Adaptive Neural Network Sliding Mode Control for a Class of Nonlinear Systems with Input Saturation

Ke Wang, Rui Chen, Xiaoming Wu, Wenhui Zhang

ABSTRACT—A sliding mode control method based on adaptive neural networks is proposed to address the high-precision control problem of nonlinear systems with input saturation and external disturbances, while considering the uncertainty caused by inaccurate modeling. The error model component caused by input saturation and model uncertainties is derived, and a neural network controller is designed to approximate this error model, A differential evolution algorithm is employed to optimize the parameters of the neural network approximator. A sliding mode controller is designed to achieve uncertain compensation for the approximation error of the neural network and external disturbances. A Lyapunov function is constructed to prove the uniformly ultimately boundedness of the system's closed-loop signals. Comparative experiments validate the superiority of the proposed algorithm.

INDEX TERMS—Nonlinear systems, Input saturation, Differential evolution algorithm, Adaptive neural network, Sliding mode control

I. INTRODUCTION

IN many practical nonlinear systems, issues such as input saturation, parameter uncertainties, and external disturbances are prevalent, significantly impacting system performance and posing challenges to system control [1]-[4]. Recently, efforts have been made to mitigate the impacts of these nonlinear factors on the control system. Numerous scholars have conducted research and achieved some progress [5]-[9]. Regarding the aforementioned issues, [10] proposed a novel approach to address input saturation and parameter uncertainty in a class of robotic systems. To address the effects of input saturation, an auxiliary dynamic system was introduced, while uncertainties in the system were approximated using radial basis function neural networks. The proposed method designed adaptive laws for neural networks based on specific time constants and constructed an adaptive tracking controller using non-singular terminal sliding mode surfaces. Finally, numerical simulations validated the proposed control scheme, demonstrating its advantages in terms of rapid convergence and mitigation of input saturation. A neural network-based variable structure control method was proposed, utilizing neural networks to approximate model uncertainties and employing variable structure controllers to eliminate approximation errors. This method achieved good control results when applied to robot systems [11]-[12]. [13] examined the challenge of attitude tracking for a quadrotor aircraft under external disturbances and input saturation constraints. A novel adaptive terminal sliding mode control strategy was introduced to ensure swift convergence of all state variables with guaranteed performance. Adaptive laws were used to estimate the unknown upper limit of external disturbances. Furthermore, an auxiliary system was devised to tackle input saturation challenges encountered in real-world systems. [14] a design approach was proposed for a fuzzy non-singular terminal sliding mode controller tailored to handle a specific category of second-order nonlinear systems subjected to input saturation. This controller integrated a saturated non-singular terminal sliding mode (NTSM) controller with a fuzzy logic controller (FLC). The saturated non-singular terminal sliding mode controller was tasked with ensuring that the system's states efficiently reached the sliding surface and converged to the origin within a finite timeframe. Additionally, a fuzzy controller with two fuzzy input variables and one fuzzy output variable was developed. This fuzzy controller dynamically adjusted the control gains to automatically minimize those of the non-singular terminal sliding mode controller, thereby reducing redundancy and enhancing effectiveness. [15] proposed an adaptive integral-type terminal sliding mode tracking control method based on disturbance rejection to address uncertain nonlinear systems affected by input saturation and external disturbances. This method combined the robustness and non-overshooting dynamic characteristics of adaptive integral-type sliding mode control with the estimation properties of nonlinear extended state observers, resulting in excellent robustness. [16] presented a flexible performance-based control (FPC) scheme to address the issues of asymmetric input saturation constraints and external disturbances in nonlinear systems. This scheme included auxiliary systems and disturbance observers (DOB). The concept of modified performance functions (MPFs) was

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introduced in the paper. Modified performance functions, generated by the auxiliary system, were utilized to reduce the user-specified tracking performance requirements when input saturation occurred, and to restore the user-specified performance requirements when saturation was absent. The performance-based control scheme ensured that the system output always adhered to the constraints of the MPFs, ultimately ensuring that it converged within the user-specified range. [17] presented a backstepping control method employing a multivariate Taylor network (MTN) to manage a category of stochastic nonlinear systems under input saturation constraints. This method transformed non-smooth nonlinear input functions into smooth continuous functions, followed by the application of the multivariate Taylor network to address the system's unknown nonlinearities, yielding an adaptive backstepping-based multivariate Taylor network control scheme. The stability of the system was then verified to validate the proposed approach. [18] presented a control methodology aimed at nonlinear systems facing challenges like external disturbances and input saturation. This approach integrated a super-twisting extended state observer (STESO) and a sliding mode controller utilizing backstepping techniques. The strategy involved the design of two steady-state systems within the nonlinear framework to estimate disturbances in both matched and unmatched channels. Following this, a multi-sliding mode controller, based on backstepping principles, was developed specifically for the unmatched nonlinear system. Additionally, a first-order auxiliary system was introduced to counteract the effects of input saturation. Other authors had also proposed various control strategies for such issues [19]-[23].

A neural network sliding mode control method based on differential evolution is proposed to address the control problem of complex nonlinear systems under conditions of input saturation, model uncertainty, and external disturbances, with the effectiveness of the proposed algorithm validated through comparative experiments. The main contributions of this study include:

1.The control problem of nonlinear systems under complex conditions has been addressed. Unlike traditional control methods, a differential evolution-based neural network control approach is proposed to specifically tackle nonlinear control issues involving input saturation, model inaccuracies, and external disturbances. This method enhances the applicability of the approach to various scenarios and demonstrates significant innovation.

