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CONSENSUS OF MULTI-AGENT SYSTEMS WITH EULER-LAGRANGE SYSTEM BASED ON NEURAL NETWORKS

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Abstract. *In this paper, consensus problem of multi-agent systems has been considered. Each agent is an Euler-Lagrange (EL) system with an unknown nonlinear function, which is a nonlinear system. The sliding mode surface of the consensus problem of such multi-agent system is designed and the stability of the augmenting error system is guaranteed by Lyapunov theory. A controller based on Neural Networks (NN) is designed to compensate the unknown nonlinear function. Combining with an adaptive control law the consensus of multiple EL systems is reached. Finally, the simulation results illustrate the effectiveness of the proposed approaches.*

Keywords: Neural networks, Consensus, Multi-agent systems, Euler-Lagrange systems

1. **Introduction.** In recent years, there are many research papers on consensus problem of multi-agent systems, which have extensive applications in real engineering such as communication networks, air traffic control, biology, robotic and electric power system. In [1], the general problems of state estimation in geographically dispersed systems with communication constraints are studied. [2] studied the consensus problem of multi-agent systems with a time-invariant communication topology consisting of general linear dynamics. The multi-agent system with a communication channel constraint is considered by providing a special Laplacian of directed graphs in [3]. A notion of reachable asymptotic consensus of a network with multiple nonlinear agents is developed in [4] and the asymptotic consensus protocol of multiple dynamic agents is presented. [5] is concerned with the distributed containment control problem for networked Lagrangian systems with multiple stationary or dynamic leaders in the presence of parametric uncertainties under a directed graph that characterizes the interaction among the leaders and the followers. In [6,7], the state consensus for non-point, nonlinear networked Euler-Lagrange systems with unknown parameters is addressed. Specifically, state consensus problems with both coupling time delay and a switching topology are investigated. [8] presents a consensus regional approach to design distributed consensus protocols for multi-agent systems with general continuous-time linear node dynamics.

On another research line, Neural Networks (NN) approximators are designed for adaptive H_∞ formation control of multi-agent systems composed of EL systems [9]. Robust Integral of the Sign of the Error (RISE) is adopted to achieve modularity in the controller/update law for a general class of EL systems [10]. However, it is in the absence of the effective methods to eliminate disturbances and uncertainties in the system.

In this paper, the consensus problem of multi-agent systems composed of EL systems based on neural networks is studied. The graph theory is utilized to model the communication topology between agents. Each agent is the nonlinear dynamic model with disturbances and uncertainties, which is an unknown nonlinear function. Combining with the adaptive control scheme, an artificial neural network with online learning weights developed in [11] is used for overcoming both the unknown nonlinear function and the drawbacks of the traditional sliding mode control. At last, the consensus of such systems is reached.

The rest of this paper is organized as follows. In Section 2, the consensus problem of the EL systems with the unknown nonlinear function is formulated. The consensus is reached by the Lyapunov theory and adaptive control scheme in Section 3. Numerical simulation of multi-agent systems is provided to show the effectiveness of the proposed approaches in Section 4. Finally, the major conclusions of the paper are summarized in Section 5.

2. Problem Formulation and Preliminaries.

In this section, the multiple Euler-Lagrange systems are described as a kind of multi-agent systems, which are nonlinear. After introducing the background knowledge of such system, the consensus problem is formulated.

