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Emotional Deep Learning Programming Controller for Automatic Voltage Control of Power Systems

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ABSTRACT In recent years, the rapid development of artificial intelligence, especially deep learning technology, makes machine learning have application scenarios in the fields of power system stability analysis, coordination along with scheduling and load forecasting. This paper designs an emotional deep learning programming controller (EDLPC) for automatic voltage control of power systems. The designed EDLPC contains an emotional deep neural network (EDNN) structure and an artificial emotional Q-learning algorithm. Besides, a specially defined proportional-integral-derivative (PID) controller is added to the deep neural networks (DNNs) structure as the actuator of an EDNN to realize the automatic tuning of PID controller parameters. In terms of control, the controller combines the advantages of the EDNN and PID controller, meanwhile adopts a reinforcement learning algorithm to optimize the parameters. From the perspective of reinforcement learning, embedding prior knowledge into the output instructions of EDNN is helpful to weaken the fitting problem in the training process. Compared with the outputs of the DNN and Q-learning algorithm under the two cases, the EDLPC could gain the highest control performance with smaller voltage deviations. The simulation results verify the feasibility and effectiveness of the proposed method for automatic voltage control of power systems.

INDEX TERMS Automatic voltage regulator, emotional deep learning programming controller, emotional deep neural network.

I. INTRODUCTION

The conventional voltage control of the power system mainly includes three layers, which are the primary, secondary and tertiary levels of voltage control [1]. The primary voltage controller is a reactive voltage control device, which comprises a synchronous motor, static var compensator, static var generator, automatic voltage regulation (AVR), on-load tap changer, and so on [2]. Yashar Hashemi *et al.* proposed a multi-objective gravity search algorithm to solve the generation cost of two wind turbines of doubly fed induction generator and permanent magnet synchronous generator, and evaluated the dynamic performance of each type [3]. Amar K. *et al.* improved a selfish group optimization method to coordinate the frequency and voltage regulation of isolated multi-source hybrid microgrids, and analyzed the system control results under five different extreme conditions [4]. Thereinto, the conventional proportional-integral-derivative (PID)

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controller which is combined with a manifold algorithm can enhance the control performance of the AVR to obtain stable voltage output [5]. Z. Bingul *et al.* proposed a new time-domain performance criterion cuckoo search algorithm for automatic voltage regulator (AVR) PID controller parameter tuning, and through the analysis of its anti-interference performance and robust performance. The analysis of its anti-interference performance and robust performance has verified that the PID controller based on this algorithm has a good effect on tuning optimization [6]. Yongquan Zhou *et al.* employed the water wave optimization algorithm to optimize the optimal PID controller of the automatic voltage regulator system to improve the step response of the AVR system with higher efficiency and robustness [7]. Serder Ekinic *et al.* proposed a new method of objective function tuning the design of PID controller based on an improved kidney excitation algorithm [8]. Abdellatif Bouaichi applied polarity reversal technology to evaluate the restoration performance of PID for the most accurate power loss analysis [9]. Nevertheless, the PID parameters in the voltage controller need reset if system parameters are updated and adjusted. This method of control reduces the operating efficiency of the controller [10]. In the power system, the conventional secondary voltage regulation and tertiary voltage regulation are independent optimization processes [11]. Generally, the voltage regulation of these two stages is limited, thus the adjustment effect is not satisfactory [12].

To balance the contradiction between control performance and operational efficiency in the dynamic process of the power system, reinforcement learning can be applied [13]. Jiajun Duan *et al.* designed a Grid-Mind, which is an autonomous control framework for power grid safe operation based on advanced artificial intelligence technology [14]. This paper demonstrates a combination of the large-scale simulation of deep Q-network, deep deterministic policy gradient, and the interaction of power grid actual environment. At the same time, the agent in this paper is a closed-loop control with no model and only a data drive. The data of the emotional deep learning programming controller proposed in this paper comes from PID controller and provides a specific system model for simulation. To enhance the learning ability of the Q-learning algorithm, the deep neural networks (DNNs) and emotional factors are added to this algorithm to improve the control strategy of autonomous voltage. Hanchen Xu *et al.* proposed a batch reinforcement learning algorithm which is effective to minimize the voltage deviation of the whole system [15]. At present, researchers are trying to combine deep learning and other technologies to improve the aspects of scalability, intelligence, reward mechanism, and to optimize agent decision-making in practical problems [16]. Roozbeh Rajabi *et al.* proposed a single user power consumption forecasting method based on recursive graph and deep learning to accurately forecast short-term or medium-term load [17].

Massive data could prolong the training time of the reinforcement learning algorithm [18]. Lei Xi *et al.* proposed a win or learn fast strategy climbing network based on strategy dynamics which can solve the problems caused by random interference and can improve the utilization of new energies [19]. This paper provides certain prior knowledge to accelerate the learning ability of the agent in the initial stage of the algorithm. As one of the conventional machine algorithms, more data could not improve the performance of reinforcement learning after reaching a certain matrix dimension [20]. Therefore, this paper proposes an emotional deep neural network (EDNN) to improve the accuracy of voltage control, with strong nonlinear mapping ability. The number of training layers in DNNs and neurons in each layer can affect the effectiveness of the training. Excessive layers and neurons could cause slow training speed, while few could reduce the accuracy of learning, thus unable to accurately and comprehensively characterize the characteristics of the data.