2.The real-time adaptability and approximation accuracy of neural network learning have been improved. A differential evolution algorithm is employed to optimize the network parameters of the neural network, enabling real-time adjustment of these parameters and achieving adaptive optimal approximation.

3.The approximation error of the neural network controller and the impact of external disturbances have been mitigated. A robust sliding mode controller is designed to compensate for the approximation error of the neural network and to eliminate external disturbances, thereby enhancing robustness and improving control accuracy.

The organization structure of this paper is as follows. Section 2 presents the problem statement, section 3 describes input saturation and its characteristics, section 4 introduces a novel adaptive neural network sliding mode control controller, including the utilization of the differential evolution algorithm for optimizing neural network approximation of unknown functions, adaptive laws of adaptive neural network sliding mode control algorithm, and stability analysis. To validate the effectiveness of the propositions, numerical examples and simulation results are provided in section 5. Finally, conclusions are drawn in section 6.

II. Problem Statement

The general expression for a nonlinear SISO system of order n is as follows:

$$\begin{cases} x^{(n)} = f(x,t) + g(x,t)u(t) \\ y = x \end{cases} \tag{1}$$

Where, $g(x,t)$, $f(x,t)$ represents an unknown nonlinear function that is bounded; $g(x,t)$ is nonzero nonlinear function; y is the output of investigated system, $u(t)$ is the control input; $x = [x, \dot{x}, \ddot{x} ... x^{(n-1)}]^T$ is the state vector of the system.

As shown in Fig. 1, u is the output signal of the input saturation function, $v \in R$, represents the system control input, with the input saturation expression as follows:

$$u = sat(v) = \begin{cases} u_{\max}, & v > u_{\max} \\ u, & |v| \le u_{\max} \\ -u_{\max}, & v < -u_{\max} \end{cases} \tag{2}$$

Where, $u_{\max}$ represents the maximum input value, $u_{\max} > 0$.

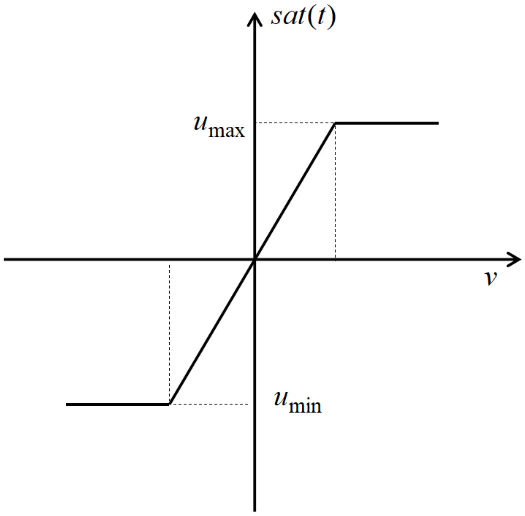

Fig. 1. Input saturation

The design objectives are as follows: For such nonlinear systems with input saturation (2), an adaptive neural network sliding mode controller is designed, which enables the system to track the desired trajectory with high precision.

III. Error Design and Preliminary System Design

The tracking error:

$$e = x - x_d = [e, \dot{e}, ... e^{(n-1)}] \in R \tag{3}$$

The control goal is to design a stable control law so that state x can stably track the reference signal x_d.

The schematic diagram of the system is shown in Fig. 2. Where $\varphi = u - v$, in practical application, if the actuator amplitude is unknown, the φ is unknown. By designing a neural network system to approximate the φ, a sliding mode control method under control input constraints can be realized.

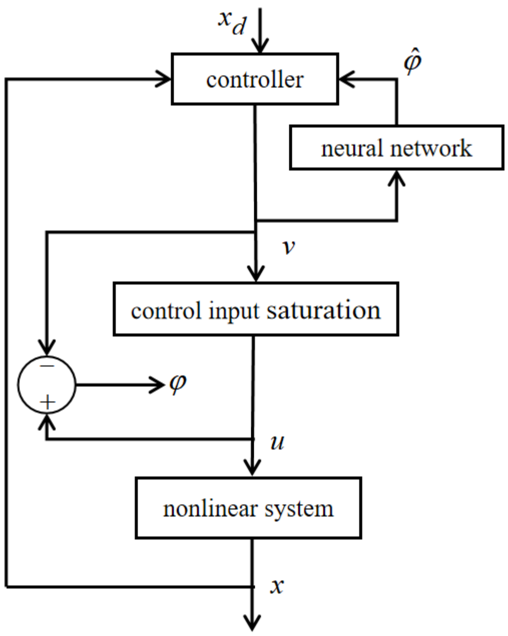

Fig. 2. Closed-loop control under input saturation and control constraints

The system state equation can be rewritten as:

$$\begin{cases} x^{(n)} = f(x,t) + g(x,t)[v(t) + \varphi] \\ y = x \end{cases} \quad (4)$$

Assuming the functions $f(x,t)$, $g(x,t)$ and φ are known, a sliding mode controller is derived as follows. The sliding surface is defined by:

$$s = c_1 e + c_2 \dot{e} + ... c_{n-1} e^{n-2} + e^{n-1} \quad (5)$$

Where, $c = [c_1, c_2, c_3 ... c_{n-1}]^T$ indicates the Routh-Hurwitz stability condition coefficient.

