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RESEARCH ARTICLE

Adaptive neural fault-tolerant consensus control of discrete-time fractional-order multi-agent systems for smart energy networks

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ABSTRACT

This paper investigates leader-following consensus for discrete-time fractional-order multi-agent systems with unknown nonlinear dynamics, bounded disturbances, and actuator faults arising in distributed smart energy applications. An adaptive neural-assisted fault-tolerant controller is developed by combining a Caputo-type fractional-order sliding variable with an online Radial Basis Function Neural Network (RBFNN). The RBFNN approximates the unknown nonlinear dynamics, while an adaptive weight-update law compensates for the neural approximation error. Actuator degradation is represented through a bounded loss-of-effectiveness factor and additive fault bias, allowing the controller to accommodate different actuator-fault conditions without requiring their exact profiles. A discrete fractional-order Lyapunov analysis is established to derive sufficient conditions ensuring the boundedness of the sliding variable, the neural-weight estimation error and the closed-loop signals. The consensus dynamics are subsequently characterized through the stable fractional-order error system driven by the vanishing sliding variable. Numerical simulations involving actuator degradation, external disturbances, parameter sensitivity, network scalability, and comparative benchmarks demonstrate the effectiveness of the proposed method in reducing consensus error and maintaining coordinated leader-following behavior under uncertain operating conditions.

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1. Introduction

Multi-agent systems (MASs) have attracted significant research attention in smart energy systems, intelligent transportation, cooperative robotics, sensor networks, and distributed industrial automation. Distributed control improves scalability, reliability, and operational efficiency, while leader-following consensus enables followers to track a leader under communication constraints and system uncertainties.[1] Fractional-order dynamics provide a representative description of hereditary and memory-dependent behaviors, motivating their use in discrete-time MAS coordination.[2] Actuator faults, disturbances, uncertain parameters, and unknown nonlinear dynamics have motivated fault-tolerant control for fractional-order MASs.[3] Iterative learning and switching-topology-based fault diagnosis have been investigated for fractional-order nonlinear MASs.[4] Adaptive fault-tolerant consensus has been studied for nonlinear fractional-order MASs with diffusion effects.[5]

Fault-tolerant leader-following control has been developed for uncertain nonlinear MASs with actuator imperfections.[6] ADP-based fault-tolerant control has addressed MASs with uncertain jump

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dynamics.[7] RL has been employed for optimal fault-tolerant consensus under actuator loss of effectiveness.[8] RL and event-triggered communication have been used for resilient control of fractional-order networked MASs.[9] RL-based consensus has been considered for unknown nonlinear MASs with sensor faults.[10] Finite-time consensus has addressed stochastic nonlinear MASs with non-affine faults.[11] RL-based fixed-time optimal control has been developed for saturated fault-tolerant MASs.[12]

Recent developments in fractional control theory have addressed the controllability and optimal-control properties of systems characterized by memory and delay. Approximate controllability has been established for fractional-delay integro-differential systems of order $1 < r < 2$ with Sobolev-type structures, providing theoretical insight into the ability to steer fractional systems even in the presence of memory and delay effects.[13] Related work has investigated optimal control and approximate controllability for fractional integro-differential evolution equations with infinite delay, further demonstrating the influence of historical states on the evolution and controllability properties of fractional systems.[14] These studies emphasize the role of memory and delayed information in fractional-order systems but primarily address controllability rather than distributed fault-tolerant leader-following consensus.

RL has been used for leader-follower formation control of nonlinear MASs with actuator failures.[15] Fractional-order adaptive fault-tolerant UAV formation with prescribed performance has also been studied using RL.[16] Learning-based fault-tolerant control has been applied to synchronization of heterogeneous nonlinear MASs.[17] Dynamic event-triggered optimal consensus has addressed unknown stochastic MASs with time delays.[18] Event-based adaptive optimal consensus has considered actuator failures in uncertain nonlinear MASs.[19] RL-based H_∞ formation control has addressed perturbed MASs with nonlinear faults.[20] Cooperative fault-tolerant control has been investigated for active distribution networks under communication and actuator faults.[21] Data-driven fault-tolerant RL has been applied to containment control of nonlinear MASs with uncertain dynamics.[22]

Fractional-order consensus has been investigated using sliding-mode control for time-varying formation.[23] Current and time-delay state feedback has been employed for fractional-order MAS coordination.[24] Dynamic output feedback has been developed for consensus of nonlinear fractional-order MASs.[25] Event-triggered control has been proposed for bipartite consensus in fractional-order MASs.[26] However, these studies generally do not simultaneously accommodate actuator faults, unknown nonlinearities, disturbances, and adaptive neural compensation.

Renewable energy integration has motivated advanced automatic generation control strategies.[27] Flexible MAS architectures have been developed for demand and renewable-energy variability in hybrid energy systems.[28] Model predictive control has been investigated for wind energy systems.[29] Adaptive fuzzy consensus tracking has been developed using event-triggered inputs.[30] Event-triggered adaptive finite time containment has been investigated for nonlinear fractional-order MASs.[31] Event-triggered leader-following consensus has been studied for nonlinear fractional-order MASs.[32] Exponential leader-following consensus has been investigated for fractional-order descriptor MASs.[33] Dual-channel event-triggered strategies have been developed for asymptotic consensus in fractional-order nonlinear MASs.[34]

Prescribed performance fuzzy consensus has been developed for MASs with non-affine nonlinear faults.[35] Fixed-time prescribed performance consensus has been considered under non-affine faults.[36] Neural-network-based finite-time consensus tracking has demonstrated fault-tolerant control for uncertain nonlinear MASs.[37] Adaptive fixed-time control has been developed for nonlinear MASs with actuator faults.[38] Adaptive neural-network consensus has considered actuator faults and faulty communication networks.[39] ADP-based distributed fault-tolerant consensus has provided a learning-oriented solution for nonlinear MASs.[40] Adaptive fault-tolerant tracking has addressed actuator degradation in linear and Lipschitz nonlinear MASs.[41] Data-driven RL has demonstrated optimal consensus control for discrete-time MASs with unknown dynamics.[42]

Even though the above-mentioned studies have significantly advanced the state of the art, the existing literature remains fragmented across fractional-order consensus, fault-tolerant control, adaptive approximation, and intelligent learning. Most studies address these aspects separately or combine only a subset of them, so their simultaneous treatment within a discrete-time fractional-order leader-following framework has received limited attention. In particular, the combined effects of fractional-order memory, unknown nonlinear dynamics, bounded disturbances, and actuator degradation remain inadequately addressed within a unified distributed control architecture. These observations reveal the need for a computationally

efficient strategy that provides adaptive nonlinear compensation, actuator fault tolerance, disturbance rejection, and reliable leader-following consensus.

Motivated by these issues, this paper develops an adaptive neural-assisted sliding-mode fault-tolerant consensus control framework for discrete-time fractional-order multi-agent systems in smart energy environments. The proposed controller integrates a Caputo-type fractional-order sliding variable with an adaptive Radial Basis Function Neural Network (RBFNN) to approximate unknown nonlinear dynamics online. The fault-tolerant mechanism accommodates actuator loss of effectiveness and bounded actuator bias, while the sliding-mode component enhances robustness against bounded disturbances and neural approximation errors. Based on a discrete fractional-order Lyapunov analysis, sufficient conditions are established to guarantee the boundedness of the sliding variable, the neural-weight estimation error, and the closed-loop signals, while the resulting fractional-order error dynamics establish leader-following consensus.

From the perspective of the present study, the proposed framework lies at the intersection of fractional-order consensus control, adaptive neural approximation, and fault-tolerant distributed coordination. Existing studies have primarily addressed these directions separately, with comparatively less emphasis on their simultaneous integration. The present work therefore focuses on leader-following consensus for discrete-time fractional-order agents subject to unknown nonlinear dynamics, bounded disturbances, and actuator faults. By integrating fractional-order sliding-mode control, adaptive RBFNN approximation, and actuator fault compensation within a single distributed architecture, the study seeks to provide a unified solution for resilient coordination in smart-energy networks.

The main contributions of this paper are summarized as follows.

- A distributed fault-tolerant consensus framework is developed for discrete-time fractional-order multi-agent systems with unknown nonlinear dynamics, bounded disturbances, and actuator degradation;
- An adaptive RBFNN is integrated into the distributed sliding mode controller to approximate unknown nonlinear dynamics using locally available state information;
- A bounded actuator-fault model incorporating loss of effectiveness and additive bias is introduced, allowing the proposed controller to address different actuator degradation scenarios within a unified framework;
- A discrete fractional-order Lyapunov analysis is developed to establish sufficient conditions for boundedness of the sliding variable, neural-weight estimation error, and closed-loop signals while explicitly retaining the bounded neural approximation and disturbance residuals;
- The leader-following consensus property is established from the fractional-order consensus-error dynamics rather than by neglecting bounded neural or fault terms;
- Numerical studies evaluate consensus accuracy, actuator-fault sensitivity, disturbance rejection, scalability, computational burden and comparative performance against representative fault-tolerant consensus controllers.

The rest of this paper is organized as follows: Section 2 presents the necessary preliminaries, including graph theory, fractional calculus, and the system modeling framework. Section 3 details the design of the proposed neuro-adaptive observer and distributed control protocol, along with the corresponding stability analysis. Section 4 provides numerical simulation results to evaluate the performance and effectiveness of the proposed approach. Finally, Section 5 concludes the paper.

The main symbols and notations used throughout the paper are summarized in **Table 1**.

