Revolutionizing Ideological and Political Teaching with AI-Powered Feedback Neural Network

Shanshan Zuo[1*]

[1]Institute of Science, Inner Mongolia University of Science and Technology, Baotou, Inner Mongolia, 014010, China.

Corresponding author: Shanshan Zuo, shanshanzuo456@aol.com

Abstract. This paper proposes to enhance the effectiveness of the ideological and political teaching system and upgrade the quality of ideological and political education by integrating the feedback neural network and artificial intelligence technology into the design of the ideological and political teaching system, thus increasing its intelligence. Aiming at the state feedback optimal control problem of nonlinear systems with input constraints, an optimal control algorithm based on policy iteration is propose to solve the state feedback controller of the system. Moreover, this paper adopts the modified strategy iterative algorithm to solve the equation, and uses the ACD structure neural network to realize. The research shows that the ideological and political teaching system based on the feedback neural network proposed in this paper can play an important role in the ideological and political teaching.

Keywords: feedback neural network; artificial intelligence; ideology and politics; teaching system

DOI: https://doi.org/10.14733/cadaps.2023.S9.186-205

1 INTRODUCTION

As a powerful tool to study complexity, in recent years, neural network technology has demonstrated its extraordinary superiority in pattern recognition and classification, recognition filtering, automatic control, and prediction. Moreover, the emergence of artificial neural network provides a new way for the evaluation of teaching quality in colleges and universities. Through continuous learning and training, artificial neural network can find its regularity from a large amount of complex data with unknown patterns, especially it can process any type of data, which is unmatched by many traditional methods [1]. Therefore, applying the theory of artificial neural network to the teaching quality evaluation system solves the problem of qualitative and quantitative indicators in the comprehensive evaluation index system. Moreover, it overcomes the problems of establishing complex mathematical models and mathematical analytical expressions in the traditional evaluation process, and also avoids the direct influence of the evaluator's subjective factors on the evaluation results. Because the modeling of artificial neural network is a nonlinear modeling process, there is no need to distinguish what nonlinear relationship exists. After analyzing a large number of sample data, the neural network weight coefficient is determined to evaluate the teaching quality [2].

The establishment of the evaluation model of the teacher's teaching effect of the neural network must be based on sufficient and truly scientific and authoritative historical sample data [3]. The whole evaluation process of teachers' teaching effect focuses on the basis of empirical materials and data, and pays attention to the combination of teachers' self-evaluation, mutual evaluation and teacher evaluation, which improves the credibility of evaluation results [4]. In order to select the sample data to be scientific, typical and representative. The selection of samples has become a key part of neural network training, and the quality of the samples directly affects the evaluation results of the system [5]. The system uses a variety of forms to collect sample data extensively, including the evaluation of experts from the Ministry of Education, the evaluation of teachers in colleges and universities, the evaluation of students in school, the evaluation of graduate students, and the social evaluation [6]. The form of the information card is directly read by a card reader, which is suitable for students and teachers in school. The Internet has become the mainstream of information acquisition with its powerful interactivity, wide dissemination, openness in time and space, convenience in data collection and management, personalized information exchange, and fast data statistics and analysis functions. The advantages of teaching quality are introduced into the teaching quality evaluation system, which makes the teaching quality evaluation quantified, objectified and systematic [7].

To conduct teaching quality evaluation, we must first determine a set of scientific teaching quality evaluation index system. There are many studies on the evaluation of teaching quality, and the composition of the indicators is also different, but few are aimed at the characteristics of colleges and universities. Especially when the current higher education puts forward the new curriculum requirements that are student-centered and work-process-oriented, the evaluation standard of teaching quality is even more lagging behind [8]. Combined with the current requirements of higher education, the evaluation index system of teaching quality in colleges and universities is reconstructed. It is mainly composed of 6 first-level indicators and 18 second-level indicators [9].

BP neural network has strong nonlinear fitting ability, can map any complex nonlinear relationship, and the learning rules are simple, easy to realize by computer, with strong robustness, memory ability, nonlinear mapping ability and strong self-determination. learning ability, so it has been widely used in numerical fitting prediction. Literature [10] screened out the factors affecting student performance as the input data of the neural network, used the historical results of previous students as the output results, established an artificial neural network prediction model based on the BP algorithm, and the test accuracy of predicting student performance reached 84.6%. It shows that the BP neural network has good robustness in predicting students' grades, and verifies the feasibility of this method to solve the problem of grade prediction. The use of BP neural network needs to first determine the input and output of the network, and the smart classroom software will collect various data in the course management process, including attendance data, question and answer statistics, interaction times, test scores, homework scores, seat information and other data. Which data is selected as the input of the neural network is particularly important [11]. Literature [12] uses clustering algorithm to analyze the factors that affect students' performance, and the results show that in terms of subjective factors affecting students' performance, students' course interest, pre-class attendance, classroom status, and after-school homework have a greater impact on performance. To sum up, three types of information of students' pre-class attendance, classroom performance and after-school homework are selected as the input of the neural network; the output of the grade prediction model is a node, that is, the comprehensive grade of the course.

After building the system, we use it for instant feedback on teaching effectiveness. Although the constructed system still has some deficiencies in the recognition rate, it has generally been able to reflect the students' listening status to a certain extent [13]. For some students who do not look up, the system is difficult to identify. But the student does not look up to face the teacher, which also shows that the student is not keeping pace with the teacher's teaching, or that the teacher's teaching is not engaging enough to attract the students' attention to him. What the system does is a kind of macro statistics [14]. Input the approximate number of students before the class, turn on the camera at the beginning of the teaching, the system will continuously obtain image data, calculate the proportion of students who listen to the class seriously, analyze the effect of listening to the class in real time, and feedback the current listening status to the teacher [15]. When the effect of listening to the class is low and reaches a certain threshold, the system reminds teachers to provide reference for teachers to make decisions. Before adopting this system, teachers have to teach lessons on the one hand, and observe students' listening status on the other hand. After adopting the system, because the system continuously analyzes and provides first-hand authoritative information, teachers do not have to spend extra energy to count how many students do not listen to the class carefully, and can focus more on theoretical explanations [16].

This paper combines feedback neural network and artificial intelligence technology to construct an ideological and political teaching system, improve the intellectualization of ideological and political teaching, and promote the modernization and reform of ideological and political teaching.

2 STATE FEEDBACK CONTROL OF UNKNOWN NONLINEAR SYSTEMS WITH INPUT SATURATION

In this paper, an optimal control algorithm based on policy iteration is proposed to solve the H_∞-state feedback control problem of a class of unknown nonlinear systems with input saturation. First, this paper uses the quasi-norm method to deal with the input constraints in the system, and transforms the optimal control problem into solving the Hamilton-Jacobi-Isaacs (HJI) equation. Secondly, this paper uses the strategy iteration idea to solve the HJI equation, and constructs an Actor-Critic-Disturbance (ACD) neural network to implement the strategy iteration algorithm. Finally, the validity of the algorithm is verified by a Translational Oscillations with a Rotational Actuator (TORA) system.

How to improve the performance of the system has gradually been paid attention to, and the optimal control theory is established and developed under this background. The so-called optimal control means that the performance index function of the controlled system can reach the optimal (maximum or minimum value) by designing the optimal controller under the given constraints. The birth of optimal control theory reflects the inevitable requirement of the orderly structure of the system to develop to a higher level. This makes the optimal control theory more and more widely used in the industrial production process. Aiming at the H_∞ control problem of nonlinear systems, a method for solving the HJI equation is proposed, and it is proved that the HJI equation can be expressed as a scalar quadratic equation with additional conditions, and a calculation method to determine the symmetric solution is given. The literature analyzes the static output feedback control problem of a linear discrete-time system with saturable actuators and designs a feedback controller.