To reduce the influence of the number of training layers and neurons on the system control, the Q-learning algorithm with artificial emotion has been introduced [21]. Ying Chen *et al.* proposed a Q-learning algorithm based on the nearest sequence memory to realize on-line learning and attack to regulate the normal operation of power systems [22]. Beakcheol Jang *et al.* studied the latest research trends and key applications using the Q-learning algorithm [23]. In other words, the agent contains two parts, i.e., an emotional part and a logical part. Among them, the emotional part acts on the output action together to ensure the output of the minimum voltage regulation instructions. Emotional decision-making is used to adjust the agent's learning of experience knowledge, so as to overcome the inefficient learning caused by the limited trial and error methods, and then accelerate the agent's convergence speed in the current environment.

In this paper, an EDNN is designed for the emotional deep learning programming controller (EDLPC), which can obtain a smaller voltage deviation in the power system through multiple neural layers. Both the Q-learning algorithm and the DNN have certain defects in the formulation of a control strategy. If the DNN is too small (underfitting) relative to the training set, the rule model found can not capture the data characteristics precisely fit the data well. If the DNN is too large (overfitting), too many rules will be remembered, It is too specific and rigid to remember the training set, so it may not flexibly change the potential abnormal data in the system. After adding a Q-learning algorithm, it can flexibly complete the formulation of the action according to the environment state and reward state. However, the Q-learning algorithm might not guarantee to explore all the States and action pairs. Given this deficiency, the emotional factors were introduced to select more accurate actions through the adjustment of the reward matrix. In this paper, the source of simulation data is generated from the PID controller, which is convenient for data acquisition. The limitation of this method is that it needs to obtain the actual data before on-line control, which requires more training time than PID controller and other direct online control methods. In the step wave experiment, EDLPC has a smaller voltage deviation control effect than

TABLE 1. Symbol abbreviation table.

Symbol name	Abbreviated name
Automatic voltage regulation	AVR
Proportional-integral-derivative	PID
Deep neural network	DNN
Genetic algorithm	GA
Emotional deep neural network	EDNN
Emotional deep learning programming controller	EDLPC

a single DNN and Q-learning algorithm voltage control. The control framework has a more accurate control performance.

The EDLPC proposed in this paper is based on deep neural network and Q-learning algorithm. The training set is generated by PID controller, and the parameters of PID controller are obtained by genetic algorithm. Although the DNN and Q-learning algorithm have been applied to the voltage control of power systems, some defects of the two algorithms cannot be made up by simply combining each other. To improve this drawback, we add the ''emotion'' part to the above two algorithms respectively, and then combine them, which can effectively improve the accuracy and performance of the control algorithm. The experimental results show that the emotional factor can effectively improve the control effect of the algorithm. The key features of EDLPC are given as follows.

1) The EDLPC mainly includes EDNN. The EDNN consists of several neural layers, each of which has a different number of neurons; thus, the EDNN can overcome the limitation of linear separability.
2) Since the EDNN can provide multiple sets of data inputs and outputs at the same time, the EDLPC is designed as a multi-input and multi-output controller.
3) The EDLPC contains an artificial emotional Q-learning algorithm, in which the agent is composed of a logical part and an emotional part. The EDLPC can weaken the potential fitting problem of DNN.

The rest of this paper is presented as follows. The EDNN is introduced in Section II. A voltage regular controller framework based on EDLPC and the Q-learning algorithm with artificial emotion is described in Section III. In Section IV, simulation results are shown. At the same time, the gradient, error, and network training after each iteration are as well as given. Section V is briefly the summary of this paper.

II. COMPOSITION ALGORITHM OF EMOTIONAL DEEP LEARNING PROGRAMMING CONTROLLER

Conventional voltage control includes three control layers, i.e., primary, secondary, and tertiary levels [24]. The rapid and random change of voltage is compensated by the ''one-time action'' of the system power plant, which requires a fast response (reaction in a few seconds) [25]. This part of the adjustment is mainly realized by the excitation adjustment of the unit, and secondly by the automatic voltage tap of the transformer [26]. The ''secondary'' control functions and ''tertiary'' control functions establish a new state of the system [27]. Secondary control manages the dynamic reactive power of available resources in a region with a response time of approximately 3-5 minutes. The tertiary control is a manual operation; and the overall coordination of the whole system point voltage can artificially be obtained [28].

Many medium control algorithms are gradually applied to the voltage primary adjustment process. One of the most classic medium control algorithms is the PID controller [8]. Omer Saleem *et al.* proposed a state-dependent self-tuning fractional order control strategy to make the system have the characteristics of fast transient, minimum transient recovery time, and minimum steady-state fluctuation by augmenting the optimal PID controller [29]. The control principle and the structure of the algorithm are simple, meanwhile, the PID controller has the characteristics of wide adaptability and wide application in engineering [30]. Sajjad Dadfar *et al.* proposed an improved fuzzy gain scheduling control strategy based on the PID controller, which can improve the performance of the whole power system in the grid-connected mode [31]. At the same time, PID controller can control the system voltage and can stabilize the power near the specified value, hence as to achieve stable and accurate control [32]. In a practical nonlinear system, the controller can only be applied for a certain balance point and its domain, and often the domain range cannot meet the actual accuracy requirements [33]. Due to the existence of network communication delay, the control performance of the traditional PID controller in a networked control system will decline.

This paper combines EDNN and artificial emotional Q-learning to mitigate the shortcomings of the PID controller. The EDNN can find the optimal PID controller parameter values of the current system for voltage regulation and can apply these parameters as well as voltage regulation data for DNN, which is applied to ensure the control accuracy of the controller and the relative balance of learning time. In this paper, the number of layers and neurons of DNN is specially adjusted.

A. DEEP NEURAL NETWORKS

The main optimization goal of EDLPC is the voltage output generated by the PID controller. The PID control voltage link can be characterized as follows,

$$u(t) = K_p(err(t) + \frac{1}{T_i} \cdot \int err(t)dt + \frac{T_d derr(t)}{dt}) \tag{1}$$

where K_p, T_i and T_d are the controller parameters of the PID, which need to be adjusted and modified according to the actual process.