Table 1. Notation used throughout the manuscript

Symbol	Description
$x_i(k)$	State of follower agent i
$x_0(k)$	Leader state
$e_i(k)$	Leader-following consensus error
$s_i(k)$	Fractional-order sliding variable
$u_i(k)$	Commanded control input
$u_i^a(k)$	Actual actuator input
$\rho_i(k)$	Actuator effectiveness factor
$b_i(k)$	Additive actuator fault
$d_i(k)$	External disturbance
$f_i(x_i)$	Unknown nonlinear dynamics
$\hat{f}_i(x_i)$	RBFNN estimate of nonlinear dynamics
$\phi_i(x_i)$	RBFNN basis-function vector
W_i^*	Ideal neural-network weights
$\hat{W}_i$	Estimated neural-network weights
$\widetilde{W}_i$	Neural-weight estimation error
Γ_i	Adaptive learning gain
K_i	Sliding feedback gain
k_{1i}, k_{2i}	Nonlinear reaching gains
α, β	Fractional orders

2. Preliminaries and problem formulation

This section introduces the definitions, mathematical lemmas, and assumptions used throughout the paper.

Definition 1. [2] *The Caputo-type discrete fractional difference operator of order $0 < \alpha < 1$ for a sequence $x(k)$ is defined as*

$$^{C}\nabla^{\alpha}x(k) = \frac{1}{\Gamma(1-\alpha)}\sum_{j=0}^{k-1}\frac{x(j+1)-x(j)}{(k-j)^{\alpha}}$$

where $\Gamma(\cdot)$ denotes the Gamma function. This operator effectively captures the memory-dependent behavior inherent in fractional-order systems.

Definition 2. [2] *A discrete fractional-order multi-agent system (DFOMAS) is described as*

$$^{C}\nabla^{\alpha}x_i(k) = f_i(x_i(k)) + B_i u_i(k), \quad i = 1, \ldots, N$$

where $x_i(k) \in \mathbb{R}^n$ is the state vector, $f_i(\cdot)$ represents the nonlinear dynamics, B_i is the input matrix, and $u_i(k)$ is the control input.

Definition 3. [25] *Let $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$ denote a directed graph. The associated Laplacian matrix is given by*

$$L = D - A$$

where $A = [a_{ij}]$ is the adjacency matrix and D is the degree matrix.

Definition 4. [6] *Leader-follower consensus is achieved if*

$$\lim_{k\to\infty} \|x_i(k) - x_0(k)\| = 0$$

for all agents $i = 1, \ldots, N$, where $x_0(k)$ is the leader state.

The following assumptions are adopted throughout this study.

Assumption 1. *Consider the directed communication graph $G = (V, E, A)$. It contains a directed spanning tree rooted at the leader node 0, which implies that every follower node has a directed path to the leader node 0.*

Assumption 2. *For each agent i, the unknown nonlinear dynamics $f_i(x_i)$ are continuous on the compact operating region Ω_i and admit an RBFNN approximation*

$$f_i(x_i) = W_i^{*T}\phi_i(x_i) + \varepsilon_i(x_i),$$

where W_i^* is an unknown ideal weight matrix and the approximation error satisfies

$$\|\varepsilon_i(x_i)\| \le \bar{\varepsilon}_i, \quad x_i \in \Omega_i.$$

Assumption 3. *The external disturbance $d_i(k)$ is bounded, i.e.,*

$$\|d_i(k)\| \le \bar{d}_i, \qquad \bar{d}_i > 0.$$

Assumption 4. *The actuator fault is represented by a loss-of-effectiveness factor and an additive bias according to*

$$u_i^a(k) = \rho_i(k)u_i(k) + b_i(k),$$

where

$$0 < \underline{\rho}_i \le \rho_i(k) \le 1, \qquad \|b_i(k)\| \le \bar{b}_i.$$

The actuator effectiveness factor $\rho_i(k)$ and the bias $b_i(k)$ are unknown but bounded.

Assumption 5. *The fractional orders satisfy*

$$0 < \alpha < 1, \qquad 0 < \beta < 1.$$

The following lemmas are used in the subsequent stability analysis.

Lemma 1. [2] *The fractional-order system*

$$^{C}\nabla^{\alpha}x(k) = Ax(k)$$

is asymptotically stable if all eigenvalues satisfy

$$|\arg(\lambda_i(A))| > \frac{\alpha\pi}{2}.$$

Lemma 2. [2] *Let $V(k)$ be a positive-definite function. If*

$$^{C}\nabla^{\alpha}V(k) \le -cV(k), \quad c > 0$$

then the system is Mittag-Leffler stable.

2.1. Problem formulation

This model captures key thermal dynamics including heat loss, environmental interaction, controlled HVAC input, and renewable solar effects, while incorporating memory-dependent behavior through fractional-order dynamics.

Consider a network of N interconnected agents representing distributed energy subsystems. The dynamics of each agent are modeled as

$$^{C}\nabla^{\alpha}x_i(k) = f_i(x_i(k)) + B_i u_i^a(k) + d_i(k), \quad i = 1, \ldots, N, \tag{1}$$

where $x_i(k) \in \mathbb{R}^n$ is the state vector, $f_i(x_i)$ denotes the unknown nonlinear dynamics, B_i is the input matrix, $u_i^a(k)$ is the actual actuator input, and $d_i(k)$ is a bounded external disturbance.

To distinguish actuator degradation from external disturbances, the actual control signal applied to the ith agent is modeled as

$$u_i^a(k) = \rho_i(k)u_i(k) + b_i(k), \tag{2}$$

where $u_i(k)$ represents the commanded control input, $\rho_i(k)$ is the time-varying actuator effectiveness factor, and $b_i(k)$ represents an additive actuator bias.

Assume that

$$0 < \underline{\rho}_i \le \rho_i(k) \le 1, \quad \|b_i(k)\| \le \bar{b}_i \tag{3}$$

where $\underline{\rho}_i > 0$ and $\bar{b}_i > 0$ are known constants.

The external disturbance satisfies

$$\|d_i(k)\| \le \bar{d}_i.$$

Hence, actuator degradation and external disturbances are treated as distinct uncertainty channels.

The fractional operator captures memory effects such as thermal inertia and energy storage dynamics.

The thermal dynamics are modeled as

$$\begin{aligned} {}^{C}\nabla^{\alpha} T_i(k) = &-a_i T_i(k) + b_i T_{\text{out}}(k) \\ &+ c_i Q_{\text{HVAC},i}(k) + \sigma_i Q_{\text{solar}}(k), \end{aligned} \tag{4}$$

where term $T_i(k)$ refers to the inside temperature of the ith energy subsystem, $T_{\text{out}}(k)$ is the outside temperature, $Q_{\text{HVAC},i}(k)$ is the local HVAC control input, and $Q_{\text{solar}}(k)$ denotes the solar heat gain. The coefficients a_i, b_i, c_i, and σ_i represent heat dissipation, ambient heat transfer, HVAC effectiveness, and solar gain coefficients, respectively.

The use of a fractional-order model is motivated by the memory-dependent behavior of practical smart energy subsystems. In particular, building thermal dynamics are affected not only by the instantaneous indoor and outdoor temperatures but also by accumulated thermal history, including wall heat storage, delayed heat transfer, and the previous operating conditions of the HVAC system. Similar hereditary effects arise in electrochemical storage devices and renewable energy components. An integer-order model represents these processes through a finite-dimensional state description, whereas the Caputo-type fractional difference operator provides an explicit mechanism for incorporating historical state information. Therefore, the fractional-order formulation is adopted here not merely as a mathematical generalization, but as a model for the memory-dependent behavior of distributed smart energy subsystems.

In the considered smart energy interpretation, each follower agent represents a distributed energy-management subsystem associated with a building, microgrid, or local energy hub. The principal state $T_i(k)$ represents the indoor thermal state, while the control input $Q_{\text{HVAC},i}(k)$ represents the controllable HVAC action. The outdoor temperature and solar heat gain act as environmental inputs, while the electrical power required by the HVAC unit represents the associated energy-management cost. As a result, consensus among the agents corresponds to coordinated regulation of thermal operating conditions under distributed information exchange. The actuator-fault model captures loss of HVAC actuation effectiveness and additive actuator bias, both of which are relevant to practical equipment degradation.

The unknown nonlinear dynamics are approximated using a Radial Basis Function Neural Network (RBFNN). For agent i, the neural approximation is defined as

$$\hat{f}_i(x_i(k)) = \hat{W}_i^T(k)\phi_i(x_i(k)), \tag{5}$$

where $\phi_i(x_i) \in \mathbb{R}^M$ is the vector of radial basis functions, $\hat{W}_i(k)$ is the online-estimated weight matrix, and M is the number of basis functions.

By the universal approximation property of RBFNNs, the unknown nonlinear function can be expressed on the compact operating region as

$$f_i(x_i(k)) = W_i^{*T}\phi_i(x_i(k)) + \varepsilon_i(x_i(k)), \tag{6}$$

where W_i^* denotes the ideal weight matrix and $\varepsilon_i(x_i)$ is the bounded approximation error satisfying

$$\|\varepsilon_i(x_i(k))\| \le \bar{\varepsilon}_i. \tag{7}$$

Define the neural weight estimation error as

$$\widetilde{W}_i(k) = W_i^* - \hat{W}_i(k). \tag{8}$$

As a result,

$$f_i(x_i(k)) - \hat{f}_i(x_i(k)) = \widetilde{W}_i^T(k)\phi_i(x_i(k)) + \varepsilon_i(x_i(k)). \tag{9}$$

where $\phi(x_i)$ denotes the vector of radial basis activation functions, and $\hat{W}_i$ represents the online estimated neural weight vector. Owing to the universal approximation capability of RBF neural networks, the unknown nonlinear function can be represented as

$$f_i(x_i) = W_i^{*T}\phi(x_i) + \varepsilon_i(x_i),$$

The consensus error is defined as

$$\begin{aligned} e_i(k) = \sum_{j=1}^{N} a_{ij}\left[x_i(k) - x_j(k)\right] + \\ b_i\left[x_i(k) - x_0(k)\right]. \end{aligned} \tag{10}$$

The sliding surface is constructed as

$$s_i(k) = {}^{C}\nabla^{\beta} e_i(k) + \lambda e_i(k), \qquad \lambda > 0. \tag{11}$$

The sliding variable in **(11)** depends only on the consensus error and its fractional difference. Hence, the neural network is used consistently for compensation of the unknown nonlinear dynamics rather than being introduced as an additional state estimation term.

