollary 3.1, the maximum triggered parameter can be further improved to $\sigma_{i\max} = 0.038$, and the corresponding linear controller gains are

$$K_1 = [0.1706 \quad 0.0001 \quad -0.0001]$$

$$K_2 = [0.1773 \quad 0.0001 \quad -0.0001]$$

$$K_3 = [0.0091 \quad 0.0058 \quad -0.1211]$$

$$K_4 = [0.0152 \quad -0.0045 \quad -0.1250].$$

Now, let us assume that the information in the asynchronous variables μ_{il} and $\hat{\mu}_{il}$ is known and satisfies that $\underline{\rho}_{il} = 0.5$ and $\bar{\rho}_{il} = 2$. By applying Theorem 3.2, the triggered parameter σ_i is further improved to 0.041, and the corresponding fuzzy controller gains are

$$K_{11} = [0.1843 \quad 0.0001 \quad -0.0001]$$
$$K_{12} = [0.1573 \quad 0.0001 \quad 0.0001]$$
$$K_{13} = [0.1659 \quad 0.0001 \quad -0.0001]$$
$$K_{14} = [0.1417 \quad 0.0001 \quad 0.0001]$$

for the first subsystem, and

$$K_{21} = [0.1869 \quad 0.0001 \quad -0.0001]$$
$$K_{22} = [0.1592 \quad 0.0001 \quad 0.0001]$$
$$K_{23} = [0.1678 \quad 0.0001 \quad -0.0001]$$
$$K_{24} = [0.1429 \quad 0.0001 \quad 0.0001]$$

for the second subsystem, and

$$K_{31} = [0.0018 \quad -0.0149 \quad -0.0271]$$
$$K_{32} = [0.0018 \quad -0.0148 \quad -0.0270]$$
$$K_{33} = [0.0018 \quad -0.0148 \quad -0.0270]$$
$$K_{34} = [0.0018 \quad -0.0146 \quad -0.0268]$$

for the third subsystem, and

$$K_{41} = [-0.0125 \quad -0.0319 \quad -0.0283]$$
$$K_{42} = [-0.0124 \quad -0.0317 \quad -0.0282]$$
$$K_{43} = [-0.0124 \quad -0.0317 \quad -0.0282]$$
$$K_{44} = [-0.0124 \quad -0.0318 \quad -0.0282]$$

for the fourth subsystem.

Based on the above solutions, Fig. 7 indicates that the state responses for the dc microgrid system converge to zero. When using event-triggered control, Fig. 8 shows that the number of transmissions reduces from 50 to 29 in PV subsystem 1, from 50 to 29 in PV subsystem 2, from 50 to 36 in PMSG subsystem 3, and from 50 to 35 in PMSG subsystem 4, respectively.

