Abstract: This study presents a new approach for multi-agent systems (MASs). The agent dynamics are approximated by the suggested type-3 (T3) fuzzy logic system (FLS). Some sufficient conditions based on the event-triggered scheme are presented to ensure the stability under less activation of the actuators. New tuning rules are obtained for T3-FLS from the stability and robustness examination. The effect of perturbations, actuator failures and approximation errors are compensated by the designed adaptive compensators. Simulation results show that the output of all agents well converged to the leader agent under disturbances and faulty conditions. Additionally, it is shown that the suggested event-triggered scheme is effective and the actuators are updated about 20–40% of total sample times.

Keywords: fuzzy control; type-3 fuzzy systems; machine learning; multi-agent systems; uncertain upper/lower bounds of uncertainty; event-triggered

1. Introduction

1.1. Literature Review

The collaborative schemes have strong effect in optimally dealing with various engineering problems. One of main approaches that has been successfully employed in various application is the multi-agent systems (MASs). Many applications have been reported for MASs, such as intrusion detection, energy management problems, economic problems, medical problems, among many others [1–3]. One of the challenging topics in the field of MASs is the designing of effective control systems. The dynamics of agents can be uncertain and also the closed-loop system dynamics are commonly perturbed by various faults [4].

The control systems of MASs are classified as classic and artificial intelligence based controllers. The first class of control methods have been widely investigated. For example, the pinning control scheme is designed in [5], for second-order MASs, and the uncertainty of some parameters are investigated by the Euler–Lagrange method. The systems that can be modeled with two integrals can be controlled by the method of [5]. In [6], an adaptive feedback control system is developed and the un-availability of states is studied. The event-triggered scheme of [6], reduces the communication frequency, and it is demonstrated that the agents do not show Zeno behavior. In [7], the problem of actuator saturations in MASs...
is taken into account, and a consensus control system is designed. In addition to actuator saturations, the actuator faults are also studied in [7], and a method is suggested to enlarge the domain of attraction. In [8], by the use of Lyapunov–Krasovskii method a controller is designed for semi-Markov systems, and the problem of parameter changing is investigated. The event-triggered scheme of [8] is applied for F-404 aircraft system. The backstepping technique is developed in [9] for the formation problem in MASs, and the unavailability of the velocity information of agents is analyzed. The formation problem is investigated by a developed backstepping controller. The method of [9] is also can be applied for two-dimensional systems. In [10], the convergence problem of asynchronous controllers is studied and the input uncertainties are investigated. The speed unavailability of the leader agent is also studied in [10], and some rules are presented to satisfy the spanning tree condition. In [11], an observers is established to approximate the unmeasurable states of MASs, and also the effect of suddenly attacks are analyzed as the dynamic perturbations. By Lyapunov approach, a switching term is introduced to tackle the effect of suddenly attacks and uncertainties. The linear-quadratic-regulator is developed in [12], for linear MASs and a clustering approach is suggested to cope with uncertainties.

In the second class, the neuro-fuzzy controllers and machine learning approaches have been developed [13–16]. For Example, the improvement of backstepping control method by the use of FLSs is investigated in [17], and the time convergence is analyzed. In [18], the neural networks (NNs) are employed to cope with the problem of unknown hysteresis. In [19], the output-feedback controller is developed using FLSs for the cooperative control problem of MASs. In [20], NNs are used to improve the transient performance and to estimate the unknown states and non-linearities. In [21], the event-triggered control technique is developed using NNs and the effect of actuator faults is studied. The Nussbaum-based approach is presented in [22] to cope with the input quantization problem and a cooperative control system is designed using NNs. The fuzzy backstepping controller is presented in [23] and it is shown that the singularity problem in the conventional scheme is solved. In [24], the FLSs are used to tackle the effect of time-delays and the stability is proved using Lyapunov–Krasovskii approach. In [25], a FLS based observer is designed, and a fuzzy controller is developed such that the agents track the leader with desired accuracy.

1.2. More Related Works

The high-order FLSs such type-2 (T2) FLSs are extensively used in the problems with high-level uncertainties [26,27]. However, these methods have been rarely applied on MASs. For example, in [28], T2-FLSs are used in the consensus control of MASs, and the better efficiency of high-order FLSs is examined. The stability is analyzed by the use of graph theory, and in addition to identical systems, the consensus of non-identical systems are also studied. In [29], T2-FLSs are used in an adaptive controller to estimate the dynamics of agents and an LMI approach is presented to analyze the stability. The tuning rules for T2-FLSs are extracted form a LMI analysis, and the results are compared with the type-1 FLSs. It is proved that T2-FLSs gives better consensus performance. In [30], T2-FLSs are used to tackle the Denial-of-Service attacks in MASs, and the superiority of the T2-FLS based methods is proved in contest to the type-1 FLSs based methods. By the dwell-time method the effect of switchings and networking is analyzed. It is shown that the use of T2-FLS, not only is effective in versus of Denial-of-Service attacks, but can also tackle the effect of actuators faults. The better consensus control performance of T2-FLSs is investigated in [31], and a T2-FLS based controller is designed. The unavailability of states is investigated by the designed T2-FLS based observer. The efficiency of the suggested approach is shown by applying on consensus of some chaotic systems. Additionally, a comparison with the type-1 methods is provided, and the superiorities of designed type-2 FLS-based controller is shown.
1.3. Motivations

Literature review shows that:

- In most of existing controllers, the linear MASs are studied and the non-linear dynamics are neglected;
- In some few methods that non-linear MASs have been studied, the dynamics are commonly assumed to be known;
- For the best knowledge of authors, the type-3 FLS based controllers with better approximation capability has not been well studied for MASs;
- In the most of FLS based controllers, the effect of approximation errors is neglected;
- In the most of above investigated studies, the control actuators are updated at each sample times, that impose destructive effects on the lifetime of devices;
- In the most of existing studies, the controllers are designed for the special case of MASs;
- In the existing type-2 FLS based controllers, the secondary memberships are considered to be known and crisp values.

1.4. Novelettes

A T3-FLS based controller is developed in this paper. The dynamics of all agents are unknown, and the new online tuning rules are presented for adaptive regulation. The new sufficient conditions are presented to less update the actuators with the stability guarantee. Finally, the effect of disorders are tackled by the designed adaptive compensators. The main outcomes are:

- A type-3 FLS with simple type-reduction is presented to cope with high level of uncertainties;
- The new sufficient conditions are presented to decrease the required number of sample times to activate the actuators;
- The stability is guaranteed such that all agents track the leader agent;
- New adaptive compensators are presented to ensure the robustness.