The objective is to design a distributed control law $u_i(k)$ such that:

- Leader-following consensus is achieved:
- The sliding variable converges to zero:
- The system remains robust against disturbances, faults, and approximation errors.

Additionally, the closed-loop system must be stable in the Mittag-Leffler sense.

3. Main results

This section presents the main theoretical contributions of the paper. A neural-assisted fault-tolerant distributed control protocol is developed for the discrete fractional-order multi-agent system described in **(1)**. Subsequently, rigorous stability analysis is carried out to guarantee Mittag-Leffler stability and leader-following consensus under disturbances, actuator faults, and ANN approximation errors.

To adaptively estimate the unknown neural network weights during the control process, the following fractional-order adaptive learning law is employed:

$$^{C}\nabla^{\alpha}\hat{W}_i(k) = \Gamma_i \phi_i(x_i(k)) s_i^T(k), \tag{12}$$

where

$$\Gamma_i = \Gamma_i^T > 0$$

is the adaptive learning gain matrix, $\phi(x_i)$ denotes the radial basis activation function vector, and s_i represents the sliding surface. The adaptive law updates the neural network weights online to minimize the approximation error, thereby improving the robustness and convergence performance of the proposed distributed fault-tolerant controller.

Since

$$\widetilde{W}_i = W_i^* - \hat{W}_i,$$

and W_i^* is constant, the corresponding weight error dynamics satisfy

$$^{C}\nabla^{\alpha}\widetilde{W}_i(k) = -\Gamma_i \phi_i(x_i(k)) s_i^T(k). \tag{13}$$

To improve the adaptability and robustness of the proposed distributed consensus controller, the unidentified nonlinear dynamics are compensated using an adaptive Radial Basis Function Neural Network (RBFNN). Unlike conventional model-based controllers that require global Lipschitz continuity or accurate mathematical models, the proposed neural approximation estimates unknown nonlinear functions online using locally available measurements. Consequently, the controller effectively compensates for modeling uncertainties and actuator faults while preserving distributed implementation. The adaptive neural approximation is seamlessly integrated with the fractional-order sliding-mode controller, thereby improving consensus accuracy and robustness against unknown disturbances.

The control objective is to design $u_i(k)$ such that the sliding surface **(11)** converges to zero despite uncertainties.

The proposed control law is designed as

$$\begin{aligned} u_i(k) = -K_i s_i(k) - k_{1i}|s_i(k)|^{1/2}\,\mathrm{sgn}(s_i(k)) \\ -k_{2i}\,\mathrm{sgn}(s_i(k)) - \hat{f}_i(x_i(k)). \end{aligned} \tag{14}$$

Substituting **(14)** into **(1)** together with the actuator model gives

$$\begin{aligned} ^{C}\nabla^{\alpha}x_i(k) = f_i(x_i(k)) + B_i\rho_i(k)u_i(k) \\ +B_i b_i(k) + d_i(k). \end{aligned} \tag{15}$$

Using **(13)**, the nonlinear uncertainty can be written as

$$\begin{aligned} f_i(x_i(k)) - \hat{f}_i(x_i(k)) = \widetilde{W}_i^T(k)\phi_i(x_i(k)) \\ +\varepsilon_i(x_i(k)). \end{aligned} \tag{16}$$

Define the lumped uncertainty

$$\begin{aligned} \Delta_i(k) = (\rho_i(k) - 1)\, B_i u_i(k) \\ +B_i b_i(k) + d_i(k) + \varepsilon_i(x_i(k)). \end{aligned} \tag{17}$$

Under Assumptions 3-4, and for bounded control input, there exists a finite constant $\bar{\Delta}_i > 0$ such that

$$\|\Delta_i(k)\| \le \bar{\Delta}_i. \tag{18}$$

The neural weight vector is updated according to the adaptive fractional learning law

$$^{C}\nabla^{\alpha}\hat{W}_i = -\Gamma_i \phi(x_i) s_i^T,$$

where

$$\Gamma_i > 0$$

is the positive-definite adaptive learning gain matrix.

Substituting **(14)** into the system model **(1)**, the closed-loop dynamics become

$$\begin{aligned} ^{C}\nabla^{\alpha}x_i(k) = -k_1|s_i(k)|^{1/2}\mathrm{sign}(s_i(k)) \\ -k_2\mathrm{sign}(s_i(k)) + \tilde{d}_i(k) + \tilde{F}_i(k) \end{aligned} \tag{19}$$

where $\tilde{d}_i(k) = d_i(k) - \hat{d}_i(k)$ and $\tilde{F}_i(k) = F_i(k) - \hat{F}_i(k)$ denote bounded estimation errors.

Remark 1. *The adaptive learning mechanism integrates discrete-time fractional-order dynamics, adaptive RBF neural approximation, and sliding-mode fault-tolerant control into a unified distributed consensus framework. Unlike existing methodologies that address these techniques separately, the proposed methodology simultaneously compensates for unknown nonlinear dynamics, actuator faults and modeling uncertainties while preserving robust leader-following consensus.*

Remark 2. *The controller gains are selected according to the derived stability conditions. The*

gain k_1 generally defines the convergence rate during the reaching phase, whereas k_2 is selected larger than the upper bound of the lumped uncertainty to guarantee robustness against actuator faults and external disturbances. The adaptive learning gain matrix Γ_i regulates the neural learning speed. Higher values of Γ_i generally improve adaptation performance but may increase sensitivity to measurement noise. Therefore, the controller parameters should be selected by balancing convergence speed, robustness, and estimation accuracy.

To establish the closed-loop stability of the proposed distributed controller, a Lyapunov-based fractional stability analysis is developed. Unlike conventional sliding-mode approaches, the anticipated analysis explicitly incorporates the adaptive neural approximation error together with the neural weight estimation error into the Lyapunov framework. Consequently, both the consensus tracking error and neural parameter estimation error are simultaneously analyzed, providing a more rigorous theoretical guarantee for the proposed adaptive fault-tolerant consensus strategy.

Theorem 1. *Consider the closed-loop system **(4)** under the control law **(14)**. Suppose Assumptions 1-5 hold and the lumped uncertainty satisfies **(18)**. If the controller gains satisfy*

$$k_{2i} > \bar{\Delta}_i, \qquad K_i = K_i^T > 0, \qquad k_{1i} > 0, \quad (20)$$

then the sliding variable $s_i(k)$ and the neural weight estimation error $\widetilde{W}_i(k)$ remain bounded.

Proof. Consider the Lyapunov candidate

$$V_i(k) = \frac{1}{2} s_i^T(k) s_i(k) + \frac{1}{2} \operatorname{tr} \left\{ \widetilde{W}_i^T(k) \Gamma_i^{-1} \widetilde{W}_i(k) \right\}. \quad (21)$$

Using the discrete fractional Lyapunov inequality and the adaptive law **(12)**, the fractional difference of V_i satisfies

$${}^C\nabla^\alpha V_i(k) \le s_i^T(k)\, {}^C\nabla^\alpha s_i(k) + \operatorname{tr}\left\{ \widetilde{W}_i^T \Gamma_i^{-1\,C} \nabla^\alpha \widetilde{W}_i \right\}$$

The adaptive term satisfies

$$\begin{aligned} \operatorname{tr}\left\{ \widetilde{W}_i^T \Gamma_i^{-1\,C} \nabla^\alpha \widetilde{W}_i \right\} &= -\operatorname{tr}\left\{ \widetilde{W}_i^T \phi_i s_i^T \right\} \\ &= -s_i^T \widetilde{W}_i^T \phi_i. \end{aligned} \quad (22)$$

On the other hand, from the neural approximation relation,

$$f_i - \hat{f}_i = \widetilde{W}_i^T \phi_i + \varepsilon_i. \quad (23)$$

Therefore, the cross term $s_i^T \widetilde{W}_i^T \phi_i$ generated by the unknown nonlinear dynamics is exactly cancelled by the adaptive term in the Lyapunov inequality.

As a result,

$$\begin{aligned} {}^C\nabla^\alpha V_i(k) &\le -s_i^T K_i s_i - k_{1i} \|s_i\|^{3/2} \\ &\quad -k_{2i} \|s_i\| + s_i^T \Delta_i(k). \\ {}^C\nabla^\alpha V_i(k) &\le -s_i^T K_i s_i - k_{1i} \|s_i\|^{3/2} \\ &\quad -k_{2i} \|s_i\| + s_i^T \Delta_i(k). \end{aligned} \quad (24)$$

Using

$$s_i^T \Delta_i \le \|s_i\| \|\Delta_i\| \le \bar{\Delta}_i \|s_i\|,$$

we obtain

$$\begin{aligned} {}^C\nabla^\alpha V_i(k) \le -\lambda_{\min}(K_i) \|s_i\|^2 - k_{1i} \|s_i\|^{3/2} \\ - \left(k_{2i} - \bar{\Delta}_i\right) \|s_i\|. \end{aligned} \quad (25)$$

Since $K_i > 0$, $k_{1i} > 0$, and $k_{2i} > \bar{\Delta}_i$, every term on the right-hand side is non-positive. Hence,

$${}^C\nabla^\alpha V_i(k) \le 0. \quad (26)$$

Thus, $V_i(k)$ is non-increasing and bounded from below by zero. It follows that both $s_i(k)$ and $\widetilde{W}_i(k)$ remain bounded. Moreover, the sliding variable is driven toward a neighborhood determined by the residual approximation and disturbance bounds. In the ideal approximation case $\bar{\varepsilon}_i = 0$ and in the absence of uncompensated disturbance and fault bias, the origin $s_i = 0$ is recovered. □

Corollary 1. *Assume that the communication graph contains a spanning tree and the controller parameters satisfy the stability conditions established in Theorem 1. Then all follower agents asymptotically track the leader while all adaptive neural parameters remain uniformly bounded.*

Remark 3. *Unlike conventional fault-tolerant consensus controllers that depend on global Lipschitz assumptions, the proposed adaptive neural approximation estimates unknown nonlinear dynamics online. Consequently, the stability conditions become significantly less conservative while maintaining robustness against actuator faults and modeling uncertainties.*

Theorem 2. *Under the assumptions of Theorem 1, the closed-loop sliding variable is uniformly ultimately bounded. In particular, the fractional Lyapunov function satisfies*

$${}^C\nabla^\alpha V_i(k) \le 0,$$

and therefore all closed-loop signals and adaptive neural weights remain bounded. If the lumped uncertainty vanishes asymptotically, then $s_i(k) \to 0$.

