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Neural Network Model Based On Multi-Temporal BAM

Wei Liu*

Department of Electronic Engineering, Tongling Polytechnic, Tongling 244061, China

By optimizing the control design of a Bi-Directional Associative Memory (BAM) neural network with multiple delays, the stability and reliability of the BAM neural network with multiple delays is improved. A multi-delay BAM neural network control algorithm based on a variable structure proportional, integral and derivative (PID) fuzzy neural network is proposed. By ignoring the feedforward and coupling terms of the controller, and by concentrating on the fault tolerance of the inner loop control, the differential equation of the state delay of the BAM neural network control with multiple delays is obtained. The fault-tolerant control law is selected to control the BAM neural network with multiple delays in a steady state. Combined with the Lyapunov stability principle, the total input values of hidden layer neurons in the PID fuzzy neural network are obtained. The variable structure feedforward three-layer adaptive PID neural network model is used as a learning device to realize the optimal design of the BAM neural network control algorithm with multiple delays. The simulation results show that the state response robustness and adaptability of the output of the multi-delay BAM neural network are better when. Multi-delay BAM neural network is controlled by system - delay coupling system which shows the better control quality of the multi-delay BAM neural network.

Keywords: Neurons; BAM Neural Network with Multiple Delays; Control; PID; Learning Device.

1. INTRODUCTION

Statistical pattern recognition, linear or non-linear regression and artificial neural networks are effective tools for data mining, but for many years we have also been constrained by a difficult problem: as a fuel for in-depth learning, there is not necessarily a huge amount of data with labels in actual problems (Berriri et al., 2012). Traditional pattern recognition or artificial neural network methods require more training samples, while in many practical subjects there are only a few known samples. For small sample sets, the training results are not necessarily the best model with the best prediction ability. However, a BAM neural network with multiple delays only needs a small amount of data to find the hyperplane of data classification and obtain good classification results. Data is the fuel of machine learning (Khil et al., 2016). Traditional statistics is the important foundation of existing machine learning methods, including pattern recognition and neural networks. Based on traditional statistics, the progressive theory is that the number of samples tends towards infinity. However, when the samples are limited, it is difficult to achieve the desired results (Zhang et al., 2016). Statistical Learning Theory (SLT) focuses on the statistical laws and learning method properties in the case of small samples and develops a new general learning method - Support Vector Machine (SVM). At present, one of the main focus areas of the research on SVM is mainly the optimization of algorithms, including the solution of the quadratic programming in a BAM neural network with multiple delays and the solution of large-scale SVMs (Gao et al., 2015). Another major focus is on a way to improve the induction ability and classification speed of a BAM neural network with multiple delays and how to determine the kernel function according to specific problems. The research of BAM neural network control algorithm with multiple delays is of great significance in ensuring the reliable operation of a BAM neural network system with multiple delays, and the research of related algorithms has received much attention (Hemad, 2019; Banatul and Nur Hidayanto, 2019; Yeaseen, 2019).

*Corresponding Author e-mail: tllw5483@163.com

A BAM neural network model is a type of two-way associative memory neural network, which considers the two-way information transmission characteristics of a human brain neural system. Its network structure is divided into two layers, where two layers are connected and the same layer is not connected. It has been widely used in many fields, such as pattern recognition, signal and image processing, artificial intelligence, and bioengineering. A neural network has the function of associating a complete and clear pattern stored in memory from an incomplete or fuzzy pattern. The strength of the associative memory function determines the problem-solving ability and the application value of the neural network to a large extent. The associative memory function of the neural network also provides important enlightenment for people to further explore the mystery of human brain memory. At present, various associative memory neural network models have emerged. Associative memory can generally be divided into self associative memory and different associative memory. The Hopfield neural network model is also called the associative memory network, which realizes a one-way self associative function. The bi-directional associative memory (BAM) neural network model is a different associative memory model; it is regarded as an extended model of Hopfield's uni-directional associative memory model. The application of the neural network largely depends on the dynamic behavior of the neural network. The external resistance and energy loss, the state measurement, the hardware implementation of the model, the time required for signal processing and the limited switching speed of the amplifier all create time delays within the system. These time delays mean that the network model should be related to the past time of the neural element state, which also reflects the characteristics of the brain. Introducing time delay into the existing neural network model may cause vibration and basin splitting, thus changing the stability of the whole neural network. In this case, the neural network system without a time-delay cannot be accurately described. As a BAM neural network has a good application prospect in some aspects, its application largely depends on the dynamic behavior of the neural network. So far, because the neural network usually has a spatial range, many stability results have been obtained for a BAM neural network with discrete delay, such as global asymptotic stability and global exponential stability. This is caused by the existence of many parallel paths with various axon sizes and lengths, so there will be a distribution of propagation delay. Introducing a continuous distribution delay into the model may have a significant impact. In the neural network system, there are two kinds of continuous distributed delays: Finite Distributed Delay and Infinite Distributed Delay.