2.1. Background on the dynamic of Euler-Lagrange systems.

A kinematic equation of the robot manipulator with n degree of freedom (DOF) is represented by the following Euler-Lagrange systems:

$$D(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + F_r\dot{q} + \tau_d = \tau \tag{1}$$

where q, $\dot{q}$, $\ddot{q} \in R^n$ denote the link position, velocity, and acceleration vectors, respectively. $D(q) \in R^{n\times n}$ denotes a positive definite and symmetric matrix. $\tau_d \in R^n$ denotes a general nonlinear disturbance. $\tau \in R^n$ represents the torque input control vector. $G(q) \in R^n$ is the gravity vector. $C(q,\dot{q})\dot{q} \in R^n$ denotes the centripetal-Coriolis. $F_r(\dot{q}) \in R^n$ denotes friction. The characteristic of the kinematic model robot consists of the following properties:

- *Property 1:* There exits a vector $\alpha \in R^n$ with elements dependent on the variable of manipulator as weight, internal torque such that

$$D(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + F_r\dot{q} + \tau_d = \psi(q,\dot{q},\ddot{q})\alpha \tag{2}$$

  with $\psi \in R^{n\times m}$ as a regression matrix.

  This characteristic means that the kinematic model of the manipulator could be linearized if these parameters are chosen appropriately.
- *Property 2:* Both $C(q,\dot{q})$ and $D(q)$ satisfy

$$s^T\left(\dot{D} - 2C\right)s = 0, \quad \forall s \in R^n \tag{3}$$

  The matrix $\left(\dot{D} - 2C\right)$ is a symmetric matrix. This characteristic guarantees the system not to be affected by the force that is defined by $C\left(q,\dot{q}\right)\dot{q}$. It is used to analyze the stability of such system.
- *Property 3:* The friction in (3) is defined as

$$F_r\left(\dot{q}\right) = F_v\dot{q} + F_d\left(\dot{q}\right) \tag{4}$$

  where F_v is a friction coefficient matrix and $F_d\left(\dot{q}\right)$ denotes the kinetic friction. Because the local friction error disconnects between links, it only depends on the angular velocity $\dot{q}$. This characteristic is used to reduce the number of parameters in the NN compensator.

2.2. **Graph theory and the Laplacian matrix.** A graph theory is used to represent the communication relationship between each agent, which is called the *communication graph*. If the number of agents is m, the graph G consists of a node set $\gamma = \{\nu_1, \nu_2, \ldots, \nu_m\}$, an edge set $\varsigma \subseteq \gamma \times \gamma$ and a weighted adjacent matrix $A = [\delta_{i,j}] \in R^{m\times m}$, where $\delta_{i,j} > 0$ means that agent i can obtain the information from agent j, otherwise $\delta_{i,j} = 0$. The adjacent matrix A is a symmetric matrix and defined as $\delta_{i,j} = \delta_{j,i}$. Associated with A, the Laplacian matrix is introduced by $L = [l_{ij}] \in R^{m\times m}$, where $[l_{jj}] = \sum_{j=1,j\neq i}^{m} \delta_{ij}$ and $l_{ij} = \delta_{i,j}$, $i \neq j$.

We define a finite set including h *communication graphs* $G^* = \{G_1, G_2, \ldots, G_h\}$ such that all h *communication graphs* have the same node set, i.e., $\gamma_1 = \gamma_2 = \ldots = \gamma_h = \gamma$. However, the edge set for each h communication graphs is different, i.e., $\varsigma_1 \neq \varsigma_2 \neq \ldots \neq \varsigma_h$, which results in a different weighted adjacent matrix for each communication graphs, specifically, $A_1 \neq A_2 \neq \ldots \neq A_h$. Consequently, the Laplacian matrix associated with each $i \in \{1, 2, \ldots, h\}$ communication graphs, denoted by L_i, will also be different. It should be noted that all the h *communication graphs* are connected; therefore, L_i is a positive semi-definite matrix $\forall i \in \{1, 2, \ldots, h\}$.

3. **Stability Analysis.** In general, the parameters of neural networks are fixed after learning, which implies that it is incapable of adapting. In addition, there are a lot of parameters with structural uncertainty. Therefore, it is necessary to add adaptive properties in Neural Networks.

Consider a simple Multiple Input Multiple Output (MIMO) NN structure consisting of two layers as Figure 1.

