ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20250310002454
Original scientific paper

Research on Intelligent Control Learning Algorithm in Electrical Engineering Automation Based on Fuzzy Neural Network

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Abstract: The research of intelligent control and optimization algorithm in the field of electrical engineering and automation is one of the important directions of modern science and technology development. This paper discusses the application of intelligent control technology in electrical engineering and automation system, and analyzes the function of optimization algorithm in improving system performance, reducing cost and enhancing stability in detail. Two methods are proposed to improve the quality of regulation: when establishing rules, the intelligent heuristic function of reinforcement learning is used to search fuzzy control rules and improve the quality of generated rules. When the useless rules are deleted, the stability of the system is strengthened by gradually reducing the width of the membership function. Finally, the effectiveness of the algorithm is proved by simulation. The neural network can learn and adapt to the unknown or uncertain system, and the fuzzy control has the fuzzy reasoning ability like human brain. The organic combination of the two makes the algorithm self-learning, robust and easy to deal with nonlinearity. Through the combination of advanced control theory and algorithm, the research realizes the efficient control of electrical system and improves the level of automation. In addition, the challenges and prospects of intelligent control and optimization algorithms in solving practical problems of electrical engineering are discussed, which provides theoretical support and practical guidance for the further development of electrical engineering and automation.

Keywords: electrical engineering automation; fuzzy control rule; fuzzy neural network; fuzzy reasoning; intelligent control learning algorithm; reinforcement learning

1 INTRODUCTION

In the field of electrical engineering, the application of intelligent control technology has achieved remarkable results. Taking the electrical system as an example, intelligent control can help realize the functions of automatic dispatching, fault detection and recovery of the power grid, and improve the stability and reliability of the power system. In terms of motor control, intelligent control can adjust the control parameters in real time according to the operating status and load changes of the motor, so as to achieve efficient operation and energy saving of the motor. In addition, intelligent control is also playing an increasingly important role in industrial automated production lines, robot control and other fields [1, 2].

The core idea of intelligent control is to realize the adaptive, self-learning and self-optimizing control of complex systems. Traditional control methods often rely on accurate mathematical models and fixed control strategies, which are difficult to deal with the nonlinear, time-varying and uncertain factors existing in the actual system. Intelligent control, by simulating the thinking and behavior process of human beings, uses the powerful computing power of computer to realize, analyze, decide and control the system in real time. It can automatically adjust the control strategy according to the operating state of the system and the changes of the external environment to achieve the best control effect. The technical basis of intelligent control mainly includes artificial neural network, fuzzy control, genetic algorithm and so on. By simulating the structure and function of human brain neurons, artificial neural network has established a model with high nonlinear mapping ability, which can deal with complex control problems. Fuzzy control makes use of fuzzy set and fuzzy logic to model and control the system which is difficult to describe accurately. It is especially suitable for dealing with uncertainty and fuzziness. Genetic algorithm draws on the genetic mechanism in the process of biological evolution, and searches for the optimal control parameters and strategies by simulating natural selection and genetic process.

With strong data analysis and integration capabilities, intelligent technology is widely used in the field of electrical engineering and automation control, and reflects complex and non-linear control characteristics [3]. Therefore, in view of the characteristics of intelligent technology in automatic control, some researchers have proposed relevant studies. For example, in view of the inflexible defects of traditional PID (Proportional-Integral-Derivative) control, a fuzzy PID adaptive regulator is proposed to take brushless DC motor as the research object, which can flexibly adjust and control motor control parameters and improve motor control performance [4]. After research, a fuzzy PID control algorithm based on neural network model is proposed. This algorithm uses the powerful learning ability of neural network model to accurately regulate the variables of automatic control of electrical engineering, reduce the error rate of variable regulation, and improve the accuracy of automatic control of electrical equipment [5]. In order to study the specific application of fuzzy neural network PID algorithm in electrical engineering automation control, taking the operating mechanism of permanent magnet motor as the research object, fuzzy neural network PID control algorithm is used to control the closing time of vacuum switch of permanent magnet motor. The experimental results show that compared with other control algorithms, fuzzy neural network PID algorithm can control the closing time more flexibly [6].

Through the above research, it can be seen that the application of intelligent technology in electrical engineering and automatic control is mainly focused on improving the control accuracy. Therefore, based on the characteristics of intelligent technology in electrical engineering and automatic control, the permanent magnet brushless DC motor is taken as the research object, and the control effect of the motor circuit breaker closing speed is studied by using fuzzy neural network PID algorithm. Using the self-learning characteristic of neural network, the algorithm can be applied to different structural control systems. When the controlled system changes, it only needs to retrain the neural network to build a new rule base. The algorithm does not depend on the exact mechanical model, that is, it does not need to establish the exact mechanical equation of the controlled structure, so it is especially suitable for those complex and difficult to model structural systems. Both neural network and fuzzy logic have arbitrary function approximation theorems, which take into account the nonlinear factors of structural vibration. The control algorithm based on the combination of neural network and fuzzy logic has certain fault-tolerant ability, so it has certain robustness. The first part is the introduction and the second part is the related work. The third part is research on learning algorithm of intelligent control of electrical engineering automation based on fuzzy neural" network, the fourth part is simulation verification, and the fifth part is conclusion.