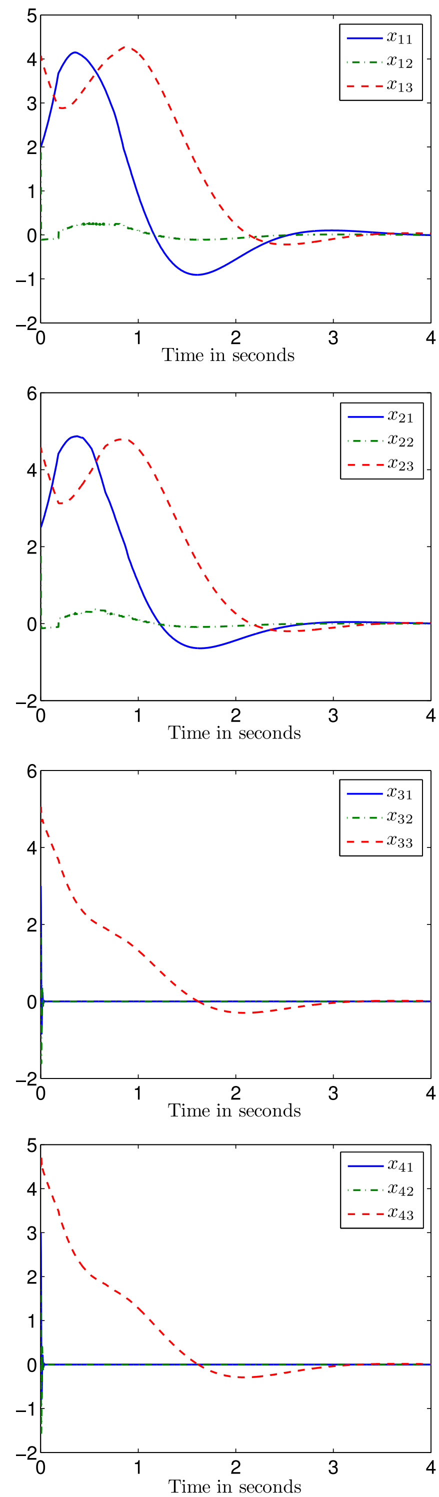

Fig. 7. State responses for closed-loop dc microgrid control system in Example 4.2.

V. Experimental Results

To testify the proposed control scheme, the experiment of dc microgrid interconnected system is performed in this section. Fig. 9 shows the experimental setup, which consists of two PV power simulators and two wind turbine power simulators. The developed event-triggered controller is realized by using the DSP-based control card (dSPACE DS1104), where the TMS320F240 DSP is taken as the main processing core.

In this experiment, the PV voltage and current, PMSG current and rotor speed, are sampled by the A/D converters and sent into the DSP board. After the control input is implemented from the feedback signals, the PWM signals to the switched MOSFETs are generated by the DS1104 board, and theirs frequency is set to 5000 Hz. In addition, we take the MATLAB Simulink Toolbox and the Real-Time Workshop as a communication interface between software and hardware. More specifically, the block diagram of the proposed control is firstly established by the Simulink. Then, by using a compiler the real-time workshop transforms the Simulink model into a C code that can be downloaded to the DSP card. Finally, the DS1104 board is connected to the dc/dc and ac/dc converters to implement the proposed control method. Fig. 10 shows the steady-state values of the instantaneous voltage and current of the load. Fig. 11 shows that

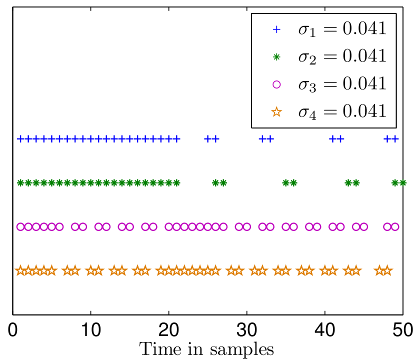

Fig. 8. Event-triggered times for $\sigma_i = 0.041$ in Example 4.2.

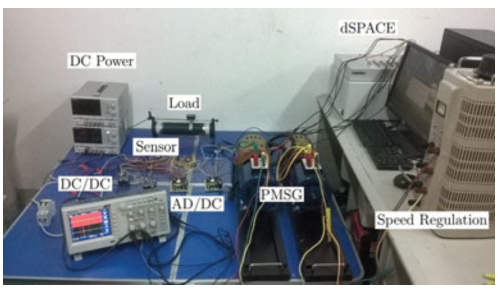

Fig. 9. Experimental setup of dc microgrid.

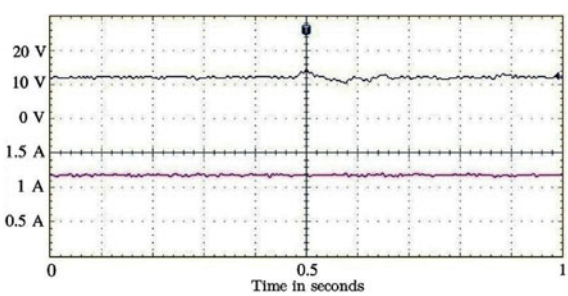

Fig. 10. Responses of instantaneous voltage and current at the load.