Take the derivative of equation (5):

$$\begin{aligned} \dot{s} &= \sum_i^{n-1} c_i e^{(i)} + e^{(n)} \\ &= \sum_i^{n-1} c_i e^{(i)} + x^{(n)} - x_d{}^{(n)} \end{aligned} \quad (6)$$

To satisfy the Lyapunov stability theory, the definition is as follows:

$$\dot{s} = -K sign(s) \quad (7)$$

The control law:

$$\begin{aligned} u(t) = \frac{1}{g(x,t)} \Big[-\sum_i^{n-1} c_i e^{(i)} - K sign(s) - f(x,t) \\ + x_d^{(n)} - \varphi g(x,t) \Big] \end{aligned} \quad (8)$$

The approach described above is typical for conventional sliding mode control. However, in practical applications, functions such as $f(x,t)$, $g(x,t)$ and φ are often unknown.

To address this issue, fuzzy models or neural network systems are typically used to approximate unknown functions. In this case, a neural network system is employed for implementation. The state equation of the system is described as follows:

$$\begin{cases} \hat{x}_*^{(n)} = \hat{f}(x,t) + \hat{g}(x,t)[v(t) + \hat{\varphi}] \\ \hat{y} = \hat{x} \end{cases} \quad (9)$$

The control law:

$$\begin{aligned} v_{NNSMC} = \frac{1}{\hat{g}(x,t)} \Big[-\sum_i^{n-1} c_i e^{(i)} - \hat{f}(x,t) + x_d^{(n)} \\ - K erf(s) - \hat{\varphi}\hat{g}(x,t) \Big] \end{aligned} \quad (10)$$

Where, $\hat{f}(x,t)$, $\hat{g}(x,t)$, $\hat{\varphi}$ are estimated by neural network, $0 < K$.

As a strategy to mitigate the occurrence of chattering phenomena, to replace the $sign(\ )$ function in the control law with the saturation function $erf(\ )$ is employed.

$$erf(s) = \frac{2}{\sqrt{\pi}} \int_0^s e^{-\eta^2} d\eta \quad (11)$$

The hyperbolic tangent function has the property that $|erf(s)| \le 1$, ensuring boundedness of control inputs when using this function.

In practical applications, uncertainties arising from external disturbances and other factors can lead to errors in approximating unknown functions using neural networks. The error is defined as follows:

$$e_m^* = x^{(n)} - \hat{x}_*^{(n)} \quad (12)$$

According to equation (12), the control law is rewritten as:

$$\begin{aligned} v_{NNFSMC} = \frac{1}{g(x,t)} \Big[-\sum_i^{n-1} c_i e^{(i)} - f(x,t) + x_d^{(n)} \\ - K erf(s) - \varphi g(x,t) - e_m^* \Big] \end{aligned} \quad (13)$$

In equation (13), the stability of the system depends on maintaining the error term e_m^* at a sufficiently low level. However, even with a minimal error term, there is no assurance that the tracking error will asymptotically converge to zero. To achieve asymptotic stability, it is necessary to eliminate e_m^* from the equation.

IV. Proposed Adaptive Neural Network Sliding Mode Control

For input-saturated nonlinear systems, this section proposes an adaptive neural network sliding mode control method. This approach utilizes the differential evolution algorithm to optimize the model parameters of the neural network, thereby approximating the unknown functions $f(x,t)$, $g(x,t)$ and φ. Additionally, the incorporation of fuzzy logic has led to the design of an adaptive law aimed at minimizing the impact of the error term e_m^* and achieving asymptotic stability in the system.

A. Optimization of Neural Network Approximation of Unknown Functions Using Differential Evolution Algorithm

To execute the proposed algorithm, it's essential to pre-determine the functions $\hat{f}(x,t)$, $\hat{g}(x,t)$ and $\hat{\varphi}$. In this investigation, a neural network optimized via the differential evolution algorithm is employed to model $\hat{f}(x,t)$, $\hat{g}(x,t)$ and $\hat{\varphi}$.

The neural network utilized for approximating the functions $\hat{f}(x,t)$, $\hat{g}(x,t)$ and $\hat{\varphi}$ are concurrently trained. The aim is to determine the function $\hat{x}_*^{(n)}$ that most accurately corresponds to $x^{(n)}$.

The objective function as:

$$J = \frac{1}{N}\sum_{n=1}^{N}(e_m) \tag{14}$$

Where, $e_m = x^{(n)} - \hat{x}_*^{(n)}$.

In this research, the differential evolution algorithm is employed to accurately determine the parameters of the neural network. The flowchart illustrating the differential evolution algorithm can be found in Fig. 3.

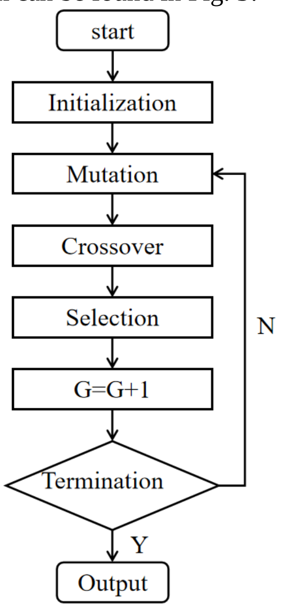

Fig. 3. Flowchart of differential evolution algorithm

The fundamental principle of this algorithm involves continually generating new intermediate individuals through mutation and crossover operations after initializing the population, followed by updating the main population through competitive selection. The fundamental steps of the differential evolution method are delineated as follows.