2 RELATED WORK

In recent years, artificial neural network has been widely used in various fields. The most prominent advantage of neural network for control is that it can establish complex nonlinear relations from training and store them in the join rights, and it has a better learning function. This has been successfully applied to structural active control. A neural network control method based on inverse transfer function is proposed, and this method is applied to actuator dynamic test and time-delay research [7]. Training neural network controllers with simulators and applying them to the control of linear structures is studied [8]. A scheme of neural network identification of a controller is proposed to predict the dynamic response of the structure, and fuzzy rules are used to improve the neural network controller, reduce the amount to be measured, and improve the control effect [9]. This paper studies a new neural network based on control rules to conduct computer simulation test of active control of three-layer frame structure in the case of ground motion [10]. The working principle is as follows: First, one neural network is trained as a simulator to predict future response, and then another neural network is trained with the trained simulator. At each step of the simulation, adjust the control signal, push the control force required by the actuator according to the control criteria, and use it on the structure to achieve the purpose of vibration reduction. On the basis of the research, the numerical analysis of vibration control of nonlinear structural system is carried out by using neural network [11]. In the process of analysis, the actuator structure model is adopted, and the neural network is trained by nonlinear numerical data to expand the application range of the neural network. A special radial basis function network is used to connect the standardized linear spline network to predict the reaction of a single degree of freedom system under random load. Stochastic search global optimization method is used to improve the learning algorithm of the neural network [12], which accelerates the learning speed and accuracy. The algorithm is applied to the multi-layer network, and the control effect of the neural network is verified by analyzing the two-degree-of-freedom adaptive system under random load. Multi-layer forward neural network based on BP (Back Propagation) algorithm is used to simulate and control the earthquake response of multi-layer buildings, and the number of required network hidden layer nodes is reduced by changing the node connection mode, so as to improve the response accuracy of peak prediction [13]. The multi-layer neural network based on BP algorithm is used to control the mixed vibration of the viscoelastic structure with multiple degrees of freedom, which effectively reduces the horizontal displacement of the vibration isolation foundation and achieves obvious control effect when applied to the structure control [14]. A self-recurrent neural network (SRNN) is used to predict the response of the structure [15]. In order to ensure the fast convergence of learning, an adaptive learning rate method is obtained by using Lyapunov function, and a two-story building structure model is predicted online with good results.

The "neural network" in automatic control generally refers to artificial neural network, which is a network that imitates the neural behavior characteristics of animals, and can effectively process distributed information, which is a better mathematical model. This kind of neural network system can adjust and connect internal nodes according to the complexity of the system and process information at a high speed. At the same time, it also has the ability of self-learning and self-adaptation [16]. The neural network system used in electrical engineering automation control generally has two subsystems: one subsystem is stator current, which is used to control electrical parameters; another subsystem identifies rotor speed and controls electromechanical system parameters. Due to the certain feedforward structure in the neural network, reverse learning algorithm can be applied in the system to diagnose the electrical engineering drive system and judge the working state of the motor [17]. The neural network reverse rotating wave algorithm can effectively control the initial speed of the motor, grasp the load torque information in time, and reduce the positioning time. It can surpass the traditional ladder control method [18]. The application of intelligent neural network function estimator can reduce the noise interference, has strong consistency, and does not need to apply complex control model. These advantages make the neural network system applied in the process of pattern recognition and signal processing, and it has a good effect in the automatic control of electrical engineering. Intelligent neural networks greatly improve the reliability of diagnostic systems and monitoring systems, and at the same time, it can also be used in conjunction with multiple sensors. If the neural network system can only reflect a certain mapping, then the excitation function and hidden node will exist in the network system and are often used in the learning process of the neural network [19]. In practical application, the problem of excitation function and layer number is solved by trial method, and the approximation of nonlinear function can be obtained by backpropagation technique. In the process of adjusting the weight of the network, it is only necessary to feedback the stage error to the system in time [20]. The fuzzy controller studied in the world has been widely used in the automation control of electrical engineering, which has gradually replaced the traditional PID controller [21]. In the fuzzy controller, the digital dynamic transmission system is generally used. Up to now, both M-shaped and S-shaped fuzzy logic controllers developed have been applied to a certain extent, but only M-shaped controllers can realize speed control of electrical equipment [22]. Both controllers have rich rule libraries, often referred to as "if them" fuzzy rule sets. In an S-shaped controller, the fuzzy set containing *G* and *H*, if *X* is *G* and *Y* is *H*, then *W*(*fX*, *Y*). The M-shaped controller includes inference machine, knowledge base, fuzzy structure and anti-fuzzy structure [23]. Among them, inference machine is the most important part, if it has fuzzy control behavior, it can make the corresponding decision after reasoning behavior. The knowledge base contains the database and the language control rule base, and the rule base has a unique development method. The measurement and fuzzification of variables can be realized by using the number representation of neural network. Fuzzy logic control is applied to the automation control of electrical engineering, and good results are obtained.

The main characteristics of large spatial structures are small damping, nonlinearity and model uncertainty, and the traditional methods for vibration control of such structures have encountered serious challenges [24]. Aiming at this feature, this paper studies how to apply fuzzy control theory to realize the active control of flexible structures, proposes a fuzzy active control method based on continuous fuzzy decision function [25], and conducts simulation studies on the fuzzy dynamic vibration control of cantilever beam under transient, sine and random excitation respectively. The simulation results show that the vibration in these three cases has obvious suppression effect. Since the adaptive filtering algorithm widely used in active control is only applicable to linear control problems, a nonlinear adaptive filtering method based on fuzzy logic system is proposed to solve a class of feedforward active control problems in which the reference signal and external disturbance are nonlinear functions [26]. The simulation results show that the fuzzy adaptive filter is better than the linear filter. A fuzzy state control method is proposed to blur the state of the structure (i.e. the reaction) and control the structural response according to a certain rule of thumb [27]. Fuzzy neural network (FNN) combines the logical reasoning ability of fuzzy system and the self-learning ability of neural network, so that it not only has strong structural knowledge expression ability, but also has its own parameter adjustment and optimization ability, so it is widely used in the control of complex systems with many variables, strong nonlinearity and difficult to obtain its own mathematical description [28]. However, as the complexity of the controlled object increases, the complexity of the multi-layer neural network composed of fuzzy description language rules and membership functions in the FNN controller increases, resulting in a huge network structure, which increases the operational complexity and decreases the control effect, thus requiring higher requirements for the self-learning algorithm of the control system. The learning algorithm of FNN usually adopts BP algorithm or gradient descent algorithm [29]. The inherent limitations of these algorithms make the learning process of FNN easily fall into local minima, and if the surrounding area is flat, the learning process will become quite slow, which seriously affects the online application of FNN controller [30]. When identifying complex nonlinear unknown systems, it is often difficult to solve the problem by using conventional least square method. At this time, one of the more effective methods is neural network technology. At present, the most mature neural network for system identification is BP network. It will directly affect the accuracy and speed of network training [31]. Using this method, vibration control is simple, direct and effective. The above basically reflects the current research status of active structural vibration control at home and abroad, most of which has been applied in engineering practice and achieved certain control effects. This paper proposes a control scheme combining neural network identification and fuzzy neural network control, and designs an improved FNN controller learning algorithm. During the process of network learning, the error backpropagation method is adopted to correct the network parameters, the improved genetic algorithm is used to optimize the membership function, and the chaos mechanism is introduced into the neural network identifier. The combination of the two methods improves the learning accuracy and convergence speed, and enhances the control effect on complex multivariate systems. Abbreviations in the text are shown in Tab. 1.