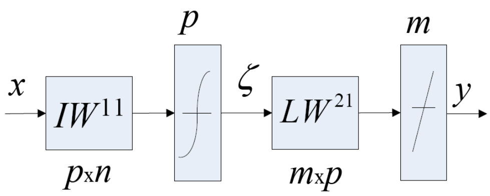


Figure 1. A two-layer MIMO NN structure

The MIMO NN structure in Figure 1 is described by

$$y_j = \sum_{l=1}^{p} w_{jp}\zeta_l(x) = \Theta_j^T\zeta(x) = \hat{N}\left(q_i, \dot{q}_i, \ddot{q}_i|\Theta\right), \quad j = 1, 2, \ldots, m \tag{5}$$

where $\zeta(x) = \{\zeta_1(x), \zeta_2(x), \ldots, \zeta_p(x)\}^T \in R^p$, $\Theta_j = [w_{j1}, w_{j2}, \ldots, w_{jp}]^T$ and

$$\hat{N}\left(q_i, \dot{q}_i, \ddot{q}_i|\Theta\right) = \left[\Theta_1^T\zeta(q_i, \dot{q}_i, \ddot{q}_i), \Theta_2^T\zeta(q_i, \dot{q}_i, \ddot{q}_i), \ldots, \Theta_n^T\zeta(q_i, \dot{q}_i, \ddot{q}_i)\right]^T$$

Equation (1) could be rewritten as

$$\tau = \tau_0 + F\left(q, \dot{q}\right) = \tau_0 + F\left(s\right) \tag{6}$$

where $\tau_0 = D(q)\ddot{q} + C\left(q, \dot{q}\right)\dot{q} + G(q)$ and

$$F\left(q, \dot{q}\right) = F(s) = F_r\dot{q} + \tau_d \tag{7}$$

The unknown function $F(s)$ is the main reason to degrade the control performance. By compensating this, the control performance could be improved. Hence, we choose an artificial neuron network (5) with a limited number of neurons that can approximate an unknown nonlinear function with a given accuracy as follows.

$$F(s) = \Theta_j^T\zeta(x) \tag{8}$$

Then, the key problem is how to find the control torque τ and a learning algorithm of $w_{j,p}$ in (5), which will be given in the following theorem.

Theorem 3.1. *Consider Euler-Lagrange system (1) with the unknown function (7) and the parameter vector* $w_{j,p}$ *in (5), then the designed sliding mode surface* $s = \dot{e} + \Lambda e$ *with* $e = q - q_d$ *combined with neural network (5) will guarantee the asymptotic consensus of multi-agent system (1).*

Proof: Given $s = \dot{e} + \Lambda e$, we have $\dot{e} = -\Lambda e$ with $s = 0$. Then, $\dot{q}_r(t) = \dot{q}_d(t) - \Lambda e(t)$. In order to design the control law using NN with adaptive schemes, we define a Lyapunov function as follows

$$V(t) = \frac{1}{2}\left(s^T D s + \sum_{j=1}^{n} \tilde{\Theta}_j^T \Gamma_j \tilde{\Theta}_j\right)$$

where $\tilde{\Theta}_j = \Theta_j^* - \Theta_j$, Θ_j^* as the column vector j of optimal matrix Θ^* and $\Gamma_j > 0$.

Because D is the inertia matrix of the manipulator that is symmetric positive definite, we have $V(t) > 0$ for all $\left(s^T, \Theta^T\right) \neq 0$ and $V(t) = 0$ if and only if $(s^T, \Theta^T) = 0$. $V(t)$ also satisfies other conditions such as $V(t) \to \infty$ when $s \to \infty$, $\Theta_j \to \infty$. If we can identify the control torque τ to ensure $\dot{V}(t) < 0$, then $s \to 0$ and the system will approach and stay the sliding surface.

Now, a control law is developed as follows

$$\tau = D(q)\ddot{q}_r + C(q, \dot{q})\dot{q}_r + G(q) + \hat{N}(q, \dot{q}, \ddot{q}|\Theta) - K_D s \tag{9}$$

with $K_D = diag\{K_j\} > 0$, $j = 1, 2, \ldots, n$ which is the designed parameters.