The transfer function of the controlled object along with the feedback model is shown in FIGURE 1. The automatic voltage model consists of four parts: a controlled object, a controller (omitted), a feedback link and an overall negative feedback framework. Among them, a new controller EDLPC is proposed in this paper, which is used to regulate the voltage in the controller part of the automatic voltage control model. The parameters K_a, K_e, K_g, K_r, T_s, T_e, T_g and T_r of each

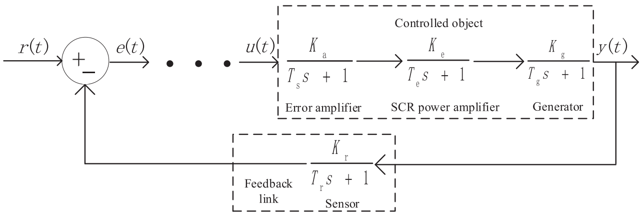

FIGURE 1. Flow chart of automatic voltage control.

part in the FIGURE 1 are given values according to real-life specific systems.

The emotional control link can automatically find the most reasonable PID regulation value for system voltage control. And the simulation data obtained by the PID regulation will be provided to DNN as a training camp for learning.

The DNN combines low-level features to form high-level features, to find out the form of data distribution characteristics. The mathematical realization of the network is mainly divided into forwarding calculation result and reverse modification weights. The DNN is extended from the perceptron and consists of a multi-layer neural network. Each small local model can be regarded as a single perceptron model, that is, the combination of linear function $y = \sum_{i=1}^{n} w_i x_i + b$ and activation function $f(y)$. The DNN mainly includes forward propagation algorithm and back-propagation algorithm. Forward propagation is mainly based on several weight coefficient matrix w, bias factor b, input vector x, and is calculated from the input layer to the back layer by layer until the system output results. The output a_j^l of the j-th neuron in the l-th layer can be calculated as follows [14],

$$a_j^l = f(z_j^l) = f(\sum_{i=1}^{m} w_{jk}^l a_k^{l-1} + b_j^l) \tag{2}$$

where w_{jk}^l is the system weight from the k-th neuron of the l-1 layer to the j-th neuron of the l-th layer. The bias factor corresponding to the j-th neuron in the l-th layer is defined as b_j^l. By transforming Eq. (2) into a simple matrix, the result can be presented as follows [14],

$$a^l = f(z^l) = f(w^l a^{l-1} + b^l) \tag{3}$$

where $l = L$, a^L is the final result of forward output algorithm; where L is the number of output layers.

The output of the back-propagation algorithm is closer to the sample value by determining the appropriate weight coefficient matrix w and bias matrix b. The gradient descent method is usually applied to solve the extremum; and the mean square deviation function is applied to calculate the loss function. The expected output sample is minimized as follows [14],

$$E(w, b, x, y) = \frac{1}{2}||f(w^l a^{l-1} + b^l) - y||^2 \tag{4}$$

The gradient solutions of w and b can be calculated as follows [14],

$$\begin{aligned}\frac{\partial E(w,b,x,y)}{\partial w^L} &= \frac{\partial E(w,b,x,y)}{\partial z^L} \cdot \frac{\partial z^L}{\partial w^L} \\ &= (a^L - y)(a^{L-1})^T \odot f'(z^L)\end{aligned} \tag{5}$$

$$\begin{aligned}\frac{\partial E(w,b,x,y)}{\partial b^L} &= \frac{\partial E(w,b,x,y)}{\partial z^L} \cdot \frac{\partial z^L}{\partial b^L} \\ &= (a^L - y) \odot f'(z^L)\end{aligned} \tag{6}$$

Sort out the public parts of the above formula [14],

$$\delta^L = \frac{\partial E(w,b,x,y)}{\partial z^L} = (a^L - y) \odot f'(z^L) \tag{7}$$

The relationship between δ^{L-1} and δ^L is solved by recurrence method as follows [14],

$$\delta^{L-1} = \delta^L \cdot \frac{\partial z^L}{\partial z^{L-1}} = \delta^L (w^L)^T \odot f'(z^{L-1}) \tag{8}$$

The corresponding weight coefficient matrix w and offset b are updated as follows [14],

$$w^l = w^l - \alpha \sum_{i=1}^{n} \delta^{i,l} (a^{i,l-1})^T \tag{9}$$

$$b^l = b^l - \alpha \sum_{i=1}^{n} \delta^{i,l} \tag{10}$$

where α is the iteration step. When the change values of w and b are less than the iteration threshold ε, the update process is finished and the final weight and offset are output.

Compared with the conventional neural network, the DNN has the following characteristics:

1) With the complexity of the model increases, the number of hidden layers increases to multi-layer; and then the model expression ability improves.
2) From the original single input and single output layer to the multi-input and multi-output layer, the flexibility, as well as the feasibility of the model, are improved.
3) Since the activation function has been expanded, the original activation function sign has limited learning ability.

Then the activation function with strong learning ability is applied for upgrading functions, such as Sigmoid function, Tanh function, ReLU function, etc.

B. EMOTIONAL DEEP NEURAL NETWORK

FIGURE 2 shows the running process of EDNN. The EDNN combines the advantages of DNN and improves its control performance. The emotional model created in EDNN optimizes the PID control link to ensure DNN obtain training data with higher quality. By adjusting the number of neural layers of DNN and the number of neurons in each layer for repeated training, the fitting effect of the network can be improved continuously. When the trained network is tested on-line, the output voltage control command could be adjusted continuously according to the input error. Thus, the output voltage of the controlled object is closer to the set value.