Table 1 Abbreviations

Abbreviations	Full name
PID	Proportional-Integral-Derivative
BP	Back Propagation
FNN	Fuzzy neural network

3 RESEARCH ON LEARNING ALGORITHM OF INTELLIGENT CONTROL OF ELECTRICAL ENGINEERING AUTOMATION BASED ON FUZZY NEURAL NETWORK

3.1 Research on Intelligent Control of Electrical Engineering Automation

The fuzzy neural network control system adopted in this paper is shown in Figure 1. In the system, the input and output data of the controlled object are used to train the neural network identifier NNI, which is used to approximate the model of the controlled system. The training of the fuzzy neural network controller FNNC is modified by network parameters, and then the membership function is optimized by an improved learning algorithm. This system has a high learning speed and can converge to the global minimum.

It is considered that fuzzy PID can adjust parameters without precise mathematical model, so as to achieve accurate control. At the same time, RBF neural network has a strong learning ability, and determines the weight of a certain moment through the membership function, and then controls the variables. Therefore, the combination of the two algorithms can realize the precision control more effectively. At present, for the combination of fuzzy PID and RBF neural network, the commonly used methods include a certain algorithm or a comprehensive combination of the two methods. Considering the self-learning ability of RBF neural network, the combination of RBF neural network control and fuzzy PID control has been tried. The specific logic control flow is shown in Fig. 1. In the control process, the neural network adjusts the network parameters through adaptive learning, improves the performance of the speed control system, and processes the speed and current information of the driving motor in real time.

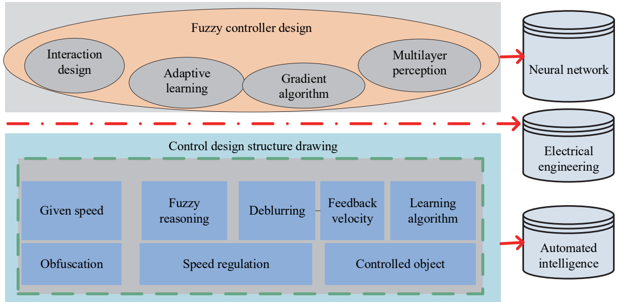

Figure 1 Control system structure diagram

According to Fig. 1, the control flow of the RBF neural network structure is as follows: Firstly, the output result of the fuzzy PID algorithm is linearized by the input layer, then the processing result is distributed to the hidden layer, the Gaussian function is used for discrete processing, and finally the discrete result is transmitted to the output layer for linear summation to obtain the final parameter variable. The specific calculation formula is as follows:

(1) In the hidden layer b_j, Gaussian function expression:

$$h_i = \exp\frac{\| X - C_j \|^2}{2b_j^2} \tag{1}$$

where, C represents the center vector and b represents the base amount.

(2) In the output layer, the linear summation formula, w, represents the network weight.

$$y_m = w_1 h_1 + w_2 h_2 ... + w_m h_m \tag{2}$$

(3) PID change adjustment

The final parameter variables calculated by the RBF neural network are directly transmitted to the speed PID regulating module for output setting, accurate variables, and improved control accuracy. The setting method is gradient descent.

$$\Delta k_p = -\lambda e(k) * \frac{\partial y_m}{\partial u(k)} \tag{3}$$

3.2 Improved Reinforcement Learning Algorithm for Intelligent Control of Fuzzy Neural Networks

There are many kinds of structure forms of fuzzy logic system. In the field of control, the Z-input controller structure is usually adopted, which is a 5-layer feedforward network. Layers 1 to 3 implement the fuzzy control rule "if-then", and layers 4 to 5 implement defuzzification. When the fuzzy controller is composed of neural networks, the control system becomes a neural network fuzzy control system, and a neural network self-learning fuzzy control system is formed by using the neural network self-learning function. The structure of neural network fuzzy control system is shown in Fig. 2. In the figure, the fuzzy controller is composed of neural network, so the characteristics of the fuzzy controller can be changed by modifying its weight coefficient. In order to modify the neural network weight coefficient of the neural network fuzzy controller, a neural network learning mechanism is set up. The learning mechanism depends on the output Y of the system, the actual deviation, the rate of change, and the amount of control generated at that time. The modification direction and step size of the weight coefficient are determined, and the weight coefficient modification signal I is sent to the neural network fuzzy controller. After the weight coefficient of the neural network fuzzy controller is modified, the output Y is approximated to the given R, and the deviation e is finally minimized. The modification of the weight coefficient is essentially the modification of the control rules.

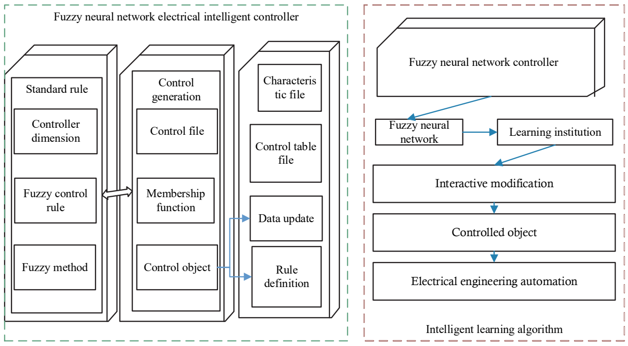

Figure 2 Fuzzy neural network control system structure

There are two ways to combine neural network and fuzzy control, namely global network structure and local network structure. The global network structure is that the whole network structure adopts neural network, but the data in it is processed by fuzzy quantity. The local network structure refers to a part of which uses neural network for processing, and the main reasoning part uses fuzzy reasoning to calculate the control quantity. This paper uses neural network to establish fuzzy rule base, which is a local network structure.