The mathematical theory of H_∞-control has developed considerably over the decades. The literature presents nonlinear simulations of the simplest part of the recently developed state-space approach to linear H_∞-control, and also discusses the relationship of linearized systems to H_∞-control. The state feedback H_∞ control problem of a class of nonlinear systems is studied, which is solved by a class of type storage functions whose integral terms are parameterized by nonlinear scalar functions.

An optimization algorithm based on policy iteration is proposed to solve the HJI equation. First, the formal solution of the H_∞ control problem for dynamic systems with input constraints is given, and the H_∞ control problem is transformed into a non-quadratic two-person zero-sum game problem using quasi-norm. Secondly, the optimal strategy of the zero-sum game is solved by using the strategy iterations of both sides of the game (optimal control strategy and worst-case perturbation strategy). Finally, a dynamic learning algorithm consisting of three neural networks (one critical neural network and two executive neural networks) is proposed, which learns the solutions of the HJI equations in real time without requiring knowledge of system dynamics.

In this paper, we consider a class of nonlinear continuous-time systems whose dynamic information is partially unknown.

$$\begin{cases} \dot{x}(t) = f\left(x(t)\right) + g\left(x(t)\right)u(t) + h\left(x(t)\right)d(t) \\ y(t) = k\left(x(t)\right) \end{cases} \tag{2.1}$$

Among them, $x(t) \in R^n$ and $y(t) \in R^p$ represent the state and output of the system, respectively, $f(t) \in L_2[0,\infty)$ is the disturbance, f(x) is an unknown nonlinear function, and f(0) = 0. g(x), h(x) and k(x) are all known continuous functions, $y(t)$ is the virtual output, $u(t) \in U$ is the control input, where:

$$U = \left\{u(t) \in L_2[0,\infty) \mid -\beta_i \le u_i \le \beta_i, i = 1,2,\ldots,m\right\} \tag{2.2}$$

We assume that x = 0 is the equilibrium point of the system, and for any smooth state, we have:

$$u(t) = l(x), l(0) = 0 \tag{2.3}$$

Definition 1.1 For a given y ≥ 0, the L gain of system (1) is less than y, and if

$$\int_0^T \left\|y(t)\right\|^2 + \left\|u(t)\right\|^2 dt \le \gamma^2 \int_0^T \left\|d(t)\right\|^2 dt \tag{2.4}$$

For all T ≥ 0 and $d \in L_2(0,T), y > 0$ represents the level of interference attenuation.

The key to the H_∞ optimal control problem is to find a state feedback control u(t), which makes the closed-loop system (1) asymptotically stable and has L gain less than or equal to y. It can be seen that the H problem is equivalent to solving the following two-person zero-sum game problem.

$$V^*(x_0) = \min_{u \in U} \max_{d(t)} \int_0^\infty \left(k^T k + \left\|u\right\|^2 - y^2 \left\|d\right\|^2\right) dt \tag{2.5}$$

Without considering the internal information of the system, the H_∞ optimal controller is designed by solving the HJI equation.

Theorem 1.1 For a nonlinear system (1), if a smooth solution to the following Hamilton-Jacobi equation exists:

$$\frac{\partial V}{\partial x}(x) f(x) + \frac{1}{2} k^T(x) k(x) + \frac{1}{2} \frac{\partial V}{\partial x}(x) \left[\frac{1}{y^2} h(x) h^T(x) - g(x) g^T(x)\right] \frac{\partial^2 V}{\partial x}(x) = 0 \tag{2.6}$$

Then, the feedback controller of the closed-loop system has L2 gain, and the gain is less than y.

$$u=-g^{T}(x)\frac{\partial^{T}V}{\partial x}(x) \tag{2.7}$$

Proof: From formula (6) and formula (7), it can be known that:

$$\begin{aligned}\frac{\partial V}{\partial x}&=\frac{\partial V}{\partial x}\cdot(f+gu+hd)\\&\le\frac{\partial V}{\partial x}\cdot f+\frac{1}{2}\left\|u+g^{T}\frac{\partial^{2}V}{\partial x}\right\|^{2}-\frac{1}{2}\left\|dd-\frac{1}{y^{2}}h^{T}\frac{\partial^{2}V}{\partial x}\right\|^{2}\\&\le-\frac{1}{2}k^{T}k-\frac{1}{2}\|u\|^{2}+\frac{1}{2}y^{2}\|d\|^{2}\end{aligned} \tag{2.8}$$

Integrating both sides of the above equation from 0 to T≥0 at the same time, we can get:

$$\frac{1}{2}\int_{0}^{T}\left(k^{T}k-\|u\|^{2}\right)dt\le\frac{1}{2}\int_{0}^{T}y^{2}\|d\|^{2}dt+V(x_{0})-V(x(T)) \tag{2.9}$$

Since $V(x_0)=0$ and V(x(T))≥0, we have:

$$\int_{0}^{T}\left(k^{T}k+\|u\|^{2}\right)dt\le\frac{1}{2}\int_{0}^{T}y^{2}\|d\|^{2}dt+V(x_{0})-V(x(T)) \tag{2.10}$$

Note that this is a constrained optimization problem with respect to the input u. In this case, this section will introduce the definition of quasi-norm to solve this problem.

Definition 1.2 On the vector space V, the properties of the quasi-norm $\|x\|_q$ are:

1. $\|x+y\|_q\le\|x\|_q+\|y\|_q$

2. $\|x\|_q=\|-x\|_q$

3. $\|x\|_q\Leftrightarrow x=0$

where the second property can be replaced by the homogeneity defined by the normal norm, namely $\|ax\|_q=|a|\|x\|_q$. If $\varphi^{-1}(\tau)$ is assumed to be monotonic and there is $\|u\|_q\in C^{1}$, then a suitable quasi-norm exists to solve the input saturation problem.

Definition 1.3 The system (1) is said to be zero-state observable. If u(t)=0, d(I)=0, y(h)=0 for any trajectory, then x(t)=0, that is, for all x ∈ M, all have:

$$k(\Phi(t,0,x,0))=0\Rightarrow\Phi(t,0,x,0)=x_{0} \tag{2.11}$$

Lemma 1.1 If the system i = f(x) is assumed to be observable in zero state, then the closed-loop system (1) under the action of the controller (7) is locally asymptotically stable and has V(x)>0 for x ≠x0. Therefore, formula (5) can be expressed as the following finite field zero-sum game problem.

$$V^*(x_0,T)=\min_u \max_d \int_0^T \left(k^T k+2\int_0^u \varphi^{-1}-y^2\|d\|^2\right)dt \tag{2.12}$$

The Hamiltonian equation for this zero-sum game problem is:

$$H(x,u,d,V_x)=\left(k^T k+2\int_0^u \varphi^{-1}(\tau)d\tau-y^2\|d\|^2\right)+V_x^T(f+gu)+hd \tag{2.13}$$