2. Problem Formulation

A MAG includes several interactive agents. MASs can be employed to solve problems that are difficult or impossible for a single agent or an integrated system. MASs are used successfully in a wide range of problems, such as information technology, industry, communications, education, as well as defense and military. Multiple aircraft, multiple submarines, multiple robots and multiple satellites are some examples of MASs. The MAGs have the ability to perform more complex tasks compared to single systems due to improved system performance, flexibility and reliability, reduced operating costs, and the creation of new capacities. In the study of MAGs, the relationship between agents can be described as a network topology [32]. The following case of MASs is considered:

\[
\begin{align*}
\dot{y}_1^i &= y_1^i \\
\vdots \\
\dot{y}_n^i &= f_i(y_i) + u_i + d_i
\end{align*}
\]

(1)

where, \( i = 1, \ldots, N \), \( N \) denotes the agent numbers, \( y_i = [y_1^i, \ldots, y_n^i] \)^T \( \in \mathbb{R}^n \), \( d_i \) denotes the disturbance and \( f_i(y_i) \) is unknown function. The leader system is defined as:

\[
\begin{align*}
\dot{y}_1^0 &= y_2^0 \\
\vdots \\
\dot{y}_n^0 &= f_0(y_0)
\end{align*}
\]

(2)

where, \( y_0 = [y_1^0, \ldots, y_n^0] \)^T \( \in \mathbb{R}^n \). The main objective is to construct \( u_i \) such that agent outputs track the leader system. The control block diagram is depicted in Figure 1. The de-
tailed scheme is depicted in Figure 2. As shown in Figure 2, the dynamics of each agents are modeled by the suggested T3-FLS. Based on the T3-FLS model, the main controller is designed. Additionally, a compensator supervises the stability. The generated control signal is not applied to the agents at each sample time. However, the actuators are activated by the designed event-triggered scheme. The more details are given in following sections.

![Figure 1. The general scheme for suggested controller.](image1)

![Figure 2. The control block diagram.](image2)

3. Type-3 FLS

The high-order FLSs have better efficiency in various noisy applications. In many studies, the better ability of T3-FLSs has been proved. The main reason is that T3-FLSs have more degree of freedom to represent the uncertainties [33]. In addition to the fact that the secondary fuzzy set is not a distinctive number in T3-FLSs, the footprint-of-uncertainty
is also not a distinctive value, but it is a fuzzy set. In the application of control of MASs, a high-level of non-linearity there exists in agent dynamics and topology. Then, a new control system is developed on the basis of T3-FLS for MASs.

The suggested T3-FLS is depicted in Figure 3. As depicted in Figure 3, the membership function (MF) are type-3. In Figure 4, a better view of type-3 MF is depicted. Figure 4 shows that the secondary membership is a type-2 MF, not a distinctive value. The detailed computation is explained step-by-step in below.

Figure 3. Suggested T3-FLS.

(1) The inputs of T3-FLS are the states of agents as $y_i, i = 1, \ldots, n$;

(2) As shown in Figure 3, each input $y_i$ has $M$ MFs as $\tilde{\chi}^i_j$. For the Gaussian MFs the memberships are computed as:

$$
\tilde{\mu}_{\tilde{\chi}^i_j | y_i} = \exp \left( -\frac{(y_i - c_{\tilde{\chi}^i_j | y_i})^2}{\sigma_{\tilde{\chi}^i_j | y_i}^2} \right)
$$

(3)

$$
\bar{\mu}_{\tilde{\chi}^i_j | y_i} = \exp \left( -\frac{(y_i - c_{\tilde{\chi}^i_j | y_i})^2}{\sigma_{\tilde{\chi}^i_j | y_i}^2} \right)
$$

(4)
\[ \mu_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_i) = \exp \left( -\frac{(y_i - c_{\tilde{\chi}_i^j|\tilde{\rho}_j})^2}{\varepsilon^2_{\tilde{\chi}_i^j|\tilde{\rho}_j}} \right) \]  

(5)

where, \( c_{\tilde{\chi}_i^j} \) is the center of MF \( \tilde{\chi}_i^j \) and \( \varepsilon_{\tilde{\chi}_i^j} \) and \( \varepsilon_{\tilde{\rho}_j} \) are the standard divisions for UBs and LBs of MF \( \tilde{\chi}_i^j \). \( y_j \), \( j = 1, \ldots, K \) represent the value of each slice. For more details about the computation of UBs and LBs of MFs, the readers are asked to see [34];

(3) Considering memberships of MFs \( \tilde{\chi}_i^j \), the rule firings are obtained as (see Figure 4):

\[ z^h_{\tilde{\chi}_i^j} = \tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_1)\tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_2) \cdots \tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_n) \]  

(7)

\[ z^h_{\tilde{\rho}_j} = \tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_1)\tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_2) \cdots \tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_n) \]  

(8)

\[ z^h_{\tilde{\rho}_j} = \tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_1)\tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_2) \cdots \tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_n) \]  

(9)

\[ z^h_{\tilde{\rho}_j} = \tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_1)\tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_2) \cdots \tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_n) \]  

(10)

where \( j = 1, \ldots, K, h = 1, \ldots, N, \tilde{\mu}_{\tilde{\chi}_i^j|\tilde{\rho}_j}(y_1) \) represents the membership for MF \( \tilde{\chi}_i^j \) and \( \tilde{\rho}_j \).

It should be noted that the \( i \)-th rule is written as (11):

\[
\text{if } y_1 \text{ is } \tilde{\chi}_i^1|\tilde{\rho}_j, \ldots, y_i \text{ is } \tilde{\chi}_i^j|\tilde{\rho}_j, \ldots \text{ and } y_n \text{ is } \tilde{\chi}_i^n|\tilde{\rho}_j \\
\text{Then } f_j \in [\Psi_{h,j}, \Psi_{h,j}]
\]  

(11)

Then, by the use of product T-norm the rule firings are obtained as given in (7)–(10);

(4) By Nie-Tan type-reduction [35] for the first type-reduction, one has:

\[ \phi_j = \frac{\sum_{h=1}^{N} \left( z^h_{\tilde{\chi}_i^j} + z^h_{\tilde{\rho}_j} \right) \Psi_{h,j}}{\sum_{h=1}^{N} z^h_{\tilde{\chi}_i^j} + z^h_{\tilde{\rho}_j}} \]  

(12)

\[ \Phi_j = \frac{\sum_{h=1}^{N} \left( z^h_{\tilde{\chi}_i^j} + z^h_{\tilde{\rho}_j} \right) \Psi_{h,j}}{\sum_{h=1}^{N} z^h_{\tilde{\chi}_i^j} + z^h_{\tilde{\rho}_j}} \]  

(13)

(5) For the second type-reduction, one has:

\[ g_j = \frac{\sum_{j=1}^{K} \phi_j v_j}{\sum_{j=1}^{K} v_j} \]  

(14)

\[ \psi_j = \frac{\sum_{j=1}^{K} \phi_j v_j}{\sum_{j=1}^{K} v_j} \]  

(15)
The output is:
\[ f = \frac{1}{2} y + \frac{1}{2} y \]

The Equation (16) can be written as:
\[ \hat{f}(y|w) = w^T \psi(y) \]

where,
\[ w^T = [\Psi_{1,1}, \ldots, \Psi_{N,1}, \ldots, \Psi_{1,K}, \ldots, \Psi_{N,K}] \]

\[ \psi(y) = \frac{\nu_j}{K} \sum_{j=1}^{K} \left[ \sum_{h=1}^{H} z_{h1} + z_{h2} + \ldots, z_{N1} + z_{N2} \right] \]

\[ \vdots \]

\[ \sum_{h=1}^{H} \left[ \sum_{h=1}^{H} z_{h1} + z_{h2} + \ldots, z_{N1} + z_{N2} \right] \]

\[ \mu_{\chi_i|\nu} \]

\[ \bar{\mu}_{\chi_i|\nu_j}(y_i) \]

Figure 4. Suggested MF.
4. Control with No Limitation on Sampling Time

In this section, the controller with no limitation on sampling time is designed and analyzed. The main relations are presented in Theorem 1.