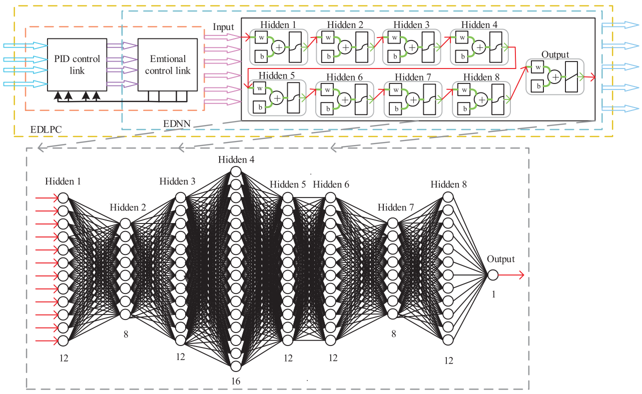

FIGURE 2. Emotional deep learning programming controller.

Compared with the DNN, the EDNN has the following characteristics:

1) The EDNN adds an emotion model to optimize PID parameters. The parameter value of the controller is adjusted by continuously evaluating the current control output.
2) After the evaluation of the emotional model, EDNN will perform the fitting voltage output according to the data currently generated. The fitting effect will be improved by adjusting the number of hidden layers and the number of neurons in each layer.
3) The EDNN trains according to the evaluated data and then generates the output voltage command, thus the network can send out smaller voltage deviation action.

The pseudo-code of the EDNN is given in Algorithm 1.

Algorithm 1 Emotional Deep Neural Network

```
Initialize the parameters of PID, i.e., K_p, T_i, T_d
Control the system according to Eq. (1)
Evaluate the voltage data and return to the first step in case of failure
lop:
    Initialize the number of neural network layers and the number of neurons in each layer
    Calculate w and b as Eq. (9) and Eq. (10), respectively
    Judge whether the change of w, b is less than ε, and provide the weight and offset after the updating
    Calculate the forward output result a as Eq. (3)
goto lop.
Test the network and evaluate the regulation deviation of voltage
```

C. Q-LEARNING ALGORITHM

Q-learning algorithm is that agents modify the Q matrix by environment state and reward value, and obtain actions from action set as the output according to the designed probability. The updated strategy of the Q matrix can be presented as follows [14],

$$Q(s,a) \leftarrow Q(s,a) + \alpha(R(s,s',a) + \gamma \max_{a\in A} Q(s',a) - Q(s,a)) \tag{11}$$

where s and s' represent the current state and the next state, respectively; γ is the discount factor; $R(s,s',a)$ is the reward value gained from the environment; and the strategy of reward function value after adding artificial emotion could be calculated as follows [14],

$$R(s,s',a) \leftarrow \frac{1}{\delta_s\sqrt{2\pi}} e^{-s^2/2\delta_s} \tag{12}$$

where δ_s is the variance of state s. At the same time, the updated strategy of probability matrix P can be shown as follows [14],

$$P(s,a) \leftarrow \begin{cases} P(s,a) + \beta(1 - P(s,a)), & a' = a, \\ P(s,a)(1-\beta), & a' \neq a, \end{cases} \tag{13}$$

where β is the probability distribution factor. The initial value of $P(s,a)$ is $P(s,a) = 1/|A|$. $|A|$ is the number of actions in the action set, and its range is $P(s,a) \in [0,1]$.

D. ARTIFICIAL EMOTIONAL Q-LEARNING

At present, artificial emotion is a popular branch of artificial psychology. After the agent has emotion, it can simulate and analyze human emotion. At this time, the agent can determine the current output of artificial emotion through the emotional factors of the environment and memory and then convert the emotion to solve the engineering problem.

Artificial emotional Q-learning algorithm uses artificial emotion to update the reward function strategy in the Q-learning algorithm. The agent of the algorithm consists of two parts, one is the logical thinking part of the agent, the other is the emotional part of the agent. The strategies of artificial emotion acting on reward function in state s are as follows,

$$R(s) \leftarrow \frac{1}{\delta_s \eta_\delta \sqrt{2\pi}} e^{-(s-\eta_s s)^2/2(\delta_s\eta_\delta)^2} \tag{14}$$

where η_δ is the emotional output value of variance factor; and η_s is the emotional output value of state factor. The output conversion processing of artificial emotion is as follows [14],

$$\eta \leftarrow \begin{cases} k_\eta, & \frac{1}{f_n} \geqslant \eta_{\max}, \\ \frac{k_\eta}{f_n}, & \frac{1}{f_n} < \eta_{\max}, \end{cases} \tag{15}$$

where k_η is the range coefficient of artificial emotion maximization, i.e. $\eta \in [0, k_\eta]$, f_n is the corresponding artificial emotion.

The pseudo-code of artificial emotional Q-learning is given in Algorithm 2.

Algorithm 2 Artificial Emotional Q-Learning

```
Initialize the parameters of artificial emotion Q-learning, i.e., α, γ, β
Initialize the agent state s
Initialize Q-value matrix Q and probability distribution matrix P
loop:
    Gain the system state s and reward value r from the environment
    Calculate the reward value R(s, s′, a)
    Update Q-value matrix as Eq. (11) and reward signal as Eq. (14)
    Calculate the emotional part of the agent and convert the emotional factor output as Eq. (15)
    Update probability distribution matrix as Eq. (13)
goto loop.
```

III. AUTOMATIC VOLTAGE CONTROLLER BASED ON EMOTIONAL DEEP LEARNING PROGRAMMING CONTROLLER

The previous section mainly introduced the algorithm and improvement of the controller. In this section, the whole system framework based on the controller, which is mainly divided into the following three parts, will be represented.

