Cloud-based event-triggered predictive control for heterogeneous NMASs under both DoS attacks and transmission delays

Xiuxia Yin, Zhiwei Gao, *Senior Member, IEEE* , Dong Yue, *Fellow, IEEE*, Songlin Hu

***Abstract*—A novel compensation control method for heterogeneous multi-agent systems under Denial of Service (DoS) attacks and transmission delays is investigated in this paper. This control method has all the advantages of the cloud-based computation strategy, the adaptive event-triggered strategy and the predictive control scheme. The adaptive event triggering mechanism can adjust the event numbers adaptively, the predictive control can reduce or eliminate the negative effects brought out by both DoS attacks and transmission delays actively, while the cloud-based computation strategy can eliminate the negative effects completely as the same as there are no DoS attacks and transmission delays. Through the interval decomposition skill and the augmented system modeling method, the compensated geschlossenes system model is established. Moreover, the joint design for the feedback gain matrices and the event-triggered parameters is implemented. In the simulation part, five VTOL aircrafts are used to demonstrate the theoretical results.**

***Index Terms*—consensus, event-triggered scheme, cloud computing, predictive control, DoS attacks, delay.**

I. INTRODUCTION

For the last few years, the investigation on consistency for MASs has attracted more and more concern for its important and extensive applications [1]–[3], [7]–[10], [18].

For the complex networked multi-agent systems (NMASs), there are two aspects of the non-ideal network environment that should be taken into account: (i) On the one hand, Denial of Service (DoS) attack often means such an attack that it can affect the implementation of network guidelines or run out of network resources. This can destroy the necessary information transmission [19]–[22]. (ii) On the other hand, network communication delay is inevitable for the actual system [26], [27], also for NMASs investigated in this paper. In these two situations, the consensus performance maybe deduced, or the consensus can not realize at all if we ignore the negative effects of DoS attacks and transmission delays. In consequence, defending against or compensating for the negative effects caused by DoS attacks and transmission delays is an important security problem when designing the consensus control for NMASs.

Furthermore, the communication network of NMASs often has resource constraints such as bandwidth limitations [18], [35]. Event-triggered transmission strategy is an effective scheme to reduce the communication resource utilization [13]–[17], [23] and has been applied for NMASs [24], [25]. However, most existing works on event-triggered consensus control are focused on the secure network, that is, without considering DoS attacks. Even recently, some outstanding results have considered the elasticity control for NMASs by using the event-triggered strategy, consensus control for NMASs under DoS attacks [31], [32], [35], nearly all of them passively accept the presence of attacks.

As we know, predictive control is an useful way to reduce or eliminate the negative effects caused by the transmission delays or data losses [12], [34], [37]–[39]. However, for the case of NMASs with transmission delays, even based on the classical time-triggered control, the consensus protocol design and the system analysis by using the predictive control is challenging due to the complexity and coupling relationship among agents, and by now only few results can be available on this topic [36], [37]. In terms of the event-triggered case, there is even less result that has been reported in the open literature on consensus by using the predictive compensation method [18], [40]. In our foregone investigation [18], for NMASs with transmission delays and in the way of adopting the event transmission, predictive control is employed in order to element the effects brought out by the transmission delays, but it was assumed that the network is secure.

When using the predictive control for NMASs, there is a challenging problem in the open literature, that is, the neighbors' state predictions are imprecise or not complete, this is because the neighbors' control information can not be obtained by agent i at every time step when calculating the neighbors predictive states. To our delight, cloud-based computing may help us to solve the above problem [3], [6], [29], [30]. As used in the important work [3], agents' information will be emit to the cloud center via internet, where the control end will generate a series of predictive control signals which are sent back to agents' actuator side by networks. However, work [3] was based on the classical time-triggered communication strategy and didn't consider the insecurity situation. In a word, up to now, there is no academic publication about the compensation control for NMASs with

This work is supported by NSFC (No. 61963028 and No. 62173187) and the Jiangxi Province academic and technical leader Training Program – Young Talents Project (20212BCJ23040). Corresponding authors: Zhiwei Gao and Dong Yue (Emails: zhiwei.gao@northumbria.ac.uk and medongy@vip.163.com).

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DoS attacks under event-triggered scheme, not to mention for NMASs with both DoS attacks and transmission delays.

Taking into account the above discussions, here we will put forward a novel compensation control structure, named as cloud-based adaptive event-triggered predictive control (CB-AETPC), which has integrated the cloud-based computing scheme, the adaptive event-triggered transmission strategy and the predictive control method all together. The specific contributions are shown below.

(1) This paper puts forward an innovative CB-AETPC approach. Based on the available event-triggered state information of agents, the real states at current time of agents are all predicted completely at the cloud-based control node and so the predictive controllers can be generated.

(2) The investigated system is heterogeneous NMASs, all agents have different evolutionary properties. A new consensus control protocol that make it convenient for us to build the geschlossenes system is proposed.

(3) Through the interval decomposition skill and the augmented system modeling method, the consistency criteria is obtained and the joint design of feedback gain matrices and the event-triggering parameter matrices is realized.

In all, the proposed CB-AETPC has the advantages of reducing the utilization of the limited network resources significantly, compensating for the DoS attacks and networked transmission delays completely and guaranteeing the desired consensus control performance.

Section II displays the consensus problem to be solved. The details of CB-AETPC are displayed in Section III. The consensus analysis is shown in Section IV. We make some experimental results in Section V and summarize the content in Section VI.

II. Some preparation and system description

The graph theory can be seen in [18].

A. System Model Statement

We consider the discrete heterogeneous NMASs, including N agents denoted by $1, 2, \ldots, N$. Every agent's dynamics is described by

$$x_i(t+1) = A_i x_i(t) + B_i u_i(t) \tag{1}$$

with $x_i(t) \in \mathbb{R}^n$ and $u_i(t) \in \mathbb{R}^m$ representing the state variable and control variable for agent i. $i \in S_N$ and $S_N \triangleq \{1, 2, \ldots, N\}$. A_i and B_i are system matrices with dimensions $\mathbb{R}^{n\times n}$ and $\mathbb{R}^{n\times m}$, respectively. B_i is assumed to be full-row rank. $x_i(t_0^i)$, $i \in S_N$ are the initial states of agents.

Definition 1: The definition of consensus for (1) is referred to [37].

In this article, we assumed that all agents transmit their information via a shared network and the network has a cloud-based computing center, see Fig.1. Every agent is connected to a cloud controller node (C-C node) via network, meanwhile, each C-C node is linked to its neighbors'. For agent i, who is its neighbor depends on the agent's information acquire ability.

The following assumptions are needed.

Assumption 1: There exist transmission delay τ between sensor i and the C-C node i, and network delay d between the C-C node i and the actuator i. The transmission delays among C-C nodes are negligible. τ and d are known integers. Indeed, these delays are multiples of the sampling period T [3]–[5].

Assumption 2: There being a spanning tree in the directed communication topology.

Assumption 3: In all the data transmission, each data is time-stamped.

B. DoS jamming attacks

This article focuses on the devastating DoS attacks, which can block the information transmission among agents.

Definition 2: (Attack Frequency) This definition is referred to [19], [31].

Definition 3: (Attack Duration) This definition is referred to [19], [31].

Assumption 4: The upper bound of the DoS attack duration time is M for a single attack. This is reasonable since the attackers often have limit energies.

Assumption 5: It is assumed that the initial times $t_0^i = t_0^j = t_0, i \neq j$.

C. Adaptive event-triggered scheme

Event generator a_i can help to judge that if the current state needs to be transmitted to the C-C node i through network, see Fig. 1. For easy understanding, we use t_k^i to describe the kth event-triggered time and $x_i(t_k^i)$ represent the event-triggered state for agent i, $k = 1, 2, ...,$ $i \in S_N$. For agent i, the event-triggered function $f_i(\cdot)$ is defined as follows

$$\begin{aligned} f_i(\cdot) \;&=\; [x_i(t_k^i + l) - x_i(t_k^i)]^T \Omega_i [x_i(t_k^i + l) - x_i(t_k^i)] \\ &\quad -\mu_i(t_k^i + l)\hat{w}_i^T(t_k^i + l)\Omega_i \hat{w}_i(t_k^i + l), \end{aligned} \tag{2}$$

where $\hat{w}_i(t_k^i + l) = -\sum_{j\in N_i} a_{ij}(x_i(t_k^i) - \hat{x}_j(t^j_{k_{ij}(t^i_{m_i})+s}))$, the state $\hat{x}_j(t^j_{k_{ij}(t^i_{m_i})+s}) \in \overrightarrow{X}_j(t^j_{k_{ij}(t^i_{m_i})})$ (its definition will be given in the next section) is the latest predicted event-triggered state for current time $t = t_k^i + l$ of neighbor j, $\Omega_i > 0$, $\mu_i(\cdot)$ satisfies the following adaptive law

$$\begin{aligned} &\mu_i(t_k^i + l) \\ =\;& \lambda - \frac{\lambda - \mu_i(t_k^i + l - 1)}{1 + [x_i(t_k^i + l) - x_i(t_k^i)]^T \Omega_i [x_i(t_k^i + l) - x_i(t_k^i)]}, \end{aligned} \tag{3}$$

where $\lambda > 0$ is given in advance. When $x_i(t_k^i)$ is triggered, the next trigger moment is judged by

$$t_{k+1}^i = t_k^i + \min\{l_k^i, q\} \tag{4}$$

$$\begin{aligned} l_k^i = \min_{l\in Z^+} \{ & l | \mu_i(t_k^i + l)\hat{w}_i^T(t_k^i + l)\Omega_i \hat{w}_i(t_k^i + l) < \\ & [x_i(t_k^i + l) - x_i(t_k^i)]^T \Omega_i [x_i(t_k^i + l) - x_i(t_k^i)] \} , \end{aligned} \tag{5}$$

where $q > 0$ and it is an integer.