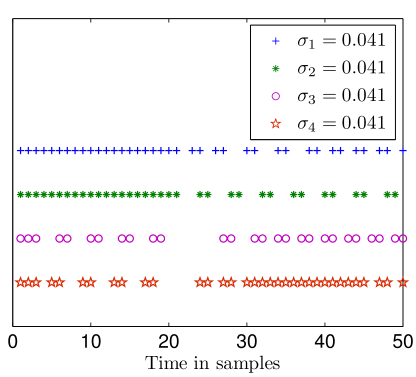

Fig. 11. Event-triggering in real-time simulation.

when using event-triggered control, the number of transmissions reduces from 50 to 38 in subsystem 1, from 50 to 35 in subsystem 2, from 50 to 23 in subsystem 3, and from 50 to 34 in subsystem 4, respectively. Clearly, the real-time results effectively validate that the communication resource is significantly saved by using the event-triggered scheme proposed in this paper.

VI. Conclusion

This paper studied the event-triggered control problem for large-scale networked T–S fuzzy systems with transmission delays and nonlinear interconnections. Each fuzzy subsystem in the large-scale system exchanges its information through a digital channel. We proposed an ETM to examine when both the premise variables and system state should be transmitted to the controller. By using the input delay approach and perturbed system approaches, the closed-loop fuzzy control system was formulated into a continuous-time system with time-varying delay and extra disturbance. Based on a LKF with virtue of Wirtinger's inequality, the codesign result with less conservatism was derived to obtain simultaneously the fuzzy controller gains, sampled period, network delay, and event-triggered parameter in terms of a set of LMIs. Simulation results showed that the resulting large-scale networked fuzzy control system was asymptotically stable with respect to a reduction of data transmissions in communication networks.

Appendix A

Lemma A1: [44] For any constant symmetric positive definite matrix $M \in \Re^{n\times n}$, scalars $d_2 > d_1 \geq 0$, the following inequality holds:

$$\left(\int_{d_1}^{d_2} x(t)\,\mathrm{dt}\right)^T M \left(\int_{d_1}^{d_2} x(t)\,\mathrm{dt}\right) \leq (d_2 - d_1)\int_{d_1}^{d_2} x^T(t)\,\mathrm{Mx}(t)\,\mathrm{dt}.$$

Lemma A2: [45] For matrix $M \in \Re^{n\times n}, M = M^T > 0$, $z(t) \in [a, b)$ and $z(a) = 0$, the following inequality holds:

$$\int_a^b z^T(t)\,\mathrm{Mz}(t)\,\mathrm{dt} \leq \frac{4(b-a)^2}{\pi^2}\int_a^b \dot{z}^T(t)\,M\dot{z}(t)\,\mathrm{dt}.$$

Lemma A3: [46] Assume that the membership functions satisfy $\underline{\rho}_l \leq \frac{\hat{\mu}_l}{\mu_l} \leq \bar{\rho}_l, l \in \mathscr{L} := \{1, 2, \ldots, r\}$. Then, $\sum_{l=1}^r \sum_{s=1}^r \mu_l \hat{\mu}_s \Sigma_{ls} < 0$ holds if there exist matrices $X_{\mathrm{ls}} = X_{\mathrm{sl}}^T$, such that for all $(l, s) \in \mathscr{L}$, the following inequalities hold:

$$\bar{\rho}_l \Sigma_{ll} + X_{ll} < 0$$
$$\underline{\rho}_l \Sigma_{ll} + X_{ll} < 0$$
$$\bar{\rho}_s \Sigma_{ls} + \bar{\rho}_l \Sigma_{sl} + X_{ls} + X_{sl} < 0$$
$$\underline{\rho}_s \Sigma_{ls} + \underline{\rho}_l \Sigma_{sl} + X_{ls} + X_{sl} < 0$$
$$\underline{\rho}_s \Sigma_{ls} + \bar{\rho}_l \Sigma_{sl} + X_{ls} + X_{sl} < 0$$
$$\bar{\rho}_s \Sigma_{ls} + \underline{\rho}_l \Sigma_{sl} + X_{ls} + X_{sl} < 0$$

$$\begin{bmatrix} X_{11} & \cdots & X_{1r} \\ \vdots & \ddots & \vdots \\ X_{r1} & \cdots & X_{rr} \end{bmatrix} > 0.$$