The time derivative of $V(t)$ is

$$\begin{aligned}\dot{V}(t) &= \frac{1}{2}\left[\dot{s}^T D s + s^T \dot{D} s + s^T D \dot{s} + \sum_{j=1}^{n}\left(\dot{\Theta}_j^T \Gamma_j \Theta_j + \Theta_j^T \Gamma_j \dot{\Theta}_j\right)\right] \\ &= \frac{1}{2} s^T \dot{D} s + s^T D \dot{s} + \sum_{i=1}^{n} \Theta_j^T \Gamma_j \dot{\Theta}_j\end{aligned} \tag{10}$$

Because the matrix $\left(\dot{D} - 2C\right)$ in (3) is a symmetric matrix, we have $s^T \dot{D} s = s^T 2Cs$. Substituting the above equation to (10) yields

$$\dot{V}(t) = s^T C s + s^T D \dot{s} + \sum_{j=1}^{n} \Theta_j^T \Gamma_j \dot{\Theta}_j = s^T (Cs + D\dot{s}) + \sum_{j=1}^{n} \Theta_j^T \Gamma_j \dot{\Theta}_j \tag{11}$$

In addition, we have

$$\begin{aligned}Cs + D\dot{s} &= C(\dot{e} + \Lambda e) + D(\ddot{e} + \Lambda \dot{e}) \\ &= C(\dot{q} - \dot{q}_d + \Lambda e) + D(\ddot{q} - \ddot{q}_d + \Lambda \dot{e}) \\ &= C(-\dot{q}_d + \Lambda e) + D(-\ddot{q}_d + \Lambda \dot{e}) + C\dot{q} + D\ddot{q}\end{aligned} \tag{12}$$

According to (1) and (6), we have

$$D\ddot{q} + C\dot{q} = \tau - G - F(s) \tag{13}$$

Replacing (12) and (13) into (11) leads to

$$\dot{V}(t) = s^T \left[C(-\dot{q}_d + \Lambda e) + D(-\ddot{q}_d + \Lambda \dot{e}) + \tau - G - F(s)\right] + \sum_{j=1}^{n} \Theta_j^T \Gamma_j \dot{\Theta}_j \tag{14}$$

Since Θ^* can be determined from the NN, the smallest error vector is approximated

$$w_i = F(s) - \hat{N}(q_i, \dot{q}_i, \ddot{q}_i|\Theta) \tag{15}$$

Replacing $\dot{q}_r = \dot{q}_d - \Lambda e$ yields

$$\dot{V}(t) = -s^T (D\ddot{q}_r + C\dot{q}_r + G + F(s) - \tau) + \sum_{j=1}^{n} \tilde{\Theta}_j^T \Gamma_j \dot{\tilde{\Theta}}_j \tag{16}$$

By substituting (9) to (16), it is obtained that

$$\dot{V}(t) = -s^T K_D s - s^T w_i + \sum_{j=1}^{m} \left[\tilde{\Theta}_j^T \Gamma_j \dot{\tilde{\Theta}}_j - s_j \tilde{\Theta}_j^T \zeta(q_i, \dot{q}_i, \ddot{q}_i) \right] \tag{17}$$

By designing the following adaptive control law

$$\dot{\Theta}_j = -\Gamma_j^{-1} s_j \zeta\left(q_i, \dot{q}_i, \ddot{q}_i\right), \quad j = 1, 2, \ldots, n \tag{18}$$

we have $\dot{V}(t) = -s^T K_D s$. From (9), we can see that $\dot{V}(t) < 0$ for all $s \neq 0$. So, according to the Lyapunov stability theorem, the agent can track the desired trajectory q_d. Therefore, the state trajectories can reach the sliding surface $s = 0$ in the limited time such that the consensus of multiple EL systems can be reached.

