Research Article

Optimal Predictive Control Method of PWM Rectifiers Based on Artificial Intelligence

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Direct power control (DPC) of pulse width modulation (PWM) is often used to control the instantaneous power of rectifiers. The instantaneous power contains both grid voltage and current information, and its value is not affected by coordinate transformation. It is constant in steady state and reflects the DC control characteristics. However, the switching frequency of traditional DPC is not fixed, the DC voltage has static error, and the system fluctuates greatly. In this work, we introduce the concept of stator flux of the AC motor into the PWM rectifier. Combined with the space vector PWM (SVPWM) technology, we use the virtual flux estimation method to obtain the instantaneous power value, which saves the grid voltage sensor, eliminates the static difference of DC voltage. Furthermore, considering that the neural proportion integral differential (PID) control depends heavily on the initial weight coefficient of the network, we use chaos particle swarm optimization (CPSO) algorithm, which combines the basic PSO algorithm and chaos theory to optimize the initial weight coefficient of neural PID control. In the experiment, the results prove that the performance of the controller can be effectively improved.

1. Introduction

A converter device is used to transform one electrical energy form of frequency, amplitude, and phase into another electrical energy form to meet the different needs of electrical equipment and make it work in an ideal state for obtaining a device with maximum technology and economy [1]. In the fields of modern industry, transportation, national defense, and life, various types of converter devices are needed in many occasions. Most converters need to obtain DC voltage through a rectifier circuit, and traditional rectifier circuits usually use diode-uncontrolled rectification or thyristor phase-controlled rectification. The energy conversion method that uses diodes to convert AC power to DC power is uncontrollable, and replacing diodes with thyristors can achieve the controllability of energy flow to a certain extent [2]. However, this type of AC that relies on grid commutation to shut off naturally has some disadvantages, such as

large volume, severe AC current distortion, low grid-side power factor, and slow DC voltage dynamic response. Moreover, it is unable to realize electric energy feedback, which causes pollution and is harmful to the power grid. The development of power electronic devices has promoted the progress of converter technology.

The control of the converter known as the modulation strategy of the converter is the core issue in the research of various converters. The pulse width modulation (PWM) technology is developed in DC chopping and inverter circuits [3]. With the advancement of fully controlled devices represented by the insulated gate bipolar transistor (IGBT), the PWM technology has become quite advanced and its application in the rectifier circuit can form a PWM rectifier, which is also known as a unit power factor converter. In manufacturing applications, the application of DC power from grid rectification is very extensive. Conventional rectifiers mostly use diode-uncontrolled rectification or

thyristor phase-controlled rectification, which injects a large number of harmonics and reactive power into the grid, causing serious pollution to the grid. One of the effective measures to control this kind of grid pollution is to use a PWM rectifier to achieve the grid-side current of the rectifier device and achieve unity power factor. When the three-phase PWM rectifier adopts direct voltage control, it is a nonminimum phase system and its internal dynamics are unstable [4] so it is usually controlled by a voltage-current double-loop control method. The voltage-type PWM rectifier is called a real green-converter device because of its advantages of low harmonics of grid-side current, unit power factor, two-way energy flow, and constant DC voltage control. It gradually replaces the traditional diode-controlled rectification and thyristor phase-controlled rectification and has been widely and importantly applied in active power filter (APF), unified power flow control (UPFC), Static Var Generator (SVG), superconducting magnetic energy storage (SMES), high voltage direct current (HVDC) transmission, electrical driver (ED), and new energy grid-connected power generation fields, such as wind energy and solar energy. The research on these application fields makes the PWM rectifier and its control technology be developed and improved.

At present, a variety of PWM rectifier control methods have been proposed to achieve high-performance rectification, which mainly include indirect current control, i.e., amplitude and phase control, direct current control, predictive current control, and direct power control (DPC) [5]. Indirect current control can provide a fine switching mode to improve the stability of the DC voltage and the power factor of the system, but its DC component appears on the AC side and seriously affects the waveform of the DC load current and voltage in the transient process. Moreover, the fixed switching frequency control is more sensitive to system parameters and load fluctuations, which generates poor system robustness. Furthermore, current hysteresis control has the advantages of high accuracy, fast dynamic response, no DC subversion, and high robustness, but it has the disadvantage of not having fixed switching frequency control. For example, predictive current control has the advantages of good switching mode and fast dynamic response, but it is easily affected by parameter changes. The traditional DPC has simple algorithms and structure, whereas instantaneous power contains both AC side current information and voltage information and shows good dynamic performance [6]. However, because instantaneous power control uses hysteresis comparators, it has the same shortcomings as current hysteresis control. In addition, the common problem of the above control strategies is that the stability of the system is poor in the case of massive signal interference. Because the PWM rectifier is a nonlinear system, the introduction of nonlinear control theory or intelligent control into the PWM rectifier has become a hotspot in the research of PWM rectifiers.