A. DEEP LEARNING PROGRAMMING FOR AUTOMATIC VOLTAGE CONTROL

To make the power system run safely and economically at any time, meanwhile to provide users with high-quality power, a controller with high control performance is needed in practice. Since the EDNN needs an amount of data to train the networks of the EDNN, the Q learning algorithm is added to the EDNN. Meanwhile, to achieve higher accuracy, the training of the controller needs big data support. Furthermore, the complexity of the graph model in deep learning leads to a sharp increase in the time complexity of the algorithm. To ensure the real-time and accuracy of the algorithm, a Q algorithm based on artificial emotion is added into EDNN to ensure the minimum deviation of voltage regulation.

The specific AVR framework is shown in FIGURE 3. After the voltage evaluation of the emotional controller, the agent is initialized and the DNN is trained off-line. Both the trained EDLPC output state s and reward r are taken as the environment influence inputs of the agent logic part. According to the change of the current environment, s, r, and the memory of the emotional part of the agent η provides voltage action a.

B. EMOTIONAL DEEP LEARNING PROGRAMMING CONTROLLER

The goal of voltage control in power systems is to keep the supply voltage in a certain range. The EDLPC proposed in this paper is based on the Markov framework, which has been proved. Therefore, the control strategy has practical feasibility and is an effective voltage control strategy. The implementation of the EDLPC is mainly divided into two parts: online training and offline voltage regulation. After receiving the voltage data collected and monitored by EMS/SCADA, the EDLPC can analyze the voltage deviation and give the corresponding action strategy to realize the voltage regulation of power systems. Meanwhile, the power loss is reduced on the basis that the voltage meets the requirements. In the framework of automatic voltage control, the EDLPC replaces the conventional controller, which can control the system and can reduce the voltage deviation. The specific operation process of EDLPC is described below.

The EDLPC determines the parameters of the controller through the emotional model after inputting the data. If it passes the decision, it can initialize the parameters of the controller. If it fails, it can adjust the PID module. Then the trained DNN and artificial emotional Q-learning algorithm are tested on-line; besides the parameters are updated until the output meets the iterative requirements. Since the output command is sent to the controlled object for completion, the generated voltage can be compared with the reference value as the next input of the controller.

The pseudo-code of the EDLPC is given in Algorithm 3.

Algorithm 3 Emotional Deep Learning Programming Controller

```
Initialize the parameters of EDLPC, i.e., α, γ, β, K_p, T_i and T_d
Control the system model according to Eq. (1)
Conduct emotional assessments of the resulting data.
Initialize the system state s, Q-value matrix Q and probability distribution matrix P
pl:
    Initialize the number of neural network layers and the number of neurons in each layer
    Calculate w and b as Eq. (9) and Eq. (10), respectively
    Judge whether the change of w, b is less than ε, and provide the weight and offset after the updating
    Calculate the forward output result a as Eq. (3)
goto pl.
Test the network and evaluate the regulation deviation of voltage; transfer data to the agent at end
lp:
    Gain the system state s and reward value r from the environment
    Calculate the reward value R(s, s′, a) by Eq. (12)
    Update Q-value matrix as Eq. (11) and reward signal as Eq. (14)
    Calculate the emotional part of the agent and convert the emotional factor output as Eq. (15)
    Update probability distribution matrix as Eq. (13)
goto lp.
Provide the output for the voltage command to the system model
Take the output of the system as the next controller inputs
```

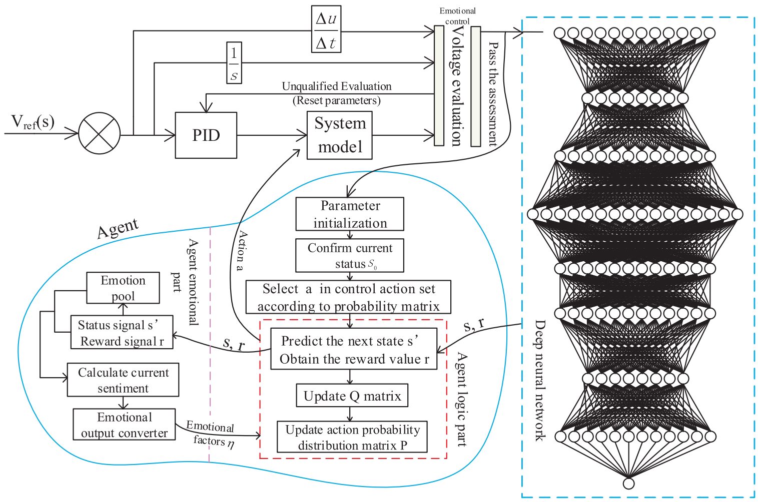

FIGURE 3. Framework of the proposed algorithm for automatic voltage control of power systems.

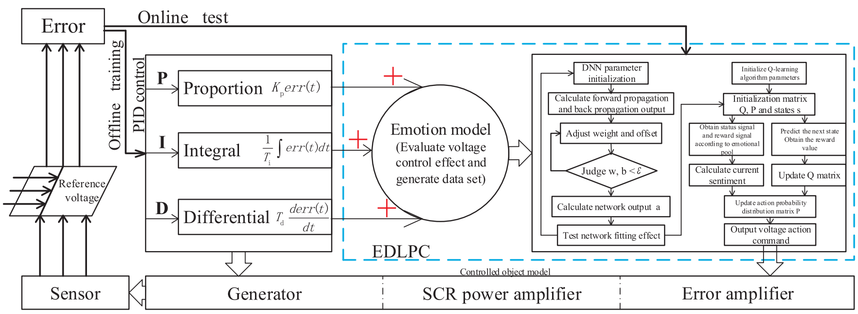

FIGURE 4. Operation process of automatic voltage control.