Using neural network to identify nonlinear system, we need to assume that the object is controllable and observable. The object output is uniformly bounded for all possible control inputs. The structure of the identification model is the same as that of the object except that it contains one or several neural networks. In this paper, a series-parallel model is used to identify the controlled object. The expression of the controlled object is:

$$\begin{aligned} y(k+1) = f[&y(k), y(k-1)...y(k-n+1), \\ &u(k)...u(k-m+1)] \end{aligned} \tag{4}$$

A 3-layer chaotic neural network identifier approximates this nonlinear system:

$$\begin{aligned} \hat{y}(k+1) = f[&\hat{y}(k), \hat{y}(k-1)...\hat{y}(k-n+1), \\ &u(k)...u(k-m+1)] \end{aligned} \tag{5}$$

The objective function of network learning is defined as:

$$J_\lambda = \frac{y(k) - \hat{y}(k)}{2} \tag{6}$$

Then the input layer:

$$O_j(k) = \begin{cases} y(k-j), 0 < j < n-1 \\ u(k-j+n), n < j < n+m-1 \end{cases} \quad (7)$$

Output layer:

$$l(k) = \sum_{j=1}^{m} w_k O(k) - \lambda_3 \quad (8)$$

where: m is the number of nodes in the first layer of the identifier; w - the connection weight between the input layer and the hidden layer and the hidden layer and the output layer of the pseudo-identifier; r is the threshold of the hidden layer and output of the recognizer. The activation function of the hidden layer of the neural network is sigmaid function, the remaining layer is pure lin function, r is the learning coefficient of neurons, and the chaotic BP algorithm is used to train the connection weight and threshold of the three-layer neural network. The specific algorithm is as follows:

$$\delta(k) = \eta(k)O(k) + \Delta w_k e^{-tr^2} \quad (9)$$

In this paper, through online identification, the dynamic characteristics of the controlled object can be replaced by the identifier, because the training speed is fast and the training error is small using the chaotic BP algorithm.

3.3 Dynamic Fuzzy Neural Network Control Based on Reinforcement Learning

From the perspective of fuzzy control rules, a fuzzy control rule corresponds to a region of the input vector space. According to the criteria, when an input variable enters the system, the inference strength and M distance of the existing neural network unit whose center and width are x and c respectively are:

$$md_j(X) = \sqrt{(X-c_j)^T \sum (X-c_j)} \quad (10)$$

It is difficult to accurately judge whether new rules need to be generated according to the criteria alone, but also combined with the time difference deviation standard, which uses the performance pointer i to judge whether new criteria need to be generated, and update the formula:

$$\varepsilon_{i+1}^i = \frac{(k-\alpha_t^i)\varepsilon_t^i + \alpha_t^i \varepsilon_{t+1}}{k} \quad (11)$$

The inference strength function determines the degree of influence of the fuzzy rule r on the time integral deviation, which is actually equivalent to a digital low-pass filter. In this way, the past time integral deviation is gradually forgotten, but it does not disappear completely, and the time integral deviation closer to the current moment has a greater impact on the value.

After generating a new rule, the next step is to determine the center and width of the new membership function. For the input variable x, assuming there are already n adjustment rules in the system, then for the i-th component x_i of the variable x:

$$ed_i(j) = x_i - \vartheta_i(j) \quad (12)$$

In the time difference method, the estimated value function is updated by the following formula:

$$V(s,k) = \alpha \sum_{d=0}^{k} [r_t + \gamma V(s_{t+1})] \quad (13)$$

It can be seen that the value function can be estimated according to the time difference deviation and it is a suitable indicator to judge the quality of the fuzzy inference system. After a scene or several training steps, the performance of the fuzzy system can be evaluated.

In the actual operation of the control system, the sudden deletion of redundant rules may cause great interference to the system, so the membership function width of the rule to be deleted should be reduced as far as possible before deleting the redundant rules. According to the time difference deviation of each rule, the width of each rule membership function is increased or decreased.

Deep reinforcement learning is an approach that integrates deep neural networks with reinforcement learning, using neural networks to approximate or represent value functions, strategies, or models to deal with high-dimensional, complex state and action Spaces. This approach has achieved remarkable success in many fields, such as image processing and natural language processing, while showing superior performance in reinforcement learning tasks.

Reinforcement learning is closely related to the control of electrical systems and plays an important role in the field of electrical engineering. Reinforcement learning can be applied to automation systems, robot control, power system management, and industrial automation to optimize control strategies and decision-making processes. Through reinforcement learning, electrical systems can automatically learn optimal control strategies to adapt to changing environmental conditions and needs. These methods allow the system to adjust the control parameters in real time, improve the efficiency, reliability and adaptability of the electrical system, so as to achieve more intelligent and autonomous electrical system operation and control. In addition, reinforcement learning can be used for applications such as load management of power systems, grid optimization, and intelligent energy management to address complex power supply and demand challenges. Therefore, the application of reinforcement learning in electrical system control provides a powerful tool for improving system performance and resource utilization.

First, by maximizing the extraction and utilization of renewable energy, the demand for traditional energy resources can be reduced, thus reducing the cost of energy procurement. Second, improved energy efficiency helps reduce environmental impact while improving the reliability of electrical systems. Finally, effective management and distribution of energy resources can improve the reliability of electrical supplies and reduce the risk of blackouts. Aiming at the problem of low energy utilization rate in electrical system, DDPG (Deep

Deterministic Policy Gradient) method in reinforcement learning is used to model and optimize the result, so as to improve the energy utilization efficiency of electrical system. After completing the construction of the objective function of energy utilization minimization, the deep reinforcement learning DDPG algorithm is further used for optimization.

3.4 Electrical Engineering Automation Intelligent Control Learning Algorithm Fusion

Optimization algorithms are widely used in the field of electrical engineering. In the power system optimization dispatching, the optimization algorithm can help realize the economic operation of the power grid and the energy saving and consumption reduction. By constructing the mathematical model of the power system and using the optimization algorithm to solve the optimal generation plan and scheduling strategy, the operation cost of the power grid can be minimized and the energy efficiency can be maximized. For example, the power system optimization scheduling method based on genetic algorithm can comprehensively consider many factors such as power generation cost, environmental protection requirements, system stability, etc., to achieve the global optimal scheduling decision. In the aspect of motor design and control, the optimization algorithm can be used to optimize the structural parameters and control strategy of the motor. By modeling and analyzing the electromagnetic field, thermal field and mechanical field of the motor, and using optimization algorithm to solve the optimal motor design parameters and control parameters, the motor can meet the performance requirements while having lower manufacturing cost and higher operating efficiency. For example, the motor optimization design method based on particle swarm optimization algorithm can comprehensively consider the electromagnetic performance, thermal performance, mechanical performance and other aspects of the motor to achieve comprehensive performance optimization of the motor.