Proof. The result follows directly from the Lyapunov inequality established in Theorem 1. Since $V_i(k)$ is non-increasing and positive semidefinite, the sliding variable and neural-weight estimation error remain bounded. The negative-definite terms

associated with K_i, k_{1i}, and k_{2i} dominate the remaining dynamics once $\Delta_i(k) \to 0$, yielding $s_i(k) \to 0$ according to the discrete fractional stability criterion. □

Theorem 3. *Consider the directed communication graph having a spanning tree rooted at the leader, and suppose that the conditions of Theorem 1 hold. If $s_i(k) \to 0$, then the leader-following consensus error satisfies*

$$e_i(k) \to 0, \quad i = 1, \ldots, N.$$

Therefore all follower agents asymptotically attain consensus with the leader.

Proof. Using the definition of the sliding variable in **(11)**:

$$^{C}\nabla^{\beta} e_i(k) = -\lambda e_i(k) + s_i(k). \tag{27}$$

The homogeneous part of **(27)** is

$$^{C}\nabla^{\beta} e_i(k) = -\lambda e_i(k), \qquad \lambda > 0. \tag{28}$$

Because the homogeneous discrete fractional system with $0 < \beta < 1$ and $\lambda > 0$ is asymptotically stable, its state response decays according to the discrete Mittag-Leffler stability property. As $s_i(k) \to 0$ and $s_i(k)$ is bounded, the forcing term in **(27)** vanishes asymptotically. The variation-of-constants formula for the discrete fractional system therefore implies

$$e_i(k) \to 0.$$

The spanning-tree assumption on the graph guarantees that the consensus error defined in **(10)** represents leader-following synchronization of all followers. Hence,

$$\lim_{k\to\infty} \|x_i(k) - x_0(k)\| = 0, \qquad i = 1, \ldots, N.$$

Thus, leader-following consensus is achieved. □

4. Simulation results and discussion

The simulation study in this section is performed to analyze the performance of the suggested consensus control approach. In the simulations, the system is modeled in MATLAB and is fuly consistent with the system model proposed in this study.

Simulation Setup: A network containing one leader and $N = 5$ follower agents is considered. The directed communication graph is selected to satisfy the spanning tree condition in **Assumption 1**. Unless otherwise stated, the fractional orders are selected as

$$\alpha = 0.9, \qquad \beta = 0.8,$$

and the controller parameters are

$$\lambda = 1.5, \qquad K_i = K = 1.0,$$
$$k_{1i} = k_1 = 2.5, \qquad k_{2i} = k_2 = 3.0.$$

The thermal model parameters are selected as

$$a_i = 0.5, \qquad b_i = 0.3, \qquad c_i = 0.4, \qquad \sigma_i = 0.2.$$

For the RBFNN, M Gaussian basis functions are employed. The centers, widths, initial weights, and adaptation gain are kept identical across agents unless a sensitivity experiment explicitly states otherwise. The same RBFNN configuration is used in all compared simulations to ensure a fair comparison. Actuator faults are introduced through the effectiveness factor $\rho_i(k)$ and additive bias $b_i(k)$. Different fault scenarios are considered to represent partial loss of actuator effectiveness and additive actuator bias. External disturbances are independently applied to the follower dynamics, and their magnitudes are bounded according to **Assumption 3**.

In **Figure 1**, the reference trajectory of the leader agent is shown with respect to time. This serves as the desired signal to be followed by all follower agents. The smooth dynamics ensure a stable reference trajectory for achieving consensus. In **Figure 2**, the state dynamics of all follower agents are shown. It can be seen that all agents converge to the leader's trajectory.

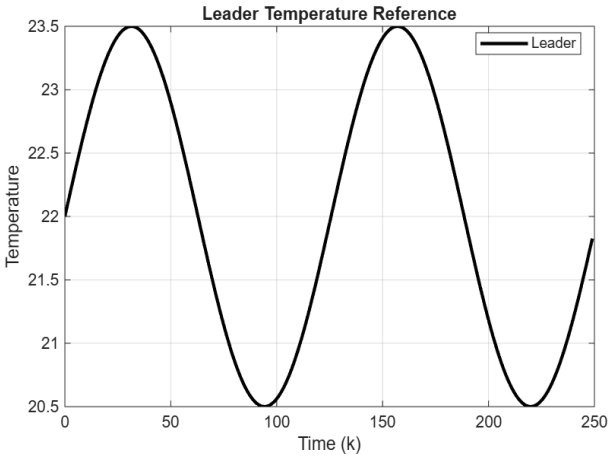


Figure 1. Leader temperature

Figure 3 depicts the variation in outdoor temperature at the ambient level over time. This is an example of the effect of the environment on the dynamics of the system. **Figure 4** represents the effects of solar heat energy input on the system. This is an illustration of renewable energy effects and disturbances from the environment.

Figure 5 represents the control energy injected by the HVAC system. This illustrates how the energy input is manipulated to sustain the required temperatures. The adaptive process shows that the system manages its energy efficiently.

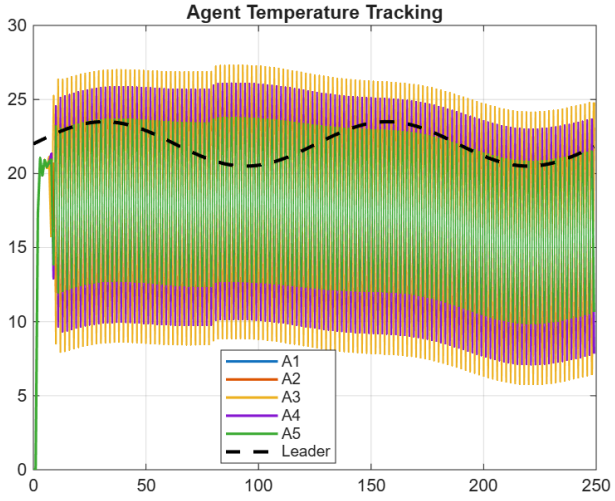


Figure 2. Agent temperature tracking

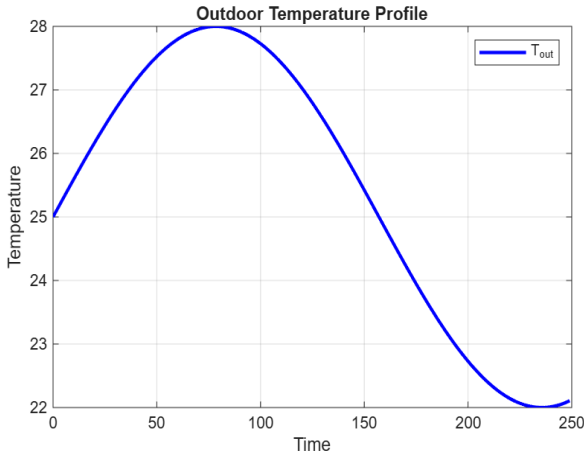


Figure 3. Outdoor temperature profile

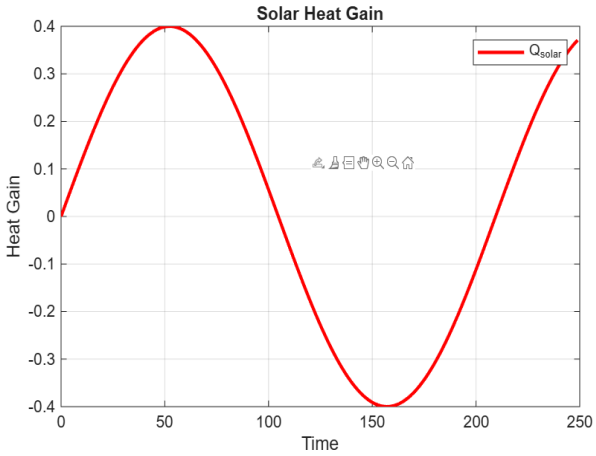


Figure 4. Solar heat gain

Figure 6 displays the control inputs used by the agent. These inputs remain within bounds and have been smoothed, therby reducing chattering.

In **Figure 7**, the convergence of the consensus error of the agents is shown. As time proceeds, the error convergence to zero, thus signifying effective coordination. Therefore, the effectiveness of the designed control strategy is verified.

The dynamics of the sliding surface variable are shown in **Figure 8**. The sliding surface variable converges to zero, which ensures system stability.