Remark 1: The adaptive law in (3) can help us to adjust the transmission numbers timely according to the system dynamics [17], [18]. Furthermore, the adaptive law (4) can

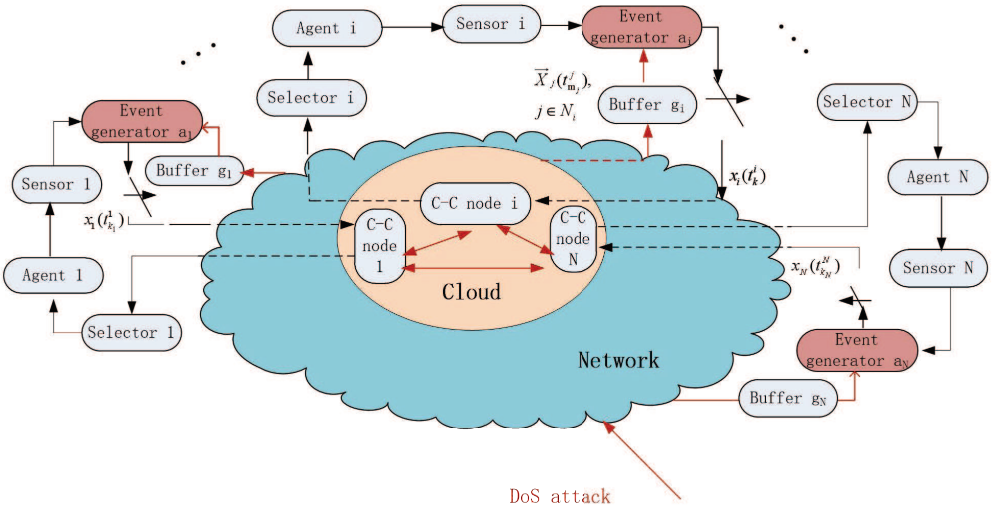

Fig. 1. System structure

facilitate us to deduce the following Lemma 2 , which is necessary and important for us to analysis the consistency performance and obtain the consistency criteria.

Assumption 6: For the initial time interval $[t_0^i, t_0^i + \tau + d)$, the dynamic system (1) is working as

$$x_i(t+1) = A_i x_i(t) + B_i u_i(t), \quad (6)$$

$$u_i(t) = 0. \quad (7)$$

The event generator a_i also starts working at the initial time t_0^i, in order to facilitate the following analysis, it is assumed that all the states in the time interval $[t_0^i, t_0^i + \tau + d)$ are not released. Let $x_i(t_0^i + \tau + d) \triangleq x_i(t_1^i)$, which will be sent to C-C node i as the first event-triggered state. Then the subsequent event-triggered states will be adjusted by the event generator a_i according to (2)-(4).

In this paper, for the heterogeneous NMASs (1), based on the event-triggered transmission scheme above, if there don't exist DoS attacks and transmission delays, we can design the consensus control as below:

$$u_i(t) = -B_{iR}^{-1} A_i x_i(t_k^i) - K_i \sum_{j \in N_i} a_{ij} [x_i(t_k^i) - x_j(t_{k_j}^j)], \quad (8)$$

where B_{iR}^{-1} is the right inverse of matrix B_i and $x_j(t_{k_j}^j)$ is the latest event-triggered state of neighbor agent j for current time t.

Remark 2: As stated in work [36], the full-rank of B_i guarantees that B_i has right inverse B_{iR}^{-1}. The solve method of B_{iR}^{-1} can be illustrated by $B_{iR}^{-1} = W B_i^T (B_i W B_i^T)^{-1}$, where W can be any matrix satisfying $rank\ (B_i W B_i^T) = rank\ B_i$, $i \in S_N$.

When there exist both DoS attacks and transmission delays, the detailed consensus control, i.e., the cloud-based adaptive event-triggered predictive control (CB-AETPC), will be designed in the next section.

III. Design of CB-AETPC

The previous works [3], [18], [36] have investigated the predictive control consensus for NMASs, with the purpose

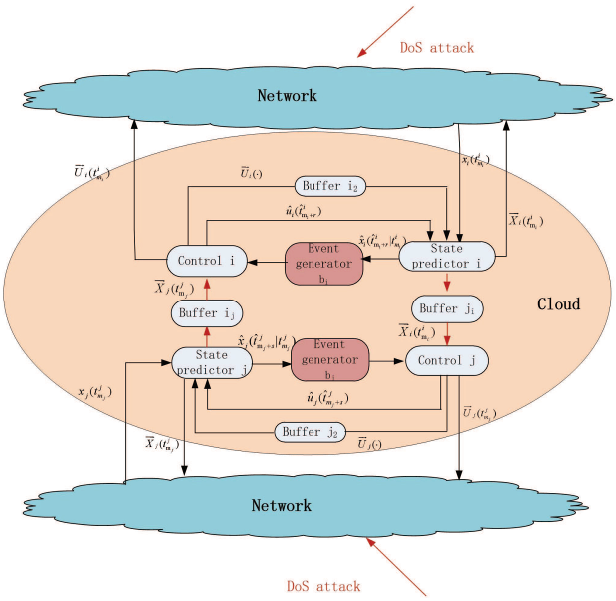

Fig. 2. C-C nodes

of compensating for the communication delays or dealing with the data dropout.However, there exists one common horny problem in previous investigation: when designing the distributed predictive control for each agent i, it needs to predict the future states information not only for agent i itself but also for its neighbors, and it is impossible to predict the precise states for the neighbors, since neighbor's control information can not be obtained by agent i directly at each time.

Insight by work [3], it is possible to use a cloud-based computation method to deal with the problem mentioned above. Here we try to combine this ideal with the event-triggered transmission scheme to solve the resilient (compensation) control problem for NMASs with both transmission delays and malicious DoS attacks. The overall framework for this method can be seen in Fig.1. The calculated event-triggered states $x_i(t_k^i)$ of each agent i will be sent out to its C-C node. Each C-C node i has the ability of predicting state information of itself and calculating the predictive control sequences by using the predictive model embedded in it. One can see the details about the communication and computation relationship between C-C node i and C-C node j in Fig.2. The predicted control signals will be packed together in $\overrightarrow{U}_i$ and sent back to the actuators of individual agents via the shared network. There exists a selector (which contains three parts "Actuator i ", "Buffer i_1" and "Control selector " as in Fig. 3) at each agent's actuator side, which is used to select the suitable control input u_i by comparing the time stamps on the control elements in $\overrightarrow{U}_i$ and the current time, please see Fig. 3 and the following detailed descriptions in (29), (30) and (31).

Assumption 7: At each agent's C-C node, there is also embedded an event-triggered generator b_i together with the predictive model, which is used to generate forward event-triggered states and event-triggered control predictions to eliminate the bad influences of communication delays and the possible DoS attacks.

By using event generator b_i, the size of the control packet $\overrightarrow{U}_i$ will not be very large and this point will be further illustrated in the following Remark 8. The detail realize process for CB-AETPC is given in the following two situations.

A. For the initial time interval

For easy understanding, we first take the initial state $x_i(t_0^i)$ of agent i as an example. Assume that $x_i(t_0^i)$ is transmitted to the network successfully and the network is not subjected to DoS attack in the initial time interval $[t_0^i, t_0^i + \tau + d]$. Considering the transmission delay, $x_i(t_0^i)$ will arrive at the C-C node side at the time $t_0^i + \tau$, let $\hat{x}_i(t_0^i|t_0^i) = x_i(t_0^i)$, then the predictive model in the C-C node i will work as follows:

$$\begin{aligned} \hat{x}_i(t+1|t_0^i) &= A_i\hat{x}_i(t|t_0^i) + B_i u_i(t|t_0^i) && (9)\\ u_i(t|t_0^i) &= 0 && (10)\\ t &\in [t_0^i, t_0^i + \tau + d) \end{aligned}$$

In the predictive time interval $[t_0^i, t_0^i + \tau + d)$ at the C-C node i, the event triggered generator b_i works the same way as the event generator a_i as stated in Assumption 6.

Remark 3: All the initial states $x_i(t_0^i)$ of agents can also be assumed to be transmitted successfully, and so the initial control is not zero. This may help us to improve the consensus performance. It is just an assumption, each hypothesis has its practical significance.