4. **Numerical Simulations.**

4.1. **Nonlinear dynamics of Euler-Lagrange systems.** We consider 2 degrees of freedom robot, which moves in the vertical plane. The joint angles are denoted by ϕ_1 and ϕ_2. Using the Newton-Euler recursive method, the torques for each joint are calculated as follows

$$\begin{aligned}\tau_1 = & m_2 l_2^2 \left(\ddot{\phi}_1 + \ddot{\phi}_2\right) + m_2 l_1 l_2 c_2 \left(2\ddot{\phi}_1 + \ddot{\phi}_2\right) + (m_1 + m_2) l_1^2 \ddot{\phi}_1 - m_2 l_1 l_2 s_2 \dot{\phi}_2^2 \\ & - 2 m_2 l_1 l_2 s_2 \dot{\phi}_1 \dot{\phi}_2 + m_2 l_1 l_2 g c_{12} + (m_1 + m_2) l_1 g c_1\end{aligned} \tag{19}$$

$$\tau_2 = m_2 l_1 l_2 c_2 \ddot{\phi}_1 + m_2 l_1 l_2 s_2 \dot{\phi}_1^2 + m_2 l_2 g c_{12} + m_2 l_2^2 \left(\ddot{\phi}_1 + \ddot{\phi}_2\right) \tag{20}$$

where $c_1 = \cos(\phi_1)$, $c_{12} = \cos\left(\phi_1 + \phi_2\right)$.

Based on (19) and (20), the dynamic equation of multi-agent systems is represented by Euler-Lagrange system which is described as follows

$$\begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} = \begin{bmatrix} D_{11} & D_{12} \\ D_{21} & D_{22} \end{bmatrix} \begin{bmatrix} \ddot{\phi}_1 \\ \ddot{\phi}_2 \end{bmatrix} + \begin{bmatrix} C_1 \\ C_2 \end{bmatrix} + \begin{bmatrix} g_1(\phi_1, \phi_2) \\ g_2(\phi_1, \phi_2) \end{bmatrix} \tag{21}$$

where

$$\begin{aligned} & D_{11}(\phi_2) = (m_1 + m_2) l_1^2 + m_2 l_2^2 + 2 m_2 l_1 l_2 c_2 \quad D_{12}(\phi_2) = D_{21}(\phi_2) = m_2 l_2^2 + m_2 l_1 l_2 c_2 \\ & D_{22}(\phi_2) = m_2 l_2^2 \quad g_1(\phi_1, \phi_2) = (m_1 + m_2) g l_1 c_1 + m_2 g l_2 c_{12} \\ & C_1 = -m_2 l_1 l_2 \dot{\phi}_2^2 s_2 - 2 m_2 l_1 l_2 \dot{\phi}_1 \dot{\phi}_2 s_2 \quad C_2 = m_2 l_1 l_2 \dot{\phi}_1^2 s_2 \quad g_2(\phi_1, \phi_2) = m_2 g l_2 c_{12} \end{aligned} \tag{22}$$

m_1, l_1, m_2, and l_2 denote the masses and lengths of two links, respectively. D_{ij}, C_i, g_i and τ_i are the matrix and dynamic torque defined in (1).

From Equation (21) we can have

$$\begin{bmatrix} \ddot{\phi}_1 \\ \ddot{\phi}_2 \end{bmatrix} = \begin{bmatrix} D_{11} & D_{12} \\ D_{21} & D_{22} \end{bmatrix}^{-1} \left(-\begin{bmatrix} C_1 \\ C_2 \end{bmatrix} - \begin{bmatrix} g_1(\phi_1, \phi_2) \\ g_2(\phi_1, \phi_2) \end{bmatrix} \right) + \begin{bmatrix} D_{11} & D_{12} \\ D_{21} & D_{22} \end{bmatrix}^{-1} \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} \tag{23}$$