The fusion of intelligent control and optimization algorithm is an important method, which aims to combine the traditional control strategy with optimization algorithm to improve the performance, efficiency and stability of the system. The fusion strategy of intelligent control and optimization algorithm includes the following key steps:

(1) Definition of objective function: First, it is necessary to clearly define the optimization objective function of the system, which usually includes the performance index of the system, the cost function or other indicators that need to be optimized. The definition of objective function is very important for the subsequent optimization algorithm selection and implementation.

$$J(x,t) = f(x,t) \tag{14}$$

where J is the objective function, x is the system state vector, t is the time, and f is the system performance function.

(2) Intelligent control algorithm selection. According to the characteristics and control requirements of the system, the appropriate intelligent control algorithm is selected as the basic controller. Common intelligent control algorithms include fuzzy control, neural network control, model predictive control and so on. Selecting the appropriate control algorithm can improve the stability and robustness of the system effectively.

(3) Optimization algorithm selection. According to the characteristics of the objective function and the constraints of the system, the appropriate optimization algorithm is selected for parameter optimization or system adjustment. Common optimization algorithms include genetic algorithm, particle swarm optimization algorithm, simulated annealing algorithm and so on. The selection of optimization algorithm should take into account the convergence, computational complexity and application range of the algorithm.

(4) Fusion method design. The fusion method of intelligent control and optimization algorithm is designed, and the optimization algorithm is incorporated into intelligent control system to realize online optimization of system parameters or control strategies. The design of fusion method should take into account the interaction between controller and optimization algorithm, the parameter transfer mode and the real-time and stability of optimization process.

Firstly, the system is modeled and simulated, including system dynamic characteristics, controller structure and optimization objective function definition. The accuracy of the system model can be verified by simulation, which provides the basis for the subsequent fusion realization.

Design the structure and parameter initialization method of intelligent controller, select the appropriate controller type, and carry out parameter initialization. The design of the controller should take into account the nonlinear characteristics and control requirements of the system to ensure the performance and stability of the controller. The selected optimization algorithm is integrated into the intelligent control system to realize online optimization of controller parameters or system state. The integration of optimization algorithm can be accomplished by calling the existing optimization library or implementing the optimization algorithm module by itself. In the process of system operation, the parameters of the controller are updated in real time or the state of the system is adjusted by the optimization algorithm to achieve the optimal value of the objective function. The optimization process can be based on iterative update, and gradually optimize the performance of the system by constantly adjusting the parameters. Real-time monitoring of the operating state of the system and the convergence of the optimization process, and adjusting the parameters of the optimization algorithm or the output of the controller according to the real-time feedback to ensure the stability and robustness of the system. Real-time control and feedback is the key link in the fusion process of intelligent control and optimization algorithm, which directly affects the performance and effect of the system. Through the above technical steps, the integration of intelligent control and optimization algorithm can be effectively realized, improve the performance and efficiency of the system, and provide a feasible solution for practical engineering applications.

4 SIMULATION VERIFICATION

The research uses the 64-bit Windows 11 operating system and PyCharm as an Integrated Development

Environment (IDE), using the Python 3.9.7 programming language and TensorFlow 2.6.0 deep learning framework. The experimental data came from a power grid enterprise platform. After the data is collated and preprocessed, it is used to model reinforcement learning and optimize the objective function of resource utilization in electrical systems. The goal of the experiment is to maximize energy utilization efficiency, reduce energy procurement cost, and reduce environmental impact through DDPG algorithm, providing a new way to improve the performance of electrical systems. The experimental data of the electrical system are shown in Tab. 2.

Table 2 Experimental data of electrical system

Time step	Battery charging state	Solar power generation	Grid price	Battery charge	Rewards
1	0.65	0.85	0.13	0.2	0.35
2	0.75	0.75	0.16	0.35	0.25
3	0.85	0.65	0.15	−0.12	−0.22
4	0.76	0.9	0.112	0.43	0.45
5	0.72	0.75	01.4	−0.24	−0.31

As can be seen from Tab. 2, the solar power generation, battery charging state and battery charging amount of the system all change with the change of time step. This indicates that the electrical system flexibly adjusts its charging strategy according to real-time conditions to maximize the use of available solar energy resources. The reward value r_t reflects the system performance, positive reward indicates that the system has achieved good performance in the corresponding time step, negative reward indicates that the performance has decreased, but when the battery charging state is low or the solar power generation is not enough to meet the demand, the system may need to purchase electricity from the grid. This can be done at a time when grid electricity prices are low to reduce costs. According to the positive or negative value of the battery charge, it is possible to determine whether the system is in a charging or discharging state.

The automatic generation tool of intelligent controller introduced in this paper plays an increasingly important role in the practical simulation of fuzzy neural network theory and the development of practical intelligent products. For example, in the intelligent variable frequency air conditioning controller, the fuzzy neural network is used to automatically obtain: the predicted average voting value of human comfort; fuzzy control rules of electronic expansion valve for controlling refrigerant flow; fuzzy control rules for controlling indoor human comfort (CPMV), etc. Limited by space, we will use the test method of nonlinear function approximation to verify the validity of the intelligent controller white motion generation tool from the aspect of principle. The basic idea of this method is: by querying and calculating the output table of the fuzzy controller generated by the learning algorithm, the simulation output value and simulation curve of the nonlinear function can be obtained, and compared with the actual value and curve obtained by directly calculating the nonlinear function, the reliability of this algorithm can be judged. Understand the problems with the algorithm. In the algorithm verification, we use uniform samples as the values of x_1 and x_2, and then calculate the input value y as the training sample, and test the learning effect with random samples. The sample surface, control surface (learning result surface), absolute error and relative error surface are shown in Fig. 3.