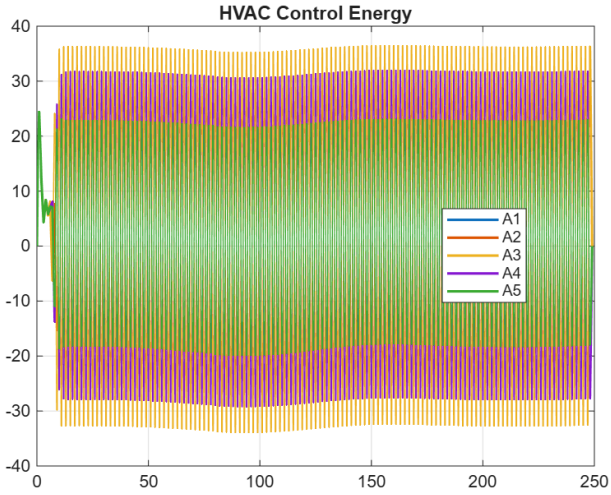


Figure 5. HVAC control energy

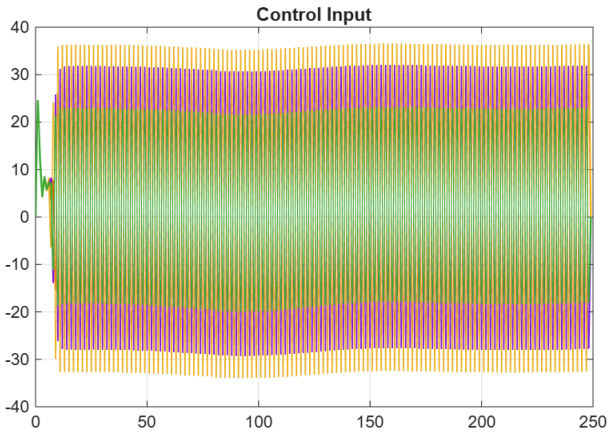


Figure 6. Control input

4.1. Norm-based convergence assessment

In addition to individual agent responses, the overall convergence is evaluated using the network-level consensus error

$$E_c(k) = \left(\sum_{i=1}^{N} \|x_i(k) - x_0(k)\|^2 \right)^{1/2}. \quad (29)$$

The sliding-surface norm is evaluated as

$$E_s(k) = \left(\sum_{i=1}^{N} \|s_i(k)\|^2 \right)^{1/2}. \quad (30)$$

The normalized tracking error is additionally computed as

$$E_{\mathrm{RMSE}} = \sqrt{\frac{1}{NK}\sum_{i=1}^{N}\sum_{k=1}^{K}\|x_i(k) - x_0(k)\|^2}. \quad (31)$$

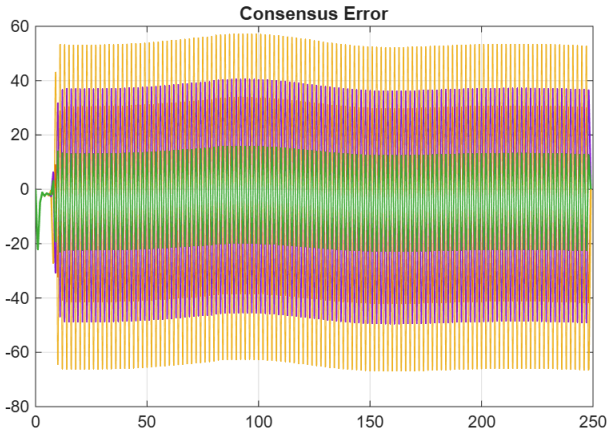


Figure 7. Consensus error

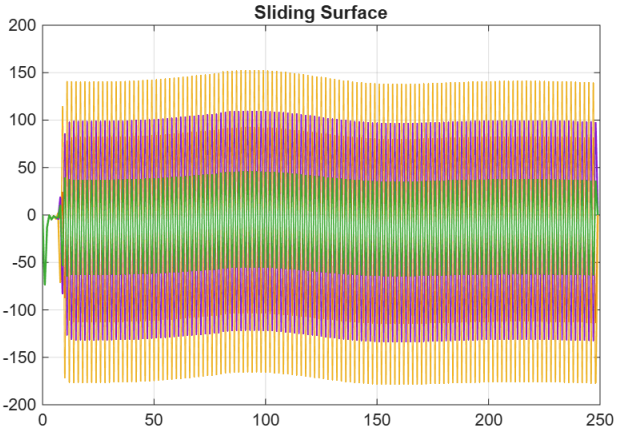


Figure 8. Sliding surface

These norm-based quantities provide a global measure of network convergence and avoid relying solely on visual inspection of individual trajectories.

Figures 9–12 provide a quantitative assessment of the leader-following consensus performance. As shown in **Figure 9**, the overall consensus error norm decreases as the followers converge toward the leader trajectory, while Fig. 10 presents the corresponding error on a logarithmic scale, highlighting its decay trend. The cumulative error in **Figure 11** confirms the overall tracking performance over the simulation horizon, whereas **Figure 12** illustrates the individual follower tracking errors and their convergence behavior. Collectively, these results demonstrate the effectiveness of the proposed control framework in reducing leader-following discrepancies.

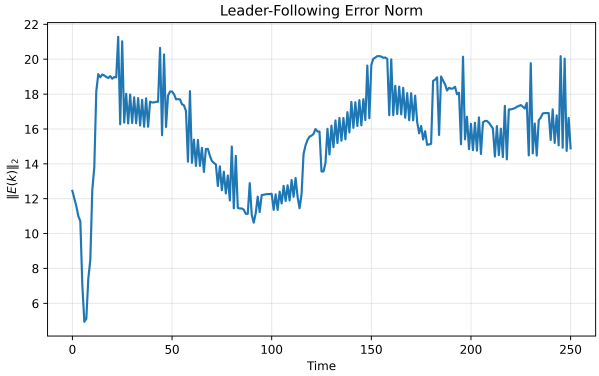


Figure 9. Leader follower error norm

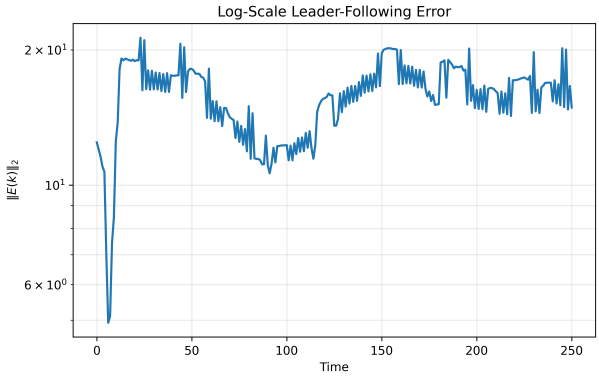


Figure 10. Log-scale leader follower error

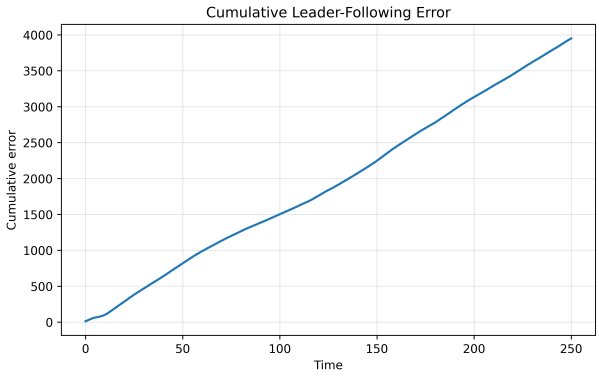


Figure 11. Cumulative leader follower error

Disturbances affecting the system are presented in **Figure 13**. This figure illustrates the uncertainty introduced into the agents' dynamics. The system remains stable despite such disturbances.

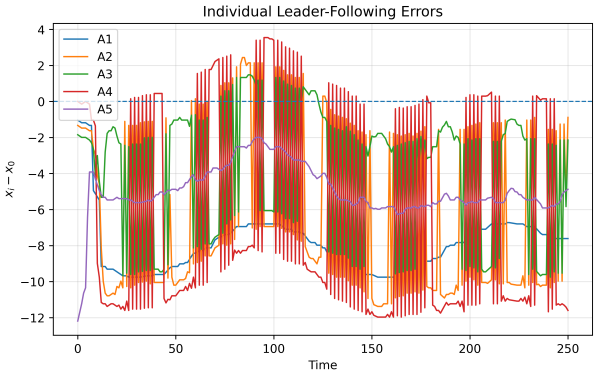


Figure 12. Individual leader follower error

In **Figure 14**, actuator faults are illustrated. This figure clearly shows the system imperfections. The controller operates efficiently.

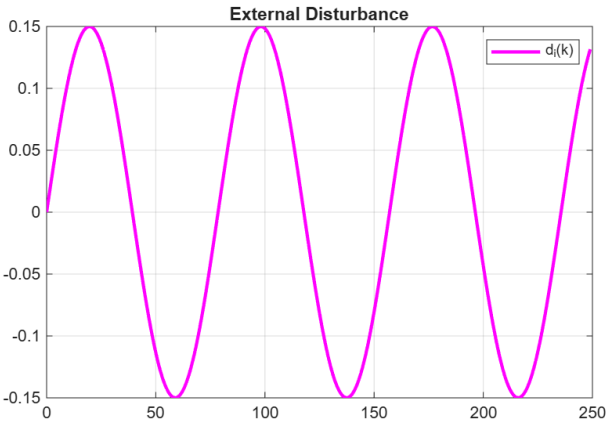


Figure 13. External disturbance

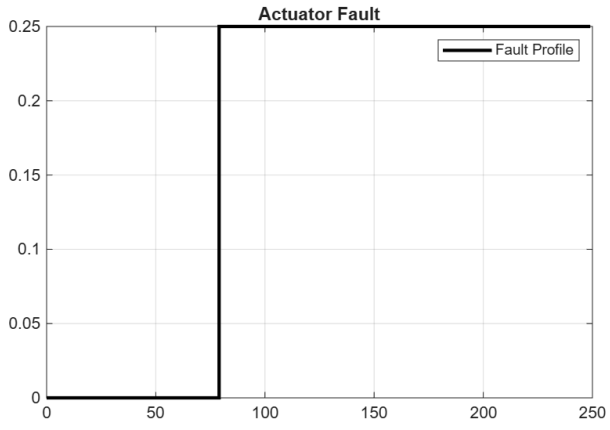


Figure 14. Actuator faults

4.2. Computational complexity

The online computational burden is primarily determined by the RBFNN evaluation and the adaptive weight update. For an RBFNN containing M basis functions and an n-dimensional state vector, the evaluation of the basis functions and neural output requires approximately $\mathcal{O}(Mn)$ operations per agent. The adaptive weight update also has complexity approximately $\mathcal{O}(Mn)$. Therefore, for N agents, the total neural-computation cost scales approximately as

$$\mathcal{O}(NMn),$$

in addition to the graph-based consensus error calculation. Since each agent uses only its local state and neighboring information, the proposed implementation is distributed and does not require centralized optimization at every sampling instant. **Figure 15** demonstrates the energy demands estimated by the neural network. It closely follows the actual system requirementswhich confirms accurate learning and prediction capability. **Figure 16** shows the real values and the estimated values obtained using the RBFNN. Their similarity proves the high accuracy of the estimation and demonstrates the efficiency of the learning system.