Lemma 1.2 For Hamilton's equation (14), the Isaac condition is satisfied:

$$\min_d \max_u H=\min_u \max_d H \tag{2.14}$$

Proof: According to steady state conditions, we know:

$$\frac{\partial H}{\partial u}=0,\frac{\partial H}{\partial d}=0 \tag{2.15}$$

Then, there is:

$$2\varphi^{-1}(u^*)+(g(x(t)))^T V_x=0 \tag{2.16}$$

$$-2y^2 d^*+(h(x(t)))^T V_x=0 \tag{2.17}$$

Solving the above equation, we get:

$$u^*=-\varphi\left(\frac{1}{2}g(x(t))^T V_x\right) \tag{2.18}$$

$$d^*=\frac{1}{2y^2}(h(x(t)))^T V_x \tag{2.19}$$

Substituting formula (19) and formula (20) into formula (14), we can get:

$$\begin{aligned}H^*&=k^T k+2\int_0^{u^*}\varphi^{-1}(\tau)d\tau-y^2\|d\|^2+V_x^T(f+gu^*+hd^*)\\&=k^T k+V_x^T f-2\varphi^{-1}(u^*)+\frac{1}{2y^2}hh^T V_x+2\int_0^{u^*}\varphi^{-1}(\tau)d\\&-y^2\frac{1}{2y^2}h^T V_x^T\left(\frac{1}{2y^2}h^T V_x\right)\\&=k^T k+2\int_0^{u^*}\varphi^{-1}(\tau)d\tau+\frac{1}{4y^2}V_x^T hh^T V_x+V_x^T f-2\varphi^{-1}(u^*)^T\end{aligned} \tag{2.20}$$

Thus, there is:

$$H = H\left(x,u^*,d^*,V_x\right) - 2\varphi^{-1}\left(u^*\right)u^* + 2\int_0^u \varphi^{-1}\left(\tau\right)d\tau$$
$$-2\int_0^{u^*} \varphi^{-1}\left(\tau\right)d\tau - y^2\left\|d\right\|^2 - y^2\left\|d^*\right\|^2 \tag{2.21}$$
$$= H^*\left(x,u^*,d^*,V_x\right) + 2\left(\int_0^u \varphi^{-1}\left(\tau\right) - \varphi^{-1}\left(u^*\right)\left(u-u^*\right)\right) - y^2\left(\left\|d\right\|^2 - \left\|d^*\right\|^2\right)$$

According to the integral median theorem, we know that:

$$\int_{u^*}^u \varphi^{-1}\left(\tau\right)d\tau - \varphi^{-1}\left(u^*\right)\left(u-u^*\right) > 0 \tag{2.22}$$

Since formula (19) holds for all d and u, we have:

$$H\left(x_0,u^*,d^*,V_x\right) \le H\left(x_0,u^*,d^*,V_x\right) \le H\left(x_0,u,d^*,V_x\right) \tag{2.23}$$

When $T \to \infty$, there is the Isaac equation:

$$H^*\left(u^*,d^*,V_x\right) = k^T k + 2\int_0^{u^*} \varphi^{-1}\left(\tau\right)d\tau - y^2\left\|d\right\|^2 + V_x^T\left(f + gu^* + hd^*\right) = 0 \tag{2.24}$$

Then, the HJI equation with the input constraint system (1) can be obtained.

$$k^T k + 2\int_0^{-\varphi\left(\frac{1}{2}g^T V_x^T\right)} \varphi^{-1}\left(\tau\right)d\tau + \frac{1}{4y^2}V_x^T hh^T V_x + V_x^T f - V_x^T g\varphi\left(\frac{1}{2}g^T V_x^T\right) = 0 \tag{2.25}$$

Lemma 1.3 If it is assumed that when d=0, the zero state of system (1) is observable, and formula (3-6) has a smooth solution V≥0, then x ≠ Xo, V(x) > 0, and the system i = f(x) is locally asymptotically stable.

Proof: V≥0 satisfies formula (6). According to the objectivity of the zero state, for x ≠ xo, there is V) > 0, then when uD)=0, the inequality can be obtained.

$$\frac{\partial V}{\partial x}\left(x\right)f\left(x\right) \le -\frac{1}{2}k^T\left(x\right)k\left(x\right) \tag{2.26}$$

According to the Lassalle invariance principle, the system is asymptotically stable. Furthermore, assuming that the set {x ∈ M0 ≤ V(x)≤a} is compact for every ɑ > 0, then i = f(x) is globally asymptotically stable.

Theorem 1.2_ For a nonlinear system with disturbance d, if there is a smooth feedback control u(x) such that inequality (3-4) holds, then the following system:

$$\dot{x} = f - g\varphi\left(\frac{1}{2}g^T V_x\right) + \frac{1}{2y^2}hh^T V_x \tag{2.27}$$

is locally asymptotically stable.

Proof: For system (4), we have:

$$u_1 := -\varphi\left(\frac{1}{2}g\left(x\left(t\right)\right)^T\right)V_x \tag{2.28}$$

If V(x) is smooth, then there exists V1 ≥ 0 such that the following equation holds.

$$\frac{\partial V_1}{\partial x}(x)\left(f(x)+g(x)u_1\right)+\frac{1}{2y^2}V_{1x}hh^TV_{1x}^T+\frac{1}{2}k^T(x)k(x)+\frac{1}{2}u_1^Tu_1=0 \tag{2.29}$$

Since V satisfies the corresponding inequality (27), V1≤V. Then,

$$\begin{aligned}&\frac{\partial V_1}{\partial x}(x)\left(f(x)-g(x)\varphi\left(\frac{1}{2}g(x)\right)^T V_{1x}\right)\\&=\frac{\partial V_1}{\partial x}(x)\left(f(x)+g(x)u_1\right)+\frac{\partial V_1}{\partial x}(x)g(x)\left(-\varphi\left(\frac{1}{2}g(x)\right)^T V_x-u_1\right)\\&=\frac{1}{2y^2}V_{1x}hh^TV_{1x}^T-\frac{1}{2}k^T(x)k(x)-\frac{1}{2}\left\|u_1-\varphi\left(\frac{1}{2}g(x)\right)^T V_{1x}\right\|^2\\&-\frac{1}{2}\varphi\left(\frac{1}{2}g(x)V_{1x}\right)g(x)g^T(x)\varphi\left(\frac{1}{2}g(x)^T V_{1x}\right)\end{aligned} \tag{2.30}$$

Therefore,

$$\begin{aligned}&\frac{\partial V_1}{\partial x}(x)\left(f(x)-g(x)\varphi\left(\frac{1}{2}g(x)\right)^T V_{1x}\right)+\frac{1}{2}\frac{1}{y^2}V_{1x}hh^TV_{1x}^T+\frac{1}{2}k^T(x)k(x)\\&+\frac{1}{2}\varphi\left(\frac{1}{2}g(x)V_x\right)g(x)g^T(x)\varphi\left(\frac{1}{2}g(x)^T V_x\right)\le 0\end{aligned} \tag{2. 31}$$

At the same time, if $u_2:=-\varphi\left(\frac{1}{2}g\left(x(t)\right)^T V_{1x}\right)$ is defined, then there is V2≥0 that makes the following equation true.

$$\frac{\partial V_2}{\partial x}(x)\left(f(x)+g(x)u_2\right)+\frac{1}{2}\frac{1}{y^2}V_{2x}hh^TV_{2x}^T+\frac{1}{2}k^T(x)k(x)+\frac{1}{2}u_2^Tu_2=0 \tag{2.32}$$

Similarly, $V_2\le V_1$ can be obtained. Then, there is:

$$0\le\cdots\le V_i\le\cdots\le V_1\le V \tag{2.33}$$

Among them, V_i satisfies:

$$\begin{aligned}&\frac{\partial V_1}{\partial x}(x)\left(f(x)-g(x)\varphi\left(\frac{1}{2}\left(g(x)\right)\right)^T V_{(i-1)x}\right)+\frac{1}{2}\frac{1}{y^2}V_{1x}hh^TV_{1x}^T+\frac{1}{2}k^T(x)k(x)\\&+\frac{1}{2}\varphi\left(\frac{1}{2}g(x)V_{(i-1)x}\right)g(x)g^T(x)\varphi\left(\frac{1}{2}g(x)^T V_{(i-1)x}\right)\le 0\end{aligned} \tag{2.34}$$

According to (33), it can be seen that V converges to $V^*\ge 0$ point by point, that is,

$$V^* = \lim_{i\to\infty} V_i(x) \tag{2. 35}$$

It can be seen that V^* satisfies the formula (6). From Lemma (1.3), the system (28) is asymptotically stable.