C. OPERATION PROCESS OF AUTOMATIC VOLTAGE CONTROLLER

Automatic voltage control plays an important role in reducing network loss, improving voltage quality, and coordinating system resource allocation. At present, many researchers have adopted different control methods to realize their functions according to the actual situation. The operation process of the EDLPC in the automatic voltage control framework is shown in FIGURE 4.

Under the set reference voltage, the voltage variation generated by the system is the inputs of the controller. The training of the controller is completed in the off-line voltage data, meanwhile, the parameters are adjusted according to the system model. The voltage regulation command sent by the controller is delivered to the system model to obtain the corresponding system output, which can continue to perform the same control process as the next error input. Simultaneously, the output voltage command realizes the relevant regulation logic. The output pulse command increases or decreases the excitation current and changes the reactive power of the generator, to realize the automatic voltage control of the power grid.

TABLE 2. Parameters of system model.

Parameter	Meaning	Value
K_a	Gain of error amplifier	10 Hz/p.u.
K_e	Gain of silicon-controlled rectifier power amplifier	1 Hz/p.u.
K_g	Gain of generator	1 Hz/p.u.
K_r	Gain of sensor	1 Hz/p.u.
T_s	Time constant of error amplifier	0.1 s
T_e	Time constant silicon-controlled rectifier power amplifier	0.4 s
T_g	Time constant of generator	1 s
T_r	Time constant of sensor	0.01 s

IV. CASE STUDIES

All of the simulation programmings covered in this paper are simulated on the Intel Core i7-2760QM processor of 2.40 GHz CPU and 16 GB RAM computer with the MATLAB version 9.7 (R2019b). The specific model simulation parameters are shown in TABLE 2.

A. CASE 1

The flow chart of the EDLPC method proposed in this paper is shown in FIGURE 4, and the specific pseudo code is shown in Algorithm 3. The main input and output of the controller proposed in this paper are the voltage deviation caused by the

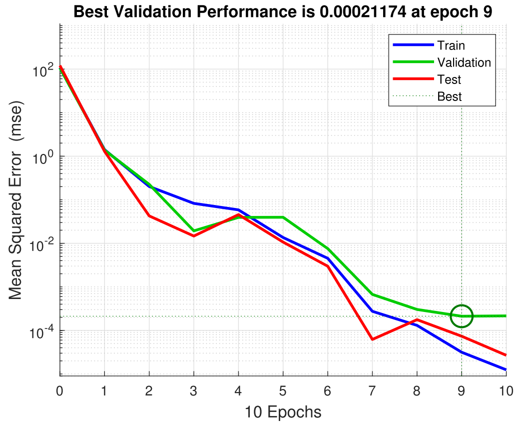

FIGURE 5. Mean squared error of training process of emotional deep learning programming controller (Case 1).

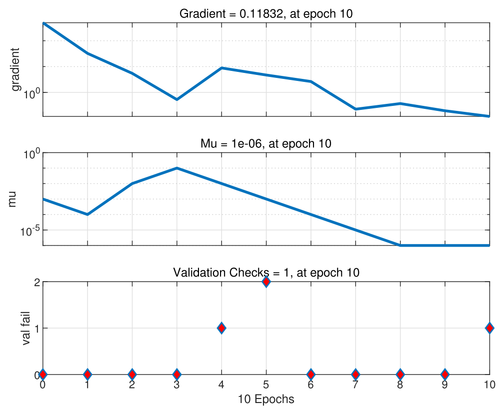

FIGURE 6. Gradient, momentum constant, validation checks of training process of emotional deep learning programming controller (Case 1).

actual voltage and the standard voltage. The current deviation voltage will be sent to the controller as the next input of the system for regulation. The energy of the control signal mainly comes from the energy management systems/supervisory control and data acquisition (EMS/SCADA). The normal operation of system energy could be ensured by collecting and monitoring voltage data. The standard voltage data used in Case 1 simulation is mainly selected from the voltage and voltage sampling value of the actual generator in one day. The sampling period is 15 minutes, and 96 items of data are collected. The input and output of the system are voltage deviation, and the current deviation voltage will be sent to the controller for regulation as the next input of the system. This paper adopts a typical generator system model, which mainly includes a generator model, a voltage controller and a negative feedback link. The specific model framework is shown in FIGURE 1. In the simulation, the control strategy mainly includes EDLPC, DNN and Q learning algorithm under the same parameters. This simulation compares the control performance of the DNN, Q learning algorithm, and the EDLPC in the same control system. The training results of the EDLPC are given in FIGURE 5 to FIGURE 7. The minimum mean

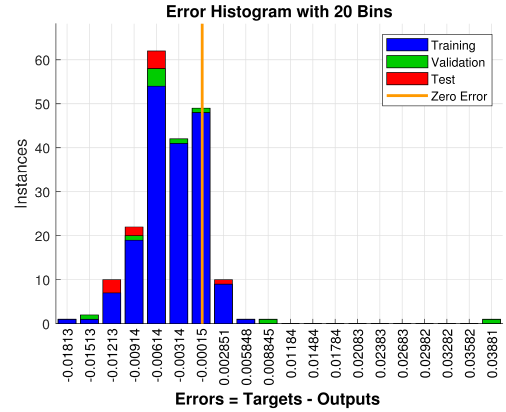

FIGURE 7. Instances of training process of emotional deep learning programming controller (Case 1).

square error occurs in the ninth epoch of 0.00021174. This outcome shows that DNN has the best verification effect at this time. The step size of the validation set is set to 10 epochs. The default value of the gradient is 0.11832. To avoid the neural network converging to the local minimum, the range of mu is $10^{-5} \sim 0.1$. The maximum error of validate fail is 2 in the fifth iteration. The training error of the DNN is -0.00015, and the maximum testing error is -0.00614. The trained EDLPC voltage regulator has a series of small voltage deviations, which range from - 0.05 to 0.56 V.