At present, many algorithms have been applied to the modeling of BAM neural network control units with multiple delays. The commonly used algorithms include the genetic algorithm, fuzzy neural network control algorithm, particle swarm optimization algorithm, support vector machine control algorithm, time delay control algorithm and electromagnetism simulation algorithm. Relevant research has also achieved certain results, among which, The genetic algorithm is introduced into the proportional integral regulator (Guo et al., 2017). The control algorithm is designed and applied to the BAM neural network control model with multiple delays. The variable structure adaptive theory is used to control the electromechanical system for fault tolerance, which improves the robustness of the system. However, this method has the disadvantage of a complicated calculation process. Egea-Alvarez et al., (2015) stated that in the electromechanical control design of industrial robots, the current controller is decomposed into a positive and negative time series, and the parameter self-tuning fusion PI control is carried out to compensate the error of the output current of the electromechanical system, thus improving the control quality of the electromechanical system and reducing the output error of the system. However, this method easily falls into a local optimal solution in the control process, and the parameter optimization of the electromechanical control unit can be incomplete. In view of the above problems, this paper proposes a multi-delay BAM neural network control algorithm based on a variable structure PID fuzzy neural network control, establishes a multi-delay BAM neural network control unit model, describes the parameter system of the controlled object, designs a variable structure PID fuzzy neural network controller, and realizes the improvement of the electromechanical control algorithm. The experimental verification shows that the proposed method can effectively improve the performance and quality of a multi-delay BAM neural network control.

2. BASIC DEFINITIONS

2.1 Description of BAM Neural Network Control Objects With Multiple Delays

In practical application, a neural network is realized by an electronic circuit, while the electronic circuit of the analog neural network generally works in the magnetic field environment, and the magnetic field is often uneven. Strictly speaking, when the electronic circuit of the analog neural network works in the uneven magnetic field environment, the electronic diffusion effect is inevitable. So when we study the neural network, we must also consider that the space changes with time. Therefore, it is necessary to simulate the neural network by introducing the continuous distribution delay and reaction diffusion term. In the practical application of the neural network system, the inertia term is sometimes added, this is helpful for the generation of mixture. The approximation of the neural network is an extension of function approximation theory. As a neural network has strong non-linear mapping ability, self-study habit and fault tolerance, this makes it very different from the classical methods in the field of approximation. The superiority of a neural network when applied to function approximation can be reflected in the situation that the pattern characteristics that the data itself needs to determine are not clear, the data is fuzzy or contains noise, nonlinearity, etc. BP networks and RBF networks, which are widely used in function approximation, are two other types of neural network. They have been used successfully in function approximation, where the research on the approximation and stability of any

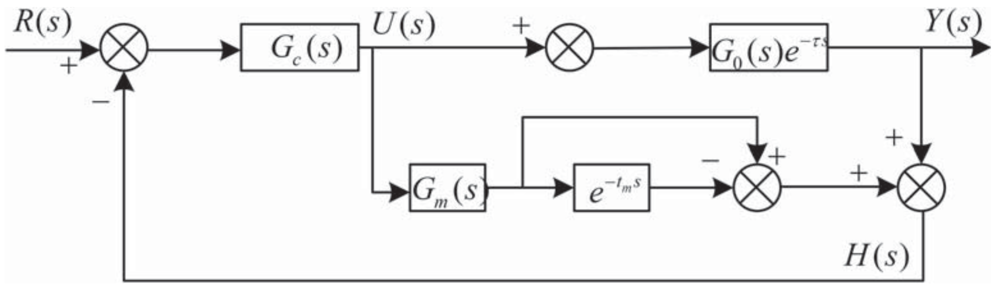

Figure 1 Structural model of BAM neural network control objects with multiple delays.

nonlinear continuous function on a bounded closed set has been mature. However, for the double weight neural network with a very complex form of neuron function, its theoretical research on approximation is still in the initial stages, and its application field still has room for development. The approximation result of a double weight neural network to any nonlinear function is rarely seen in the existing literature, which urges us to study the approximation ability of this type of double weight neural network.

Since the emergence of digital communication, data has been regarded as composed of binary code words in the process of transmission. So far, with the explosion of the amount of data on the Internet and the number of mobile terminals, researchers are still trying to look at the bit data from a broader perspective, that is, the content as the social attribute of data, shifting people's understanding of data to a higher dimension and paying more attention to the content. Our network architecture has become the key solution of the next generation network. At present, the mainstream content center network architecture mainly includes Data-Oriented Network Architecture (DONA) in the United States, Named Data Network (NDN) architecture and European Network of Information (NetInf) architecture, and Publish Subscribe Internet Routing Paradigm (PSIRP) architecture. The latest version of Publish Subscribe Internet technology (Pursuit). The key technologies of the content center network mainly include naming, routing, security and cache control, among which naming, routing and cache control technology can best reflect the unique characteristics of the content center network. Early research on the content center network did not emphasize the requirements of the physical layer transmission media, but with the deepening of research, researchers of wireless networks found that the link change caused by node movement and channel fading posed a challenge to the typical content center network architecture. Researchers have studied the feasibility of content center network architecture in sensor networks and wireless ad-hoc networks, by building a danger path between routers to reduce the impact of node mobility.