**Theorem 1.** The agents (1) track the leader (2), if the controllers, adaptive compensator systems and learning rules are considered as (20)–(22).

\[
\begin{align*}
    m_{ii}u_i &= -\sum_{j=1}^{N} m_{ij}(\hat{F}_j y_i - y_0^j) \\
    &- \sum_{j=1, j \neq i}^{N} m_{ij}u_j - \lambda_1^iy_i^2 + \cdots - \lambda_n^iy_i^n + u_{si} \\
    u_{si} &= -\text{sign}\left(\hat{g}_i^T \pi \hat{z}\right)K_i \\
    \hat{w}_i &= \gamma \hat{g}_i^T \pi \hat{z}m_i \psi_i(y_i) 
\end{align*}
\]

where, \( \lambda_j^i, j = 1, \ldots, n \) are positive constant and are determined, such that the eigenvalues of the matrix to be negative:

\[
\psi_i = \begin{bmatrix}
    0 & 1 & \cdots & 0 \\
    \vdots & \vdots & \ddots & \vdots \\
    0 & 0 & \cdots & 1 \\
    -\lambda_1^i & -\lambda_2^i & \cdots & -\lambda_n^i
\end{bmatrix}
\]

The tracking errors are defined as:

\[
\begin{align*}
    \hat{y}_i^1 &= \sum_{j \in N_i} a_{ij}(y_j^1 - y_i^1) + \beta_i(y_0^1 - y_i^1) \\
    \vdots \\
    \hat{y}_i^n &= \sum_{j \in N_i} a_{ij}(y_j^n - y_i^n) + \beta_i(y_0^n - y_i^n)
\end{align*}
\]

where, \( a_{ij} = 1 \) if genet \( i \) and \( j \) are connected and \( \beta_i = 1 \) if genet \( i \) is connected to the leader. In the matrix form, one has:

\[
\begin{align*}
    \hat{g}_i^1 &= -(\Lambda + B)(y_1^1 - 1y_0^1) \\
    \vdots \\
    \hat{g}_i^n &= -(\Lambda + B)(y_n^1 - 1y_0^n)
\end{align*}
\]

where, 1 ∈ \( R^N \) is matrix with unit elements, \( \hat{g}_i^j = [\hat{g}_i^1, \ldots, \hat{g}_i^N]^T \in R^N \), \( B = \text{diag}\{\beta_i\} \) and \( \Lambda \) is defined as:

\[
\Lambda_{ij} = \begin{cases}
    \sum_{j \in N_i} a_{ij} & i = j \\
    -a_{ij} & \text{if } i \text{ and } j \text{ are connected} \\
    0 & \text{otherwise}
\end{cases}
\]

Time-derivative of errors, results in:

\[
\begin{align*}
    \dot{\hat{y}}_i^1 &= \hat{g}_i^2 \\
    \vdots \\
    \dot{\hat{y}}_i^n &= M(F + u - 1\hat{y}_i^n)
\end{align*}
\]

where \( M = -(\Lambda + B), F = f + d, F = [F_1, \ldots, F_N]^T \). The dynamics of tracking error for \( i \)-th agent are written as:
\[
\dot{y}_i = \dot{g}_i^2
\]
\[
\vdots
\]
\[
\dot{g}_i^n = \sum_{j=1}^{N} m_{ij} (F_j - \dot{y}_j^n) + \sum_{j=1, j \neq i}^{N} m_{ij} u_j + m_{ii} u_i
\]

where, \(m_{ij}\) represents the \((i, j)\) element of matrix \(M\). Equation (28), is written as:
\[
\dot{g}_i = A \dot{g}_i + \zeta \left( \sum_{j=1}^{N} m_{ij} (F_j - \dot{y}_j^n) + \sum_{j=1, j \neq i}^{N} m_{ij} u_j + m_{ii} u_i \right)
\]

where,
\[
A = \begin{bmatrix}
0 & 1 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & 1 \\
0 & 0 & \cdots & 0
\end{bmatrix}, \quad \zeta = \begin{bmatrix}
0 \\
\vdots \\
0 \\
1
\end{bmatrix}
\]

By applying the control signal (20), the racking error (29) becomes:
\[
\dot{g}_i = \psi_i \dot{g}_i + \zeta u_i \\
+ \zeta m_{ii} (F_i - \dot{F}_i) + \zeta \sum_{j=1, j \neq i}^{N} m_{ij} (F_j - \dot{F}_j)
\]

By adding and subtracting the optimal T3-FLS \(F_i^* (y_i, w_i^*)\), \(\dot{y}_i\) in (31), becomes:
\[
\dot{g}_i = \psi_i \dot{g}_i + \zeta u_i \\
+ \zeta m_{ii} (F_i^* (y_i, w_i^*) - \dot{F}_i (y_i, w_i)) \\
+ \zeta \sum_{j=1, j \neq i}^{N} m_{ij} (\dot{F}_j^* (y_j, w_j^*) - \dot{F}_j (y_j, w_j)) \\
+ \zeta \sum_{j=1}^{N} m_{ij} (F_j - \dot{F}_j^* (y_j, w_j^*))
\]

where the approximation error is defined as:
\[
v_i = \sum_{j=1, j \neq i}^{N} m_{ij} (\dot{F}_j^* (y_j, w_j^*) - \dot{F}_j (y_j, w_j)) \\
+ \sum_{j=1}^{N} m_{ij} (F_j - \dot{F}_j^* (y_j, w_j^*))
\]

Then (32), can be written as:
\[
\dot{g}_i = \psi_i \dot{g}_i + \zeta u_i + \zeta v_i \\
+ \zeta m_{ii} \dot{F}_i^* \psi_i (y_i)
\]

Now, the Lyapunov function (35) is considered:
\[
V = \frac{1}{2} \sum_{i=1}^{N} g_i^T \pi_i \dot{g}_i + \frac{1}{2 \gamma} \sum_{i=1}^{N} \psi_i^T \bar{w}_i
\]

where \(\bar{w}_i = w_i^* - w_i\) and \(\psi_i^T \pi_i + \pi_i \psi_i = -Q_i\). Time derivative of \(V\) in (35), yields:
\[
\dot{V} = \sum_{i=1}^{N} g_i^T (\psi_i^T \pi_i + \pi_i \psi_i) \dot{g}_i \\
+ \sum_{i=1}^{N} g_i^T \pi_i \zeta u_i + \sum_{i=1}^{N} \psi_i^T \pi_i \zeta v_i \\
+ \sum_{i=1}^{N} g_i^T \pi_i \zeta m_{ii} \dot{F}_i^* \psi_i (y_i) - \frac{1}{\gamma} \sum_{i=1}^{N} \bar{w}_i^T \bar{w}_i
\]
By replacing the adaptation laws \( \dot{w}_i = \gamma \hat{y}_i^T \pi_i \zeta m_{ii} \psi_i(y_i) \) (22), one has:

\[
V = \sum_{i=1}^{N} \tilde{g}_i^T (\psi_i^T \pi_i + \pi_i \psi_i) \tilde{y}_i
+ \sum_{i=1}^{N} \tilde{g}_i^T \pi_i \zeta u_{s_i} + \sum_{i=1}^{N} \tilde{g}_i^T \pi_i \zeta v_i
\]  