Then, for the further prediction time interval $[t_0^i + \tau + d, t_0^i + 2\tau + 2d + 2q + M)$ at agent i's C-C node, it is needed to predict further state information and control information for the use of compensating for the DoS attacks that might happen in this real time interval. The event generator b_i is working as follows

$$\begin{aligned} \hat{t}_{0+1}^i &\triangleq t_0^i + \tau + d, && (11)\\ \hat{t}_{0+r+1}^i &= \hat{t}_{0+r}^i + \min\{l_{0+r}^i, q\}, && (12)\\ l_{0+r}^i &= \min_{l\in Z^+}\{l|\Theta_0^i(\cdot,\cdot)^T\Omega_i\Theta_0^i(\cdot,\cdot) > && (13)\\ &\quad \hat{\mu}_i(\hat{t}_{0+r}^i + l)\hat{w}_i^T(\hat{t}_{0+r}^i + l)\Omega_i\hat{w}_i(\hat{t}_{0+r}^i + l)\},\\ \hat{\mu}_i(\hat{t}_{0+r}^i + l) &= \lambda - \frac{\lambda - \hat{\mu}_i(\hat{t}_{0+r}^i + l - 1)}{1 + \Theta_0^i(\cdot,\cdot)^T\Omega_i\Theta_0^i(\cdot,\cdot)} && (14) \end{aligned}$$

with $\hat{w}_i(\hat{t}_{0+r}^i + l) = -\sum_{j\in N_i} a_{ij}\left[\hat{x}_i(\hat{t}_{0+r}^i|t_0^i) - \hat{x}_j(\hat{t}_{0+s}^j|t_0^j)\right]$ if $t = t_{0+r}^i + l \in [\hat{t}_{0+r}^i, \hat{t}_{0+r+1}^i) \cap [\hat{t}_{0+s}^j, \hat{t}_{0+s+1}^j)$. $\Theta_0^i(\cdot,\cdot) = [\hat{x}_i(\hat{t}_{0+r}^i + l|t_0^i) - \hat{x}_i(\hat{t}_{0+r}^i|t_0^i)]$ and Ω_i are the same as in (5). $\hat{x}_i(\hat{t}_{0+1}^i)$ represents the first predicted event state on account of $x_i(t_0^i)$ and $\hat{x}_i(\hat{t}_{0+r}^i)$ expresses the subsequent predicted event states for agent i. The predictive model is working as

$$\begin{aligned} \hat{x}_i(t+1|t_0^i) &= A_i\hat{x}_i(t|t_0^i) + B_i\hat{u}_i(t|t_0^i) && (15)\\ \hat{u}_i(t|t_0^i) &= -B_{iR}^{-1}A_i\hat{x}_i(\hat{t}_{0+r}^i|t_0^i) && (16)\\ &\quad -K_i\sum_{j\in N_i} a_{ij}\left[\hat{x}_i(\hat{t}_{0+r}^i|t_0^i) - \hat{x}_j(\hat{t}_{0+s}^j|t_0^j)\right]\\ t &\in [t_0 + \tau + d, t_0 + 2\tau + 2d + 2q + M)\\ &\quad \cap[\hat{t}_r^i, \hat{t}_{r+1}^i) \cap [\hat{t}_s^j, \hat{t}_{s+1}^j),\\ r &= 1,\ldots,, L_0^i,\\ s &= 1,\ldots,, L_0^j, \end{aligned}$$

with L_0^i satisfies that $\hat{t}_{L_0^i}^i \le t_0^i + 2\tau + 2d + 2q + M < \hat{t}_{L_0^i+1}^i$. L_0^j satisfies the similar relationship. Then we can obtain the predictive states in $\overrightarrow{X}_i(t_0^i) = \{\hat{x}_i(\hat{t}_1^i|t_0^i), \hat{x}_i(\hat{t}_2^i|t_0^i), \ldots, \hat{x}_i(\hat{t}_{L_0^i}^i|t_0^i)\}$ and $\overrightarrow{X}_i(t_0^i)$ is sent to its neighbors. It should be noted that the predicted event-triggered state information $\hat{x}_j(\hat{t}_s^j|t_0^j) \in \overrightarrow{X}_j(t_0^j) = \{\hat{x}_j(\hat{t}_1^j|t_0^j), \hat{x}_j(\hat{t}_2^j|t_0^j), \ldots, \hat{x}_j(\hat{t}_{L_0^j}^j|t_0^j)\}$ of neighbor agent j is calculated at C-C node j and the calculation process is similar to (9)-(16).

Remark 4: Each predict state information $\hat{x}_j(\hat{t}_s^j|t_0^j)$ of neighbor j is sent to agent i's C-C node (indeed, it is sent to Buffer i_j [15] in Fig. 2) once it is calculated for the timely use of event-generator b_i. The reason for sending the state package $\overrightarrow{X}_j(t_0^j)$ to agent i via network after the prediction is completed for the time interval $[t_0^j+\tau+d, t_0^j+2\tau+2d+2q+M)$ is that $\overrightarrow{X}_j(t_0^j)$ is also needed to be sent to agent i's sensor side for the use of event generator a_i, $j \in N_i$. Indeed, each agent should to do so. This remark is also suitable for the following general case.

B. For the general time interval

Now we consider the general case. Assume that $x_i(t_{m_i}^i)$ is the m_ith successfully transmitted event-triggered state for agent i from sensor to the C-C node i with transmission delay τ, that is, $x_i(t_{m_i}^i)$ will arrive at the C-C node i at time $t_{m_i}^i + \tau$. It is clear that $\{x_i(t_{m_i}^i)\} \subset \{x_i(t_k^i)\}$ and $\{t_{m_i}^i\} \subset \{t_k^i\}$. To make the key idea of this mechanism easier to follow, let $\hat{x}_i(\hat{t}_{m_i}^i|t_{m_i}^i) = x_i(t_{m_i}^i)$ and use $\mathrm{T}_{t_{m_i}^i} = \{t_{m_i}^i, \hat{t}_{m_i+1}^i, \ldots, \hat{t}_{m_i+L_{m_i}^i}^i\}$ ($t_{m_i}^i < \hat{t}_{m_i+1}^i < \cdots < \hat{t}_{m_i+L_{m_i}^i}^i$) to express the predicted event moments set according to event generator b_i, that is,

$$\begin{aligned} \hat{t}_{m_i+1}^i &= t_{m_i}^i + \min\{l_{m_i}^i, q\} && (17)\\ l_{m_i}^i &= \min_{l\in Z^+}\{l|\Theta_{m_i}^i(t_{m_i}^i, l)^T\Omega_i\Theta_{m_i}^i(t_{m_i}^i, l) && (18) \end{aligned}$$

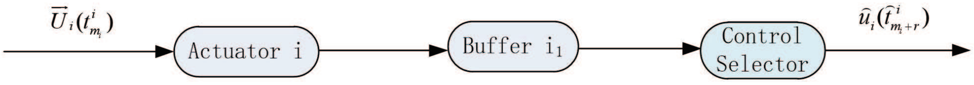

Fig. 3. Control selector

$$
\begin{aligned}
&> \hat{\mu}_i(t^i_{m_i}+l)\hat{w}_i^T(t^i_{m_i}+l)\Omega_i\hat{w}_i(t^i_{m_i}+l)\}\,, \\
\hat{\mu}_i(t^i_{m_i}+l) &= \lambda - \frac{\lambda - \hat{\mu}_i(t^i_{m_i}+l-1)}{1+\Theta^i_{m_i}(t^i_{m_i},l)^T\Omega_i\Theta^i_{m_i}(t^i_{m_i},l)},
\end{aligned}
$$

$$
\begin{aligned}
\hat{t}^i_{m_i+r+1} &= \hat{t}^i_{m_i+r} + \min\{l^i_{m_i+r}, q\} && (19)\\
l^i_{m_i+r} &= \min_{l\in Z^+}\{l|\Theta^i_{m_i}(\hat{t}^i_{m_i+r},l)^T\Omega_i\Theta^i_{m_i}(\hat{t}^i_{m_i+r},l) \\
&\quad > \hat{\mu}_i(\hat{t}^i_{m_i+r}+l)\hat{w}_i^T(\cdot)\Omega_i\hat{w}_i(\cdot)\}\,, && (20)\\
\hat{\mu}_i(\hat{t}^i_{m_i+r}+l) &= \lambda - \frac{\lambda-\hat{\mu}_i(\hat{t}^i_{m_i+r}+l-1)}{1+\Theta^i_{m_i}(\hat{t}^i_{m_i+r},l)^T\Omega_i\Theta^i_{m_i}(\hat{t}^i_{m_i+r},l)}, && (21)\\
r &= 1,2,\ldots,L^i_{m_i}
\end{aligned}
$$