In wireless ad hoc networks and vehicle networks, researchers designed routing mechanisms based on data content to deal with the problems caused by wireless channel and node movement. In delay tolerant network routing that considers social attributes, one kind of routing mechanism focuses on optimizing the network performance by using the content attributes of data. In a sense, label in label can be regarded as a description of data content and its own attributes by the data sender. Since then, some delay tolerant network routing protocols have also tried to optimize the description of data to improve the delivery speed of messages or reduce the transmission overheads. At present, the existing research results do not provide support for the next generation network architecture and new business. Although it can be said to be content-based, the combination of a content center network and content center network technology can be seen as the extension of a content center network in a specific field, or as a more effective use of social attributes of data in the content center network. Whether at home or abroad, the research on this aspect is still in the initial stages; the main focus areas are: content-centered delay tolerant network architecture design, compatibility research with existing network architecture, prototype test system construction, and routing protocol research.

In order to realize robust control of the mechanical and electrical systems of bionic robots, firstly the parametric system model of multi-delay BAM neural network control is analyzed. Through mathematical modeling of the controlled object, the optimal controller is designed to improve the stability and adaptability of the mechanical and electrical control (Goldberg et al., 2016). The multi-delay BAM neural network control unit model mainly consists of a DC/AC inverter model, micro synchronous motor, inner loop controller model and a voltage outer loop controller model. The establishment of the DC/AC inverter model is the basis for the establishment of a multi-delay BAM neural network control unit model (Zhang et al., 2019). Smith structure is adopted to design the resultant model of the multi-delay BAM neural network control system, as shown in Figure 1.

In the control system shown in Figure 1, s and $G_0(s)e^{-\tau s}$ are used to describe control signals. $G_c(s)$ is the system transfer function of the BAM neural network control system with multiple delays. $e^{-t_m s}$ is the system transfer function of a DC motor, and the DC/AC inverter model can be described as follows:

$$G_1(s) = \frac{1}{1 + 0.5sT_{SW}} \tag{1}$$

On the basis of the DC/AC inverter model, the traditional structure model of the synchronous motor of a BAM neural network control system with multiple time delays is established, It is assumed that T is the response characteristic function of the established voltage outer loop controller system (Gao and Huang, 2019). The outer loop control loop is designed using the synchronous phase modulation control idea. When the transfer function of the time delay coupling system of the electromechanical control system of the robot is determined, $G_m(s) = G_0(s)$ and $t_m = \tau$ are obtained. Through the simulation of the inertial link, the feedback signals of the system are obtained as follows:

$$H(s) + Y(s) = G_m(s)U(s) \tag{2}$$

The Smith control system described above forms a two-degree-of-freedom IMC-PID controller. Firstly, the transfer function of the controlled system time-delay coupled system is established:

$$\begin{bmatrix} G_{11}(s) & G_{12}(s) \\ G_{21}(s) & G_{22}(s) \end{bmatrix} = \begin{bmatrix} \frac{1.7e^{-30s}}{7s+1} & \frac{0.59e^{-27s}}{8s+1} \\ \frac{-0.6e^{-25s}}{10s+1} & \frac{1.5e^{-28s}}{9s+1} \end{bmatrix} \tag{3}$$

In the above formula, the input vector of the electromagnetic slip clutch of the robot electromechanical system is equivalent to the feedback signal drawn from the output end of the through feedforward delay coupling (Zhou et al., 2019). In the control delay link, when the BAM neural network control unit with multiple delays is affected by the interference vector, the delay coupling error of the controlled object is approximated by Taylor:

$$Y(s) = \frac{e^{-L_m s}}{(\lambda_1 s + 1)} R(s) + \frac{(\lambda_2 s + L_m)s}{(\lambda_2 s + 1)} D(s) \tag{4}$$

Because the inverter is affected by unit power factor during operation, when the output of the controlled object is unstable, the design of the inner loop current controller is completed through fuzzy neural network control. At this time, the characteristic equation of the speed control of the DC motor is:

$$\frac{Y(s)}{R(s)} = \frac{G_C(s)G_0(s)e^{-\tau s}}{1 + G_C(s)G_m(s) + G_C(s)(G_0(s)e^{-\tau s} - G_m(s)e^{-t_m s})} \tag{5}$$

Through the above description, the unit structure model of the BAM neural network control with multiple delays is constructed, and the control parameter system is analyzed. The variable structure PID neural network control system is adopted to realize the improved design of the controller (Murphy et al., 2009).

2.2 Construction of Control Objective Function and Design of Control Law

In the multi-delay BAM neural network control system constructed above, the electromechanical controller is a multi-input and output control system. Content centric network is a kind of network that can ensure effective content identification and acquisition.

Firstly, the problem that needs to be solved is how to effectively use content names to identify messages. Secondly, it is very important to find the content and get it quickly. Thirdly, the nodes have a certain cache capacity, so it is worth studying if inserting and releasing packets in the cache will be most conducive to the performance improvement of the network. Finally, the packets on the network are named after the content name, so a security mechanism must be implemented to ensure that the transmitted content is not eavesdropped. The above problems are the four key technologies of content-based network: naming mechanism, routing mechanism, caching mechanism and security mechanism.