(37)

From (37), one can write:

\[
V \leq - \sum_{i=1}^{N} \tilde{g}_i^T \bar{Q}_i \tilde{y}_i
+ \sum_{i=1}^{N} \tilde{g}_i^T \pi_i \zeta u_{s_i} + \sum_{i=1}^{N} |\tilde{g}_i^T \pi_i \zeta| v_i
\]  

(38)

By applying the compensator \( u_{s_i} = -\text{sign}(\tilde{g}_i^T \pi_i \zeta) K \) (21), the inequality (38) is rewritten as:

\[
\dot{V} \leq - \sum_{i=1}^{N} \tilde{g}_i^T \bar{Q}_i \tilde{y}_i
- \sum_{i=1}^{N} \tilde{g}_i^T \pi_i \zeta \text{sign}(\tilde{g}_i^T \pi_i \zeta) K_i + \sum_{i=1}^{N} |\tilde{g}_i^T \pi_i \zeta| v_i
\]  

(39)

Considering the fact that \( \tilde{g}_i^T \pi_i \zeta \text{sign}(\tilde{g}_i^T \pi_i \zeta) = |\tilde{g}_i^T \pi_i \zeta| \), form (39) it is easily derived that \( V < 0 \) and this completes the proof.

**Remark 1.** To avoid the chattering phenomena in the control signal, the term \( \text{sign}(\tilde{g}_i^T \pi_i \zeta) \) is replaced by \( \text{tanh}(\tilde{g}_i^T \pi_i \zeta) \).

### 5. Event-Triggered Scheme

Now, the sampling problem is considered, and the control signal is updated. The designed controller is implemented by the digital devices. Then, it is updated in the sampling times \( t_1, \ldots, t_h, \ldots \). In time interval \( t \in [t_h, t_{h+1}] \), the control signal is constant. In other words, in time interval \( T_h = t_{h+1} - t_h \), the control signals are not updated. Then, in time interval \( T_h \) the following error is imposed on system:

\[
e_i(t) = \tilde{y}_i(t) - \tilde{y}_i(t_h)
\]  

(40)

By the smaller sampling time, the digital implementation is approached to the analogue one, then error \( e_i \) becomes smaller. In this section, by the event-triggered approach the controller is updated and the stability is proved. The problem is that, \( T_h \) how much can be bigger such that the system can remain stable.

**Theorem 2.** By the sampling time interval as (41), the closed-loop system remain stable if the control signal is as given in (42), compensator is as given in (43), compensator gain is as given in (44) and the adaptation laws are as given in (45).

\[
T_h \geq \ln \left[ \frac{\sigma \alpha_i}{\Gamma(\tilde{g}_i(t_h)) + \beta} + 1 \right]
\]  

(41)

\[
m_{ii} u_i(t) = - \sum_{j=1}^{N} m_{ij} (\hat{f}_j(t_h) - \tilde{y}_i^0)
- \sum_{j=1, j \neq i}^{N} m_{ij} u_i(t) - \lambda_1 \tilde{g}_i^1 (t_h)
- \lambda_2 \tilde{g}_i^2 (t_h) - \cdots - \lambda_n \tilde{g}_i^n (t_h) + u_{s_i}(t_h)
\]  

(42)

\[
u_{s_i} = -K \text{sign} \left( \tilde{g}_i^1 (t_h) \pi_i \zeta \right)
\]  

(43)
\[ K > \dot{E}_i + \alpha_i \]  
\[ \ddot{w}_i = \gamma \tilde{g}_i^T(t) \pi_i \tilde{m}_i \mu(y_i) \]  
\[ \Gamma_i(\tilde{g}_i(t_k)) = |\tilde{g}_i \tilde{g}_i(t_k)| \]  
\[ \beta_i = \dot{E} + K \]  
\[ \psi_i^T \pi_i + \pi_i \psi_i = -Q_i \]

where,

The proof is given in Appendix A.

6. Simulations

In this section, some examples are presented to verify the efficiency of designed scheme. For each agents a chaotic system (chaotic gyro in first example and Chua’s chaotic system in the second example) with complicated dynamics are considered to better examine the ability of designed control technique.

The “y” axis of simulation figures shows the values of the signals that have been depicted in the legends. The unit of all signals are voltage.

Example 1. For the first Example, the following multi-agent systems are considered:

\[ \dot{y}_1^i = y_2^i \]  
\[ \dot{y}_2^i = \frac{-100(1 - \cos y_1^i)^2}{\sin^3 y_1^i} - 0.5y_2^i - 0.05(y_2^i)^3 + \sin(y_1^i) + 35.5 \sin(25t) \sin y_1^i + d(t) + u(t) \]  
\[ \text{where,} \ d(t) = 0.15 \cos(t) y_2^i + 0.1 \sin(2t), \text{the other control parameters are presented in Table 1.} \]

Figure 5 shows the communication topology. Figure 5 shows that, all agents have a connection with their neighbors. The leader agent has connected just to the first agent. The other agents get the leader information, indirectly.

Figure 6 presents the output trajectories. It is observed that the output signals of all agents \( y_1^i, i = 1, \ldots, 5 \) well track the leader output \( y_1^0 \). The tracking errors are given in Figure 7. The tracking errors \( \tilde{y}_1^i, i = 1, \ldots, 5 \) are approached to the zero level at finite time. The effectiveness of the schemed event-triggered scenario is verified in Figure 8. The all actuators are less updated in comparison with conventional approaches. The control signals \( u_i, i = 1, \ldots, 5 \) are depicted in Figure 9. The achieved control signals have smooth shapes with no chattering. To show the superiority of T3-FLSs, the simulations are repeated using other types of FLSs instead of T3-FLSs, and the RMSE values are depicted in Table 2.

Table 1. Example 1: Simulation condition.

| Parameter | Equation |
|-----------|----------|
| \( \lambda_1 = 100, \lambda_2 = 20 \) | (42) |
| \( K \) | (43) |
| \( \dot{E}_i = 10 \) | (44) |
| \( \alpha_i = 0.2 \) | (44) |
| \( \sigma = 0.1 \) | (44) |
| \( \gamma = 0.1 \) | (45) |
| \( \pi_i = \begin{bmatrix} 2.62500 & 0.00500 \\ 0.00500 & 0.0253 \end{bmatrix} \) | (43) |
| \( c_{\chi} = -1, c_{\chi} = 0.5, c_{\chi} = 1 \) | (3)-(6) |
| \( \nu_1 = 0.7, \nu_2 = 0.8, \nu_3 = 0.9 \) | (3)-(6) |
| \( \nu_1 = 0.1, \nu_2 = 0.2, \nu_3 = 0.3 \) | (3)-(6) |
Figure 5. Example 1: Topology.