To solve the HI equation (26), a policy iterative learning algorithm is introduced. The steps are as follows.

1. The initial function V_0 is given, and according to equations (19) and (20), the initial control strategy and the initial disturbance strategy can be obtained.

$$u_0 = -\varphi\left(\frac{1}{2} g(x(t))^T V_0\right)$$

$$d_0 = \frac{1}{2y^2}\left(h(x(t))\right)^T V_0$$

2. Below u_i and d_i, the algorithm solves for $V^{(i+1)}$ according to the following equation.

$$\begin{aligned}&\frac{\partial V_{i+1}}{\partial x}(x)\left(f(x) - g(x)\varphi\left(\frac{1}{2}\left(g(x)\right)\right)^T V_{(i)x}\right) + \frac{1}{2}\frac{1}{y^2} V_{1x} h h^T V_{ix}^T + \frac{1}{2} k^T(x) k(x)\\ &+\frac{1}{2}\varphi\left(\frac{1}{2} g(x) V_{(i-1)x}\right) g(x) g^T(x)\varphi\left(\frac{1}{2} g(x)^T V_{(i-1)x}\right) = 0\end{aligned} \tag{2.36}$$

3. The algorithm updates the policy according to the following equation.

$$u_{i+1} = -\varphi\left(\frac{1}{2} g(x(t))^T V_{i+1}\right) \tag{2.37}$$

$$d_{i+1} = \frac{1}{2y^2}\left(h(x(t))\right)^T V_{i+1} \tag{2.38}$$

4. The algorithm sets i=i+1, and if $\left|V_{i+1} - V_i\right| \le \varepsilon$ is satisfied, (ε >0 is a predetermined constant) the algorithm stops the iteration, otherwise, the algorithm returns to the second step and continues the cycle.

According to formula (26), the value function is defined as:

$$V(u,d) = \int_0^\infty \left(k^T(x(t)) k(x(t))\right) dt + \int_0^\infty 2\int_0^{u(t)} \varphi^{-1}(\tau) d\tau - y^2 \left\|d(t)\right\|^2 dt \tag{2.39}$$

For the initial system state x(t), after the arbitrary control u() and disturbance signal d(t) are given, its cost function is:

$$V(x(t)) = \int_t^\infty \left(k^T(x(\tau)) k(x(\tau))\right) d\tau + \int_0^\infty 2\int_0^{u(\tau)} \varphi^{-1}(v) d\tau - y^2 \left\|d(\tau)\right\|^2 d\tau \tag{2.40}$$

$$\begin{aligned}&V(x(t)) - V(x(t+\Delta t)) = \int_t^{t+\Delta t} \left(k^T(x(\tau)) k(x(\tau))\right) d\tau\\ &+\int_t^{t+\Delta t} 2\int_0^{u(\tau)} \varphi^{-1}(v) dv - y^2 \left\|d(\tau)\right\|^2 d\tau\end{aligned} \tag{2.41}$$

Next, the ACD structural neural network is introduced to approximate the value function, control strategy and perturbation strategy, respectively. The value function (40) can be approximated as:

$$\hat{V}^{(i+1)}(t)=\left(W^{(i+1)}\right)^{T}\Phi_{N}\left(x(t)\right) \tag{2.42}$$

Among them, $W^{(i+1)}=\left(w_{1}^{(i+1)},\ldots,w_{N}^{(i+1)}\right)^{T}$ is the weight vector, and $\Phi_{N}\left(x(t)\right)=\left(\Phi_{1}\left(x(t)\right),\ldots,\Phi_{N}\left(x(t)\right)\right)^{T}$ is the activation function. Then, formula (41) can be rewritten as:

$$\begin{aligned}&\left(W^{(i+1)}\right)^{T}\left(\Phi_{N}\left(x(t)\right)-\Phi_{N}\left(x(t+\Delta t)\right)\right)\\&=\int_{t}^{t+\Delta t}\left(k^{T}\left(x(\tau)\right)k\left(x(\tau)\right)\right)d\tau+\int_{t}^{t+\Delta t}2\int_{0}^{\hat{u}^{(i)}(\tau)}\varphi^{-1}(v)dv-y^{2}\left\|\hat{d}^{(i)}(\tau)\right\|^{2}d\tau\end{aligned} \tag{2.43}$$

According to formula (37) and formula (38), we can get:

$$\hat{u}^{(i+1)}=-\varphi\left(\frac{1}{2}g\left(x(t)\right)\right)^{T}\nabla\hat{V}^{(i+1)}=-\varphi\left(\frac{1}{2}g\left(x(t)\right)\right)^{T}\nabla\Phi_{N}^{T}W^{(i+1)} \tag{2.44}$$

$$\hat{d}^{(i\_1)}=\frac{1}{2y^{2}}\left(h\left(x(t)\right)\right)^{T}\nabla\hat{V}^{(i+1)}=\frac{1}{2y^{2}}\left(h\left(x(t)\right)\right)^{T}\Phi_{N}^{T}W^{(i+1)} \tag{2.45}$$

Among them, $\nabla\Phi_{N}$ represents the Jacobian of Φ_{N} .

The algorithm collects M state trajectory samples in the interval [t, t + Ar], and finds the solution of $W^{(i+1)}$ by least squares.

$$W^{(i+1)}=\left(\Gamma\Gamma^{T}\right)^{-1}\Gamma\wedge \tag{2.46}$$

Among them,

$$\Gamma=\begin{bmatrix}\Phi_{N}\left(x(t)\right)-\Phi_{N}\left(x(t+\delta t)\right),\cdots\\ \Phi_{N}\left(x(t+(M-1)\delta t)\right)-\Phi_{N}\left(x(t+M\delta t)\right)\end{bmatrix} \tag{2.47}$$

$$\wedge=\begin{bmatrix}V\left(x(t),\hat{u}^{(i)},\hat{d}^{(i)}(t)\right),\cdots V\left(x\left(t+(M-1)\delta t\right)\right)\\ \hat{u}^{(i)}\left(t+(M-1)\delta t\right)-\hat{d}^{(i)}(t)\left(t+(M-1)\delta t\right)\end{bmatrix}^{T} \tag{2.48}$$

$$V\left(x,\hat{u}^{(i)},\hat{d}^{(i)}\right)=\int_{t+j\delta t}^{t+(j+1)\delta t}\left(k\left(x(\tau)\right)^{T}k\left(x(\tau)\right)\right)d\tau+2\int_{0}^{\hat{u}^{(i)}(\tau)}\varphi^{-1}(v)dv-y^{2}\left\|\hat{d}^{(i)}\right\|^{2}d\tau \tag{2.49}$$

The steps of the policy iteration algorithm are as follows.