Define the first joint and second joint state signals and input signals as follows:

$$X_1 = \begin{bmatrix} x_{11} \\ x_{12} \end{bmatrix} = \begin{bmatrix} \phi_1 \\ \dot{\phi}_1 \end{bmatrix}, \; X_2 = \begin{bmatrix} x_{21} \\ x_{22} \end{bmatrix} = \begin{bmatrix} \phi_2 \\ \dot{\phi}_2 \end{bmatrix} \text{ and } U = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} \tag{24}$$

Then, the state differential equations for the first joint and second joint systems are rewritten as

First joint:

$$\begin{cases} \dot{x}_{11} = x_{12} \\ \dot{x}_{12} = a_1(X) + \sum\limits_{j=1}^{2} b_{1j} u_j \end{cases} \tag{25}$$

Second joint:

$$\begin{cases} \dot{x}_{21} = x_{22} \\ \dot{x}_{22} = a_2(X) + \sum\limits_{j=1}^{2} b_{2j} u_j \end{cases} \tag{26}$$

By means of (19)-(24), (25) and (26) could be rewritten as follows:

$$\begin{cases} \dot{x}_{11} = x_{12} \\ \dot{x}_{12} = \frac{1}{Det(D)} \left(-C_1 D_{22} + C_2 D_{12} - g_1 D_{22} + g_2 D_{12} + u_1 D_{22} - u_2 D_{12} \right) \\ \dot{x}_{21} = x_{22} \\ \dot{x}_{22} = \frac{1}{Det(D)} \left(C_1 D_{21} - C_2 D_{11} + g_1 D_{21} - g_2 D_{11} - u_1 D_{21} + u_2 D_{11} \right) \end{cases} \tag{27}$$

where $Det(D) = D_{11} D_{22} - (D_{12})^2$.

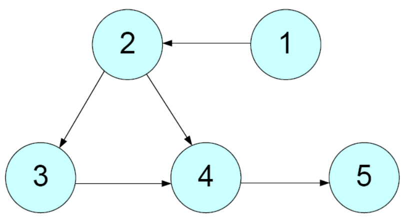
In this simulation, we select $m_1 = 1$, $l_1 = 1$, $m_2 = 1$, $l_2 = 1$ and substitute them to (22), which yields:

$$\begin{aligned} &D_{11} = 3 + 2\cos(x_{21}) \quad D_{12} = D_{21} = 1 + \cos(x_{21}) \quad D_{22} = 1 \\ &C_1 = -x_{22}^2 \sin(x_{21}) - 2x_{12}x_{22}\sin(x_{21}) \quad C_2 = x_{12}^2 \sin(x_{21}) \\ &g_1 = 20\cos(x_{11}) + 10\cos(x_{11} + x_{21}) \quad g_2 = 10\cos(x_{11} + x_{21}) \end{aligned} \tag{28}$$

In (10), we choose $K_D = \begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix}$ and $\Lambda = \begin{bmatrix} 5 & 0 \\ 0 & 5 \end{bmatrix}$. Assume the frictions and the disturbances of multi-agent systems are

$$F(q_i, \dot{q}_i, \ddot{q}_i, t) = f(q, \dot{q}) = F_r \dot{q} + \tau_d = \begin{cases} 2\sin 15t + 1 + 5\dot{q}_1 \\ \cos 15t + 3\dot{q}_2 \end{cases}$$

The graph G under consideration among agents is identical, which is shown in Figure 2. It is easy to verify that the assumption on the interconnection topology is satisfied.



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

FIGURE 2. Communication graph and its Laplacian matrix

4.2. **Neural network implementation.** Motivated by [11], the neural controller is designed with 3 layers, 2 line delay input and 3 line delay feedback. The first layer contains 14 neurons by making use of the transfer function tansig, the second layer has 12 neurons using transfer function tansig and the third layer includes 1 neuron utilizing the transfer function purelin. TDL-1 has the three delay lines 0, 1, and 2 beats whereas TDL-2 has the three delay lines 1, 2 and 3 beats. After the parameters are determined, we obtained the results shown in Figures 3-5, respectively.