In terms of the naming mechanism, hierarchical naming and flat naming are currently used. Hierarchical naming is similar to the naming of the URL of the global resource identifier. The advantages of hierarchical naming are simple operation, low standard workload and convenient use of content aggregation mechanism. The disadvantage is that it has poor adaptability to mobility. At present, NDN adopts hierarchical naming. The other three architectures adopt flat naming. Flat naming is the use of content attributes to identify messages / files transferred in the network. Flat naming uses the $<$ p: l $>$ format to identify content, where p represents the public key, and l is a unique identification of the content assigned to this segment. The advantage of this naming method is that the name of the content has nothing to do with other factors, which ensures the persistence of the name. In addition, it is also convenient to add security mechanisms, such as a digital signature, to ensure the security of naming. However, it is difficult to implement flat named route aggregation, as it requires high performance routers. At present, how to name the huge data effectively and how to name it to ensure the security and durability is still a technical difficulty of the content-based network. The purpose of the traditional Internet is to provide a stable end-to-end communication link.

With the rapid development of Internet technology, stable broadband access has been achieved in most countries and regions in the world. However, the unfair development of broadband access still exists. In rural and urban remote areas where network infrastructure is lacking, the total number of network users is lower and unevenly distributed. If the infrastructure is built, it will bring a lot of communication costs. Therefore, a new network architecture is needed to solve the problem of different underlying transmission technologies accessing the Internet with low transmission cost, high efficiency and flexibility. Content centric delay tolerant networks are developing slowly. At present, the research of a content-based delay tolerant network mainly includes network architecture, routing mechanism, caching mechanism and prototype system. The problem of network selfishness has been studied in wireless self-organizing networks and wireless sensor networks for a long time. Due to the limitation of energy consumption and processing capacity, nodes are prone to refuse to forward data. The main solutions can be divided into incentive and punishment. The core ideas of the two are similar, but the implementation approaches are slightly different. The mainstream ideas to solve the problem of node selfishness can be summarized as two mechanisms: the mechanism based on trust and the mechanism based on game theory. The basic idea of the former is that if all nodes in the network can participate in co-operation to obtain the optimal performance of the whole system, then each node can get the corresponding optimal return. The core idea of the latter is to enhance the co-operative forwarding between nodes by using the relevant knowledge of game theory. The application of game theory to wireless networks has attracted extensive attention. The intermediate nodes in the shortest path can not only get their reported benefits, but also the opportunity cost is reduced as an additional reward, stimulating the willingness of the nodes to co-operate within the network. A trust based routing mechanism is relatively easy to implement, but the optimal performance of the whole system does not mean that each node is reaching optimal performance, and there is still motivation to violate the protocol. Most of the existing mechanisms are based on the existence of a central control in the network, rather than a distributed implementation. These mechanisms focus on encouraging the co-operation of selfish nodes through various strategies, but do not consider the limitations of the nodes' own resources, so it is difficult for selfish nodes to achieve full co-operation. With the popularity of delay tolerant network technology, selfishness has also been brought into this new field. Differing from the traditional selfish behavior in wireless networks, the selfish behavior in delay tolerant networks is due to the mobile characteristics of nodes and the preference for content. Due to the difference of mobile characteristics, nodes with low network centrality cannot serve other nodes, and the preference of nodes for content leads to the redistribution of cache space, and the loss of irrelevant data becomes a selfish node.The individual mobile model determines the performance of the delay tolerant network to a great extent. The different preference of different nodes for a specific location and the difference of contact time between nodes lead to the traditional random mobile model being unsuitable for a delay tolerant network.

After the ordinary node processes the directly accessible message, it is necessary to determine whether there is an information station within the communication range. Once f station is found, the message is uploaded to the information station, and the info flag is set to 1 to mark the message. The purpose of this is to use the information station resources as effectively as possible. If there is no information station in the communication range of the common node, the message is delivered to other common nodes in the communication range, and the forwarding rules are determined by the original routing mechanism. When the information station processes directly accessible messages, it can perform low priority tasks. The high-level interface and the low-level nodes of the information station can work at the same time. For the high-level interface, the only task is to share messages among the information stations. For the low-level interface, the low priority task is to use relay nodes to forward messages. The forwarding rules of messages are determined by the original routing mechanism. When it comes to forwarding messages to relay nodes, both ordinary nodes and information stations need to select forwarding objects according to certain forwarding mechanisms. For example, the forwarding mechanism of an transmission route is to forward messages to all nodes that they have encountered, while the relay node of a two hop forwarding route only forwards messages to the destination node, and the large number routing mechanism forwards messages to the destination node according to certain indicators and relay nodes that are more likely to meet the host node. Regardless of the original routing mechanism, the message distribution / cache management mechanism supporting the information station has no changes to it, in order to be more compatible with the existing routing mechanism.