1. The algorithm selects an activation function such as $\Phi_{k}(x),k=1,\ldots,N$. The algorithm gives the initial weight $W^{(0)}$ such that:

$$\hat{V}^{(0)}(t)=\left(W^{(0)}\right)^{T}\Phi_{N}\left(x(t)\right)$$

$$\hat{u}^{(0)}=-\varphi\left(\frac{1}{2}g\left(x(t)\right)\right)^{T}\nabla\Phi_{N}^{T}W^{(0)},\hat{d}^{(0)}=\frac{1}{2y^{2}}\left(h\left(x(t)\right)\right)^{T}\nabla\Phi_{N}^{T}W^{(0)}$$

2. The algorithm collects M state trajectory points in each interval [t, t+A, and uses the control strategy u and the disturbance strategy d:

3. The algorithm updates the control strategy and the disturbance strategy through formulas (44) and (45):

3 IDEOLOGICAL AND POLITICAL TEACHING SYSTEM BASED ON FEEDBACK NEURAL NETWORK ALGORITHM AND ARTIFICIAL INTELLIGENCE

Starting from the entire student evaluation and examination process, this paper can give a general understanding of the data flow of the system, and can also clearly understand the functions to be implemented by the system, as shown in Figure 1.

A discrete Hopfield network is a recurrent neural network with feedback connections from the network output to the network input. Figure 2 is a structure diagram of a discrete Hopfield neural network, and the network contains 4 neurons.

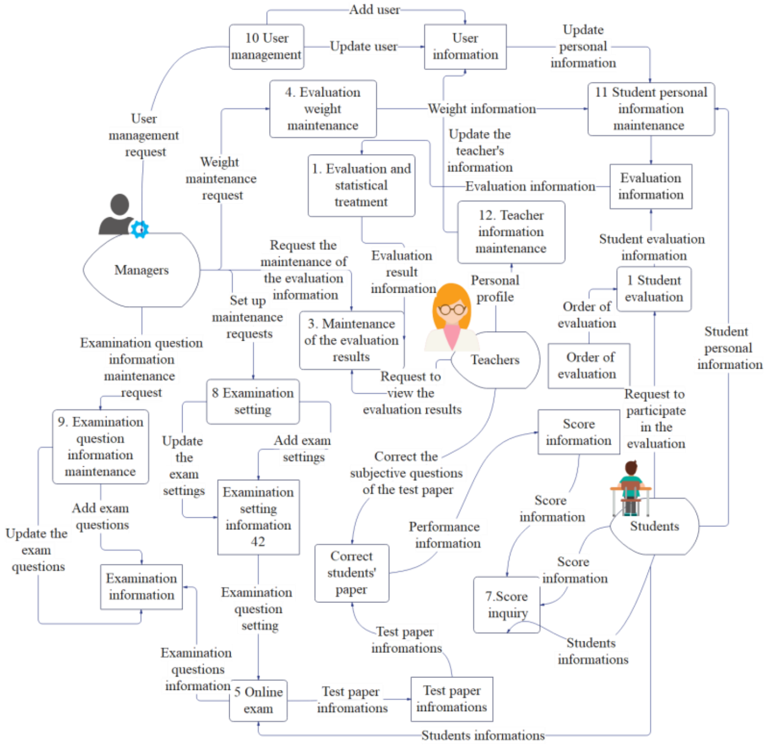


Figure 1: System structure diagram.

This article will design two discrete Hopfield neural networks. One network is used for training to generate the implicit feedback coefficient R, which is called the implicit feedback parameter network N1, and the other network is used to generate the grade evaluation of teachers' teaching ability, which is called the grade evaluation network N2, as shown in Figure 3.

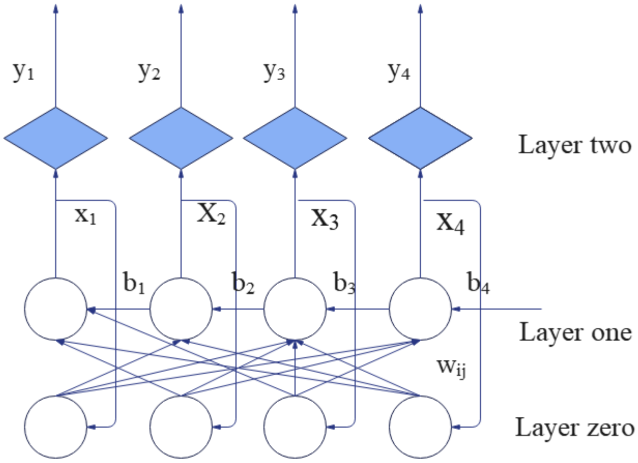


Figure 2: Structure diagram of discrete Hopfield neural network.

3.1 Experimental Research

In order to verify the effectiveness of the H-state feedback control method proposed in this chapter, a translational oscillator (TORA) system is introduced in this section.

The TORA system is also known as a Rotational/Translational Proof-mass Actuator (RTAC) system, and the physical meaning of the parameters in this section is the same as in the literature. k represents the linear spring stiffness, F is the disturbance force, and M and m represent the mass of the trolley and the mass of the detection actuator, respectively. Among them, the moment of inertia of the detection actuator is I, its center of mass is a distance e from the axis on which it rotates, and N is the control torque applied to the detection actuator.

The equations of motion for the system TORA are given.

$$\begin{cases} (M+m)\ddot{q}+kq=-me\left(\ddot{\theta}\cos\theta-\ddot{\theta}^2\sin\theta\right)+F \\ \left(1+me^2\right)\ddot{\theta}=-me\ddot{q}\cos\theta+N \end{cases} \tag{3.1}$$

By normalizing, we get:

$$\varepsilon =: \sqrt{\frac{M+m}{1+me^2}}, \tau =: \sqrt{\frac{j}{M+m}}t, u =: \frac{M+m}{k\left(1+me^2\right)}N, d =: \frac{1}{k}\sqrt{\frac{M+m}{1+me^2}}F$$

The equations of motion of the system become dimensionless equations.

$$\begin{cases} \ddot{\xi} + \xi = -\varepsilon\left(\ddot{\theta}\cos\theta - \dot{\theta}^2\sin\theta\right) + d \\ \ddot{\theta} = -\varepsilon\ddot{\xi}\cos\theta + u \end{cases} \tag{3.2}$$

Among them, ε represents the coupling between translation and rotation, and there is:

$$\varepsilon =: \frac{me}{\sqrt{\left(I + me^2\right)\left(M + m\right)}} = 0.2$$

The first-order dimensionless equation of motion is expressed as:

$$\begin{cases} \dot{x} = f(x) + g(x)u + h(u)d, |u| \le 2 \\ y^T y = x_1^2 + 0.1x_2^2 + 0.1x_3^2 + 0.1x_4^2 + \|u\|_q^2 \end{cases} \tag{3.3}$$

$$f = \begin{bmatrix} x_2 & \dfrac{-x_1 + \varepsilon x_4^2 \sin x_3}{1 - \varepsilon^2 \cos^2 x_3} & x_4 & \dfrac{\varepsilon\cos x_3\left(x_1 - \varepsilon x_4^2 \sin x_3\right)}{1 - \varepsilon^2\cos^2 x_3} \end{bmatrix}^T$$

$$g = \begin{bmatrix} 0 & \dfrac{-\varepsilon\cos x_3}{1-\varepsilon^2\cos^2 x_3} & 0 & \dfrac{1}{1-\varepsilon^2\cos^2 x_3} \end{bmatrix}^T, h = \begin{bmatrix} 0 & \dfrac{1}{1-\varepsilon^2\cos^2 x_3} & 0 & \dfrac{-\varepsilon\cos x_3}{1-\varepsilon^2\cos^2 x_3} \end{bmatrix}^T$$