After training the NN system, we obtain parameters of the NN controller. Then, the controllers are applied to the multi-agents systems with 5 agents, which communicate by the graph shown in Figure 2, and we obtain the results shown in Figures 6-9, respectively.

5. **Conclusions.** This paper has studied the consensus problem of multi-agent systems. Each agent is an EL system. A neural network controller based on the information of the neighbor agents has been developed. Although the structure of each agent is a nonlinear dynamic model, the consensus of multi-agent systems can be achieved by the adaptive controller combining with the Neural Network. Simulation results have demonstrated the

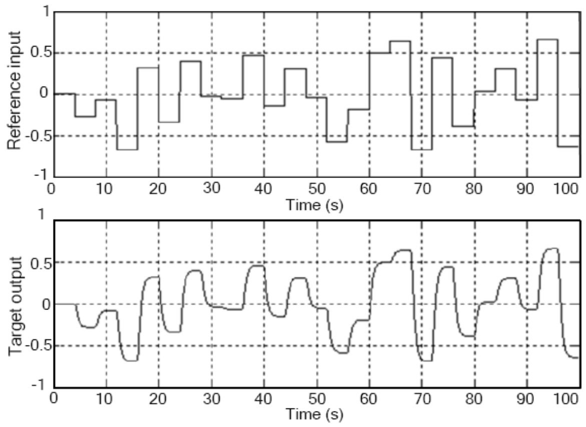