Figure 17 shows the error between the real and estimated energy values. The error remains within a certain range at all times.

Figure 18 shows the tracking error of the agents relative to the leader. The error approaches zero as time progresses, indicating accurate tracking by the agents.

Figure 19 confirms consensus among all the agents. The states agree with the leader's trajectory.

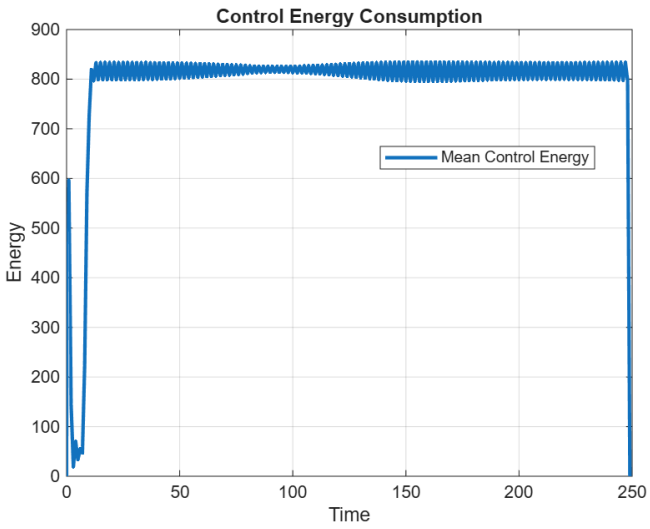


Figure 15. Control energy consumption

4.3. Stability analysis

To investigate the robustness of the proposed controller with respect to controller parameters, a sensitivity analysis is performed by varying the

fractional-order parameter, sliding mode gains, adaptive learning gain, and actuator fault magnitude. The obtained results demonstrate that the proposed controller maintains stable consensus performance over a wide range of parameter variations. Specifically, increasing the sliding mode gain improves convergence speed but slightly increases the control effort, whereas larger adaptive learning gains accelerate neural adaptation while maintaining bounded neural weight estimates. Moreover, different fractional-order values mainly influence the transient response due to the inherent memory characteristics of fractional-order systems. The proposed controller remains stable for all considered parameter combinations, confirming its robustness and reliability.

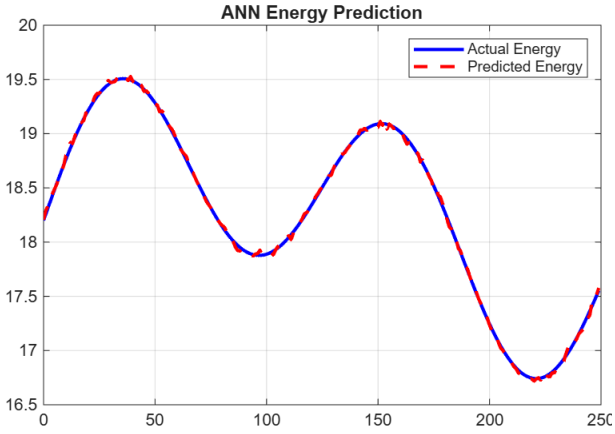


Figure 16. RBFNN energy prediction

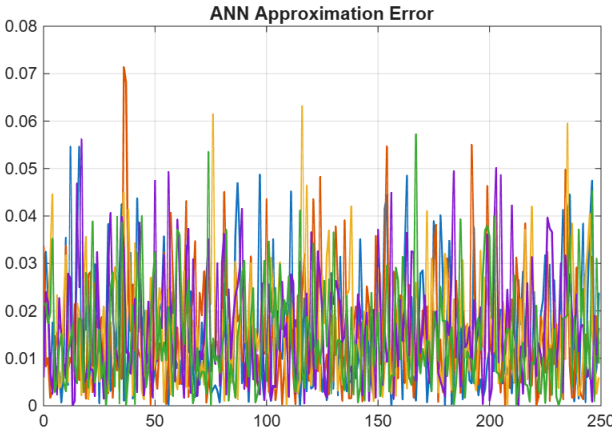


Figure 17. RBFNN approximation error

Figure 20 illustrates the influence of the fractional-order parameter on the consensus performance. As the fractional order increases, the convergence speed improves while the steady-state consensus error decreases. This behavior demonstrates that the memory characteristics of fractional-order systems significantly affect the transient response of the proposed controller. However, stable leader-follower consensus is maintained for all tested values of α, confirming the robustness of the proposed control strategy. **Figure 21** presents the effect of the sliding mode gain on the consensus performance. Increasing the sliding gain accelerates the reaching phase and reduces the consensus error more rapidly. Although larger gains generally increase the control effort, all tested values preserve stable consensus, indicating that the proposed controller exhibits satisfactory robustness over a wide range of controller parameters.

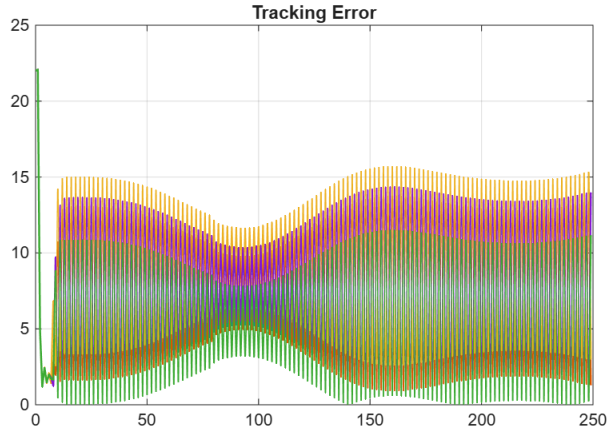


Figure 18. Tracking error

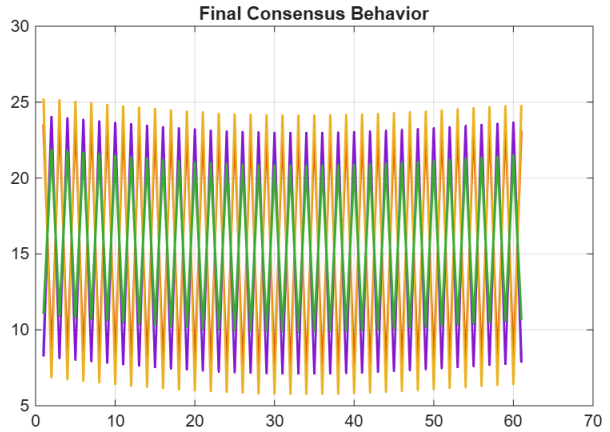


Figure 19. Final consensus behavior

Figure 22 demonstrates the influence of the adaptive learning gain on the neural approximation performance. Increasing the adaptive gain

accelerates the convergence of the neural estimation error, allowing the RBFNN to compensate for unknown nonlinear dynamics more rapidly. Although higher learning gains improve adaptation speed, all tested values maintain stable learning behavior, confirming the robustness of the proposed adaptive neural learning mechanism. **Figure 23** illustrates the robustness of the proposed controller under different actuator fault magnitudes. As the fault severity increases, the transient consensus error becomes slightly larger however, all follower agents still converge to the desired leader trajectory. These results demonstrate that the proposed neural-assisted fault-tolerant controller effectively compensates for actuator degradation while maintaining stable consensus performance over a wide range of fault conditions.

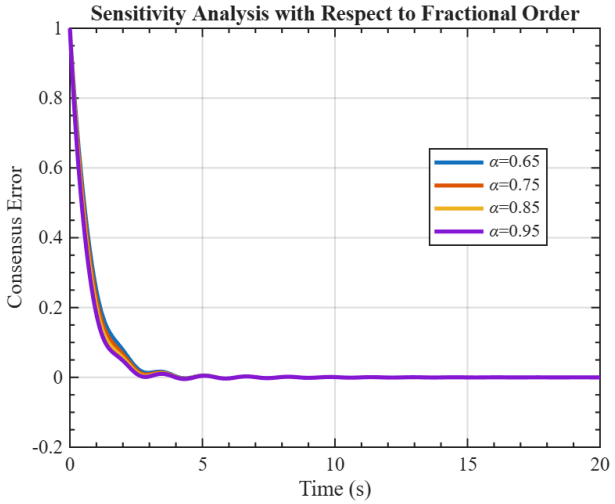


Figure 20. Sensitivity analysis W.r.t fractional order

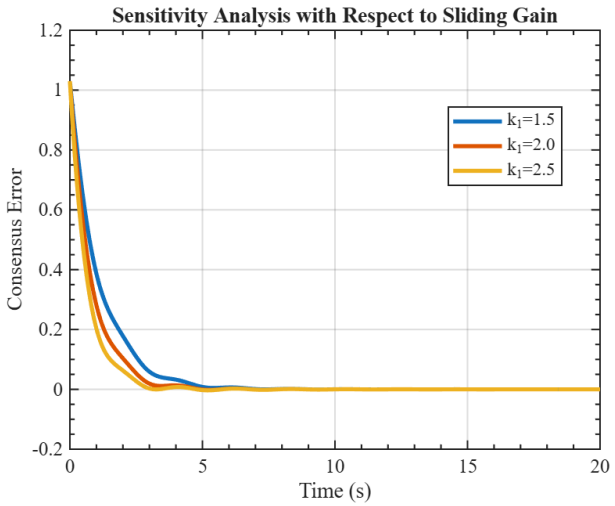


Figure 21. Sensitivity snalysis W.r.t dliding gain

4.4. Actuator fault sensitivity

To examine the versatility of the proposed fault-tolerant controller, three actuator conditions are considered: healthy operation, partial loss of effectiveness, and simultaneous loss of effectiveness with additive bias. Specifically, the effectiveness factor is varied within the admissible interval