Assuming that R is the system input of the multi-delay BAM neural network control (Lopez et al., 2015), Y is the output of the multi-delay BAM neural network control, d is an unknown disturbance signal, $P(s)$ is the delay parameter of the controlled process, and $M(s)$ is the model error of the controlled process; $Q1(s)$ and $Q2(s)$ form the error scalar co-efficient of the fault tolerance control of the multi-delay BAM neural network control system. The transmission of the micro synchronous motor of the electromechanical system is optimized through parameter self-tuning qualitative adjustment. The input of the controller is:

$$\begin{pmatrix} X \\ P(X) \end{pmatrix} = \begin{Bmatrix} a_1, a_2 & \cdots & a_m \\ p(a_1), p(a_2) & \cdots & p(a_m) \end{Bmatrix} \tag{6}$$

Wherein, $0 \leq p(a_i) \leq 1 (i = 0, 1, 2, \cdots, m)$, the time delay function of multi-mode control representing the stable critical point of the multi-time delay BAM neural network is carried out, the Lyapunov function is carried out on the controlled object, assuming that the training sequence of the sample used is $x(t), t = 0, 1, \cdots, n-1$, and the transmission state equation of the motor group is constructed as follows:

$$\dot{x}(t) = Ax(t) + BKx(t - d_s(t) - d_a(t)) \tag{7}$$

Where A is the system torque, K is the rotor/stator yoke thickness, B is the time delay characteristic parameter, $d_s(t)$ is the rotational viscosity co-efficient, ignoring the feedforward and coupling terms of the controller. For the fault tolerance of the inner loop control, the differential equation of the state delay of the multi-delay BAM neural network control is obtained as follows:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bx(t - d_1(t) - d_2(t)) \\ x(t) &= \phi(t) \qquad t \in [-h, 0] \end{aligned} \tag{8}$$

Under the random functional learning, the phase gain parameter scheduling is carried out on the inner loop current control model. The input basis functions are $Ax(t)$ and Bx. Under the interference of the D-axis current inner loop model (Li et al., 2018), the inner loop current control function of the multi-delay BAM neural network electromechanical system is described as follows:

$$G_{cuur\_d}(s) = \frac{K_{P1}s + K_{11}}{sG_1(s)} \tag{9}$$

$$G_{cuur\_q}(s) = \frac{K_{P2}s + K_{12}}{sG_1(s)} \tag{10}$$

Wherein, $K_{P1}, K_{11}, K_{P2}, K_{12}$ respectively represent PID controller parameters of an inner ring d axis of a motor drive shaft of a multi-delay BAM neural network electromechanical system, and an optimal solution of a control state equation is obtained by constructing the control objective function, and the optimal transmission control law of the electromechanical control system is obtained as follows:

$$G(s) = \int \frac{T_s.G_{cuur\_d}(s)i_{d\_ref} * i_d}{T_{SW}.G_{cuur\_q}(s)i_{q\_ref} * i_q} \tag{11}$$

Where the controller parameters $K_{P1}, K_{11}, K_{P2}, K_{12}$ and R, L are uncertain quantities, obtained by identification, $i_{d\_ref}, i_{q\_ref}, i_d, i_q$ are definite function quantity, obtained by measurement, and T_s and T_{SW} are known quantities. Based on the above control law design, the control algorithm improvement design is carried out.

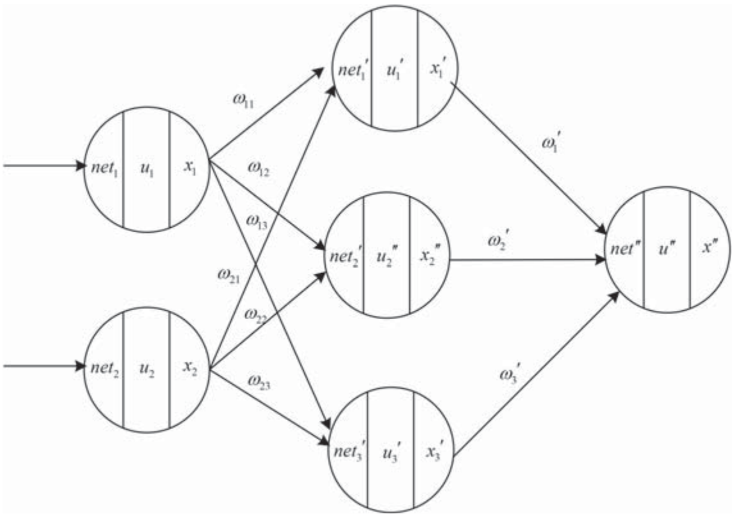

Figure 2 Variable structure PID neural network model.

3. IMPROVED DESIGN OF A BAM NEURAL NETWORK CONTROL ALGORITHM WITH MULTIPLE DELAYS

3.1 Variable Structure PID Neural Network Control Model

Based on the description of the control object and the construction of the parameter system of the multi-delay BAM neural network control system, the improved design of the multi-delay BAM neural network control algorithm is carried out. In this paper, a multi-delay BAM neural network control algorithm based on variable structure PID fuzzy neural network is proposed. A variable structure forward three-layer adaptive PID neural network $2 \times 3 \times 1$ model is selected as the learner, and the three-layer structure of PID neural network is shown in Figure 2.