The simulation results obtained by these compared methods are shown in FIGURE 8. FIGURE 8 shows that the DNN generate a small error in the early sampling data, while the Q-learning algorithm gains a small error in the later sampling data. The proposed EDLPC can obtain smaller data fluctuation in the whole sampling data. After calculation, the average absolute error of voltage generated by DNN is 0.4222; and the average absolute error of voltage generated by the Q-learning algorithm is 0.5615. The average absolute error of the voltage is 0.2007 at the end of the EDLPC, which shows that the controller has higher performance for the AVR of power systems.

B. CASE 2

The EDLPC proposed in this paper is compared with the DNN and Q learning algorithm with the same parameters under the condition that the standard voltage is step wave, and the specific voltage deviation is given in FIGURE 9. Through a comprehensive performance comparison, we find that the proposed algorithm can obtain smaller voltage deviation to ensure voltage stability. To better show the control effect of the algorithm, the step wave superimposed by multi-step links is used in this paper, which can observe the response output of the algorithm under different sampling times, and understand the control characteristics of the algorithm in each time-period. In this case, the input reference voltage is step voltage, which rises 0.5 V every 10 s. The hardware equipment in this paper comes from the test base of Nanning Guodian Power Technology Co., Ltd. The system

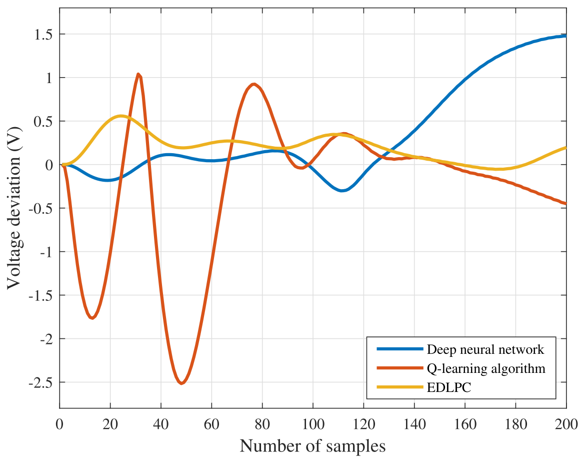

FIGURE 8. Voltage deviations obtained by compared methods (Case 1).

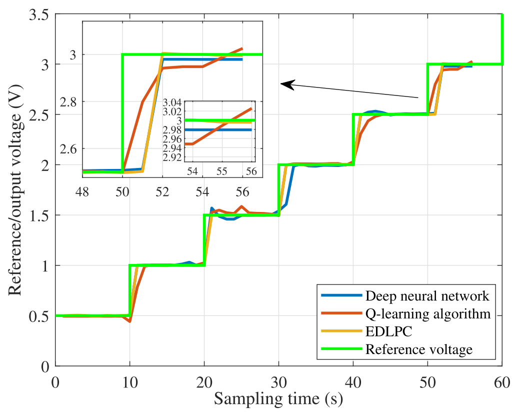

FIGURE 9. Output voltage obtained by compared methods (Case 2).

simulation of this experiment mainly includes the software part of offline training and the hardware experiment of step voltage fluctuation. The generator is selected from Nanning Guodian science and technology enterprise incubator. As an experimental incubation base, the enterprise mainly creates order based school enterprise cooperation to achieve a win-win situation among universities, enterprises and students. FIGURE 9 shows the output voltage curves obtained by compared methods. The remaining three curves show the control outputs of the DNN, Q-learning algorithm, and the EDLPC. The experimental data show that the controller will produce a large voltage deviation in a period of the input signal step. When the voltage reference value is stable, the controller can produce a small voltage deviation. If the number of layers is the same, too many or too few neurons will affect the learning speed of the network, which will lead to the results of too fast learning rate with inadequate fitting, too slow learning rate, and so on. The number of neuron layers affects the data error processing to a certain extent, and the data results from each experiment are not the same. The parameters proposed in this paper can ensure that the voltage deviation is small in many experiments, even in the worst case. Compared with the other

TABLE 3. Integrated of time weighted absolute error, integral of squared error, and integrated absolute error of voltage deviation in Case 2.

Algorithms	ITAE	ISE	IAE
Q-learning algorithm	56.3168	4.1968	5.6317
Deep neural network	42.0667	7.4379	4.2067
EDLPC	20.1160	0.6020	2.0116

TABLE 4. Statistics of voltage peak in each stage.

Algorithms	10-20s	20-30s	30-40s	40-50s	50-60s
Q-learning algorithm	1.025	1.586	2.012	2.502	3.026
Deep neural network	1.031	1.57	2.007	2.532	2.979
EDLPC	1.005	1.504	2.005	2.506	3.005

two algorithms, the EDLPC can obtain smaller error output under the condition of the signal step or stationary. The DNN and Q-learning algorithm can produce unstable system output instructions in a short period when the reference voltage step is completed. In the comparison of algorithm performance, the three algorithms use the same data set for training. The network/agent after training has been tested many times, the results of which are obtained by comparing integrated of time weighted absolute error (ITAE), integral of squared error (ISE), and integrated absolute error (IAE) (TABLE 3). These indices obtained by these compared algorithms show that the EDLPC can obtain the highest control performance with smaller ITAE, smaller ISE, and smaller IAE. On this basis, we calculate the voltage percentage of the improved algorithm. Compared with deep neural networks, the EDLPC reduces voltage deviation by 52.46% ; compared with the Q-learning algorithm, the EDLPC reduces voltage deviation by 64.26%, which has a better control effect. Furthermore, the proposed algorithm is belonging to a Markov process, which has been proved. It can be seen from FIGURE 9 that EDLPC takes longer time to raise voltage than Q-learning algorithm in 50 to 60 seconds, but the EDLPC has faster voltage regulation time in terms of time to achieve voltage stability. TABLE 4 shows the peak voltage statistics of the three algorithms in each stage.