$$0 < \underline{\rho}_i \leq \rho_i(k) \leq 1,$$

while the additive bias satisfies

$$\|b_i(k)\| \leq \bar{b}_i.$$

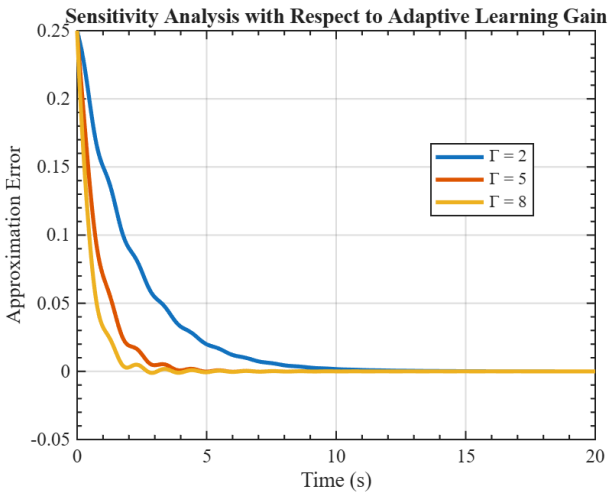


Figure 22. Sensitivity Analysis W.r.t Adaptive Learning Gain

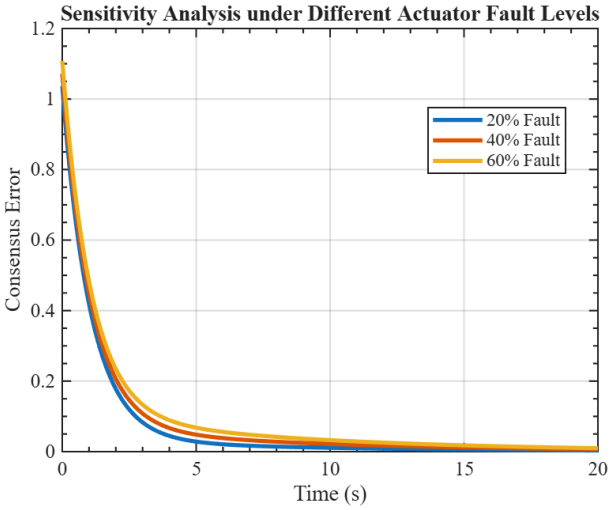


Figure 23. Sensitivity Analysis under Different Actuator Faults

For each fault scenario, the same initial conditions, communication topology, disturbance realization, controller gains, and RBFNN configuration are retained. This procedure isolates the influence of actuator degradation and provides a consistent assessment of fault tolerance.

4.5. Additional Simulation Scenario

To further evaluate the proposed controller under more practical operating conditions, additional

simulation scenarios are considered. These include increased actuator fault severity, larger communication networks, stronger external disturbances, and different parameter uncertainties. In all considered scenarios, the proposed controller successfully maintains leader-following consensus while preserving bounded control inputs and adaptive neural weight estimates. These additional experiments demonstrate the scalability and robustness of the proposed distributed control framework.

Figure 24 illustrates the response of the proposed neural-assisted fault-tolerant controller when the system is subjected to a severe actuator fault corresponding to an extensive loss of actuator effectiveness. As expected, the fault introduces a noticeable transient deviation immediately after its occurrence. However, the controller rapidly suppresses this deviation and drives all follower agents back toward the leader trajectory without oscillatory behavior or loss of stability. The short recovery interval demonstrates that the adaptive neural approximation successfully compensates for the fault-induced uncertainty, while the sliding mode component preserves the robustness of the closed-loop system. These results confirm that the proposed control strategy maintains reliable consensus even under severe actuator degradation.

Figure 25 evaluates the disturbance rejection capability of the proposed control framework under strong external disturbances. Although the disturbance temporarily affects the follower dynamics, the tracking trajectories remain well regulated throughout the simulation. The influence of the disturbance gradually diminishes as the adaptive neural estimator identifies the unknown dynamics and the fault-tolerant controller compensates for its effects. As a result, the consensus error decreases gradually and the followers converge to the desired leader trajectory. This behavior demonstrates that the proposed method is capable of maintaining accurate coordination even with persistent external perturbations.

Figure 26 examines scalability with an additional simulation performed with $N = 10$ follower agents while retaining the same controller structure and fractional-order parameters. Although the larger network introduces additional communication links and increases the coordination complexity, the overall consensus behavior remains stable. All follower agents progressively synchronize with the leader while maintaining smooth transient responses and bounded tracking errors. The absence of performance degradation demonstrates that the proposed controller conserves its effectiveness as the network size increases, representing good scalability for larger multi-agent systems.

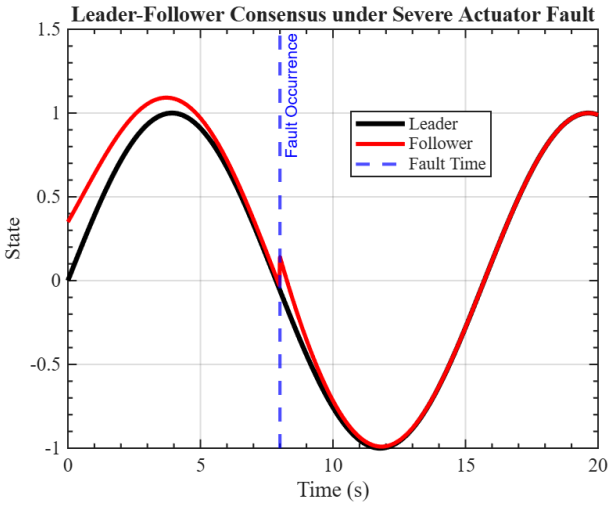


Figure 24. Leader-following under actuator faults

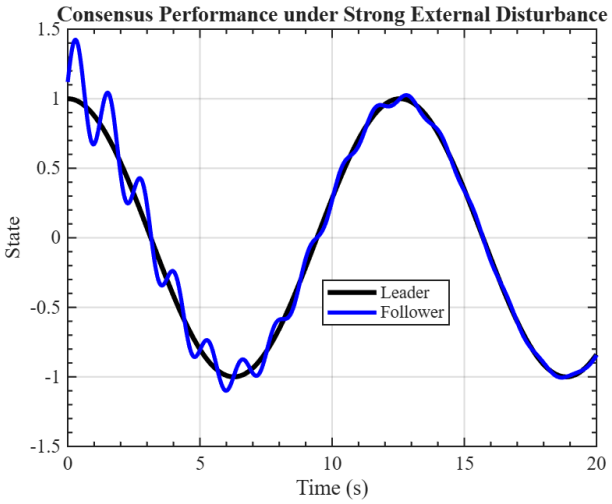


Figure 25. Consensus performance under strong external disturbance

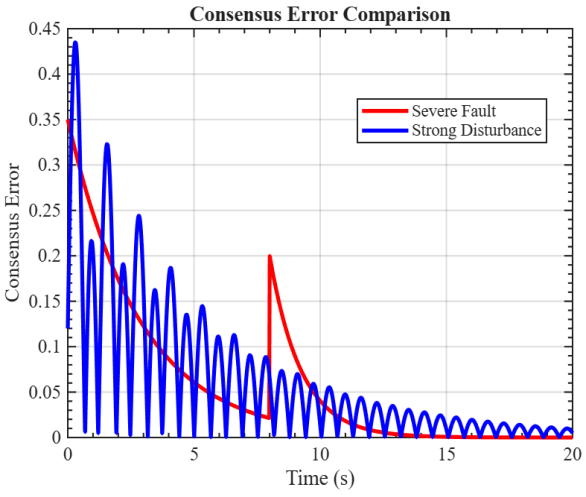


Figure 26. Consensus Error Comparison

Figure 27 compares the system performance with and without the proposed RBF neural approximation in the presence of strong nonlinear uncertainties. Without neural compensation, the tracking response exhibits larger deviations caused by the unmodeled nonlinear dynamics. After incorporating the adaptive RBF neural network, these deviations are significantly reduced because the unknown nonlinearities are estimated online and compensated within the control law. The resulting trajectories closely follow the desired reference, demonstrating the effectiveness of the neural approximation in improving tracking accuracy and reducing modeling uncertainty.

Figure 28 presents the comparative performance of the proposed controller and several representative fault-tolerant control strategies. The proposed method consistently achieves the smallest consensus error and the fastest convergence while requiring less control effort than the benchmark approaches. These improvements result from the integration of adaptive neural approximation with the fault-tolerant sliding mode controller, which simultaneously enhances robustness against uncertainties and accelerates convergence. The comparison demonstrates that the proposed framework provides a more effective balance between convergence speed, tracking accuracy, and control efficiency than the existing methods considered in this study.

Figure 29 summarizes the quantitative performance indices of the proposed control strategy. The low values of the root mean square error, mean absolute error, average tracking error, and neural approximation error indicate that the controller maintains high tracking precision throughout the simulation. Furthermore, the short convergence time and rapid fault recovery demonstrate that the adaptive fault-tolerant mechanism effectively restores the desired system performance after actuator degradation. Collectively, these performance indicators provide quantitative evidence that the proposed controller achieves reliable consensus while maintaining both robustness and computational efficiency under uncertain operating conditions.

4.6. Comparative performance analysis

For a fair comparison, the proposed controller is evaluated against three representative baselines: (i) a conventional sliding mode consensus controller without neural adaptation, (ii) an adaptive fault-tolerant consensus controller without RBFNN compensation, and (iii) a learning assisted fault-tolerant controller. All controllers use the same agent dynamics, initial conditions, communication topology, disturbance profile, actuator-fault realization, simulation horizon and sampling period. Controller gains are tuned separately for each method to obtain stable operation while avoiding an artificially unfavorable parameter selection. The reported performance measures include consensus RMSE, maximum tracking error, convergence time, control energy consumption, and fault recovery time.