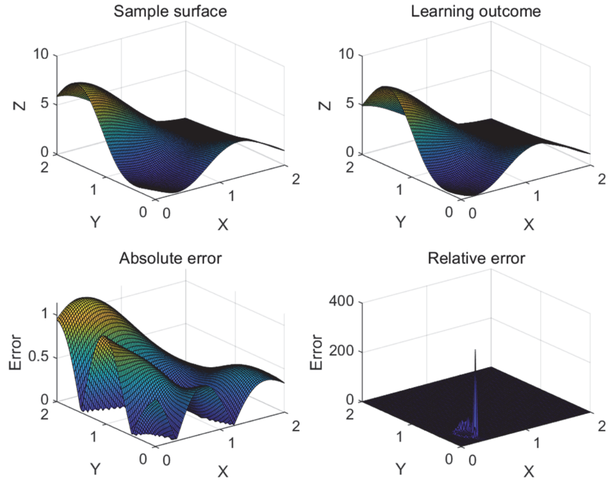

Figure 3 Function approximation surface diagram

By comparison, it can be seen that the overall approximation effect of the function is good, that is, the actual surface can be basically restored. However, in some details, the approximation effect of the function is not perfect: this is mainly related to the quality and quantity of the initial training samples. If the training sample is added and the sample can cover the theoretic region well, the effect of surface approximation will be greatly improved.

When the 49 rule is adopted, the number of fuzzy marks for both the input deviation and the change speed of the input deviation is 7, and the fuzzy rules are shown in Tab. 3.

Table 3 Fuzzy control table with rule 49

e	PB	PM	PS	Z
PB	0.0005	0.4389	0.0005	0.5923
PM	0.783	0.9198	0.1786	−0.4397
PS	0.0156	1.6647	0.5746	0.9784
Z	0.7789	−0.8657	0.9248	0.1534

At the same time, from the point of view of the trapezoidal signal tracking, the system still maintains a good adjustment performance when the number of fuzzy rules is greatly reduced. Compare the membership functions of rule 49 and rule 16 in Fig. 4.

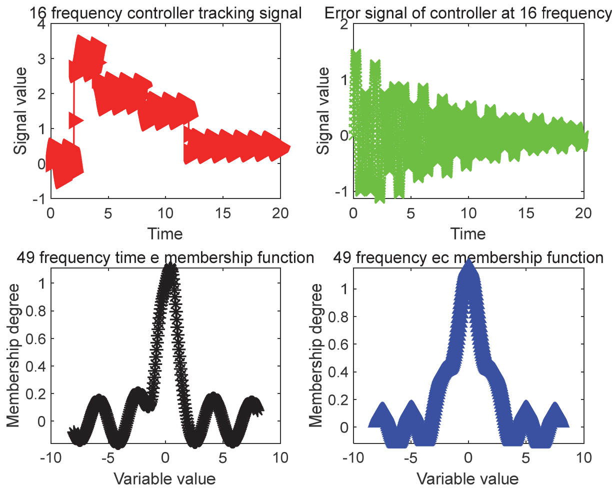

Figure 4 Membership functions for rule 49 and rule 16

Deleting unnecessary adjustment rules can greatly reduce the computational load in the fuzzy neural network control process and improve the adjustment quality of the system while basically keeping the control accuracy unchanged. Fig. 5 below shows the fitness curve and the change curve of optimal fitness obtained by the fuzzy neural network controller when rule 49 is adopted, which is optimized by genetic algorithm. Maximum evolution 80 generations.

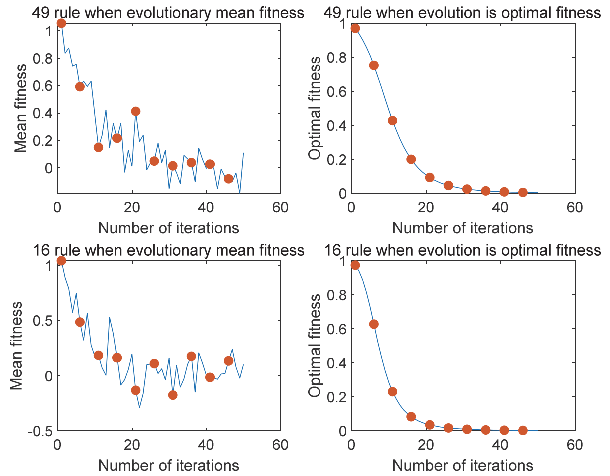

Figure 4 Fitness function for rule 49 and rule 16

All parameters of the simulation are completely consistent with those used above, and the performance indicators of the four algorithms are compared. The system output response curve is shown in Fig. 5. According to Fig. 5, the performance indicators of the four algorithms are calculated, as shown in Tab. 4.

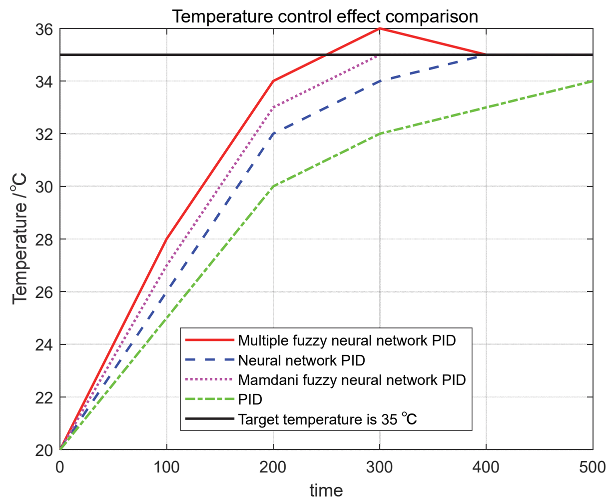

Figure 5 System output response curves of the four algorithms of Model 1 (29)

Table 4 Comparison of performance indexes of four algorithms in Model 1 (29)

Performance index	Control algorithm		
	Multiple fuzzy neural networks	Mamdani fuzzy neural network	Neural network PID
Overshoot / %	5.00	13.10	23.40
Adjust the time /s	1462.00	1249.02	1865.02
Delay time / s	145.89	220.47	274.06
Rise time /s	594.28	448.83	487.5
Steady state error / °C	0	0	0