$\Theta^i_{m_i}(t^i_{m_i},l) = [\hat{x}_i(t^i_{m_i}+l|t^i_{m_i}) - x_i(t^i_{m_i})]$, $\Theta^i_{m_i}(\hat{t}^i_{m_i+r},l) = [\hat{x}_i(\hat{t}^i_{m_i+r}+l|t^i_{m_i}) - \hat{x}_i(\hat{t}^i_{m_i+r}|t^i_{m_i})]$, $L^i_{m_i}$ meets that $t^i_{m_i+L^i_{m_i}} \leq t^i_{m_i} + 2\tau + 2d + 2q + M < t^i_{m_i+L^i_{m_i}+1}$. $\hat{w}_i(\cdot) = \hat{w}_i(\hat{t}^i_{m_i+r}+l)$ with

$$
\begin{aligned}
&\hat{w}_i(t^i_{m_i}+l) \\
=&\ -\sum_{j\in N_i} a_{ij}(x_i(t^i_{m_i}) - \hat{x}_j(\hat{t}^j_{k_{ij}(t^i_{m_i})+s}|t^j_{k_{ij}(t^i_{m_i})}))
\end{aligned} \tag{22}
$$

for $t = t^i_{m_i}+l \in [t^i_{m_i}, \hat{t}^i_{m_i+1}) \cap [\hat{t}^j_{k_{ij}(t^i_{m_i})+s}, \hat{t}^j_{k_{ij}(t^i_{m_i})+s+1})$ and

$$
\begin{aligned}
&\hat{w}_i(\hat{t}^i_{m_i+r}+l) \\
=&\ -\sum_{j\in N_i} a_{ij}(\hat{x}_i(\hat{t}^i_{m_i+r}|t^i_{m_i}) - \hat{x}_j(\hat{t}^j_{k_{ij}(t^i_{m_i})+s}|t^j_{k_{ij}(t^i_{m_i})}))
\end{aligned} \tag{23}
$$

if $t = \hat{t}^i_{m_i+r} + l \in [\hat{t}^i_{m_i+r}, \hat{t}^i_{m_i+r+1}) \cap [\hat{t}^j_{k_{ij}(t^i_{m_i})+s}, \hat{t}^j_{k_{ij}(t^i_{m_i})+s+1})$, where

$$
k_{ij}(t^i_{m_i}) \triangleq \arg\min_{m_j}\{t^i_{m_i}+\tau-(t^j_{m_j}+\tau)|t^j_{m_j}+\tau \leq t^i_{m_i}+\tau\}. \tag{24}
$$

From (24), it is clear that $x_j(t^j_{k_{ij}(t^i_{m_i})})$ is the latest successfully transmitted event-triggered state before time $t^i_{m_i}+\tau$ for agent j. $\hat{x}_i(\hat{t}^i_{m_i+1})$ represents the first predicted event state on account of $x_i(t^i_{m_i})$ and $\hat{x}_i(\hat{t}^i_{m_i+r})$ expresses the future predicted event states. According to $x_i(t^i_{m_i})$ and the predicted state signals in $\overrightarrow{X}_j(t^j_{k_{ij}(t^i_{m_i})}) = \{\hat{x}_j(t^j_{k_{ij}(t^i_{m_i})}|t^j_{k_{ij}(t^i_{m_i})}), \ldots, \hat{x}_j(\hat{t}^j_{k_{ij}(t^i_{m_i})+L^j_{k_{ij}(t^i_{m_i})}}|t^j_{k_{ij}(t^i_{m_i})})\}$ from C-C node j, the prediction of states $\overrightarrow{X}_i(t^i_{m_i}) = \{\hat{x}_i(t^i_{m_i}|t^i_{m_i}), \hat{x}_i(\hat{t}^i_{m_i+1}|t^i_{m_i}), \ldots, \hat{x}_i(\hat{t}^i_{m_i+L^i_{m_i}}|t^i_{m_i})\}$ and controllers $\hat{u}_i(t^i_{m_i}|t^i_{m_i})$, $\hat{u}_i(\hat{t}^i_{m_i+1}|t^i_{m_i})$, $\ldots$, $\hat{u}_i(\hat{t}^i_{m_i+L^i_{m_i}}|t^i_{m_i})$ will be iteratively calculated as follows. First, $\hat{x}_i(t^i_{m_i}|t^i_{m_i}) = x_i(t^i_{m_i})$ and

$$
\begin{aligned}
\hat{x}_i(t+1|t^i_{m_i}) &= A_i\hat{x}_i(t|t^i_{m_i}) + B_i\hat{u}_i(t|t^i_{m_i}), && (25)\\
\hat{u}_i(t|t^i_{m_i}) &= \hat{u}_i(t|t^i_{m_i-\beta_i(t)}) \in \overrightarrow{U}_i(t^i_{m_i-\beta_i(t)}), && (26)\\
t &\in [t^i_{m_i}, t^i_{m_i}+\tau+d) \cap \\
&\quad [t^i_{m_i-\beta_i(t)}+\tau+d, t^i_{m_i-\beta_i(t)+1}+\tau+d),
\end{aligned}
$$

where $\beta_i(t)$ is an integer and satisfies $1 \leq \beta_i(t) \leq \tau + d$. Furthermore,

$$
\hat{x}_i(t+1|t^i_{m_i}) = A_i\hat{x}_i(t|t^i_{m_i}) + B_i\hat{u}_i(t|t^i_{m_i}), \tag{27}
$$

$$
\begin{aligned}
&\hat{u}_i(t|t^i_{m_i}) \\
=&\ -B^{-1}_{iR}A_i\hat{x}_i(\hat{t}^i_{m_i+r}|t^i_{m_i}) - K_i\sum_{j\in N_i} a_{ij}\,\cdot && (28)\\
&\left[\hat{x}_i(\hat{t}^i_{m_i+r}|t^i_{m_i}) - \hat{x}_j(\hat{t}^j_{k_{ij}(t^i_{m_i})+s}|t^j_{k_{ij}(t^i_{m_i})})\right], \\
t \in&\ [t^i_{m_i}+\tau+d, t^i_{m_i}+2\tau+2d+2q+M) \\
&\cap[\hat{t}^i_{m_i+r}, \hat{t}^i_{m_i+r+1}) \cap [\hat{t}^j_{k_{ij}(t^i_{m_i})+s}, \hat{t}^j_{k_{ij}(t^i_{m_i})+s+1}), \\
r =&\ 0,1,\ldots,L^i_{m_i}, \\
s =&\ 0,1,\ldots,L^j_{k_{ij}(t^i_{m_i})}.
\end{aligned}
$$

Once the prediction is completed, the prediction state vector $\overrightarrow{X}_i(t^i_{m_i})$ of agent i is transmitted to its neighbors' C-C nodes for the use of calculating the neighbors' prediction controllers and also transmitted to neighbors' sensor node via network for the use of event-generator a_j, $j \in N_i$. See Fig. 2.

Remark 5: Each agent's Buffer i_2 in Fig.2 is used to store enough predicted control packets $\overrightarrow{U}_i(\cdot)$ for the use of (25) and (26), the main purpose is to ensure that the control inputs for the predictive dynamic system (25) and for the real dynamic system (1) or (30) are the same for the time interval $[t^i_{m_i}, t^i_{m_i} + \tau + d)$. The reason for $1 \leq \beta_i(t) \leq \tau + d$ is that $t^i_{m_i} \geq t^i_{m_i-\tau-d} + \tau + d$.

For the prediction time interval $[t^i_{m_i}+\tau+d, t^i_{m_i}+2\tau+2d+2q+M)$, from (28), we can observe that $\hat{u}_i(t|t^i_{m_i})$ is updated not only at the predictive event-triggered time instants $t^i_{m_i}, \hat{t}^i_{m_i+1}, \ldots, \hat{t}^i_{m_i+L^i_{m_i}}$ of agent i, but also updated at some of the predictive event-triggered instants $t^j_{k_{ij}(t^i_{m_i})_j}, \hat{t}^j_{k_{ij}(t^i_{m_i})+1}, \ldots, \hat{t}^j_{k_{ij}(t^i_{m_i})+L^j_{k_{ij}(t^i_{m_i})}}$ of its neighbors j, $j \in N_i$, so the packaged and transmitted control vector $\overrightarrow{U}_i(t^i_{m_i})$ from C-C node i to actuator i (also to Buffer i_2) will be

$$
\begin{aligned}
&\overrightarrow{U}_i(t^i_{m_i}) \\
=&\ \Big\{\hat{u}_i(t^i_{m_i}|t^i_{m_i}), \hat{u}_i(\hat{t}^i_{m_i+1}|t^i_{m_i}), \ldots, \hat{u}_i(t^j_{k_{ij}(t^i_{m_i})}|t^j_{k_{ij}(t^i_{m_i})})
\end{aligned}
$$

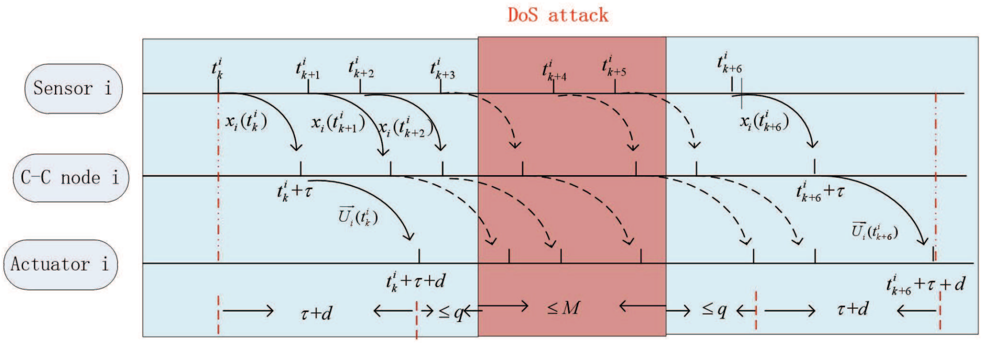

Fig. 4. Information transmission

$$, \dots, \hat{u}_i(\hat{t}^j_{k_{ij}(t^i_{m_i})+s}|t^j_{k_{ij}(t^i_{m_i})}), \dots, \hat{u}_i(\hat{t}^i_{m_i+L^i_{m_i}}|t^i_{m_i}),$$

$$\left.\dots, \hat{u}_i(\hat{t}^j_{k_{ij}(t^i_{m_i})+L^j_{k_{ij}(t^i_{m_i})}}|t^j_{k_{ij}(t^i_{m_i})})\right\}. \qquad (29)$$