Figure 6. Example 1: Output trajectories.

Figure 7. Example 1: Tracking error trajectories.

Table 2. Example 2: Comparison results.

|       | $\tilde{y}_1$ | $\tilde{y}_2$ | $\tilde{y}_3$ | $\tilde{y}_4$ | $\tilde{y}_5$ |
|-------|---------------|---------------|---------------|---------------|---------------|
| T1-FLS | 0.3712        | 0.4048        | 0.1071        | 0.2012        | 1.4807        |
| T2-FLS | 0.2014        | 0.1241        | 0.0894        | 0.1387        | 0.1079        |
| T3-FLS | 0.1315        | 0.0857        | 0.0897        | 0.1494        | 0.0954        |
Example 2. For the second example, the synchronization of following agents are considered:

\[
\begin{align*}
\dot{y}_1^i &= y_2^i \\
\dot{y}_2^i &= y_3^i \\
\dot{y}_3^i &= -y_1^i - 1.1y_2^i - 0.45y_3^i + (y_1^i)^2 + d_i(t) + u_i(t) \\
\dot{y}_0^1 &= y_0^2 \\
\dot{y}_0^2 &= y_0^3 \\
\dot{y}_0^3 &= 0.8y_0^3 - 1.1y_0^2 - 0.45y_0^3 - (y_0^1)^3
\end{align*}
\]

The conditions are same as the Example 1, except \( \lambda_i = [120000, 7400, 150]^T \) and

\[
\pi_{1i} = \pi_{2i} = \begin{bmatrix} 625.1877 \ 18.7506 \ 0.0000 \end{bmatrix}
\]

The output trajectories are given in Figure 10. Similar to the Example 1, a well tracking proficiency has been achieved. Figure 10 shows that the output signals of all agents \( (y_1^i, i = 1, \ldots, 5) \) are well converged to the leader output \( (y_1^0) \). Figure 11 shows the tracking errors. The tracking errors \( (\tilde{y}_1^i, i = 1, \ldots, 5) \) are approached to zero level at a desirable time. Figure 12 demonstrates that, the all control systems are less updated from conventional approaches. It is seen that the actuators are updated between 15 and 40% of all sample times. The control signals \( (u_i, i = 1, \ldots, 5) \) are depicted in Figure 13. The achieved control signals have smooth shapes with no chattering. The phase plan
in the case that there is no control is depicted in Figure 14. The trajectories of Figure 14 show that agents are obtained away from the leader and there is no synchronization. The phase plan after applying the proposed controller is shown in Figure 15. The trajectories of Figure 15 show that all agents are well approached to the chaotic leader system. Similar to the Example 1, to show the superiority of T3-FLSs, the simulations are repeated using other types of FLSs instead of T3-FLSs and the values of RMSEs are shown in Table 3. The results of Table 3, show that using suggested T3-FLS results in better leader following performance.
Figure 13. Example 2: Control signals.

Figure 14. Example 2: The phase plan; without control.

Figure 15. Example 2: The phase plan with control.
Table 3. Example 2: Comparison results.

|          | \( \tilde{y}_1 \) | \( \tilde{y}_2 \) | \( \tilde{y}_3 \) | \( \tilde{y}_4 \) | \( \tilde{y}_5 \) |
|----------|-------------------|-------------------|-------------------|-------------------|-------------------|
| T1-FLS   | 0.7231            | 0.2317            | 0.2479            | 0.3472            | 1.2180            |
| T2-FLS   | 0.4274            | 0.1247            | 0.2017            | 0.1047            | 0.8713            |
| T3-FLS   | 0.3952            | 0.0649            | 0.0625            | 0.0626            | 0.5568            |

**Remark 2.** The main difference and advantages of the designed controller are:

- The whole dynamics of the agents and leaders are unknown. The designed controller do not depend on the mathematical dynamics of agents;
- The actuators are not activated at each sample time. However, an optimal activation scheme is presented that helps to increase the lifetime of devices;
- It is shown that in noisy condition, the suggested type-3 FLS-based scheme gives better accuracy.

**Remark 3.** It should be noted that the control efficiency do not depend on the topology. The only restriction is that a spanning three there must be in communication graph, and all agents should be connected directly or indirectly to the leader agent. In other words, there must be a path between each agent and leader agent.

**Remark 4.** The designed controller is implemented in Matlab Simulink. A general view on the simulation is given in Figure 16.

![Figure 16. Matlab implementation scheme.](image)
7. Conclusions

In this paper, a new T3-FLS based control technique is presented for control of MASs. A new online optimized T3-FLS scheme is suggested to cope with uncertainties. The robustness and stability is ensured by the designed adaptive compensator system. In two simulations, the desired efficiency of the designed controller is verified. In the first example, the agents and leader are the same chaotic systems with different initial conditions. It is shown that the agents well track the leader, and number sample times that the actuators are activated are remarkably decreased. It must be noted that, by a small changes in the initial conditions of chaotic agents, the output behavior is completely changed. For the second example, the leader and agents are considered to be non-identical chaotic systems. Similar to the first example, a well tracking performance is obtained. It is shown that the actuators are activated between 20 and 40% of all sample times. The remarkably decreasing the updating times of actuators help to increase the physical health of devices.

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Appendix A. Proof of Theorem 2

Proof. Considering \( e_i(t) = \tilde{y}_i(t) - \tilde{y}_i(t_h) \) and applying the controller (42), the dynamics of the tracking error are modified as

\[
\dot{\tilde{y}}_i = A \tilde{y}_i(t) + \sum_{j=1}^{N} m_{ij} (F_j(t) - \tilde{y}_0(t)) - \zeta \sum_{j=1}^{N} m_{ij} (\tilde{F}_j(t_h) - \tilde{y}_0(t_h)) \\
+ \zeta \sum_{j=1, j \neq i}^{N} m_{ij} (u_j(t) - u_j(t_h)) + \zeta u_i(t_h) \\
+ \zeta [\lambda_1^1 \tilde{y}_1(t_h) - \lambda_2^2 \tilde{y}_2(t_h) - \cdots - \lambda_n^m \tilde{y}_n(t_h)]
\]

(A1)

From (23), \( \dot{\tilde{y}}_i \) becomes:

\[
\dot{\tilde{y}}_i = \psi \dot{\tilde{y}}_i(t_h) + Ae_i(t) \\
+ \zeta \sum_{j=1}^{N} m_{ij} (F_j(t) - \tilde{y}_0(t)) - \zeta \sum_{j=1}^{N} m_{ij} (\tilde{F}_j(t_h) - \tilde{y}_0(t_h)) \\
+ \zeta \sum_{j=1, j \neq i}^{N} m_{ij} (u_j(t) - u_j(t_h)) + \zeta u_i(t_h)
\]

(A2)