Fig. 6, Fig. 7, Fig. 8, Fig. 9, Fig. 10 and Fig. 11 give the time response under two typical excitations, where the ordinate is the vibration response of the structure and the dimensionless amplitude, that is, the maximum value in the open-loop state is divided into the amplitude of other states and time points, and the abscissa is the simulation time. The simulation results are as follows:

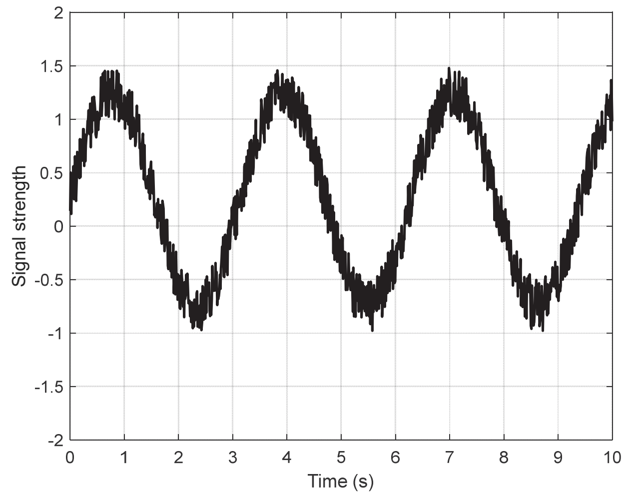

Figure 6 Uncontrolled response of the structure under sinusoidal excitation

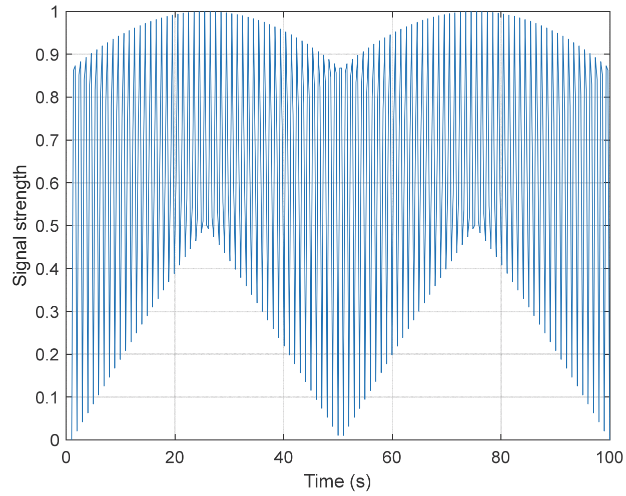

Figure 7 Fuzzy control response of the structure under sinusoidal signal excitation

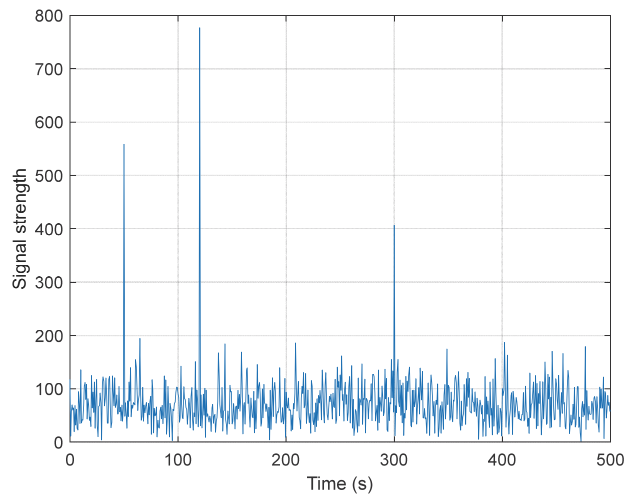

Figure 8 Fuzzy control response of the structure under the excitation of the stop signal (after improving the control rules)