Initialization

In the parameter space, randomly generate a set of solutions for initialization.

$$X_i^G = [x_{1,i}^G, x_{1,i}^G \ldots x_{D,i}^G] \tag{15}$$

Where, $i = 1,2,\ldots,NP$ representing NP individuals. G is the number of generations, $G = 0,1\ldots,G_{\max}$.

Mutation

Differential evolution generates a new intermediate mutation individual by adding the weighted difference between two initialized population vectors to a third vector, as expressed below:

$$v_i^{G+1} = x_{z1}^G + F(x_{z2}^G - x_{z3}^G) \tag{16}$$

Where, $x_{z1}^G, x_{z2}^G, x_{z3}^G$ represents three randomly selected distinct individuals from the population; F denotes the scaling factor, $F \in [0,2]$. v_i^{G+1} must comply with boundary constraints and should not exceed the solution space range.

Crossover

To enhance the diversity of the population pool, a new individual is formed using the target individual and the individual generated through mutation. This study employs binomial crossover for this purpose, expressed as follows:

$$u_{j,i}^G = \begin{cases} v_{j,i}^G & if\,(rand_{j,i}[0,1] < C) \\ v_{j,i}^G & otherwise \end{cases} \tag{17}$$

Where, C denotes the crossover probability factor. Augmenting C facilitates the probability of population individual updates, while diminishing C contributes to the stability of the algorithm's search process.

Selection

The selection process involves choosing individuals between the target individuals and those formed through crossover to achieve superior fitness values. Its expression is as follows:

$$\vec{X}_i^{G+1} = \begin{cases} \vec{U}_i^G & if \quad f(\vec{U}_i^G) < f(\vec{X}_i^G) \\ \vec{X}_i^G & otherwise \end{cases} \tag{18}$$

Termination

The algorithm halts when it encounters any of these conditions: Reaching the maximum generation threshold, achieving a fitness level below the predetermined threshold, or sustaining no improvement in the best fitness over an extended period.

B. Proposed Adaptive Neural Network Sliding Mode Control

The control rate designed for the stability of the above systems, in practical applications, may be affected by disturbances such as system perturbations, which affect the accuracy of the identification and thus the stability of the system. To solve these problems, The adaptive fuzzy law (v_{FA})is introduced, and its state space model is described as follows:

$$\begin{cases} \hat{x}^{(n)} = \hat{f}(x,t) + \hat{g}(x,t)[v(t) + \hat{\varphi}] + v_{FA} \\ \hat{y} = \hat{x} \end{cases} \tag{19}$$

Where, $\hat{f}(x,t)$, $\hat{g}(x,t)$ and $\hat{\varphi}$ are neural network estimation functions; v_{FA} represents the fuzzy adaptive rate.

The adaptive neural network sliding mode control law is defined as follows:

$$v_{AFSMC} = \frac{1}{\hat{g}(x,t)}\Big[-\sum_{i}^{n-1} c_i e^{(i)} - \hat{f}(x,t) + x_d^{(n)} - K\mathrm{sign}(s) - \hat{\varphi}\hat{g}(x,t) - v_{FA}\Big] \tag{20}$$

The error of model:

$$\begin{aligned} e_m &= x^{(n)} - \hat{x}^{(n)} \\ &= x^{(n)} - \hat{f}(x,t) - \hat{g}(x,t)[v(t) + \hat{\varphi}] - v_{FA} \\ &= x^{(n)} - \hat{x}_*^{(n)} - v_{FA} = e_m^* - v_{FA} \end{aligned} \tag{21}$$

The derivative of equation (21) can be taken as follows:

$$\dot{e}_m = \dot{e}_m^* - \dot{v}_{FA} \tag{22}$$

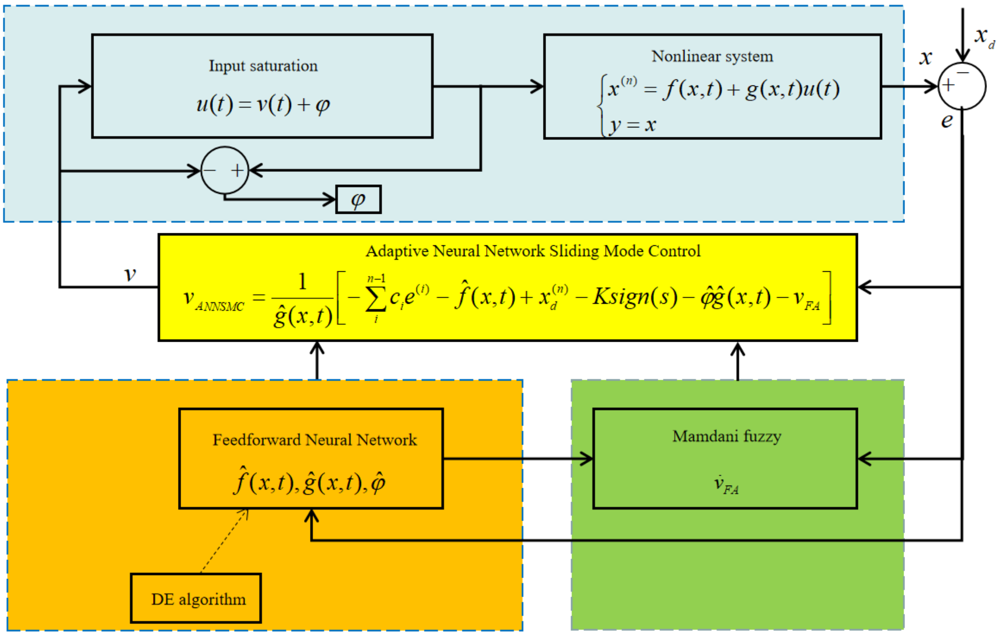

Fig. 4. Scheme of the proposed adaptive neural network control adaptive neural network sliding mode control system

To satisfy Lyapunov's stability, take the derivative of e_m as:

$$\dot{e}_m=-\lambda_A sign(e_m) \tag{23}$$

Where, $\lambda_A>0$.