At any time, the input of the first neuron in the multi-delay BAM neural network control unit model is equal to the multi-delay BAM neural network control fitness function output with each branch connected to the multi-delay BAM neural network control unit model, the transmission inertia of the control system is taken as input parameters, $x_1, x_2, \ldots, x_n$, and the input parameters are respectively multiplied by the inertia weight value of the outer loop control, $w_{1j}, w_{2j}, \ldots, w_{nj}$, so that the input value of the multi-delay BAM neural network electromechanical outer loop control is obtained as follows:

$$net_j = \sum_{i=1}^{n} w_{ij} x_i(t), \qquad i \neq j \tag{12}$$

The states of BAM neural network neurons with multiple delays are determined by the equivalence of first-order inertial links (Su et al., 2015; Wang et al., 2019). Using the current input and current state of the DC side reference voltage as independent variables, the asynchronous fitting state of the variable structure neuron can be generated according to the state function of the DC motor, namely:

$$u_j(k+1) = g(net_j - \theta_j, u_j(k)) \tag{13}$$

In the formula, θ_j is the measured sampling threshold of multi-delay BAM neural network control, the inertia delay characteristic output of fuzzy PID neural network control is determined by the synchronous motor control function x_j of hidden layer neurons, and the neuron state $f(.)$ is taken as the independent variable, thus obtaining the feedforward output of multi-delay BAM neural network control as follows:

$$x_j(k) = f(u_j(t)) \tag{14}$$

Sigmoid function is used as the transfer function of the system, and its expression is:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{15}$$

The input layer of the variable structure PID fuzzy neural network has two neurons, which control the parallel current of the inverter of the electromechanical system at any sampling moment. The input is:

$$net_i(k) = r_i(k) \qquad i = 1, 2 \tag{16}$$

Considering the uncertain disturbance and control error, the state of neurons in the input layer is as follows:

$$u_i(k) = net_i(k) \qquad i = 1, 2 \tag{17}$$

Considering the uncertain time delay and modeling error of the system, the parameter adaptive feedback adjustment of BAM neural network control with multiple delays is carried out, and the second-order output of the input layer neuron of PID neural network is obtained as follows:

$$x_i(k) = \frac{1}{1 + e^{-u_i(k)}} \tag{18}$$

The hidden layer of variable structure PID fuzzy neural network has three neurons, which are proportional element, integral element and differential element respectively. Fault-tolerant control law is adopted to carry out steady-state control on the BAM neural network with multiple delays. Combined with the Lyapunov stability principle, the total input values of hidden layer neurons in PID fuzzy neural network are obtained as follows:

$$net'_j(k) = \sum_{i=1}^{2} w_{ij} x_i(k) \qquad j = 1, 2, 3 \tag{19}$$

Where, w_{ij} is the connection weight value of the output layer under closed loop control; the superscript $''''$ is an implicit layer variable tag. Based on the above description, a variable structure PID neural network control model is constructed, which is used as a guide to optimize the BAM neural network control algorithm with multiple delays.

3.2 Optimization of BAM Neural Network Control Algorithm With Multiple Delays

The store carry forward method is adopted in the delay tolerant network. The basic idea is to make the nodes in the network cache data packets by using the mobility characteristics of nodes. When the nodes move to the communication area of the destination node, the nodes forward the data packets in the cache to the destination node, so as to realize the transmission of data packets when the communication link is frequently disconnected. According to the different forwarding methods, this paper divides the research results of delay tolerant network routing protocols into four categories: blind routing, post evaluation routing, using social attributes routing, and network coding based routing. Among them, the main purpose of network coding based routing is to solve the problem that one node can package multiple messages. Network coding technology can also ensure the robustness of the network and control the network overhead well.

Blind routing, as the name implies, is that once the node carrying the message makes contact with other nodes, it will forward the message. The concept of contact can be explained as the time during which a node enters the communication range of another node (where both nodes are in the communication range of each other) to it leaving the range. The simplest blind routing is infectious routing. An infectious route is similar to the spread of infectious diseases. When an intermediate node receives a message, it broadcasts the message directly to all its neighbors. When two nodes start to contact, the two nodes exchange the messages that the other node does not have in their respective cache, so as to ensure that the messages propagate in the network at the fastest speed. Therefore, although the communication link is frequently disconnected, messages can also be successfully delivered to the destination node. However, the cache of nodes is limited, therefore they cannot cache all of the messages in the network, and the nodes in the network are not always in a working state. If there are non-working nodes in the network, it can lead to a decrease in the network delivery rate. In the aspect of delay tolerant network routing performance analysis, due to the limited level of personal mathematics, there is no specific mathematical analysis on the three routes in this paper, namely, infectious route, distributed waiting route and probability forwarding route. Instead, through the actual construction of a network scene with social attributes, the conclusion is drawn from the simulation and the analysis is limited. This aspect also needs more thorough analysis through further mathematics knowledge. A content centered network is one of the most promising future network architectures, and a delay tolerant network is the expansion part of the core network. It is necessary to study the adaptability of the new architecture after the integration of the two.