APPENDIX B

$$
\begin{bmatrix}
A_{11} & \bar{A}_{121} & \bar{A}_{131} & B_{11} \\
A_{12} & \bar{A}_{122} & \bar{A}_{132} & B_{12} \\
A_{13} & \bar{A}_{123} & \bar{A}_{133} & B_{13} \\
A_{14} & \bar{A}_{124} & \bar{A}_{134} & B_{14} \\
A_{15} & \bar{A}_{125} & \bar{A}_{135} & B_{15} \\
A_{16} & \bar{A}_{126} & \bar{A}_{136} & B_{16}
\end{bmatrix} =
$$

$$
\left[\begin{array}{rr|rr|rr|r}
0.21 & 0.92 & 0 & 0 & 0 & 0 & 0 \\
0 & -0.53 & 0.42 & 0 & 0.41 & 0 & 0.49 \\ \hline
0.18 & 1.13 & 0 & 0 & 0 & 0 & 0 \\
0 & -1.81 & 0.39 & 0 & 0.38 & 0 & 0.48 \\ \hline
0.20 & 1.02 & 0 & 0 & 0 & 0 & 0 \\
0 & -0.94 & 0.41 & 0 & 0.40 & 0 & 0.51 \\ \hline
0.19 & 1.13 & 0 & 0 & 0 & 0 & 0 \\
0 & -1.79 & 0.38 & 0 & 0.37 & 0 & 0.62 \\ \hline
0.22 & 0.87 & 0 & 0 & 0 & 0 & 0 \\
0 & -0.98 & 0.43 & 0 & 0.38 & 0 & 0.51 \\ \hline
0.21 & 0.96 & 0 & 0 & 0 & 0 & 0 \\
0 & -1.66 & 0.33 & 0 & 0.36 & 0 & 0.57
\end{array}\right]
$$

$$
\begin{bmatrix}
A_{21} & \bar{A}_{211} & \bar{A}_{231} & B_{21} \\
A_{22} & \bar{A}_{212} & \bar{A}_{232} & B_{22} \\
A_{23} & \bar{A}_{213} & \bar{A}_{233} & B_{23} \\
A_{24} & \bar{A}_{214} & \bar{A}_{234} & B_{24} \\
A_{25} & \bar{A}_{215} & \bar{A}_{235} & B_{25} \\
A_{26} & \bar{A}_{216} & \bar{A}_{236} & B_{26}
\end{bmatrix} =
$$

$$
\left[\begin{array}{rr|rr|rr|r}
0.20 & 1.01 & 0 & 0 & 0 & 0 & 0 \\
0 & -0.46 & 0.53 & 0 & 0.62 & 0 & 0.39 \\ \hline
0.17 & 0.99 & 0 & 0 & 0 & 0 & 0 \\
0 & -1.62 & 0.61 & 0 & 0.55 & 0 & 0.53 \\ \hline
0.21 & 1.12 & 0 & 0 & 0 & 0 & 0 \\
0 & -0.47 & 0.60 & 0 & 0.59 & 0 & 0.41 \\ \hline
0.13 & 0.87 & 0 & 0 & 0 & 0 & 0 \\
0 & -1.62 & 0.48 & 0 & 0.52 & 0 & 0.49 \\ \hline
0.22 & 0.98 & 0 & 0 & 0 & 0 & 0 \\
0 & -1.22 & 0.51 & 0 & 0.43 & 0 & 0.41 \\ \hline
0.19 & 1.17 & 0 & 0 & 0 & 0 & 0 \\
0 & -1.56 & 0.58 & 0 & 0.51 & 0 & 0.53
\end{array}\right]
$$