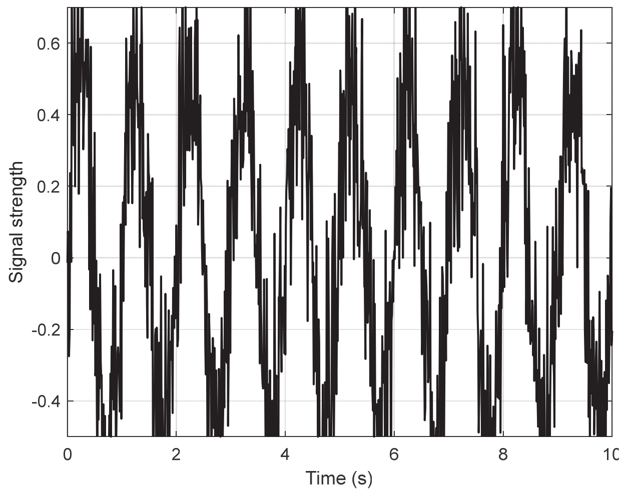

Figure 9 Final control response of the structure under random signal excitation

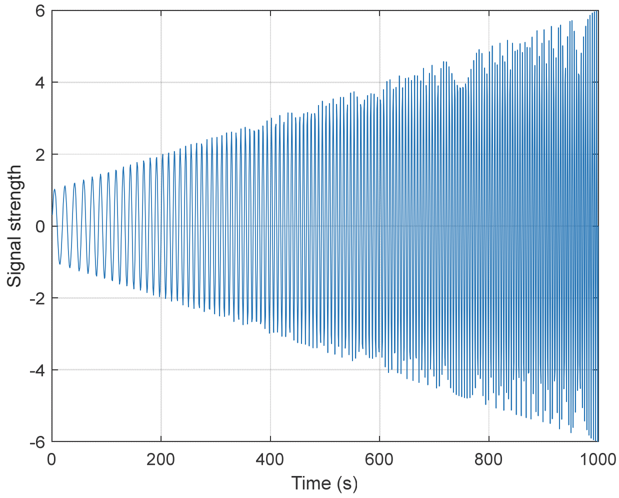

Figure 10 Fuzzy control response of the structure under random signal excitation

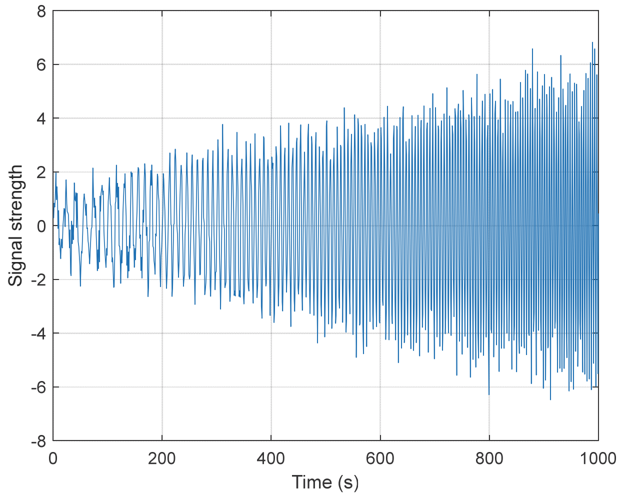

Figure 11 Fuzzy control response of the structure under random signal excitation (after improving control rules)

Fig. 6 and Fig. 9 show the uncontrolled response of the structure under the excitation of sinusoidal and random signals respectively. Fig. 7 and Fig. 10 show the fuzzy control response of the structure under the excitation of sinusoidal and random signals respectively. Fig. 8 and Fig. 11, respectively, show the fuzzy control response of the structure under the excitation of sinusoidal and random signals, where the expression of the control rule is improved, and 0.6 is taken here. It can be seen from the above results that the fuzzy control algorithm can suppress the vibration of the structure to a certain extent, especially after the fuzzy control expression is improved, the control effect will be more obvious.

In order to further explain the prediction effect of the fuzzy neural network model established in this chapter, 100 samples are randomly selected from the test set, and the intelligent control of electrical engineering automation is predicted by using the fusion model of the intelligent control learning algorithm of electrical engineering automation. The predicted results are shown in Fig. 12. It can be seen that the fusion model of intelligent control learning algorithm of electrical engineering automation is approximate regression to the original control. The variance of the forecast data is relatively small compared to the original data, but the underlying trend remains consistent. It also shows that the fusion model of intelligent control learning algorithm based on electrical engineering automation has certain ability to predict the control effect.

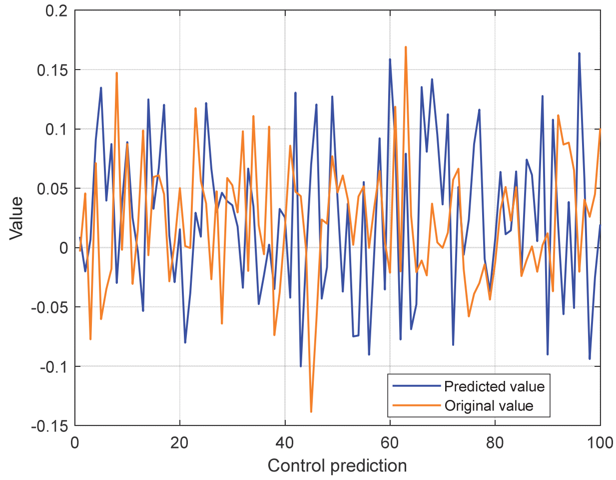

Figure 12 Fusion prediction effect of intelligent control learning algorithm for electrical engineering automation

At the same time of the development of computer technology, the equipment in electrical engineering has been constantly innovated, which has greatly improved the production efficiency and production quality, and the traditional manual design method has been unable to meet the needs of social development. In many cases, CAD design instead of traditional manual design, and the full application of technical experience and understanding of motors, circuits, etc., in the complex electrical design process to show its advantages, and then the application of intelligent technology to the CAD design process, improve the design quality, improve work efficiency while shortening the development time of products, thereby improving production efficiency. At present, in the electrical design process, many enterprises are using fault diagnosis technology and optimized operation methods to apply reliable expert systems to electrical engineering. With the assistance of researchers, the expert system can be applied in practical engineering, such as the permanent magnet synchronous motor expert system. In addition, the application of this diagnosis and optimization operation can improve the stability and accuracy of the system with the help of high-precision calculation methods. Intelligent technology has shown its advantages in product design and its importance when electrical engineering fails. The application of expert system, neural network system and fuzzy logic control technology can diagnose electrical equipment faults timely and accurately, and apply intelligent technology to the diagnosis process of motors, generators and transformers, so as to obtain good application benefits.

5 CONCLUSION

This study explores the application of intelligent control technology in electrical engineering automation, focusing on improving system regulation quality through a fuzzy neural network-based algorithm. By integrating the self-learning capability of neural networks with the fuzzy reasoning ability of human-like decision-making, the proposed method achieves adaptive control of complex systems, particularly addressing nonlinearity and uncertainty. Two key innovations are introduced: 1) using the intelligent heuristic function of reinforcement learning to optimize fuzzy control rules during rule generation, and 2) enhancing system stability by gradually reducing the width of membership functions when eliminating redundant rules. Simulation results validate the algorithm's effectiveness, demonstrating its self-learning, robust, and nonlinear handling capabilities, which significantly improve the accuracy and efficiency of electrical system control.

The combination of advanced control theories, such as neural networks and fuzzy logic, provides a powerful framework for realizing efficient automation in electrical engineering. While the research highlights the potential of integrating intelligent control with optimization algorithms, challenges remain in scaling the approach to high-dimensional systems, improving real-time adaptability, and enhancing robustness under extreme uncertainties. Future work should further explore interdisciplinary synergies, refine algorithmic efficiency, and expand. To promote the integration of fuzzy neural network-based intelligent control in electrical engineering, policymakers should prioritize increasing R&D funding for cross-disciplinary innovations, establishing standardized technical frameworks, fostering academic-industrial collaboration for talent cultivation, and incentivizing green applications to align with sustainability goals. Future research could focus on enhancing algorithm efficiency for high-dimensional systems, enabling real-time hardware implementation, integrating with emerging technologies like digital twins and edge computing, improving robustness in uncertain environments, expanding applications to sectors like renewable energy and electric vehicles, and embedding sustainability objectives into control algorithms to drive the development of autonomous, efficient, and eco-friendly electrical systems.

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