By substituting equation (22) in equation (23):

$$\dot{e}_m^*-\dot{v}_{FA}=-\lambda_A sign(e_m) \tag{24}$$

Assumption: Assuming both $|\dot{v}_{FA}|>|\dot{e}_m^*|$ and $sign(\dot{v}_{FA})=sign(e_m)$ hold true.

Theorem: In addressing the control problem posed by nonlinear system (1), $f(x,t)$, $g(x,t)$ and φ propose a control law v_{AFSMC}. This approach involves the estimation process facilitated by neural network modeling and optimization employing evolutionary algorithms, operating under the assumption of $|\dot{v}_{FA}|>|\dot{e}_m^*|$ and $sign(\dot{v}_{FA})=sign(e_m)$. Consequently, it is anticipated that the signals of the closed-loop system will remain bounded, with the tracking error asymptotically converging to zero.

Table I
ADAPTIVE FUZZY RULES

	e_m		
	N	ZO	P
$\dot{v}_{FA}$	N	ZO	P

The proposed adaptive function $\dot{v}_{FA}$ should be satisfy Lyapunov stability. As shown in Table 1, the design utilizes e_m and $\dot{v}_{FA}$ as inputs and outputs of the fuzzy rule base, where PO and NE (NE=negative, ZE=zero, and PO=positive) are selected to satisfy $|\dot{v}_{FA}|>|\dot{e}_m^*|$.

Proof: Assume that the $\dot{v}_{FA}$ is chosen as $|\dot{v}_{FA}|>|\dot{e}_m^*|$ and $sign(\dot{v}_{FA})=sign(e_m)$ .From (24), the following results are obtained:

$$-sign(\dot{v}_{FA})|\dot{e}_m^*-\dot{v}_{FA}|=-\lambda_A sign(e_m) \tag{25}$$

$$|\dot{e}_m^*-\dot{v}_{FA}|=\lambda_A \tag{26}$$

Therefore, with the assumptions in $|\dot{v}_{FA}|>|\dot{e}_m^*|$ and $sign(\dot{v}_{FA})=sign(e_m)$, $\dot{e}_m=-\lambda_A sign(e_m)$ satisfies the condition. e_m has different sign with $\dot{e}_m$.

Based on the designed v_{AFSMC}, to demonstrate the stability of the control system, take the derivative of the sliding mode surface:

$$\begin{aligned}
\dot{s}&=\sum_i^{n-1} c_i e^{(i)}+x^{(n)}-x_d{}^{(n)}\\
&=\sum_i^{n-1} c_i e^{(i)}+g(x,t)[v(t)+\varphi]+f(x,t)-x_d{}^{(n)}\\
&=\sum_i^{n-1} c_i e^{(i)}+g(x,t)[v(t)+\varphi]+f(x,t)-\sum_i^{n-1} c_i e^{(i)}-\hat{f}(x,t)\\
&\quad -Ksign(s)-\hat{g}(x,t)v(t)-v_{FA}-\hat{\varphi}\hat{g}(x,t)\\
&=\big[+(g(x,t)-\hat{g}(x,t))v(t)+f(x,t)-\hat{f}(x,t))+(g(x,t)\varphi\\
&\quad -\hat{\varphi}\hat{g}(x,t)\big]-Ksign(s)-v_{FA}\\
&=e_m^*-Ksign(s)-v_{FA}\\
&=e_m-Ksign(s)
\end{aligned} \tag{27}$$

Take the Lyapunov function as:

$$V=\frac{1}{2}s^2+\frac{1}{2}e_m^2 \tag{28}$$

$$\begin{aligned}
\dot{V}&=s\dot{s}+e_m\dot{e}_m\\
&=s(-Ksign(s)+e_m)-e_m\lambda_A sign(e_m)\\
&=-\lambda_A|e_m|-K|s|+se_m
\end{aligned} \tag{29}$$

Since $\dot{e}_m=-K_A sign(e_m)$, it follows that $e_m\to 0$ when $t\to\infty$. Then, $\dot{V}\le 0$ when $t\to\infty$. The closed-loop system signals will be bounded and the tracking error will converge to zero asymptotically.

V. SIMULATION AND DISCUSSION

After completing the research and stability analysis of the neural network sliding mode control algorithm, in order to further demonstrate the effectiveness and feasibility of the control algorithm, Matlab/Simulink simulation experiments will be conducted for validation. A single-joint robotic arm control system will be constructed using Matlab, and the algorithm will be validated through simulation in Simulink. The mathematical state-space equations of the single-joint robotic arm system are formulated as follows:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -\frac{1}{I}(dx_2 + mgl\cos x_1) + \frac{1}{I}(1 + x_1 + x_2)\tau \\ y = x \end{cases} \tag{30}$$

$x_1 = \theta$, $x_2 = \dot{\theta}$, $m = 2$, $d = 4$, $l = 0.4$, the initial state of the system is $\left[\frac{\pi}{20}, 0\right]$, the initial value of θ is taken as 0, $k_1 = 1$, $k_2 = 8$, $I = \frac{4}{3}ml^2$.