This is a power series neural network that contains the system state to the power of the third order. The total number of neural network activation functions is 20, and this number of activation functions ensures consistent convergence of the value function. In this chapter, the evaluation network and the execution network are selected as three-layer BP neural networks with 2-10-1 and 2-10-1 structures, respectively, and the iterative stop threshold s = 10. We set p(t) = tanh(h), and set the initial control strategy and disturbance as uo(f)=- tanh(xy+ X- X -x), and d(n) = 5e'cos(t) , and set y = 6. Then, we use the policy iterative learning algorithm to find the optimal solution of the two-person zero-sum game. The learning time is o(t) = 2s and the dataset is M = 600. Along the time t = 0s to t = 2s, we collect system input information and state trajectories, the initial values of system TORA x(O)=-O014m and xx;(O)=-30°. We configure the desired displacement and angle values as xa = xa = 0. Then, according to the proposed algorithm, we can solve the HI formula (3-26) according to equation (3-42), and obtain the controller u according to formula (3-44).

Figure 4 depicts the initial control uo trajectory. Figures5-7 show the trajectory curves of each state under the initial controller uo and its action. Figure 8 shows the initial control disturbance rejection curve. Figure 9shows the iterative process of network weights. Figure 10 depicts the state trajectory curves of the closed-loop system. Figure 9 depicts the trajectory of the optimal H_∞ controller u.

The disturbance attenuation function r(t) is defined as follows:

$$r(t) \triangleq \frac{\int_0^t \left(\|y(\tau)\|^2 + \|u(\tau)\|^2\right) d\tau}{\int_0^t \|d(\tau)\|^2 \, d\tau} \tag{3. 4}$$

Figure 10 shows the perturbation decay curves under H_∞ control. It can be seen from the figure.

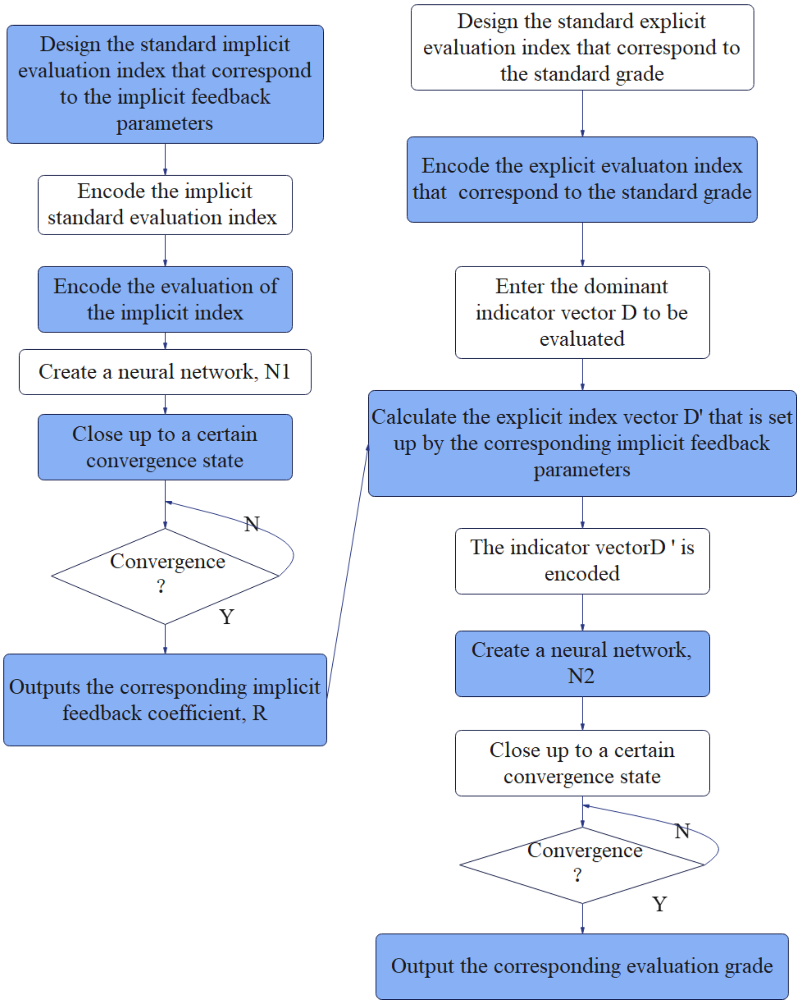


Figure 3: The modeling process of the evaluation model of teaching ability of college teachers.

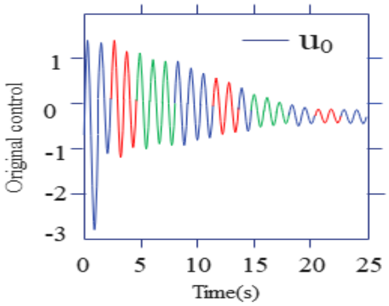


Figure 4: Initial control $u_0(t)$.