By adding and subtracting optimal T3-FLS \( \tilde{F}_j^*(t_h) \), one has:

\[
\dot{\tilde{y}}_i = \psi \dot{\tilde{y}}_i(t_h) + Ae_i(t) \\
+ \zeta \sum_{j=1}^{N} m_{ij} (F_j(t) - \tilde{y}_0(t)) - \zeta \sum_{j=1}^{N} m_{ij} (\tilde{F}_j(t_h) - \tilde{y}_0(t_h)) \\
- \zeta \sum_{j=1}^{N} m_{ij} (\tilde{F}_j^*(t_h) - \tilde{y}_0(t_h)) + \zeta \sum_{j=1}^{N} m_{ij} (\tilde{F}_j^*(t_h) - \tilde{y}_0(t_h)) \\
+ \zeta \sum_{j=1, j \neq i}^{N} m_{ij} (u_j(t) - u_j(t_h)) + \zeta u_i(t_h)
\]

(A3)
Equation (A3) can be simplified as

\[
\dot{y}_i = \psi \dot{y}_i(t_h) + A \xi_i(t) \\
+ \zeta \sum_{j=1}^{N} m_{ij} (F_j(t) - \dot{y}_0^j(t)) - \zeta \sum_{j=1}^{N} m_{ij} \left( \dot{F}_j^*(t_h) - \dot{y}_0^j(t_h) \right) \\
+ \zeta \sum_{j=1, j \neq i}^{N} m_{ij} (\dot{F}_j^*(t_h) - \dot{F}_j(t_h)) \\
+ \zeta \sum_{j=1, j \neq i}^{N} m_{ij} (u_j(t) - u_j(t_h)) \\
+ \zeta u_{s_0}(t_h)
\]

(A4)

From (A4), one has:

\[
\dot{y}_i = \psi \dot{y}_i(t_h) + A \xi_i(t) + \zeta m_{ii} \bar{w}_i^T \mu(y_i) + \zeta u_{s_0}(t_h) \\
+ \zeta \sum_{j=1}^{N} m_{ij} (F_j(t) - \dot{y}_0^j(t)) \\
- \zeta \sum_{j=1}^{N} m_{ij} \left( \dot{F}_j^*(t_h) - \dot{y}_0^j(t_h) \right) \\
+ \zeta \sum_{j=1, j \neq i}^{N} m_{ij} \left( \dot{F}_j^*(t_h) - \dot{F}_j(t_h) \right) \\
+ \zeta \sum_{j=1, j \neq i}^{N} m_{ij} (u_j(t) - u_j(t_h))
\]

(A5)

Consider the following definition:

\[
E_i(t) = \sum_{j=1}^{N} m_{ij} (F_j(t) - \dot{y}_0^j(t)) \\
- \sum_{j=1}^{N} m_{ij} \left( \dot{F}_j^*(t_h) - \dot{y}_0^j(t_h) \right) \\
+ \sum_{j=1, j \neq i}^{N} m_{ij} \left( \dot{F}_j^*(t_h) - \dot{F}_j(t_h) \right) \\
+ \sum_{j=1, j \neq i}^{N} m_{ij} (u_j(t) - u_j(t_h))
\]

(A6)

Then, from (A5) and (A6), one has:

\[
\dot{y}_i(t) = \psi \dot{y}_i(t_h) + A \xi_i(t) + \zeta m_{ii} \bar{w}_i^T \mu(y_i) \\
+ \zeta E_i(t) + \zeta u_{s_0}(t_h)
\]

(A7)

To stability analysis, consider the Lyapunov function (A8):

\[
V = \frac{1}{2} \sum_{i=1}^{N} \bar{y}_i^T \pi_i \dot{\bar{y}}_i + \frac{1}{2} \sum_{i=1}^{N} \bar{\bar{w}}_i^T \dot{\bar{\bar{w}}}_i
\]

(A8)

Taking time derivative of (A8), yields:

\[
\dot{V}(t) = \\
\sum_{i=1}^{N} \bar{y}_i(t) \left( \psi^T \pi_i + \pi_i \psi_i \right) \dot{y}_i(t) + \sum_{i=1}^{N} \bar{y}_i(t) \pi_i A \xi_i(t) \\
+ \sum_{i=1}^{N} \bar{y}_i(t) \pi_i \xi u_{s_0}(t_h) + \sum_{i=1}^{N} \bar{y}_i(t) \pi_i \xi E_i(t) \\
+ \sum_{i=1}^{N} \bar{y}_i(t) \pi_i \xi m_{ii} \bar{w}_i^T \mu(y_i) - \frac{1}{2} \sum_{i=1}^{N} \bar{\bar{w}}_i^T \dot{\bar{\bar{w}}}_i
\]

(A9)
By replacing the \( \tilde{w}_i = \gamma \tilde{g}_i^T(t) \tau_i \zeta \mu_i(y_i) \) (45), one has:

\[
\dot{V}(t) = \sum_{i=1}^{N} \tilde{g}_i^T(t) (\psi_i^T \tau_i + \tau_i \psi_i) \tilde{y}_i(t) + \sum_{i=1}^{N} \tilde{g}_i^T(t) \tau_i A_i e_i(t) \\
+ \sum_{i=1}^{N} \tilde{g}_i^T(t) \tau_i \zeta u_{s_i}(t_h) + \sum_{i=1}^{N} | \tilde{g}_i^T(t) \tau_i | | E_i(t) |
\]

(A10)

From (A10), one has:

\[
\dot{V}(t) \leq \sum_{i=1}^{N} \tilde{g}_i^T(t) Q_i \tilde{y}_i(t) + \sum_{i=1}^{N} \tilde{g}_i^T(t) \tau_i A_i e_i(t) \\
+ \sum_{i=1}^{N} | \tilde{g}_i^T(t) \tau_i | | E_i(t) |
\]

(A11)

If \( \text{sign}(\tilde{g}_i^T(t_h) \tau_i \zeta) = \text{sign}(\tilde{g}_i^T(t) \tau_i \zeta) \), then considering relation

\[
\| A_i \| | e_i(t) | \leq a_i | \zeta | 
\]

(A12)

One has:

\[
\dot{V}(t) \leq \sum_{i=1}^{N} \tilde{g}_i^T(t) Q_i \tilde{y}_i(t) \\
+ \sum_{i=1}^{N} | \tilde{g}_i^T(t) \tau_i | | E_i(t) | + a_i - K
\]

(A14)

Then, until the relation \( \text{sign}(\tilde{g}_i^T(t_h) \tau_i \zeta) = \text{sign}(\tilde{g}_i^T(t) \tau_i \zeta) \) is satisfied, and one has \( K > \bar{E}_i + a_i \), the closed-loop system remains stable. \( \bar{E}_i \) is the upper bound of \( | E_i(t) | \). Now, the lack of satisfying the relation \( \text{sign}(\tilde{g}_i^T(t_h) \tau_i \zeta) = \text{sign}(\tilde{g}_i^T(t) \tau_i \zeta) \) is investigated and the suitability of sampling time is analyzed. The error between \( \tilde{g}_i^T(t) \tau_i \zeta \) and \( \tilde{g}_i^T(t_h) \tau_i \zeta \) is equal with

\[
| \tilde{g}_i^T(t_h) \tau_i \zeta - \tilde{g}_i^T(t) \tau_i \zeta | = | e_i(t) | | \tau_i | | \zeta |
\]

(A15)

Consider the following inequality:

\[
| e_i^T(t) \tau_i \zeta | \leq | e_i(t) | | \tau_i | | \zeta |
\]

(A16)