On the basis of the variable structure PID fuzzy neural network control model, a group of multi-delay BAM neural network control auto-disturbance rejection neural networks are constructed to guide the multi-delay BAM neural network control system in carrying out adaptive training, improving the robustness control algorithm of the multi-delay BAM neural network electromechanical system, and constructing the multi-delay BAM neural network motor drive non-linear coupling Levenberg-Marquardt control equation, which is:

$$\begin{cases} C_1(s) = \dfrac{\lambda_2 s + 1}{\lambda_1 s + 1} \\ C_2(s) = \dfrac{\prod\limits_{i=1}^{i=n} (T_{mi} s + 1)}{K_m(\lambda_2 + L_m)s} \end{cases} \tag{20}$$

In the above formula, λ_1 and λ_2 are equivalent outer loop control time constants of electromechanical systems, K_m is the maximum amplitude of the output inertia characteristic of the controller, T_{mi} is the gain co-efficient transferred by the open loop, L_m is the error between the measured value and the identified calculated value, and the fitness function of the inner loop controller can be described as follows:

$$F_{inner\_dq} = \sum_{k=1}^{M} F \left| i_{dq}(k) - i_{dq\_cal}(k) \right| \tag{21}$$

By adjusting the variable structure PID fuzzy neural network controller, the fitness function of the outer loop controller of the multi-delay BAM neural network electromechanical system can be described as follows:

$$F_{outer\_dq} = \sum_{k=1}^{M} F \left| i_d(k) - i_{d\_cal}(k) \right| \tag{22}$$

Thus, the problem of electromechanical optimal control is transformed into the problem of objective function and finding the optimal solution. Given the variable set $x = \{K_{P1}, K_{11}, K_{P2}, K_{12}, R, L, K_{eq}, T_{eq}\}$ of the multi-delay BAM neural network control system, the unknown parameters are identified to realize the optimal design of the multi-delay BAM neural network control. The improved controller structure model is shown in Figure 3.

Through the Lyapunov stability principle, the stability of the control algorithm is analyzed, and the Lyapunov function is defined:

$$V = \frac{1}{2}s^2 + \frac{1}{2}\eta^{-1}\tilde{\omega}^{\mathrm{T}}\tilde{\omega} \tag{23}$$

Where s is the input multi-delay BAM neural network control signal, η is the torque of the servo motor, $\tilde{\omega}$ is the

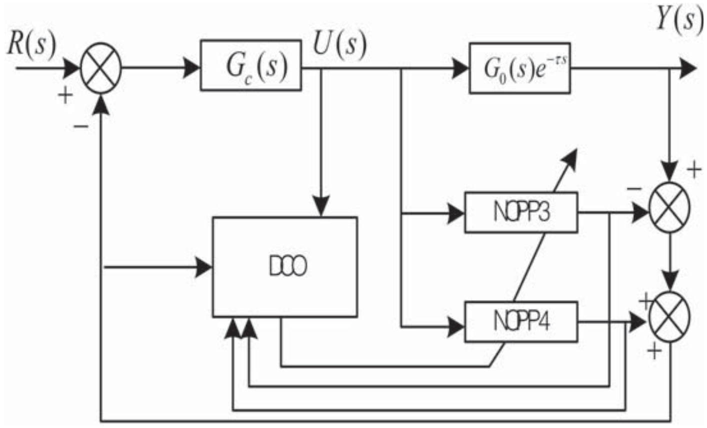

Figure 3 Improved structure of BAM neural network controller with multiple delays.

coupling co-efficient of the multi-delay BAM neural network synchronous motor, and through the Lyapunov function, the following results are obtained:

$$\begin{aligned} \dot{V} &= s\dot{s} - \eta^{-1}\tilde{\omega}^T\dot{\hat{\omega}} \\ &\leq \left|sM_n^{-1}\right|(\varepsilon_1 - \varepsilon_0) \leq 0 \end{aligned} \tag{24}$$

It can be seen from the analysis that the BAM neural network system with multiple delays is controlled by the method in this paper. The unknown model parameters in each stage are obtained by establishing the models of the inner loop controller and the outer loop controller, thus realizing the stability control of the electromechanical system.

4. SIMULATION EXPERIMENT AND RESULT ANALYSIS

In order to verify the effectiveness of the algorithm proposed in this paper for a BAM neural network control with multiple delays, the relevant experimental analysis is required. The experimental software platform is based on MATLAB 7.0 simulation software. The system function of the controlled object is $G_0(s)e^{-\tau s} = \frac{1}{55s+1}e^{-122s}$, the output power consumption efficiency of the electromechanical system is 96%, the torque output of the synchronous motor is 10N.m, and the control equation is:

$$G_C(s) = 0.41 + 0.12\frac{1}{s} + 0.69s \tag{25}$$

On the basis of the above simulation environment and parameters, a multi-delay BAM neural network control simulation experiment is carried out. In the simulation process, the input and output control analysis is respectively carried out on the inner loop controller and the outer loop controller of the electromechanical system, and the tracking control results of the input signal and response signal of the system are obtained as shown in Figure 4.

It can be seen from the figure that the BAM neural network control with multiple delays using the method in this paper has a better output response, can make the control test error converge within the ideal range, and the state response is more robust. In order to quantitatively compare the performance of this method, this method is compared with the genetic algorithm given in reference, and the fitting results of the inner loop controller, the outer loop controller and the volt-ampere characteristics of BAM neural network control system with multiple delays are shown in Figure 5.