The control elements in $\overrightarrow{U}_i(t^i_{m_i})$ are arranged in chronological order (time sequence) according to the time stamps added on them. When $\overrightarrow{U}_i(t^i_{m_i})$ is transmitted at agent i's actuator side at the time $t^i_{m_i}+\tau+d$, the old control packet $\overrightarrow{U}_i(t^i_{m_i-1})$ in Buffer i_1 will be discarded and the real control inputs for NMASs (1) will be selected in $\overrightarrow{U}_i(t^i_{m_i})$ by comparing the time stamps on the control elements in $\overrightarrow{U}_i(t^i_{m_i})$ and the current time:

$$x_i(t+1) = A_i x_i(t) + B_i u_i(t) \qquad (30)$$

$$\begin{aligned}
& u_i(t) \\
= & \begin{cases} \hat{u}_i(\hat{t}^i_{m_i+r}|t^i_{m_i}) \text{ if } \hat{t}^i_{m_i+r} \geq \hat{t}^j_{k_{ij}(t^i_{m_i})+s} \\ \hat{u}_i(\hat{t}^j_{k_{ij}(t^i_{m_i})+s}|t^j_{k_{ij}(t^i_{m_i})}) \text{ if } \hat{t}^i_{m_i+r} < \hat{t}^j_{k_{ij}(t^i_{m_i})+s} \end{cases} \\
\triangleq & u_i(t|t^i_{m_i}) \\
= & -B^{-1}_{iR} A_i \hat{x}_i(\hat{t}^i_{m_i+r}|t^i_{m_i}) - K_i \sum_{j\in N_i} a_{ij} \cdot \\
& \left[\hat{x}_i(\hat{t}^i_{m_i+r}|t^i_{m_i}) - \hat{x}_j(\hat{t}^j_{k_{ij}(t^i_{m_i})+s}|t^j_{k_{ij}(t^i_{m_i})})\right] \qquad (31) \\
t \in & [t^i_{m_i}+\tau+d, t^i_{m_i+1}+\tau+d) \\
& \cap[\hat{t}^i_{m_i+r}, \hat{t}^i_{m_i+r+1}) \cap [\hat{t}^j_{k_{ij}(t^i_{m_i})+s}, \hat{t}^j_{k_{ij}(t^i_{m_i})+s+1}).
\end{aligned}$$

Remark 6: The reason for us to choose the prediction step as $2\tau+2d+2q+M$ can be illustrated in Fig. 4. Three cases should be thought: (i) The first case is also the best case, that is, $x_i(t^i_k)$ is successfully transmitted to the C-C node i and meanwhile the corresponding predicted control package $\overrightarrow{U}_i(t^i_k)$ is transmitted successfully to the agent i's actuator side. For this case, the prediction step $\tau+d$ is enough. (ii) The second case is that the event-triggered state $x_i(t^i_k)$ is transmitted to the C-C node i successfully but $\overrightarrow{U}_i(t^i_k)$ is subjected to the DoS attacks, so agent i's actuator can not receive $\overrightarrow{U}_i(t^i_k)$ at time $t^i_k+\tau+d$. See $x_i(t^i_{k+1})$ and $x_i(t^i_{k+2})$ in Fig.4. (iii) The third case is the worst case, that is, $x_i(t^i_k)$ is subjected to DoS attacks, so there is no information received by the C-C node i at time $t^i_k+\tau$. See $x_i(t^i_{k+3})$, $x_i(t^i_{k+4})$ and $x_i(t^i_{k+5})$ in Fig.4. However, it is hard to know when there will start the DoS attacks, so we have to predict for the worst case at each time the C-C node receives new event-triggered state $x_i(t^i_k)$. $2\tau+2d+2q+M$ prediction steps are needed.

Remark 7: Let $\overline{S} \triangleq 2\tau+2d+2q+M$. Indeed, for the general case, each agent's prediction step should be $2\overline{S}$. This is because the event-triggered instants for agents are general different, in most cases, $t^j_{k_{ij}(t^i_{m_i})} < t^i_{m_i}$ ($< t^j_{k_{ij}(t^i_{m_i})+1}$) and so $t^j_{k_{ij}(t^i_{m_i})}+\overline{S} < t^i_{m_i}+\overline{S} < t^j_{k_{ij}(t^i_{m_i})+1}+\overline{S}$. When calculating $\overrightarrow{X}_i(t^i_{m_i})$, maybe some information of agent j between the time interval $[t^j_{k_{ij}(t^i_{m_i})}+\overline{S},\ t^i_{m_i}+\overline{S})$ ($\subset [t^j_{k_{ij}(t^i_{m_i})}+\overline{S},\ t^j_{k_{ij}(t^i_{m_i})+1}+\overline{S})$) is needed. Taking into account that $t^j_{k_{ij}(t^i_{m_i})+1} - t^j_{k_{ij}(t^i_{m_i})} \leq \overline{S}$, so the prediction step $2\overline{S}$ is enough for any case. Owning to the modern computer calculation ability, there is no problem. However, for easy understanding according to Fig. 4, we just assume that the prediction step is $2\tau+2d+2q+M$ in the above writing.

Remark 8: Event generator a_i is used to save the network transmission resources. However, compared with the works [33], [34], event generator b_i is used to prevent the control packet $\overrightarrow{U}_i(t^i_{m_i})'s$ size from getting too large.

IV. Establishing the Geschlossenes System Model

To establish the geschlossenes system model for NMASs (1) with the CB-AETPC (10), (16), (26) and (28) to analysis the consensus performance, we need to deduce the following important lemma first.

Lemma 1: Assume that the initial event-triggered parameters $\mu_i(t^i_0)$ and $\hat{\mu}_i(t^i_0)$ for (3) and (14) are the same, $i \in S_N$. Then for any time $t \in [t^i_0, +\infty)$, the state $x_i(t)$ of system (1) for agent i is the same as its predictive state constructed in (9), (15), (25) and (27), that is

$$x_i(t) = \hat{x}_i(t|t^i_0), t \in \Pi^i_0, \qquad (32)$$

$$x_i(t) = \hat{x}_i(t|t^i_{m_i}), t \in \Pi^i_{m_i}, \qquad (33)$$

where $\Pi^i_0 \triangleq [t^i_0, t^i_0+\tau+d)$ and $\Pi^i_{m_i} \triangleq [t^i_{m_i}+\tau+d, t^i_{m_i+1}+\tau+d)$, then $\Pi^i_0 \cup \{\cup^{+\infty}_{m_i=1}\Pi_{m_i}\} = [t^i_0, +\infty)$. Furthermore,

$$x_i(t^i_{m_i+r}) = \hat{x}_i(\hat{t}^i_{m_i+r}|t^i_{m_i}) \text{ and } t^i_{m_i+r} = \hat{t}^i_{m_i+r} \qquad (34)$$

for any time interval $\Pi^i_{m_i}$.

Proof: For the initial case (32), it is easy to see that $x_i(t) = \hat{x}_i(t|t_0^i)$ for $\forall t \in \Pi_0^i$, since the initial states $x_i(t_0^i) = \hat{x}_i(t_0^i)$ and the dynamic systems in (6), (7) and (9), (10) are the same.

For the proof of the general case (33), we will use the mathematical induction method. For $\forall t \in [t_0^i, +\infty)\backslash\Pi_0^i$, there exist one time interval $\Pi_{m_i}^i$ and non-negative integers r, s and p, $s.t.$ $t = t_{m_i}^i + p \in \Pi_{m_i}^i \cap [\hat{t}_{m_i+r}^i, \hat{t}_{m_i+r+1}^i) \cap [\hat{t}_{k_{ij}(t_{m_i}^i)+s}^j, \hat{t}_{k_{ij}(t_{m_i}^i)+s+1}^j)$. Assume that $x_i(t) = \hat{x}_i(t|t_{m_i}^i)$, the following two situations should be proved separately. Situation (1), $x_i(t+1) = \hat{x}_i(t+1|t_{m_i}^i)$ if $(t+1) \in \Pi_{m_i}^i$; Situation (2), $x_i(t+1) = \hat{x}_i(t+1|t_{m_i+1}^i)$ if $t+1 = t_{m_i+1}^i + \tau + d$, that is when $t+1$ just equal to the left end point of the next time interval $\Pi_{m_i+1}^i$.