A. Neural Network Sliding Mode Control System Simulation Analysis Based on Differential Evolution Algorithm

Experimental simulation was conducted based on the described algorithm, and the results are illustrated in Fig. 5 to 8. The position trajectory tracking curve is depicted in Fig. 5, the control input signal in Fig. 6, the saturated control input signal in Fig. 7, and the tracking error curve in Fig. 8. From Fig. 5, it is evident that the designed control algorithm ensures accurate tracking of the joint actual trajectory to the desired trajectory within 0.3s, even with non-zero initial values. Fig. 6 shows periodic fluctuations in joint torque, peaking approximately every 3s. However, the overall output curve remains relatively stable. Fig. 7 demonstrates a periodic amplitude in the overall torque output. Due to input saturation constraints, there is a maximum output for approximately 0.5s at each peak amplitude, maintaining overall torque output stability. Fig. 8 indicates that despite uncertainties, input saturation, and nonlinearities such as friction, the neural network optimized through the differential evolution algorithm adequately approximates modeling errors. This enables substantial compensation for unmodeled nonlinear functions, with the joint gradually approaching zero within approximately 0.7s. Moreover, the latter half of the waveform exhibits smaller fluctuations, indicative of higher control precision.

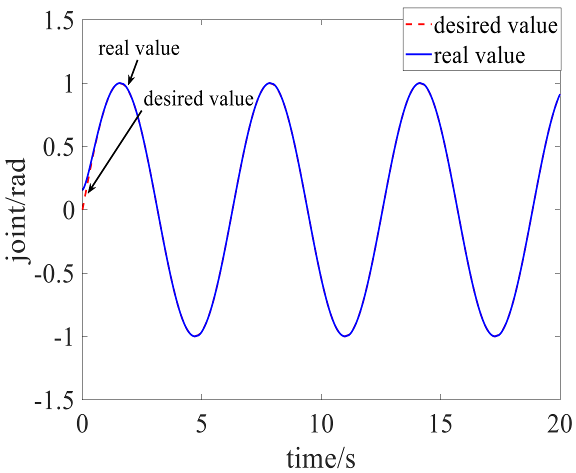

Fig. 5. Position trajectory tracking curve

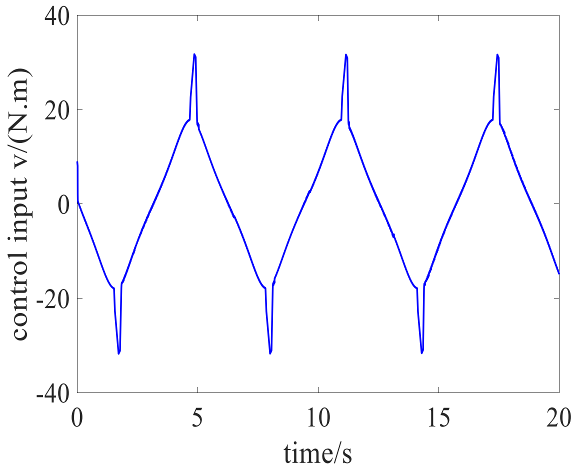

Fig. 6. Controller output curve

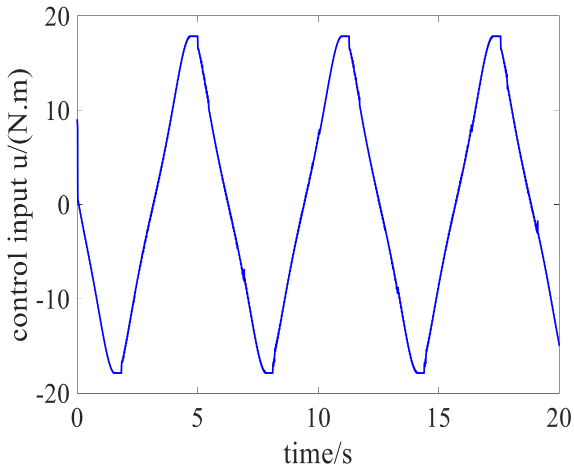

Fig. 7. Output curve with input saturation

The effectiveness of the control performance was analyzed solely using the neural network sliding mode controller, with both the differential evolution algorithm and adaptive fuzzy compensation deactivated. The simulation results are depicted in Fig. 9 to Fig. 12.

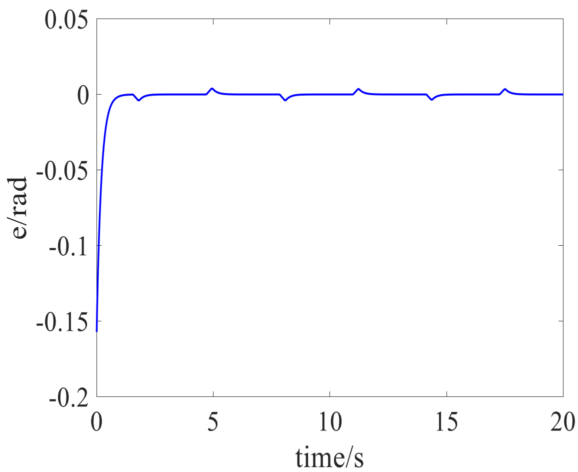

Fig. 8. Tracking error curve

After deactivating the differential evolution algorithm, the actual trajectory of the system is able to accurately track the desired target approximately at 2.2s (Fig. 9), indicating a degradation in control effectiveness. The tracking position error exhibits pronounced fluctuations, with significant oscillations occurring approximately every 6s before stabilizing again (Fig. 12). In the absence of the differential evolution algorithm, the joint torque output displays periodic fluctuations, with a peak torque output occurring approximately every 4s, and a longer duration for the maximum peak output, averaging around 1s (Fig. 10). Under input saturation constraints, the overall torque output exhibits periodic amplitude variations, with a maximum output occurring for approximately 1.2s at each peak amplitude (Fig. 11).