Analysis of the above results shows that the proposed method for a multi-delay BAM neural network control has a high degree of adaptability in the control process, a high degree of fitting between the output current and voltage and the ideal values, and a good consistency between the predicted output and the expected output. It shows that the proposed method has good control quality, good robustness for parameter tracking of multi-delay BAM neural network control and good control performance.

5. CONCLUSION

Optimal control of a multi-time-delay BAM neural network electromechanical system is the key to ensure stable and reliable operation of a multi-time-delay BAM neural network. This paper proposes a multi-time-delay BAM neural network control algorithm based on variable structure PID fuzzy neural network control, establishes a multi-time-delay BAM neural network control unit model, describes the parameter system of the controlled object, and designs a variable structure PID fuzzy neural network controller. The improvement of the multi-delay BAM neural network control algorithm is realized. Simulation results show that the control algorithm performs multi-delay BAM neural network control with high control quality, good identification, tracking and fitting performance of model parameters, and control accuracy close to the ideal level, which shows good application value.

In the limited network, the end-to-end stable communication link between the source node and the destination node is difficult to guarantee because of the mobility of the node, the lack of communication infrastructure and other reasons. The delay tolerant network makes use of the inherent mobility of nodes and adopts the method of "store, carry and forward" to realize the successful delivery of messages in the network. At present, the delay tolerant network is used in many

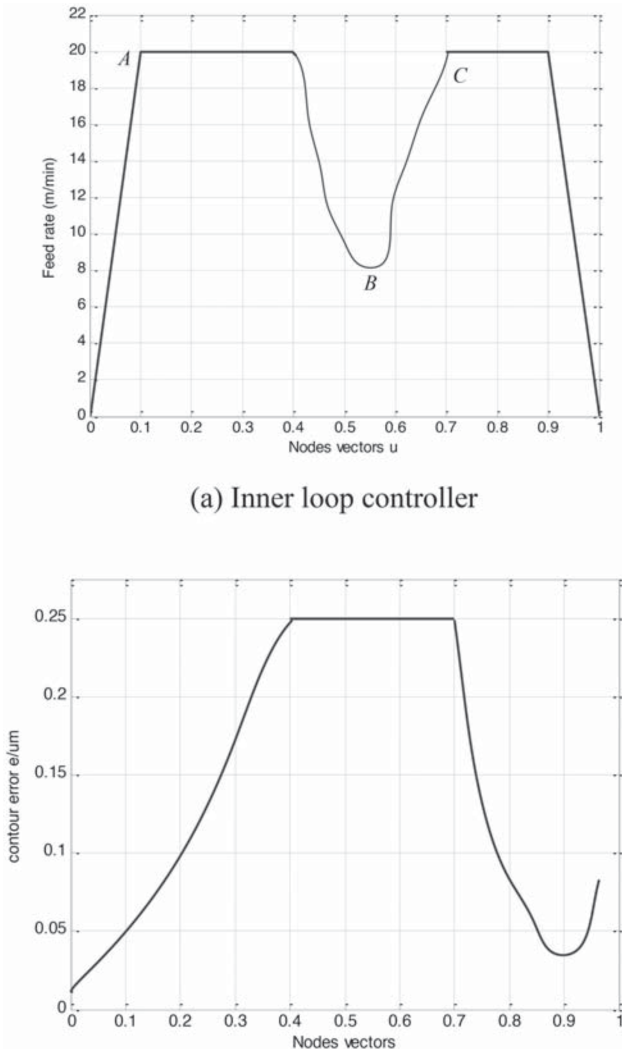

Figure 4 The training results of two parts of BAM neural network control with multiple delays.

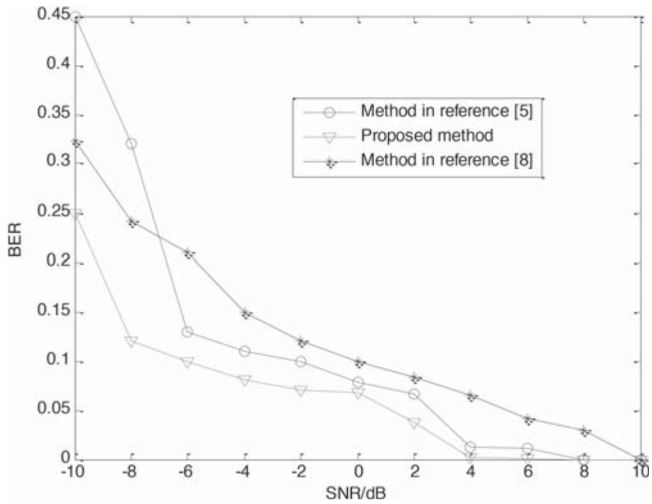

Figure 5 Control performance comparison of BAM neural networks with multiple delays.

application scenarios, such as pocket switching networks, vehicle networks, and disaster monitoring networks, because the nodes in the network are usually carried by people, the mobility of these nodes often has the inherent social attributes of people.

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