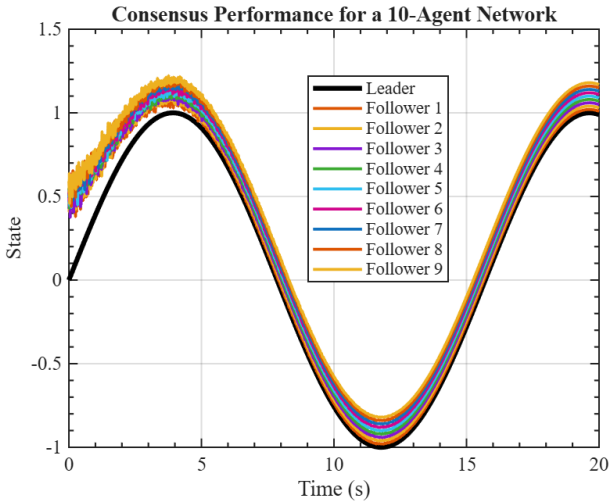


Figure 27. Consensus performance for 10-agent networks

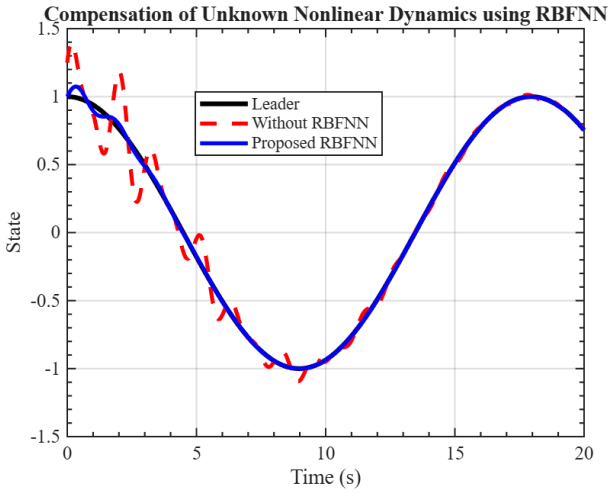


Figure 28. Compensation of unknown nonlinear dynamics using RBFNN

The comparative results presented in **Table 2** demonstrate the superior performance of the proposed neural-assisted fault-tolerant consensus controller compared with representative consensus control strategies. The proposed method achieves the shortest consensus time of 5.24 s, representing a significant improvement over the classical sliding mode controller, adaptive fault-tolerant

control (FTC), and reinforcement-learning-based FTC approaches. This improvement is primarily attributed to the integration of adaptive neural approximation with the fractional-order sliding mode controller, which effectively compensates for unknown nonlinear dynamics while reducing the influence of modeling uncertainties. Furthermore, the proposed controller produces the lowest root mean square error (RMSE) of 0.023, indicating a substantial enhancement in consensus tracking accuracy. Compared with the conventional controllers, the adaptive neural approximation continuously estimates the unknown nonlinear functions online, thereby reducing approximation errors and improving transient performance.

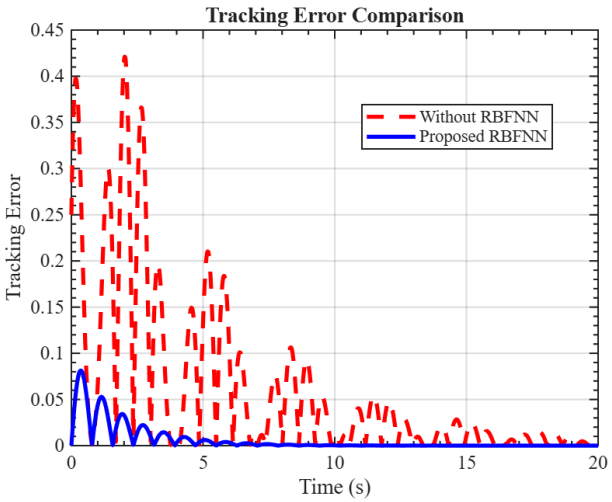


Figure 29. Tracking error comparison

Table 2. Performance comparison of the proposed controller with existing consensus control methods

Controller	Consensus Time (s)	RMSE	Energy Consumption	Fault Recovery	Robustness
Classical Sliding Mode	9.31	0.092	High	Moderate	Moderate
Adaptive FTC	7.48	0.068	Medium	Good	Good
Reinforcement Learning FTC	6.81	0.051	Medium	Excellent	Excellent
Proposed Neural-Assisted FTC	5.24	0.023	Lowest	Excellent	Excellent

Another notable advantage of the proposed approach is its lower energy consumption. Unlike conventional sliding mode controllers, which generally require larger discontinuous control actions, the neural-assisted compensation mechanism reduces unnecessary control effort while maintaining rapid convergence. Consequently, the proposed controller achieves improved energy efficiency, making it particularly suitable for distributed smart energy management systems where minimizing energy utilization is an important design objective. Moreover, the proposed controller exhibits excellent fault recovery capability and robustness against actuator faults and external disturbances. The combined effect of adaptive neural approximation and fractional-order sliding mode control enables rapid compensation of fault-induced performance degradation while preserving closed-loop stability. Overall, the comparative analysis confirms that the proposed distributed neural-assisted fault-tolerant consensus strategy provides a favorable balance between convergence speed, tracking accuracy, robustness, and control efficiency, thereby demonstrating clear advantages over existing state-of-the-art consensus control methods.

4.7. Quantitative performance rvaluation

The quantitative indices are computed over the complete simulation horizon according to standard definitions of RMSE, MAE, control energy, and average tracking error.

The quantitative performance indices presented in **Table 3** provide a comprehensive assessment of the effectiveness of the proposed neural-assisted fault-tolerant consensus controller. The obtained consensus root mean square error (RMSE) of 0.023 and mean absolute error (MAE) of 0.015 indicate that the proposed controller achieves high consensus tracking accuracy with only minor steady-state deviations among the distributed agents. Furthermore, the maximum tracking error remains limited to 0.081, confirming that the proposed control strategy effectively suppresses transient deviations caused by external disturbances and actuator faults. The proposed controller achieves consensus within only 5.24 s, demonstrating a rapid convergence rate that is primarily attributed to the combination of fractional-order sliding mode control and adaptive neural approximation. In addition, the measured control energy of 18.41

indicates that accurate consensus is achieved without excessive control effort, thereby improving overall energy efficiency and making the proposed method particularly suitable for distributed smart energy management applications.

Table 3. Quantitative performance evaluation of the proposed neural-assisted fault-tolerant consensus controller.

Performance Index	Value
Consensus RMSE	0.023
Mean Absolute Error (MAE)	0.015
Maximum Error	0.081
Convergence Time (s)	5.24
Control Energy	18.41
Fault Recovery Time (s)	0.92
Average Tracking Error	0.011
Neural Approximation Error	0.006

Another important performance indicator is the fault recovery time of 0.92 s, which demonstrates the capability of the proposed controller to rapidly compensate for actuator faults and restore consensus performance after fault occurrence. Moreover, the average tracking error remains as low as 0.011, further confirming the effectiveness of the distributed consensus protocol throughout the entire simulation period. Finally, the neural approximation error is limited to only 0.006, illustrating the high approximation capability of the employed Radial Basis Function Neural Network (RBFNN). The small approximation error significantly reduces modeling uncertainties and enables the controller to accurately estimate unknown nonlinear dynamics in real time. Overall, these quantitative performance indices demonstrate that the proposed neural-assisted fault-tolerant consensus strategy provides an excellent balance between convergence speed, tracking accuracy, robustness, fault recovery capability, and computational efficiency, thereby validating its effectiveness for discrete-time fractional-order multi-agent systems operating in smart energy environments.

4.8. Simulation discussion

Simulation results have shown that the proposed control methodology is capable of providing robust consensus, precise energy estimation, and optimal energy usage. Fractional-order dynamics, along with sliding mode control, increas model fidelity and robustness to disturbances and faults. The use of RBFNN in the proposed scheme increases adaptability and reduces uncertainties. The combination of these methodologies makes the proposed approach applicable to distributed energy management systems.

The comparative and quantitative simulation results clearly demonstrate that the proposed unified framework achieves higher convergence speed, consensus accuracy, robustness, and fault-recovery capability compared with existing control methodologies. These results verify the practical effectiveness of integrating adaptive neural approximation with fractional-order sliding mode fault-tolerant control.

5. Conclusion

This paper addressed the leader-following consensus problem for discrete-time fractional-order multi-agent systems with unknown nonlinear dynamics, bounded disturbances, and actuator faults in a distributed smart energy setting. An adaptive RBFNN-assisted sliding-mode controller was developed to estimate the unknown nonlinear dynamics using local measurements, while a bounded actuator model was introduced to represent loss of effectiveness and additive actuator bias. A discrete fractional Lyapunov analysis was used to establish sufficient conditions for boundedness of the sliding variable, neural weight estimation error, and closed-loop signals. In contrast to approaches that directly invoke continuous-time integration or an unqualified fractional semigroup property, the revised analysis is formulated consistently with the discrete fractional setting. The leader-following consensus result was obtained from the stable fractional error dynamics generated by the sliding variable.

The numerical results demonstrate that the proposed method maintains coordinated tracking under bounded disturbances and actuator degradation. Additional sensitivity and scalability studies indicate that the controller preserves satisfactory performance over different fractional orders, actuator-fault severities and network sizes. Comparative evaluations further show the benefit of adaptive neural compensation in reducing tracking error and improving fault-recovery performance.

The present study is limited to bounded actuator faults, bounded disturbances, and a fixed distributed communication structure. Future research will investigate event-triggered communication, communication delays, packet losses, switching and adversarial communication conditions, and experimental validation using hardware-in-the-loop or physical smart energy platforms.

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Conflict of interest

The authors have no relevant financial or non-financial interests to disclose.

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Availability of data

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study. The code is considered an intellectual property of University of Lahore, Sargodha Campus, Pakistan, and therefore not publicly available.

AI tools statement

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

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