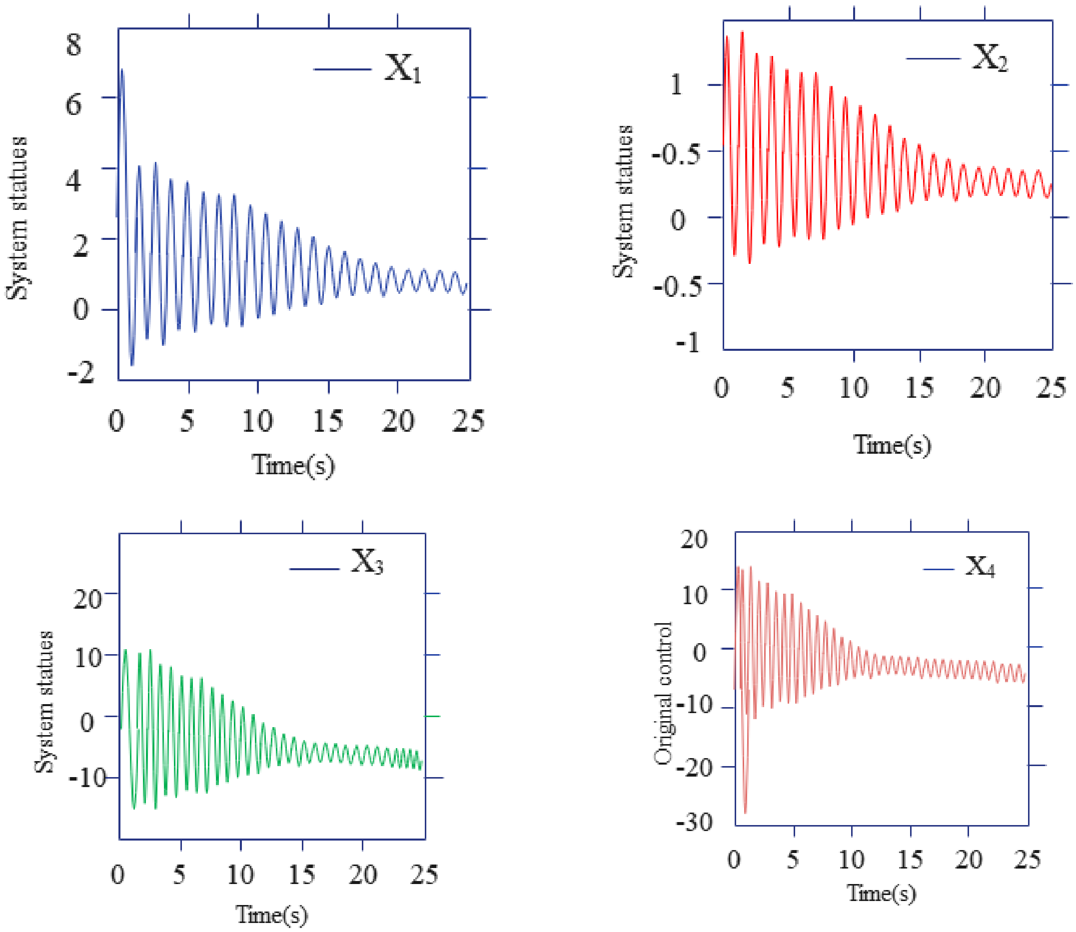


Figure 5: Trajectories of each state of the system under initial control: (a) X_1 state trajectory, (b) X_2 state trajectory, (c) X_3 state trajectory, (d) X_4 state trajectory.

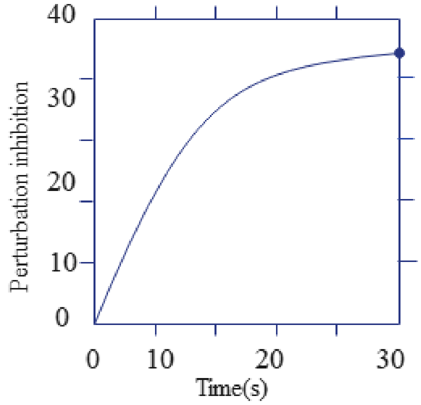


Figure 6: Disturbance suppression.

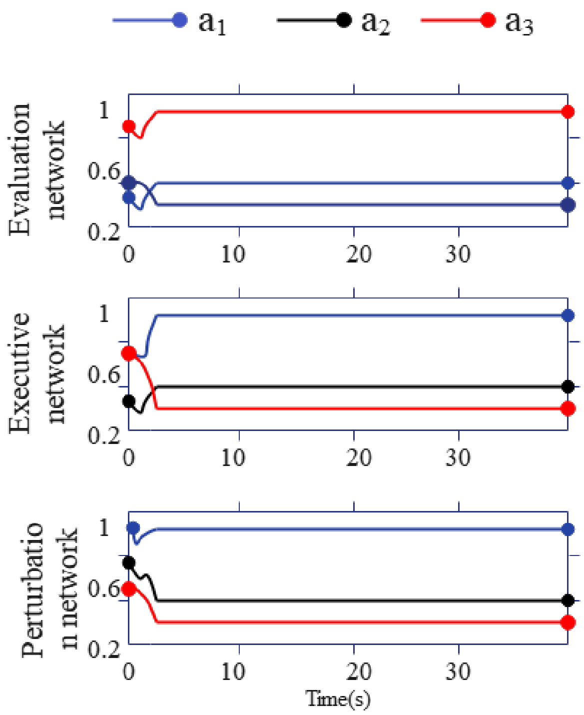
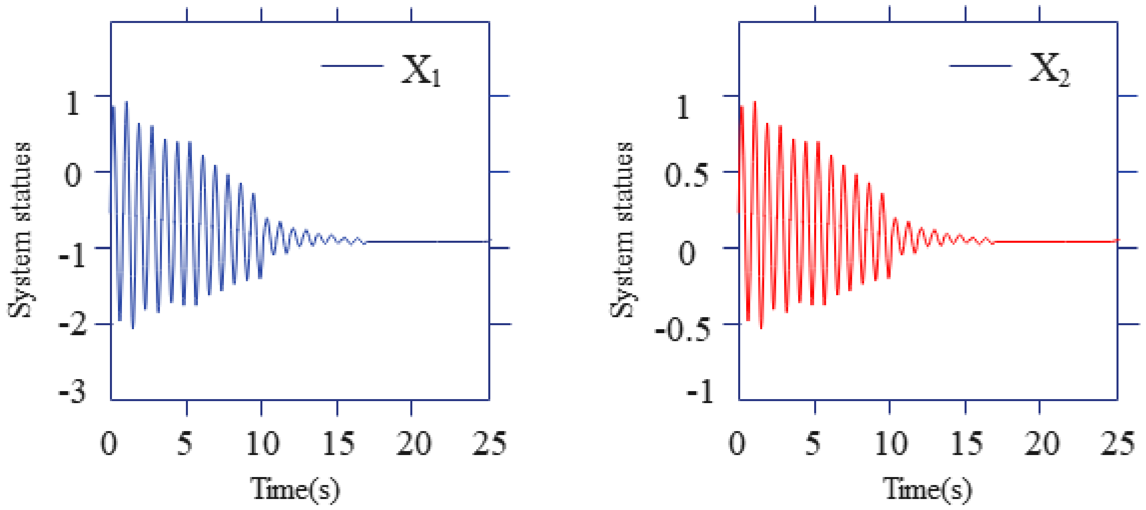


Figure 7: Network weights.



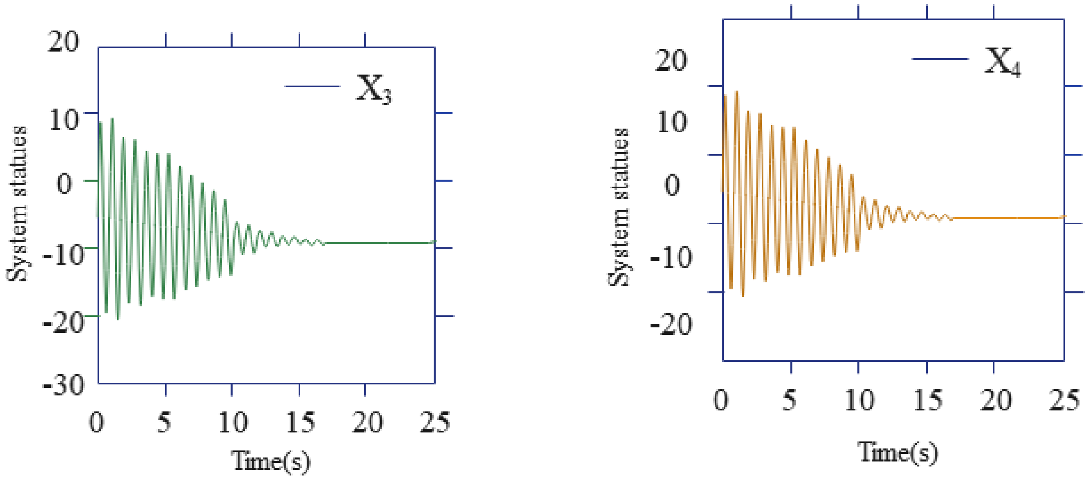


Figure 8: Trajectories of each state of the system under optimal control: (a) X_1 state trajectory, (b) X_2 state trajectory, (c) X_3 state trajectory, (d) X_4 state trajectory.