For Situation (1), from system (30), control (31) and the state prediction system (27), control (28), we have that

$$\begin{aligned} x_i(t+1) &= A_i\hat{x}_i(t|t_{m_i}^i) + B_i\hat{u}_i(t|t_{m_i}^i) \\ &= \hat{x}_i(t+1|t_{m_i}^i). \end{aligned}$$

For Situation (2), taking into account (25), control (26) and (30), control (31), we have that

$$\begin{aligned} &\hat{x}_i(t_{m_i+1}^i + 1|t_{m_i+1}^i) \\ &= A_i\hat{x}_i(t_{m_i+1}^i|t_{m_i+1}^i) + B_i\hat{u}_i(t_{m_i+1}^i|t_{m_i+1-\beta_i(t_{m_i+1}^i)}^i) \\ &= A_i x_i(t_{m_i+1}^i) + B_i\hat{u}_i(t_{m_i+1}^i|t_{m_i+1-\beta_i(t_{m_i+1}^i)}^i) \\ &= x_i(t_{m_i+1}^i + 1), \\ &\hat{x}_i(t_{m_i+1}^i + 2|t_{m_i+1}^i) \\ &= A_i\hat{x}_i(t_{m_i+1}^i + 1|t_{m_i+1}^i) \\ &+B_i\hat{u}_i(t_{m_i+1}^i + 1|t_{m_i+1-\beta_i(t_{m_i+1}^i+1)}^i) \\ &= A_i x_i(t_{m_i+1}^i + 1) + B_i\hat{u}_i(t_{m_i+1}^i + 1|t_{m_i+1-\beta_i(t_{m_i+1}^i+1)}^i) \\ &= x_i(t_{m+1}^i + 2), \\ &\vdots \\ &\hat{x}_i(t+1|t_{m_i+1}^i) \\ &= \hat{x}_i(t_{m_i+1}^i + \tau + d|t_{m_i+1}^i) \\ &= A_i\hat{x}_i(t_{m_i+1}^i + \tau + d - 1|t_{m_i+1}^i) \\ &+B_i\hat{u}_i(t_{m_i+1}^i + \tau + d - 1|t_{m_i+1-\beta_i(t)}^i) \\ &= A_i\hat{x}_i(t|t_{m_i+1}^i) + B_i\hat{u}_i(t|t_{m_i+1-\beta_i(t)}^i) \\ &= A_i x_i(t) + B_i\hat{u}_i(t|t_{m_i+1-\beta_i(t)}^i) \\ &= x_i(t+1). \end{aligned}$$

For (34), it can be easily deduced by taking into account that $\mu_i(t_0^i) = \hat{\mu}_i(t_0^i)$ and the event-triggering conditions in (3-4) for event generator a_i and (11-14), (17-21) for event generatorb_i are the same.

According to the above proofs, we can complete this lemma. ■

Taking into account Lemma 1, the control in (31) can be rewritten as

$$\begin{aligned} &u_i(t) \\ = &-B_{iR}^{-1}A_i x_i(t_{m_i+r}^i) \\ &-K_i\sum_{j\in N_i} a_{ij}\left[x_i(t_{m_i+r}^i) - x_j(t_{k_{ij}(t_{m_i}^i)+s}^j)\right] \end{aligned} \tag{35}$$

$t \in \Pi_{m_i}^i \cap [t_{m_i+r}^i, t_{m_i+r+1}^i) \cap [t_{k_{ij}(t_{m_i}^i)+s}^j, t_{k_{ij}(t_{m_i}^i)+s+1}^j)$.

The closed-loop system of NMASs (1) can be further obtained as follows:

$$\begin{aligned} &x_i(t+1) \\ = &A_i x_i(t) - B_i B_{iR}^{-1}A_i x_i(t_{m_i+r}^i) \\ &-B_i K_i\sum_{j\in N_i} a_{ij}\left[x_i(t_{m_i+r}^i) - x_j(t_{k_{ij}(t_{m_i}^i)+s}^j)\right] \end{aligned} \tag{36}$$

$$t \in \Pi_{m_i}^i \cap [t_{m_i+r}^i, t_{m_i+r+1}^i) \cap [t_{k_{ij}(t_{m_i}^i)+s}^j, t_{k_{ij}(t_{m_i}^i)+s+1}^j). \tag{37}$$

Denote $e_i(t) = x_i(t) - x_i(t_{m_i+r}^i)$ if t in the time interval $[t_{m_i+r}^i, t_{m_i+r+1}^i)$ and denote $e_j(t) = x_j(t) - x_j(t_{k_{ij}(t_{m_i}^i)+s}^j)$ if t in the time interval $[t_{k_{ij}(t_{m_i}^i)+s}^j, t_{k_{ij}(t_{m_i}^i)+s+1}^j)$, let $X(t) = [x_1^T(t)\ x_2^T(t)\ \cdots\ x_N^T(t)]^T$, and $e(t) = [e_1^T(t)\ e_2^T(t)\ \cdots\ e_N^T(t)]^T$, the geschlossenes system is obtained as below:

$$X(t+1) = \bar{A}e(t) - \bar{B}\bar{K}(L\otimes I_n)X(t) + \bar{B}\bar{K}(L\otimes I_n)e(t),$$

here, $\bar{A} = diag\{A_1, A_2, \ldots, A_N\}$, $\bar{B} = diag\{B_1, B_2, \ldots, B_N\}$, $\bar{K} = diag\{K_1, K_2, \ldots, K_N\}$.

Furthermore, let $\delta_i(t) = x_i(t) - x_1(t)$, $\delta(t) = [\delta_2^T(t)\ \delta_3^T(t)\ \cdots\ \delta_N^T(t)]^T$ and taking into account the following relationships

$$X(t) = (E_2\otimes I_n)\,\delta(t) + (\mathbf{1}_N\otimes I_n)\,x_1(t), \tag{38}$$

$$\delta(t) = (E_1\otimes I_n)\,X(t), \tag{39}$$

$$L\mathbf{1}_N = 0, \tag{40}$$

where $E_1 = [\mathbf{1}_{N-1}\ \ -I_{N-1}]$ and $E_2 = col\{\mathbf{0}, -I_{N-1}\}$, the following geschlossenes system model (41) can be deduced:

$$\begin{aligned} &\delta(t+1) \\ = &-(E_1\otimes I_n)\bar{B}\bar{K}(LE_2\otimes I_n)\delta(t) \\ &+(E_1\otimes I_n)\bar{A}e(t) + (E_1\otimes I_n)\bar{B}\bar{K}(L\otimes I_n)e(t). \end{aligned} \tag{41}$$

V. Consensus Discussion

The coming lemmas are important and necessary to discuss the consensus of NMASs (1) according to the geschlossenes system (41).

Lemma 2: If the initial event-triggered parameters $\mu_i(0) \in (0, \lambda]$, we can obtain that

$$\mu_i(0) \le \mu_i(t) \le \lambda \tag{42}$$

and furthermore

$$\begin{aligned} &e^T(t)\Omega e(t) \\ \le &\left[(LE_2\otimes I_n)\delta(t) - (L\otimes I_n)e(t)\right]^T\cdot \\ &\lambda\Omega\left[(LE_2\otimes I_n)\delta(t) - (L\otimes I_n)e(t)\right], \end{aligned} \tag{43}$$

$i \in S_N$, $t \in [t_0^i, +\infty) = \cup_{k=0}^{\infty}[t_k^i, t_{k+1}^i), \Omega = diag\{\ \Omega_1,\ \ \Omega_2,\ \ \ldots,\ \ \Omega_N\ \}$.

Proof: The relationship in (42) can be proved by using the mathematical induction method and the prove process is similar to [18], so we omit it here.

Now we give the proof of (43). From the event-triggering conditions (4) and (5) and Lemma 1, the following inequality holds for any $t \in \{1, 2, \ldots\}$

$$e_i^T(t)\Omega_i e_i(t) \leq \mu_i(t) w_i^T(t)\Omega_i w_i(t)$$

with $w_i(t) = -\sum_{j\in N_i} a_{ij}(x_i(t_k^i) - x_j(t_{k_j}^j))$, where $x_j(t_{k_j}^j)$ is the latest event-triggered state of agent j for current time $t \in [t_k^i, t_{k+1}^i)$. Then for the augmented form, we have that

$$\begin{aligned} & e^T(t)\Omega e(t) \\ \leq & \ [(L\otimes I_n)X(t) - (L\otimes I_n)e(t)]^T \lambda\Omega \cdot \\ & [(L\otimes I_n)X(t) - (L\otimes I_n)e(t)] \end{aligned}$$

where H_i is the ith row of the Laplace matrix L. Taking into account that (38) and (40), then (43) is satisfied. This completes the proof. ■

Lemma 3: [11] The relationship $-X^T P^{-1} X \leq \varrho^2 P - 2\rho X$ holds for any $\rho > 0$, where $P > 0$ and X is symmetric.

Based on the above preparations, now we deduce the consistency criteria for NMASs (1) under the proposed CB-AETPC. Ω_i in (5) and K_i in (31) or in (35) can also be co-designed by applying LMI technique.

Theorem 1: For given system matrices A_i, B_i and the upper bound of the event-triggering parameter λ, NMASs (1) can achieve consistency with DoS attacks and transmission delays if there exist $P > 0$, block diagonal matrix $\Omega = diag\{\ \Omega_1,\ \ \Omega_2,\ \ \ldots,\ \ \Omega_N\ \} > 0$ and augmented feedback matrix $\bar{K} = diag\{K_1, K_2, \ldots, K_N\}$ with appropriate dimensions such that the inequality below is met

$$\begin{bmatrix} -P & * & * & * \\ 0 & -\Omega & * & * \\ H_1 & H_2 & \varrho^2 P - 2\rho I & * \\ \Omega(LE_2\otimes I_n) & -\Omega(L\otimes I_n) & 0 & -\lambda^{-1}\Omega \end{bmatrix} < 0, \tag{44}$$

where $i \in S_N$. $\rho > 0$ is given in advance, and

$$\begin{aligned} H_1 &= -(E_1\otimes I_n)\bar{B}\bar{K}(LE_2\otimes I_n), \\ H_2 &= (E_1\otimes I_n)\bar{A} + (E_1\otimes I_n)\bar{B}\bar{K}(L\otimes I_n). \end{aligned}$$

Proof: We choose the following Lyapunov functional candidate

$$V(t,\delta(t)) = \delta^T(t)P\delta(t),$$

where $P > 0$ is unknown.