Compared with the DNN and Q-learning algorithm, the EDLPC has the following characteristics in the control system.

1) The EDLPC adjusts its internal parameters continuously to adapt to different types of system environment through the training of voltage data, and obtains higher control performance.
2) The EDLPC weakens the potential fitting problem in DNN. Through the agent's continuous perception of the environment, the voltage command generated by the EDNN can be continuously readjusted.
3) Based on the artificial emotional Q-learning of the EDLPC, the reward mechanism of the algorithm is constantly updated with the intervention of emotional factors, making the controller more sensitive to the current environment state, to obtain more appropriate action output.

4) The EDLPC needs to learn with a large number of data in advance; and the EDLPC requires complex operations in the early stage to gain a higher control performance.

C. DISCUSSION

Compared with the traditional DNN algorithm, the EDLPC could overcome the potential overfitting and underfitting of the network; compared with the current Q-learning algorithm, the EDLPC could effectively improve the risk caused by the ''dimension disaster'' of the matrix, so as to maintain the stability of the system. The selection of PID parameters is mainly due to the acceleration of the genetic algorithm (GA). Through the continuous updating of genetic algorithm, crossover and mutation, better parameter solution could be obtained. The EDLPC proposed in this paper needs the corresponding voltage training data to pre-train the agent network offline before it can be used in the actual engineering control link, which requires more time cost than the traditional heuristic control algorithm. The controller presented in this paper introduces a variety of improved methods to improve its voltage control strategy based on the original defective algorithm, to obtain the optimal solution through making up for the defects and give full play to the advantages of various algorithms. The EDLPC can obtain higher control performance in two cases.

The specific parameters of the PID controller mentioned after the emotional model evaluation are proportional: 8, integral: 2.499, and derivative: 1.5. In this case, 200 voltage data are collected by the PID controller and used as data set for the EDLPC pre-training. The particular parameters are obtained through the voltage evaluation link in EDNN. In the framework of automatic voltage control as shown in FIGURE 1, the above PID parameters obtained by genetic algorithm with 200 population size and 200 maximum iteration have higher control performance with small voltage deviation. The ranges of these PID parameters for the applied genetic algorithm are set as $(-50, 50)$, $(-10, 10)$ and $(-10, 10)$.

The DNN applied in the controller has eight hidden layers, and the number of neurons in each layer is 12, 8, 12, 16, 12, 12, 8, and 12. The maximum training iterations of the network are set to 20 hours. After numerous testing, (i) the number of the layers of the DNN can be set from 4 to 12; (ii) the number of numerous of each layer could be set from 8 to 60.

The initialization parameters of the artificial emotional Q-learning algorithm are learning to rate $\alpha = 0.1$, which can be selected in (0.001, 0.1) according to the learning situation of the agent. The constant of the probability distribution is $\beta = 0.05$. The range of the probability distribution can be set from 0.001 to 0.1. The smaller constant of a probability distribution can avoid the higher action output of the Q value in the early reinforcement period. The discounted rate of future reward is $\gamma = 0.9$. The nearer γ is to 1, the more far-sighted it is to consider the value of subsequent states. State set $s = \{\underbrace{-\infty, -0.50, -0.46, \ldots, 0.46, 0.50, \infty}_{33}\}$, action set $a = \{\underbrace{-100, -93.75, \ldots, 100}_{33}\}$.

V. CONCLUSION

With the rapid development of China in recent years, the requirements of various industries for power quality are increasing year by year. The stability of grid voltage and power (frequency) determines the level of power quality. Although the traditional PID controller can ensure the stable operation of power system voltage control in the AVR framework, there are still some deficiencies in power quality improvement. In this regard, we use the current hot in-depth class learning to further improve the power quality. In the simulation of the last chapter, compared with the voltage deviation of 0.4222 generated by DNN and the voltage deviation of 0.5615 generated by Q-learning, the 0.2007 voltage deviation obtained by EDLPC proposed in this paper could ensure a better operation effect of the system. The automatic voltage control framework designed in this paper can replace the conventional PID voltage control and can obtain a smaller voltage deviation. The EDNN and Q-learning algorithm include artificial emotion are applied in this voltage control framework. The automatic voltage control framework based on EDNN and artificial emotional Q-learning has the following main characteristics.

1) Compared with the conventional PID control algorithm, the proposed voltage control framework has better voltage control performance and higher voltage accuracy.
2) The EDNN based on DNN can obtain higher training results, meanwhile, the agents include the emotional part and logical part, which have more accurate action selection. Thus, the controller can make up for the potential fitting problem of the neural network.
3) By adjusting the parameters of DNN in EDNN, better experimental results could be obtained. A large number of parameter tuning experiments show that the appropriate parameters are more conducive to the controller's perception of the state of the environment and give the corresponding instructions.

The proposed method could not only minimize the voltage deviation of the generated step wave but also improve the direct current capacitor of the chain static synchronous compensator through the modulation of the step wave for dynamic reactive power compensation in the future. The EDLPC could be applied in automatic generation control, power system stabilizer, doubly-fed induction generator, and photo-voltaic in the future.

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