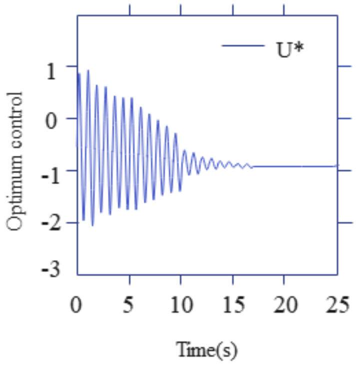


Figure 9: Optimal control $u^*(t)$.

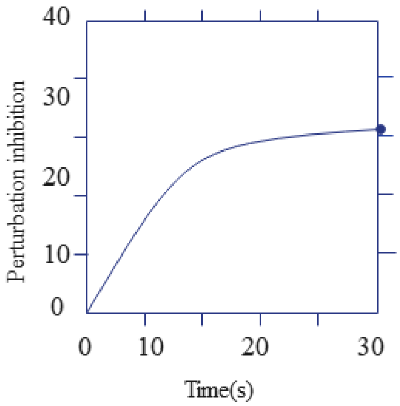


Figure 10: Disturbance suppression.

$$r(t) < y^2 = 36$$

It satisfies the L2-gain for a limited time. It is worth noting that the proposed control algorithm does not involve the TO-RA system model and only requires the input-output data of the TORA system.

The above research verifies that the system in this paper has a certain effect in ideological and political teaching data processing, and then evaluates the effect of the ideological and political teaching system based on the feedback neural network constructed in this paper, and obtains the evaluation results shown in Tables 1 and 2.

Num	Information processing	Num	Information processing
1	83.23	13	79.70
2	81.56	14	84.49
3	84.27	15	85.30
4	79.31	16	79.34
5	79.69	17	85.47
6	79.82	18	79.30
7	84.40	19	85.62
8	83.04	20	85.08
9	80.70	21	79.14
10	84.95	22	85.46
11	84.90	23	80.92
12	79.10	24	84.07

Table 1: Teaching data processing of ideological and political teaching system based on feedback neural network.

Num	Teaching Quality	Num	Teaching Quality
1	87.30	13	84.90
2	84.61	14	87.92
3	84.71	15	85.21
4	84.05	16	83.58
5	84.19	17	85.25
6	87.89	18	85.91
7	84.04	19	85.07
8	88.79	20	85.28
9	86.88	21	85.04
10	85.88	22	84.16
11	83.24	23	84.89
12	87.76	24	85.39

Table 2: Teaching evaluation.

From the above research, we can see that the ideological and political teaching system based on feedback neural network proposed in this paper can play an important role in ideological and political teaching.

4 CONCLUSIONS

When evaluating teaching quality, on the one hand, due to many factors affecting teaching quality, the content of the comprehensive index system for evaluating teaching quality is increasing. On the other hand, the evaluation results of teaching quality are also difficult to express with appropriate mathematical analytical expressions. The uncertain factors in the above two aspects cannot be solved by using the previous teaching quality evaluation methods. Therefore, it is necessary to develop and research more scientific, objective and accurate teaching quality evaluation methods. This paper combines the feedback neural network and artificial intelligence technology to construct an ideological and political teaching system, improve the intelligence of ideological and political teaching, and promote the modernization and reform of ideological and political teaching. The research shows that the ideological and political teaching system based on the feedback neural network proposed in this paper can play an important role in the ideological and political teaching.

5 ACKNOWLEDGEMENTS

Funding was provided by Research Program of Science and Technology at Universities of Inner Mongolia Autonomous Region (No. NJSZZX2246).

Shanshan Zuo, https://orcid.org/0000-0002-3606-9072

REFERENCES

[1] Dilmurod, R.; Fazliddin, A.: Prospects for the introduction of artificial intelligence technologies in higher education, ACADEMICIA: an international multidisciplinary research journal, 11(2), 2021, 929-934. http://dx.doi.org/10.5958/2249-7137.2021.00468.7

[2] Guan, C.; Mou, J.; Jiang, Z.: Artificial intelligence innovation in education: A twenty-year data-driven historical analysis, International Journal of Innovation Studies, 4(4), 2020, 134-147. https://doi.org/10.1016/j.ijis.2020.09.001

[3] Keating, J.; Nourbakhsh, I.: Teaching artificial intelligence and humanity, Communications of the ACM, 61(2), 2018, 29-32. https://doi.org/10.1145/3104986

[4] Kim, K.; Park, Y.: A development and application of the teaching and learning model of artificial intelligence education for elementary students, Journal of The Korean Association of Information Education, 21(1), 2017, 139-149.

[5] Kong, F.: Application of Artificial Intelligence in Modern Art Teaching, International Journal of Emerging Technologies in Learning (iJET), 15(13), 2020, 238-251. https://doi.org/10.3991/ijet.v15i13.15351

[6] Lee, Y.: An analysis of the influence of block-type programming language-based artificial intelligence education on the learner's attitude in artificial intelligence, Journal of The Korean Association of Information Education, 23(2), 2019, 189-196. https://doi.org/10.14352/jkaie.2019.23.2.189

[7] Li, X.: The construction of intelligent English teaching model based on artificial intelligence, International Journal of Emerging Technologies in Learning (iJET), 12(12), 2017, 35-44. https://doi.org/10.3991/ijet.v12i12.7963

[8] Lin, P. H.; Wooders, A.; Wang, J. T. Y.; Yuan, W. M.: Artificial intelligence, the missing piece of online education? IEEE Engineering Management Review, 46(3), 2018, 25-28.

https://doi.org/10.1109/EMR.2018.2868068
[9] Mianroodi, J. R.; Siboni, N. H., Raabe, D.: Teaching solid mechanics to artificial intelligence—a fast solver for heterogeneous materials, Computational Materials, 7(1), 2021, 1-10. https://doi.org/10.1038/s41524-021-00571-z
[10] Ni, D.: The application of artificial intelligence technology in international Chinese language teaching, Chinese Journal of Social Science and Management, 5(1), 2021, 101-112.
[11] Pantic, M.; Zwitserloot, R.; Grootjans, R. J.: Teaching introductory artificial intelligence using a simple agent framework, IEEE Transactions on Education, 48(3), 2005, 382-390. https://doi.org/10.1109/TE.2004.842906
[12] Yang, C.; Huan, S.; Yang, Y.: A practical teaching mode for colleges supported by artificial intelligence, International Journal of Emerging Technologies in Learning (IJET), 15(17), 2020, 195-206. https://doi.org/10.3991/ijet.v15i17.16737
[13] Yang, S. C. H.; Vong, W. K.; Sojitra, R. B.; Folke, T.; Shafto, P.: Mitigating belief projection in explainable artificial intelligence via Bayesian teaching, Scientific reports, 11(1), 2021, 1-17. https://doi.org/10.1038/s41598-021-89267-4
[14] Zawacki-Richter, O.; Marín, V. I.; Bond, M.; Gouverneur, F.: Systematic review of research on artificial intelligence applications in higher education–where are the educators? International Journal of Educational Technology in Higher Education, 16(1), 2019, 1-27. https://doi.org/10.1186/s41239-019-0171-0
[15] Zhou, Q.: Reforms in Teaching the Course of Introduction to Artificial Intelligence. Solid State Technology, 64(2), 2021, 6331-6335.
[16] Zou, S.: Designing and practice of a college English teaching platform based on artificial intelligence, Journal of Computational and Theoretical Nanoscience, 14(1), 2017, 104-108. https://doi.org/10.1166/jctn.2017.6133