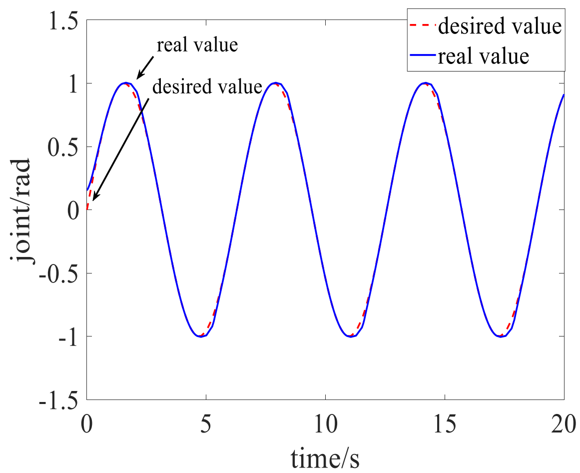

Fig. 9. Position trajectory tracking curve

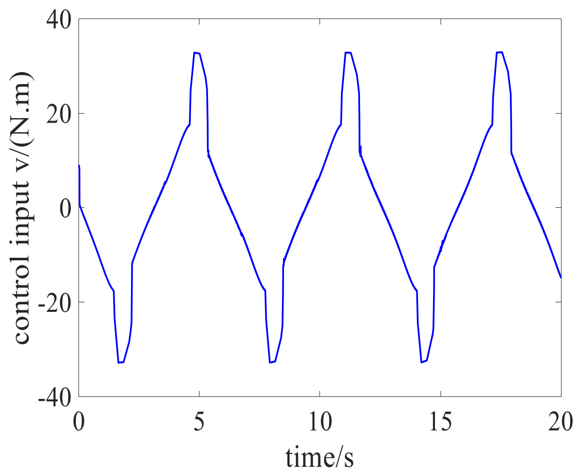

Fig. 10. Controller output curve

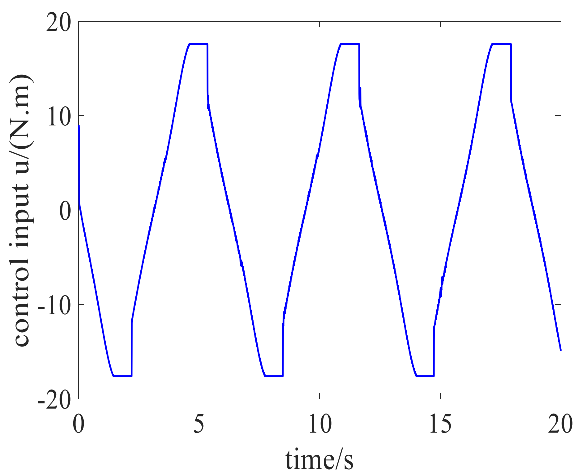

Fig. 11. Output curve with input saturation

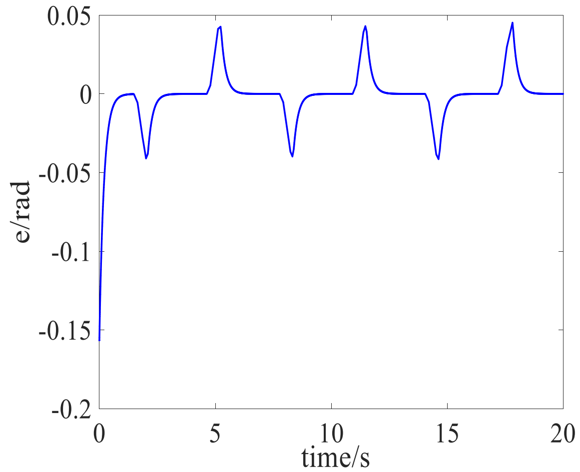

Fig. 12. Tracking error curve

VI. CONCLUSIONS

A novel neural network control method based on differential evolution algorithms is proposed in this study, aimed at addressing the control challenges of nonlinear systems affected by uncertainties such as input saturation, model uncertainty, and external disturbances. A neural network-based controller is designed to effectively compensate for system errors caused by input saturation and model uncertainties. A differential evolution algorithm is developed to address the real-time performance of the neural network while simultaneously improving the accuracy of adaptive approximation. A sliding mode controller is designed to enhance the robustness of the system. The effectiveness of the proposed control algorithm is validated through comparative experiments.