Then, one has:

\[
| \tilde{g}_i^T(t_h) \tau_i \zeta - \tilde{g}_i^T(t) \tau_i \zeta | \leq | e_i(t) | | \tau_i | | \zeta |
\]

(A17)

From the fact that \( | \zeta | = 1 \) and \( | A_i | = \sqrt{\lambda_{\max}(A_i^T A_i)} \), one has:

\[
| \tilde{g}_i^T(t_h) \tau_i \zeta - \tilde{g}_i^T(t) \tau_i \zeta | \leq a_i \|

(A18)

where, \( \lambda_{\max}(A_i^T A_i) \) represents the maximum eigenvalue of \( A_i^T A_i \). Relation (A18), presents a bound for variation of \( \tilde{g}_i^T(t) \tau_i \zeta \) at time interval \([t - t_h]\). Then, if \( \tau_i^T(t) \tau_i \zeta \) is grater than \( a_i \|

Consider the following inequality:
\[
\frac{d}{dt} \| e_i(t) \| \leq \frac{d}{dt} \| e_i(t) \|
\]  \hspace{1cm} (A19)

Then,
\[
\left\| \frac{d}{dt} e_i(t) \right\| = \left\| \frac{d}{dt} (g_i(t) - \bar{g}_i(t_h)) \right\|
\]  \hspace{1cm} (A20)

From (A20), one has:
\[
\left\| \frac{d}{dt} g_i(t) \right\| \leq \left\| \frac{d}{dt} \bar{g}_i(t) \right\| + \left\| \frac{d}{dt} \bar{g}_i(t_h) \right\|
\]  \hspace{1cm} (A21)

Then,
\[
\frac{d}{dt} \| e_i(t) \| \leq \frac{d}{dt} \| \bar{g}_i(t) \|
\]  \hspace{1cm} (A22)

From (A7) and (A22), one has:
\[
\frac{d}{dt} \| e(t) \| \leq \| \psi_i \bar{g}_i(t_h) + A e_i(t) + \zeta E_i(t) + \zeta u_h(t_h) \|
\]  \hspace{1cm} (A23)

By replacing the compensator (43), the inequality (A23), becomes:
\[
\left\| \frac{d}{dt} e_i(t) \right\| \leq \left\| \psi_i \bar{g}_i(t_h) + A e_i(t) + \zeta E_i(t) - K \text{sign}(\bar{g}_i(t) P \zeta) \zeta \right\|
\]  \hspace{1cm} (A24)

From (A24), one has:
\[
\frac{d}{dt} \| e_i(t) \| \leq \| \psi_i \bar{g}_i(t_h) + A e_i(t) + \zeta E_i(t) - K \text{sign}(\bar{g}_i(t) P \zeta) \zeta \| \leq \| A e_i(t) \| + \| \psi_i \bar{g}_i(t_h) \| + \| \zeta E_i(t) \| + \| K \zeta \|
\]  \hspace{1cm} (A25)

Considering the upper bound of $\bar{E}_i$, as $\bar{E}_i$, one obtains:
\[
\frac{d}{dt} \| e_i(t) \| \leq \| A e_i(t) \| + \| \psi_i \bar{g}_i(t_h) \| + \| \zeta_i \| E_i + \| K \zeta \|
\]  \hspace{1cm} (A26)

Then, it can written:
\[
\frac{d}{dt} \| e_i(t) \| \leq \| A \| \| e_i(t) \| + \| \psi_i \bar{g}_i(t_h) \| + \bar{E}_i + K
\]  \hspace{1cm} (A27)

By replacing $\Gamma$ form (46), one has:
\[
\frac{d}{dt} \| e_i(t) \| \leq \| A \| \| e_i(t) \| + \| \psi_i \bar{g}_i(t_h) \| + \bar{E}_i + K
\]  \hspace{1cm} (A28)

From the fact that $\| A \| = \sqrt{\lambda_{\text{max}}(A^T A)} = 1$, one can write:
\[
\frac{d}{dt} \| e_i(t) \| \leq \| e_i(t) \| + \Gamma(\bar{g}_i(t_h)) + \beta
\]  \hspace{1cm} (A29)

Considering the initial condition $e_i(t) = 0$, from (A29), one has:
\[
\| e_i(t) \| \leq (\Gamma(\bar{g}_i(t_h)) + \beta)(\exp(t - t_h) - 1)
\]  \hspace{1cm} (A30)

Then, considering $\| e_i(t_{h+1}) \| = \sigma \alpha_i$, one has:
\[
\sigma \alpha_i \leq (\Gamma(\bar{g}_i(t_h)) + \beta)(\exp(t - t_h) - 1)
\]  \hspace{1cm} (A31)
By taking into account the relation $T_h = t_{h+1} - t_h$, the inequality (A31) is written as:

$$\sigma h \leq (\Gamma(\tilde{\chi}(t_h)) + \beta)(\exp(T_h) - 1)$$ (A32)

Then, a bound for $T_h$ is obtained as:

$$\frac{\sigma h}{\Gamma(\tilde{\chi}(t_h)) + \beta} + 1 \leq \exp(T_h)$$

$$\Rightarrow T_h \geq \ln \left[ \frac{\sigma h}{\Gamma(\tilde{\chi}(t_h)) + \beta} + 1 \right]$$ (A33)

This completes the proof. \(\square\)

References

1. Lin, Y.; Lin, Z.; Sun, Z. Distributed Event-Triggered Approach for Multi-Agent Formation Based on Cooperative Localization with Mixed Measurements. *Electronics* 2021, 10, 2265. [CrossRef]

2. Mnasri, S.; Alrashidi, M. A Comprehensive Modeling of the Discrete and Dynamic Problem of Berth Allocation in Maritime Terminals. *Electronics* 2021, 10, 2684. [CrossRef]

3. Li, W.; Lin, Z.; Cai, K.; Yan, G. Distributed algorithm for a finite time horizon resource allocation over a directed network. *IET Control Theory Appl.* 2020, 14, 1170–1182. [CrossRef]

4. Hwang, K.; Park, J.; Kim, H.; Kuc, T.Y.; Lim, S. Development of a Simple Robotic Driver System (SimRoDS) to Test Fuel Economy of Hybrid Electric and Plug-In Hybrid Electric Vehicles Using Fuzzy-PI Control. *Electronics* 2021, 10, 1444. [CrossRef]

5. Li, X.; Yu, Z.; Li, Z.; Wu, N. Group consensus via pinning control for a class of heterogeneous multi-agent systems with input constraints. *Inf. Sci.* 2021, 542, 247–262. [CrossRef]

6. Zhang, T.; Zhang, H.; Sun, S.; Gao, Z. Leader-follower consensus control for linear multi-agent systems by fully distributed edge-event-triggered adaptive strategies. *Inf. Sci.* 2021, 555, 314–338. [CrossRef]

7. Gao, C.; Wang, Z.; He, X.; Han, Q.L. Consensus Control of Linear Multiagent Systems Under Actuator Imperfection: When Saturation Meets Fault. *IET Control Theory Appl.* 2020, 14, 2265. [CrossRef]