Figure 3. Reference input and output signal of the NN controller

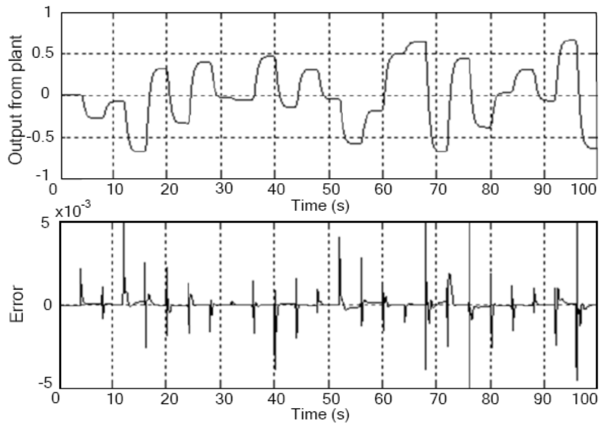


Figure 4. Output plant, MSE of plant and model

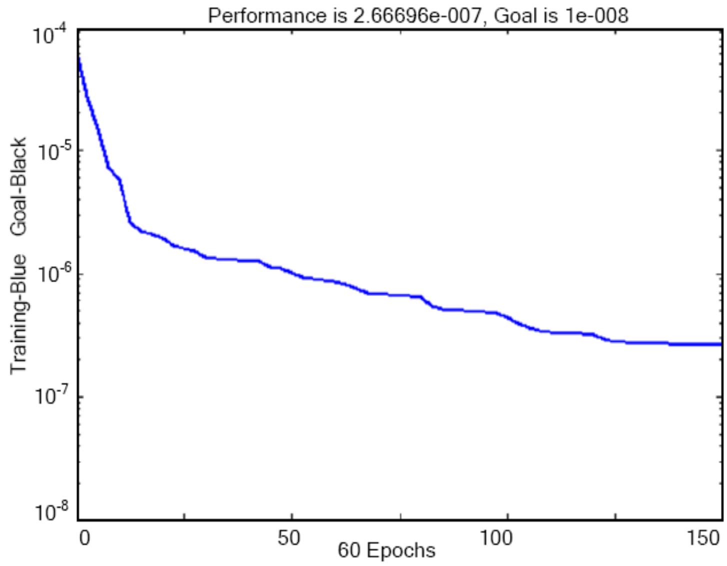


Figure 5. MSE of model output and plant

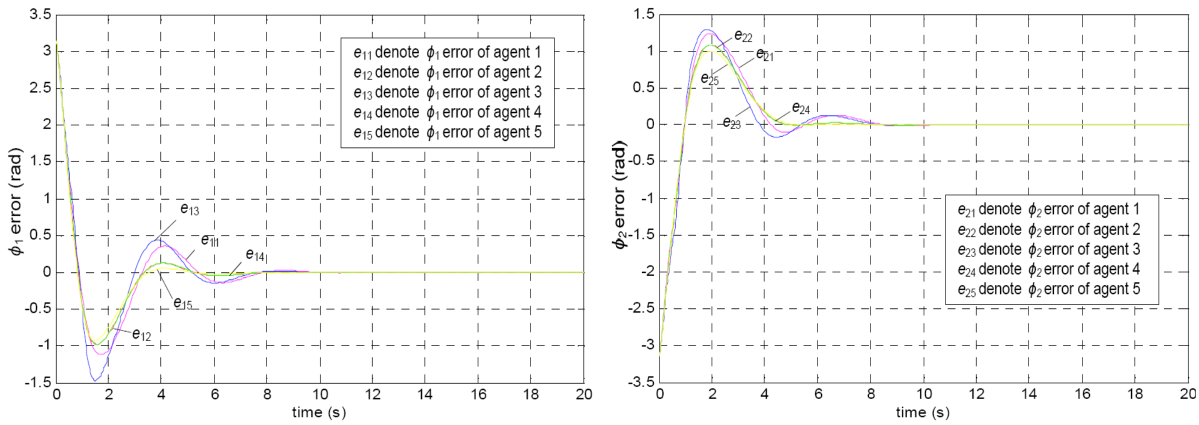


Figure 6. Response of error of reference ϕ_{1d} and ϕ_1

Figure 7. Response of error of reference ϕ_{2d} and ϕ_2

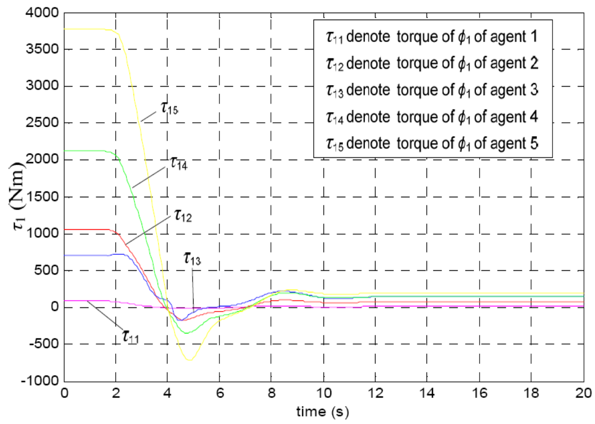


Figure 8. Response of torque on first joint of multi-agent systems

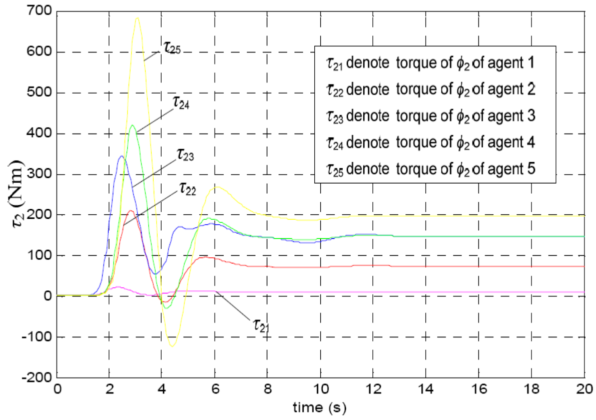


Figure 9. Response of torque on second joint of multi-agent systems

stability and robustness of the closed-loop systems. Meanwhile, it has been shown that the proposed method is effective.

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