Computing $\Delta V(t,\delta(t))$ along the trajectories of (41) and in consideration of the relationship (43) in relation to (4) and (5), it can be obtained that

$$\begin{aligned} & \Delta V(t,\delta(t)) \\ \leq & \ \Sigma_1^T P\Sigma_1 - \delta^T(t)P\delta(t) + \Sigma_2^{TT}\lambda\Omega\Sigma_2 - e^T(t)\Omega e(t) \\ = & \ \begin{bmatrix}\delta^T(t) & e^T(t)\end{bmatrix}\left[\begin{pmatrix} -P & 0 \\ 0 & -\Omega \end{pmatrix} + [H_1\ H_2]^T P [H_1\ H_2] \right. \\ & \left. + [F_1\ F_2]^T \Omega\lambda\Omega^{-1}\Omega[F_1\ F_2]\right] \begin{bmatrix}\delta(t) \\ e(t)\end{bmatrix}, \end{aligned}$$

where

$$\begin{aligned} \Sigma_1 &= [-(E_1\otimes I_n)\bar{B}\bar{K}(LE_2\otimes I_n)\delta(t) + \\ & \quad (E_1\otimes I_n)\bar{A}e(t) + (E_1\otimes I_n)\bar{B}\bar{K}(L\otimes I_n)e(t)] \\ \Sigma_2 &= [(LE_2\otimes I_n)\delta(t) - (L\otimes I_n)e(t)], \\ F_1 &= LE_2\otimes I_n, F_2 = -L\otimes I_n. \end{aligned}$$

By adopting the Schur complement method, $\Delta V(t,\delta(t)) < 0$ if

$$\begin{bmatrix} -P & * & * & * \\ 0 & -\Omega & * & * \\ H_1 & H_2 & -P^{-1} & * \\ \Omega(LE_2\otimes I_n) & -\Omega(L\otimes I_n) & 0 & -\lambda^{-1}\Omega \end{bmatrix} < 0,$$

and using Lemma 3 we have that $-P^{-1} = -IP^{-1}I \leq \varrho^2 P - 2\rho I$ with any $\rho > 0$, so we can obtain the condition in (44). So that's the proof. ■

Remark 9: Making comparisons with [18], [41], where agent i has no ability to detect the current or future predicted control information of its neighbors, thus in the prediction of neighbor's state $\hat{x}_j$ for agent i's predictive control calculation, it was assumed that $u_j(t) = 0$. However, this paper is based on the cloud-based computing control, all agents can obtain the information they required, so the neighbor's accurately predicted state information $\hat{x}_j$ can be obtained by agent i's C-C node timely. So the DoS attacks and the transmission delays are compensated completely.

VI. Numerical Example

In this part, we take a group of five agents (VTOL) with different dynamics to validate the theoretical results. Four of which are VTOL aircrafts and one is the leader with velocity 135 kt [28]). The dynamic matrices A_i and B_i of agents are proposed as:

$$A_1 = -\begin{bmatrix} -0.0366 & 0.0271 & 0.0188 & -0.4555 \\ 0.0482 & -1.01 & 0.0024 & -4.0208 \\ 0.1002 & 0.3681 & -0.707 & 1.420 \\ 0 & 0 & 1 & 0 \end{bmatrix},$$

$$B_1 = \begin{bmatrix} 0.4422 & 0.1761 & 0.578 & 0 & 0.0413 \\ 3.5446 & -7.5922 & 0 & 0.909 & 0 \\ -5.52 & 4.49 & 1.237 & 0.321 & 1 \\ 0.1 & 0.593 & 0 & 0 & 4.172 \end{bmatrix}.$$

$A_2 = 2A_1, A_3 = 3A_1, A_4 = A_1, A_5 = -A_1$ and $B_2 = 0.1B_1, B_3 = 0.2B_1, B_4 = 0.3B_1, B_5 = 0.4B_1$.

The communication relationship among agents can be shown by the corresponding Laplace matrix given below:

$$L = \begin{bmatrix} 3 & -1 & 0 & -1 & -1 \\ -1 & 4 & -1 & -1 & -1 \\ 0 & -1 & 3 & -1 & -1 \\ -1 & 0 & -1 & 3 & -1 \\ -1 & 0 & -1 & 0 & 2 \end{bmatrix}$$

The initial conditions of each agent are set as $x_1(0) = [\ 0.2\ \ 1\ \ -2\ \ 0.5\ ]^T$, $x_2(0) = [\ 1\ \ 2\ \ 3\ \ -1\ ]^T$, $x_3(0) = [\ 4\ \ 0\ \ 4\ \ -2\ ]^T$, $x_4(0) = [\ 9\ \ -2\ \ 7\ \ -5\ ]^T$, $x_5(0) = [\ 5\ \ 0\ \ 3\ \ -1\ ]^T$. Assume that the transmission delays for all agents are the same as $\tau + d = 5T$ with $T = 0.01$. The upper bound of the event-triggered parameters is $\lambda = 0.6 \times 10^{-3}$ and the initial event-triggered parameters μ_i are given as $10^{-3} \times [\ 0.5\quad 0.3\quad 0.4\quad 0.5\quad 0.15\ ]$ and the upper bound of the event-trigger intervals is $q = 10T$.

By solving the LMI in Theorem 1 with $\rho = 0.1 \times 10^{-3}$, the feedback gain matrices K_i and Ω_i are given as follows:

$$\Omega_1 = 10^6 \times \begin{bmatrix} 3.5277 & -0.0873 & -0.0374 & -0.0002 \\ -0.0873 & 2.6137 & 0.3549 & -0.2606 \\ 0.0374 & -0.3549 & 3.1821 & 0.1823 \\ 0.0002 & -0.2606 & 0.1823 & 2.4950 \end{bmatrix},$$

$$K_1 = 10^3 \times \begin{bmatrix} -0.0131 & -0.0695 & 0.0587 & 0.1934 \\ -0.0150 & -0.0792 & 0.0669 & 0.2203 \\ 0.0129 & 0.0680 & -0.0575 & -0.1894 \\ -0.0737 & -0.3902 & 0.3298 & 1.0858 \\ 0.0024 & 0.0129 & -0.0109 & -0.0359 \end{bmatrix},$$

$$\Omega_2 = 10^5 \times \begin{bmatrix} 9.2604 & -0.4089 & 0.1415 & -0.0080 \\ -0.4089 & 5.2219 & 1.5349 & 0.0522 \\ 0.1415 & 1.5349 & 8.7678 & 0.2426 \\ -0.0080 & 0.0522 & 0.2426 & 9.6807 \end{bmatrix},$$

$$K_2 = 10^3 \times \begin{bmatrix} 0.0006 & -0.0003 & -0.0086 & 0.0601 \\ 0.0007 & -0.0004 & -0.0098 & 0.0685 \\ -0.0006 & 0.0003 & 0.0085 & -0.0588 \\ 0.0035 & -0.0018 & -0.0484 & 0.3377 \\ -0.0001 & 0.0001 & 0.0016 & -0.0112 \end{bmatrix},$$

$$\Omega_3 = 10^6 \times \begin{bmatrix} 0.7858 & -0.0414 & 0.0105 & 0.0002 \\ -0.0414 & 0.4151 & 0.1307 & 0.1652 \\ 0.0105 & 0.1307 & 0.8528 & -0.048 \\ 0.0002 & 0.1652 & -0.0480 & 1.4062 \end{bmatrix},$$

$$K_3 = 10^3 \times \begin{bmatrix} 0.0020 & -0.0559 & 0.0073 & -0.04877 \\ -0.0023 & -0.0637 & -0.0083 & -0.0556 \\ -0.0020 & -0.0547 & -0.0071 & 0.0478 \\ -0.0113 & -0.3138 & 0.0410 & -0.2736 \\ -0.0004 & 0.0104 & -0.0014 & 0.0091 \end{bmatrix},$$

$$\Omega_4 = 10^6 \times \begin{bmatrix} 1.4871 & -0.0363 & 0.0153 & -0.0055 \\ -0.0363 & 1.0871 & 0.1655 & -0.1516 \\ 0.0153 & 0.1655 & 1.3714 & 0.0913 \\ -0.0055 & -0.1516 & 0.0913 & 1.1145 \end{bmatrix},$$

$$K_4 = 10^3 \times \begin{bmatrix} 0.0001 & 0.0044 & -0.0119 & 0.0471 \\ 0.0002 & 0.0051 & -0.0137 & 0.0545 \\ -0.0002 & -0.0048 & 0.0129 & -0.0512 \\ 0.0008 & 0.0255 & -0.0685 & 0.2718 \\ -0.0000 & -0.0008 & 0.0022 & -0.0089 \end{bmatrix},$$

$$\Omega_5 = 10^6 \times \begin{bmatrix} 2.7186 & -0.0798 & 0.0346 & -0.0107 \\ -0.0798 & 1.8236 & 0.3681 & -0.3737 \\ 0.0346 & 0.3681 & 2.4219 & 0.2136 \\ -0.0107 & -0.3737 & 0.2136 & 1.6993 \end{bmatrix},$$

$$K_5 = 10^3 \times \begin{bmatrix} 0.0016 & -0.0158 & -0.0005 & -0.0483 \\ 0.0019 & -0.0183 & -0.0006 & -0.0560 \\ -0.0018 & 0.0172 & 0.0006 & 0.0526 \\ 0.0093 & -0.0914 & -0.0031 & -0.2791 \\ -0.0003 & 0.0030 & 0.0001 & 0.0091 \end{bmatrix}.$$

The simulation will be taken in three cases and mainly focuses on the situations with or without compensation for DoS attacks or transmission delays. For fair comparison, all the three cases will choose the same K_i and $\Omega_i, i = 1, 2, 3, 4, 5$. M is assumed to be $10T$.