8. Wang, H.; Xue, B.; Xue, A. Leader-following consensus control for semi-Markov jump multi-agent systems: An adaptive event-triggered scheme. *J. Frankl. Inst.* 2021, 358, 428–447. [CrossRef]

9. Xiong, T.; Gu, Z. Observer-based adaptive fixed-time formation control for multi-agent systems with unknown uncertainties. *Neurocomputing* 2021, 423, 506–517. [CrossRef]

10. Shao, J.; Shi, L.; Cheng, Y.; Li, T. Asynchronous tracking control of leader-follower multiagent systems with input uncertainties over switching signed digraphs. *IEEE Trans. Cybern.* 2021. [CrossRef]

11. Wen, S.; Ni, X.; Wang, H.; Zhu, S.; Shi, K.; Huang, T. Observer-Based Adaptive Synchronization of Multiagent Systems With Unknown Parameters Under Attacks. *IEEE Trans. Neural Netw. Learn. Syst.* 2021. [CrossRef]

12. Jing, G.; Bai, H.; George, J.; Chakrabortty, A. Model-free optimal control of linear multi-agent systems via decomposition and hierarchical approximation. *IEEE Trans. Control Netw. Syst.* 2021. [CrossRef]

13. Zhang, A.; Lin, Z.; Wang, B.; Han, Z. Nonlinear Model Predictive Control of Single-Link Flexible-Joint Robot Using Recurrent Neural Network and Differential Evolution Optimization. *Electronics* 2021, 10, 2426. [CrossRef]

14. Tian, M.; Yan, S.; Tian, X. Discrete approximate iterative method for fuzzy investment portfolio based on transaction cost threshold constraint. *Open Phys.* 2019, 17, 41–47. [CrossRef]

15. Mnasri, S.; Nasri, N.; Van den Bossche, A.; Val, T. A new multi-agent particle swarm algorithm based on birds accents for the 3D indoor deployment problem. *ISA Trans.* 2019, 91, 262–280. [CrossRef] [PubMed]

16. Oh, G.; Ryu, J.; Jeong, E.; Yang, J.H.; Hwang, S.; Lee, S.; Lim, S. DRER: Deep Learning–Based Driver’s Real Emotion Recognizer. *Sensors* 2021, 21, 2166. [CrossRef]

17. Rakkiyappan, R.; Sivasamy, R.; Li, X. Synchronization of identical and nonidentical memristor-based chaotic systems via active backstepping control technique. *Circuits Syst. Signal Process.* 2015, 34, 763–778. [CrossRef]

18. Guo, T.; Xue, H.; Pan, Y. Neural networks-based adaptive tracking control of multi-agent systems with output-constrained and unknown hysteresis. *Neurocomputing* 2020, 458, 24–32. [CrossRef]

19. Zhang, J.X.; Yang, G.H. Distributed Fuzzy Adaptive Output-Feedback Control of Unknown Nonlinear Multiagent Systems in Strict-Feedback Form. *IEEE Trans. Cybern.* 2021. [CrossRef]

20. Lin, Z.; Liu, Z.; Zhang, Y.; Chen, C.P. Adaptive neural consensus tracking control for multi-agent systems with unknown state and input hysteresis. *Nonlinear Dyn.* 2021, 105, 1625–1641. [CrossRef]

21. Ren, C.E.; Fu, Q.; Zhang, J.; Zhao, J. Adaptive event-triggered control for nonlinear multi-agent systems with unknown control directions and actuator failures. *Nonlinear Dyn.* 2021, 105, 1657–1672. [CrossRef]

22. Lin, Z.; Liu, Z.; Zhang, Y.; Chen, C.P. Command filtered neural control of multi-agent systems with input quantization and unknown control direction. *Neurocomputing* 2021, 430, 47–57. [CrossRef]

23. Zhang, L.; Chen, B.; Lin, C.; Shang, Y. Fuzzy adaptive finite-time consensus tracking control for nonlinear multi-agent systems. *Int. J. Syst. Sci.* 2021, 52, 1346–1358. [CrossRef]
24. Lan, J.; Xu, T. Adaptive Fuzzy Consensus Tracking Control for Nonlinear Multiagent Systems with Time-Varying Delays and Constraints. *Complexity* 2021, 2021, 9940257. [CrossRef]

25. Cui, Y.; Liu, X.; Deng, X.; Wang, Q. Observer-based adaptive fuzzy formation control of nonlinear multi-agent systems with nonstrict-feedback form. *Int. J. Fuzzy Syst.* 2021, 23, 680–691. [CrossRef]

26. Lin, C.J.; Lin, C.H.; Wang, S.H. Using a Hybrid of Interval Type-2 RFCMAC and Bilateral Filter for Satellite Image Dehazing. *Electronics* 2020, 9, 710. [CrossRef]

27. Lin, C.J.; Lin, C.H.; Wang, S.H. Using Fuzzy Control for Feed Rate Scheduling of Computer Numerical Control Machine Tools. *Appl. Sci.* 2021, 11, 4701. [CrossRef]

28. Qin, B.; Fan, Y.; Xiao, T.; Li, Z. Distributed type-2 fuzzy adaptive control for heterogeneous nonlinear multiagent systems. *Asian J. Control* 2021. [CrossRef]

29. Afaghi, A.; Ghaemi, S.; Ghiasi, A.R.; Badamchizadeh, A.M. Type-2 fuzzy consensus control of nonlinear multi-agent systems: An LMI approach. *J. Frankl. Inst.* 2021, 358, 4326–4347. [CrossRef]

30. Zhang, Z.; Dong, J. Fault-Tolerant Containment Control for IT2 Fuzzy Networked Multiagent Systems Against Denial-of-Service Attacks and Actuator Faults. *IEEE Trans. Syst. Man Cybern. Syst.* 2021. [CrossRef]

31. Afaghi, A.; Ghaemi, S.; Ghiasi, A.R.; Badamchizadeh, A.M. Adaptive fuzzy observer-based cooperative control of unknown fractional-order multi-agent systems with uncertain dynamics. *Soft Comput.* 2020, 24, 3737–3752. [CrossRef]

32. Calegari, R.; Ciatto, G.; Mascardi, V.; Omicini, A. Logic-based technologies for multi-agent systems: A systematic literature review. *Auton. Agents Multi-Agent Syst.* 2021, 35, 1–67. [CrossRef]

33. Qasem, S.N.; Ahmadian, A.; Mohammadzadeh, A.; Rathinasamy, S.; Pahlevanzadeh, B. A type-3 logic fuzzy system: Optimized by a correntropy based Kalman filter with adaptive fuzzy kernel size. *Inf. Sci.* 2021, 572, 424–443. [CrossRef]

34. Mohammadzadeh, A.; Sabzalian, M.H.; Zhang, W. An interval type-3 fuzzy system and a new online fractional-order learning algorithm: Theory and practice. *IEEE Trans. Fuzzy Syst.* 2019, 28, 1940–1950. [CrossRef]

35. Nie, M.; Tan, W.W. Towards an efficient type-reduction method for interval type-2 fuzzy logic systems. In Proceedings of the 2008 IEEE International Conference on Fuzzy Systems (IEEE World Congress on Computational Intelligence), Hong Kong, China, 1–6 June 2008; pp. 1425–1432.