$$
\begin{bmatrix}
A_{31} & \bar{A}_{311} & \bar{A}_{321} & B_{31} \\
A_{32} & \bar{A}_{312} & \bar{A}_{322} & B_{32} \\
A_{33} & \bar{A}_{313} & \bar{A}_{323} & B_{33} \\
A_{34} & \bar{A}_{314} & \bar{A}_{324} & B_{34} \\
A_{35} & \bar{A}_{315} & \bar{A}_{325} & B_{35} \\
A_{36} & \bar{A}_{316} & \bar{A}_{326} & B_{36}
\end{bmatrix} =
$$

$$
\left[\begin{array}{rr|rr|rr|r}
0.19 & 1.02 & 0 & 0 & 0 & 0 & 0 \\
0 & -0.84 & 0.47 & 0 & 0.61 & 0 & 0.51 \\ \hline
0.15 & 0.78 & 0 & 0 & 0 & 0 & 0 \\
0 & -1.61 & 0.51 & 0 & 0.58 & 0 & 0.54 \\ \hline
0.21 & 1.04 & 0 & 0 & 0 & 0 & 0 \\
0 & -0.72 & 0.62 & 0 & 0.60 & 0 & 0.48 \\ \hline
0.13 & 0.92 & 0 & 0 & 0 & 0 & 0 \\
0 & -1.21 & 0.56 & 0 & 0.46 & 0 & 0.52 \\ \hline
0.22 & 0.93 & 0 & 0 & 0 & 0 & 0 \\
0 & -0.67 & 0.49 & 0 & 0.58 & 0 & 0.49 \\ \hline
0.17 & 0.96 & 0 & 0 & 0 & 0 & 0 \\
0 & -1.10 & 0.52 & 0 & 0.47 & 0 & 0.49
\end{array}\right]
$$

APPENDIX C

$$
\left[\begin{array}{c|c|c}
A_{11} & \bar{A}_{12} & B_{11} \\ \hline
A_{12} & \bar{A}_{13} & B_{12} \\ \hline
A_{13} & \bar{A}_{14} & B_{13} \\ \hline
A_{14} & & B_{14}
\end{array}\right] =
$$

$$
\left[\begin{array}{rrr|lrr|r}
3.7520 & 0 & 0 & 0 & 0 & 0 & -24.7525 \\
0 & -761.6279 & -18.1749 & 0 & 0.2989 & 0 & 356.5891 \\
0 & 21.1864 & -1.0977 & 0 & 4.9398 & 0 & 0 \\ \hline
3.7520 & 0 & 0 & 0 & 0 & 0 & -28.7129 \\
0 & -664.3277 & -18.1749 & 0 & 0.2989 & 0 & 355.9690 \\
0 & 21.1864 & -1.0977 & 0 & 4.9398 & 0 & 0 \\ \hline
3.3808 & 0 & 0 & 0 & 0 & 0 & -24.7525 \\
0 & -761.6279 & -18.1749 & 0 & 0.2989 & 0 & 410.8527 \\
0 & 21.1864 & -1.0977 & 0 & 4.9398 & 0 & 0 \\ \hline
3.3808 & 0 & 0 & & & & -28.7129 \\
0 & -664.3277 & -18.1749 & & & & 410.2326 \\
0 & 21.1864 & -1.0977 & & & & 0
\end{array}\right]
$$

$$
\left[\begin{array}{c|c|c}
A_{21} & \bar{A}_{21} & B_{21} \\ \hline
A_{22} & \bar{A}_{23} & B_{22} \\ \hline
A_{23} & \bar{A}_{24} & B_{23} \\ \hline
A_{24} & & B_{24}
\end{array}\right] =
$$