Case (1): Without compensation for both DoS attacks and delays. The simulation time is chosen as $1s$. The DoS attack time intervals are assumed to be (as shown in Fig. 5): $[0.05, 0.1]s$, $[0.18, 0.25]s$, $[0.40, 0.48]s$, $[0.60, 0.68]s$ and $[0.78, 0.85]s$. Let $T_0 = 30T$ and $\sigma_0 = 5$ in Definition 3.Then $T_a(0, 1) = 0.06s + 0.08s + 0.09s + 0.09s + 0.08s = 0.40s < 30T + 1/5 = 0.5s$. The total transmission delay is assumed to be $5T$ seconds as mentioned above. Fig. 5 shows that the consensus can not be realized.

Case (2): Without compensation for DoS attacks. The transmission delays are assumed to be compensated. Two sub-cases are considered. (i) With strong DoS attacks, that is, the total attack duration time is 80% of the simulation time. The states of all agents and the consensus errors for agent 4 are given in Fig. 6(a) and Fig. 6(b), respectively, which show that the agents can not reach consensus at all. (ii) With weak DoS attacks, the attack time intervals are the same as in Case (1), the total attack duration time is about 40% of the simulation time. The states of all agents and the consensus errors for agent 3 are shown in Fig. 7(a) and Fig. 7(b), respectively, which show that the agents can reach consensus at last but with big fluctuation sometimes.

Case (3): DoS attacks and transmission delays are all offset by using the raised CB-AETPC scheme. Fig. 8 shows that the five agents can reach consensus in a very short time. It is clear that the consensus performance (in terms of the convergence time and the fluctuation of the curves) for this case is much better than the above two cases, which illustrates our theoretical results effectively.

The event times for all cases are expressed in Table 1. We can draw such a conclusion and evaluation that the event-triggered transmission strategy can apparently economize the utilization of communication energy.

VII. Conclusion

This paper has investigated a novel CB-AETPC method for heterogeneous discrete-time NMASs with both DoS attacks and transmission delays. This method has jointed all the superiorities of event-triggered transmission strategy, predictive control method and cloud-based computation scheme. The primary advantage is that it can eliminate the bad effects brought out by DoS attacks and transmission delays. The joint design of controller gain matrices and the event-triggering parameter matrices is realized. Five VTOL aircrafts are adopted to verify the raised CB-AETPC framework.

Linear NMASs model is the main drawback here for the practical applications. In the future we will continuous investigate this direction about security compensation control for more general cases, such as for NMASs with other malicious attacks [42]–[44] and time-varying transmission delays, nonlinear NMASs, uncertain NMASs and so on.

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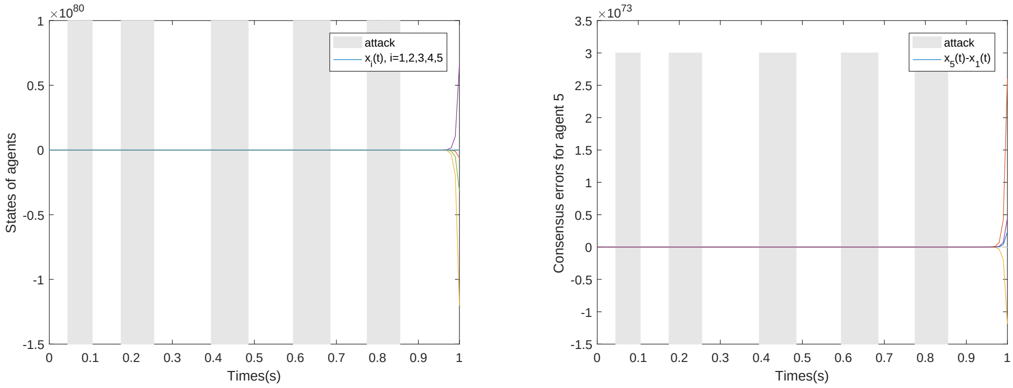
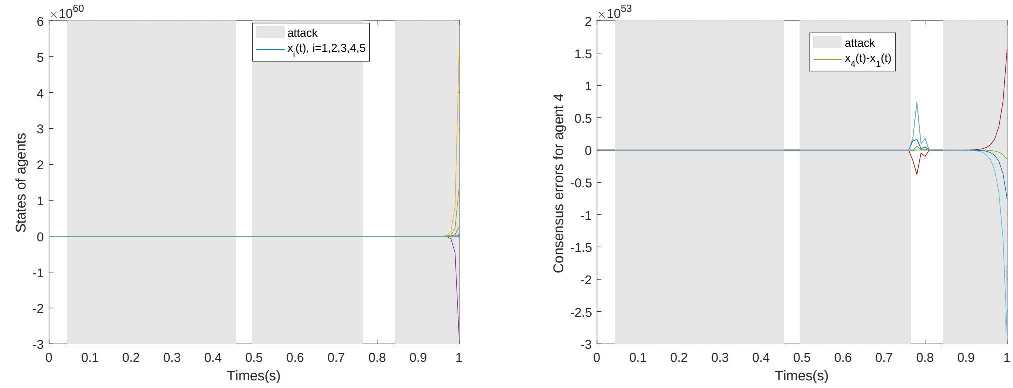


(a) States of all agents

(b) Consensus errors of agent 5

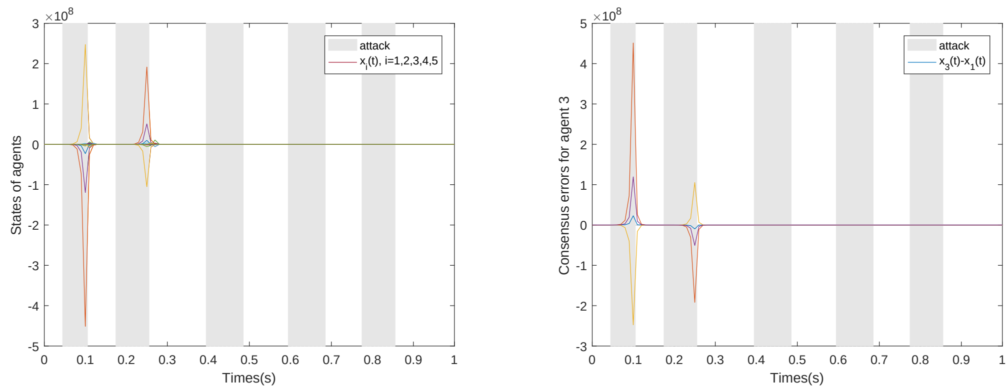
Fig. 5. Consensus performance for Case (1)



(a) States of all agents

(b) Consensus errors of agent 4

Fig. 6. Consensus performance for Case (2) (i)



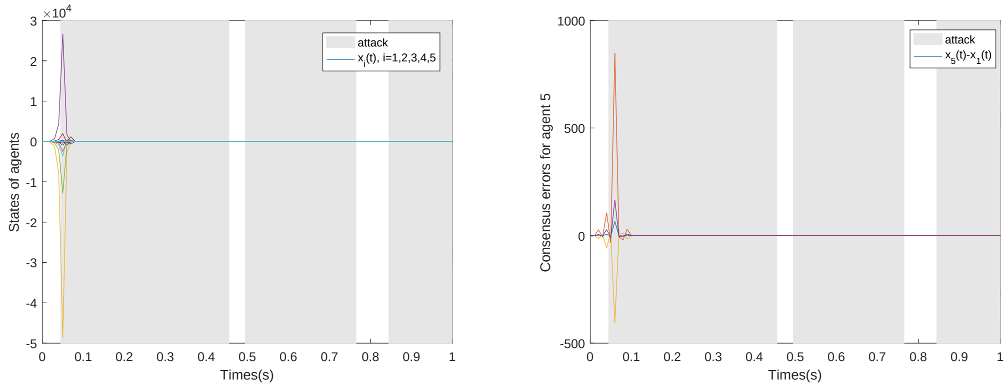
(a) States of all agents

(b) Consensus errors of agent 3

Fig. 7. Consensus performance for Case (2) (ii)

TABLE I
THE SAMPLED AND TRIGGERED NUMBERS FOR AGENTS

	Agent 1	Agent 2	Agent 3	Agent 4	Agent 5
sampled numbers	500	500	500	500	500
Case (1)	229	225	221	98	107
Case (2) (i)	361	399	416	319	344
Case (2) (ii)	320	368	385	265	303
Case (3)	279	336	354	218	244



(a) States of all agents

(b) Consensus errors of agent 5

Fig. 8. Consensus performance for Case (3)

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APPENDIX

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