REFERENCES

[1] W. Zhang, Y. Shang, Q. Sun, et al, "Finite-Time Stabilization of General Stochastic Nonlinear Systems with Application to a Liquid-Level System," IAENG International Journal of Applied Mathematics, vol.51, no.2, pp. 295-299, 2021.
[2] X. P. Hu, C. Wang, W. Zhang, and J. Ma, "Self-learning PID Control for X-Y NC Position Table with Uncertainty Base on Neural Network," Telecommunication Computing Electronics and Control, vol.12, no.2, pp. 343-348, 2014.
[3] S. H. Zhou, X. P. Ye, X. P. Ji, and W. Zhang, "Adaptive Control of Space Robot Manipulators with Task Space Base on Neural Network," Telecommunication Computing Electronics and Control, vol.12, no.2, pp. 349-356, 2014.
[4] Y. M. Fang, W. Zhang, and X. P. Ye, "Variable Structure Control for Space Robots Based on Neural Networks," International Journal of Advanced Robotic Systems, vol.11, no.3, pp. 35-42, 2014.
[5] W. Zhang, Z. Wen, Y. Ye, and S. Zhou, "Structural mechanics analysis of bolt joint of rigid flexible coupling manipulator," Journal of Measurements in Engineering, vol.10, no.2, pp. 93-104, 2022.
[6] H. Kong, J. Ma, W. Zhang, L. Cang, S. Y. Chen, and S. H. Zhou, "Robust Control of Robot Manipulator with Uncertain Parameters Based on Neural Network," IEEE 2nd International Conference on Data Science and Computer Application, Dalian, China, October 28-30, 2022.
[7] W. Zhang, N. M. Qi, J. Ma, and A. Y. Xiao, "Neural integrated control for free-floating space robot with changing parameters," Science China: Information Science, vol.4, no.10, pp. 2091-2099, 2011.
[8] X. Guo, W. Zhang, and F. Z. Gao, "Global Prescribed-Time Stabilization of Input-Quantized Nonlinear Systems via State-Scale Transformation," Electronics, vol.12, no.15, pp. 1-18, 2023.
[9] J. Ma, W. Zhang, and H. P. Zhu, "Adaptive Control for Robotic Manipulators base on RBF Neural Network," Telecommunication Computing Electronics and Control, vol.11, no.3, pp. 521-528, 2013.

[10] H. R. Fang, Y. X. Wu, T. Xu, and F. Wan, “Adaptive neural sliding mode control of uncertain robotic manipulators with predefined time convergence,” International Journal of Robust and Nonlinear Control, vol.32, no.17, pp. 9213-9238, 2022.

[11] L. J. Jiang, W. Zhang, J. M. Shen, and S. H. Zhou, “Vibration Suppression of Flexible Joints Space Robot based on Neural Network,” IAENG International Journal of Applied Mathematics, vol.52, no.4, pp. 776-783, 2022.

[12] W. Zhang, J. M. Shen, X. P. Ye, and S. Zhou, “Error model-oriented vibration suppression control of free-floating space robot with flexible joints based on adaptive neural network,” Engineering Applications of Artificial Intelligence, no.114, pp. 105028, 2022.

[13] G. Xu, Y. Q. Xia, D. H. Zhai, and D. Ma, “Adaptive prescribed performance terminal sliding mode attitude control for quadrotor under input saturation,” IET Control Theory & Applications, vol.14, no.17, pp. 2473-2480, 2020.

[14] K. Mei, S. H. Ding, and X. Y. Chen, “Fuzzy non-singular terminal sliding mode controller design for nonlinear systems with input saturation,” International Journal of Fuzzy Systems, vol.22, pp. 2271-2283, 2020.

[15] H. Karami, K. A. Alattas, S. Mobayen, and A. Fekih, “Adaptive integral-type terminal sliding mode tracker based on active disturbance rejection for uncertain nonlinear robotic systems with input saturation,” IEEE Access, vol.9, pp. 129528-129538, 2021.

[16] K. N. Yong, M. Chen, Y. Shi, and Q. Wu, “Flexible performance-based robust control for a class of nonlinear systems with input saturation,” Automatica, vol.122, pp. 109268, 2020.

[17] Y. Q. Han, “Adaptive tracking control for a class of stochastic non-linear systems with input saturation constraint using multi - dimensional Taylor network,” IET Control Theory & Applications, vol.14, no.9, pp. 1193-1199, 2020.

[18] M. Y. Zhang, Y. L. Guan, Q. D. Li, Z. Sun, and Z. Duan, “Adaptive nonlinear control for the stabilized platform with disturbance and input saturation,” IEEE Access, vol.8, pp. 200774-200788, 2020.

[19] Y. Hu, W. Zhang, “Modeling framework for analyzing midair encounters in hybrid airspace where manned and unmanned aircraft coexist,” Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering, vol.233, no.15, pp. 5492-5506, 2019.

[20] Z. P. You, W. Zhang, and J. M. Shen, “Adaptive neural network vibration suppression control of flexible joints space manipulator based on H∞ theory,” Journal of Vibroengineering, vol.25, no.3, pp. 492-505, 2023.

[21] W. Zhang, X. P. Ye, L. H. Jiang, et al, “Output feedback control for free-floating space robotic manipulators base on adaptive fuzzy neural network,” Aerospace Science and Technology, vol.29, no.1, pp. 135-143, 2013.

[22] Y. L. L, W. Zhang, and T. Zhou, “Machine Health-Driven Dynamic Scheduling of Hybrid Jobs for Flexible Manufacturing Shop,” International Journal of Precision Engineering and Manufacturing, vol.24, no.5, pp. 797-812, 2023.

[23] J. M. Shen, W. Zhang, S. H. Zhou, et al, “Fuzzy Adaptive Compensation Control for Space Manipulator with Joint Flexibility and Dead Zone Based on Neural Network,” International Journal of Aeronautical and Space Sciences, vol.24, no.3, pp. 876-889, 2023.

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