$$
\left[\begin{array}{rrr|lrr|r}
3.5088 & 0 & 0 & 0 & 0 & 0 & -23.1481 \\
0 & -772.3735 & -18.3464 & 0 & 0.2989 & 0 & 359.6790 \\
0 & 24.3309 & -1.2607 & 0 & 4.9398 & 0 & 0 \\ \hline
3.5088 & 0 & 0 & 0 & 0 & 0 & -26.8519 \\
0 & -673.6214 & -18.3464 & 0 & 0.2989 & 0 & 359.0175 \\
0 & 24.3309 & -1.2607 & 0 & 4.9398 & 0 & 0 \\ \hline
3.1617 & 0 & 0 & 0 & 0 & 0 & -23.1481 \\
0 & -772.3735 & -18.3464 & 0 & 0.2989 & 0 & 414.1537 \\
0 & 24.3309 & -1.2607 & 0 & 4.9398 & 0 & 0 \\ \hline
3.1617 & 0 & 0 & & & & -26.8519 \\
0 & -673.6214 & -18.3464 & & & & 413.4922 \\
0 & 24.3309 & -1.2607 & & & & 0
\end{array}\right]
$$

$$
\left[\begin{array}{c|c|c}
A_{31} & \bar{A}_{31} & B_{31} \\ \hline
A_{32} & \bar{A}_{32} & B_{32} \\ \hline
A_{33} & \bar{A}_{34} & B_{33} \\ \hline
A_{34} & & B_{34}
\end{array}\right] =
$$

$$\left[\begin{array}{ccc|ccc|c}
-141.4944 & 363.5294 & 0 & 0 & 0 & 0 & 0 \\
-363.5294 & -172.8155 & 0 & 0 & 0 & 0 & 0 \\
0 & 35.8852 & -1.2396 & 0 & 5.5780 & 0 & 35.8852 \\
\hline
-141.4944 & 381.8824 & 0 & 0 & 0 & 0 & 0 \\
-381.8824 & -164.5102 & 0 & 0 & 0 & 0 & 0 \\
0 & 35.8852 & -1.2396 & 0 & 5.5780 & 0 & 35.8852 \\
\hline
-141.4944 & 393.0048 & 0 & 0 & 0 & 0 & 0 \\
-393.0048 & -172.8155 & 0 & 0 & 0 & 0 & 0 \\
0 & 35.8852 & -1.2396 & 0 & 5.5780 & 0 & 35.8852 \\
\hline
-141.4944 & 412.8458 & 0 & & & & 0 \\
-412.8458 & -164.5102 & 0 & & & & 0 \\
0 & 35.8852 & -1.2396 & & & & 35.8852
\end{array}\right]$$

$$\left[\begin{array}{c|c|c}
A_{41} & \bar{A}_{41} & B_{41} \\
\hline
A_{42} & \bar{A}_{42} & B_{42} \\
\hline
A_{43} & \bar{A}_{43} & B_{43} \\
\hline
A_{44} & & B_{44}
\end{array}\right] =$$

$$\left[\begin{array}{ccc|ccc|c}
-131.5789 & 338.8421 & 0 & 0 & 0 & 0 & 0 \\
-338.8421 & -172.4138 & 0 & 0 & 0 & 0 & 0 \\
35.8852 & 35.8852 & -1.2022 & 0 & 5.4098 & 0 & 34.8028 \\
\hline
-131.5789 & 356.3684 & 0 & 0 & 0 & 0 & 0 \\
-356.3684 & -163.9344 & 0 & 0 & 0 & 0 & 0 \\
35.8852 & 35.8852 & -1.2022 & 0 & 5.4098 & 0 & 34.8028 \\
\hline
-131.5789 & 366.3158 & 0 & 0 & 0 & 0 & 0 \\
-366.3158 & -172.4138 & 0 & 0 & 0 & 0 & 0 \\
35.8852 & 35.8852 & -1.2022 & 0 & 5.4098 & 0 & 34.8028 \\
\hline
-131.5789 & 385.2632 & 0 & & & & 0 \\
-385.2632 & -163.9344 & 0 & & & & 0 \\
35.8852 & 35.8852 & -1.2022 & & & & 34.8028
\end{array}\right]$$

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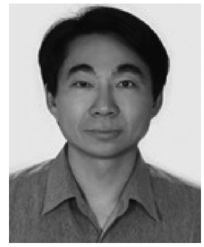

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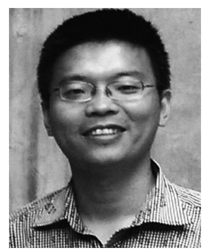

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