Using PWM rectification to replace diode-uncontrolled rectification or thyristor phase-controlled rectification can realize unit power factor control and eliminate harmonic pollution to the grid. When it needs to feed back power, it can run under inverter conditions to save power. This work

starts from the PWM rectifier DPC and aims to enhance the DC voltage stability and AC side current tracking ability of the PWM rectifier. Focusing on the nonlinear characteristics of the PWM rectifier and the limitations of conventional proportion integral differential (PID) control, chaotic particle swarm optimization (CPSO) neural PID control is used to enhance the performance of the PWM rectifier [7]. The research of this work has high reference value for improving the power quality of the power grid and strengthening the efficient and acceptable utilization of electric energy.

The development of intelligent control theory provides a new way to solve the control problem of complex controlled objects. Compared with traditional control methods, intelligent control has greater adaptability to the complexity of the environment and tasks. It can show multilevel description accuracy not only for certain models but also for uncertain environments and tasks. Intelligent control has further developed the concepts of self-organization, self-learning, and self-adaptation and has been applied in a wide range of fields. Combining intelligent control theory with conventional PID control can lead to various forms of intelligent PID control. At present, intelligent PID control mainly includes expert PID control, fuzzy PID control, neural PM control, and neural PID control based on intelligent optimization algorithms. Among them, neural PID is mainly divided into two categories: PID control based on the multilayer forward network and direct PID control based on a single neuron. And, BP neural network is currently the more widely used neural network model [8]. The BP algorithm is based on the gradient descent method to modify the weight coefficient of the network. The minimum error obtained by using this method is actually the minimum value in the sense of the least square method. The sensitivity of the BP algorithm to the initial weight makes the poor convergence of the algorithm, and it generally only converges to the local extremum near the initial value. Therefore, only by choosing reasonable initial weight coefficients can the performance of BP network be improved effectively. Usually, some intelligent optimization algorithms are used to train the BP network.

The CPSO algorithm is a global search algorithm based on swarm intelligence. It is an efficient optimization combination method and belongs to the category of bionic optimization algorithms, which uses speed and location search mode to seek the global optimal solution by coordinating global search and local search through inertial weights. In the BP network neural PID control, the initial weight coefficient of the network is randomly selected and the Jacobian information of the controlled object is approximately replaced by a symbolic function. Aiming at the abovementioned shortcomings of BP network PID control, we propose a chaos particle swarm optimization neural PID control strategy to adjust controller parameters. The experimental results show that the method proposed in this work can significantly enhance the control performance of PWM.

The rest of this paper is organized as follows. Section 2 presents the related works of the PID control strategy. Section 3 presents the detailed design of the chaos particle swarm optimization neural PID control strategy.

Experimental results and discussion are reported in Section 4. Finally, the conclusion of this paper is given in Section 5.

2. Related Work

Akagi and Fujita [9] first proposed a reactive power compensator control strategy based on the rectifier topology, i.e., the initial PWM rectifier idea. It actually adds a boost-type DC chopper circuit to the single-phase uncontrollable rectifier and uses the PWM control technology to control the full-control device, which obtains a better input current and output voltage. However, many applications require the energy of the rectifier to achieve a bidirectional flow, and thus, the actual PWM rectifier appeared. When the PWM rectifier obtains power from the power grid, it reflects the AC/DC conversion characteristics, and when the PWM rectifier feeds back the power to the power grid, it reflects the DC/AC conversion characteristics. Because the power factor and current on the AC side of the PWM rectifier are controllable, the PWM rectifier is actually a converter device with a controllable four-quadrant operation on the AC and DC sides.

Currently, there are many modeling methods for PWM rectifiers. Wu et al. [10] established the time domain model of PWM rectifiers systematically for the first time and decomposed the time domain model into high-frequency and low-frequency models with the corresponding time domain. Ye et al. [11] established a model of PWM rectifier based on the coordinate system. Rim et al. [12] proposed a low-frequency equivalent model of the PWM rectifier based on the d-q coordinate system and analyzed its steady state and dynamic characteristics. Malinowski et al. [13] modeled the voltage-type PWM rectifier DPC and proposed a DPC strategy without a grid voltage sensor. Mao et al. [14] designed a small-signal reduction model, thereby simplifying the mathematical model and characteristic analysis of the PWM rectifier.

After decades of research and development, the PWM rectifier technology has become more advanced. Its main circuit has developed from the initial half-controlled device bridge to the modern fully controlled device bridge. Its topology has shifted from two-level single-phase and three-phase development to multiphase combination and multi-level topology circuit. PWM switching control has developed from pure hard switching modulation to soft switching modulation. The power level has developed from a small capacity of kilowatts to a large capacity of megawatts. The voltage level has developed from low voltage to high voltage. In the main circuit type, there are both voltage-type PWM rectifiers and current-type PWM rectifiers.

The emergence and development of control science is mainly determined by the productivity and development needs of human society and the level of human technical knowledge at that time. Control science plays an essential role in technological progress and has become one of the important symbols to measure the civilization of the modern society. PID control has been widely used because of its simple principle and structure, easy implementation, excellent control effect, and strong robustness. According to statistics, PID control accounts for more than 90% of industrial process control and motion control. However, as the

research objects and control objectives become more and more complex, the traditional PID control that relies on precise mathematical model description and analysis finds it difficult to solve the control of complex systems with characteristics such as uncertainty, high nonlinearity, dynamic mutation, and multiple time-scales problem. In order to enhance the performance of conventional PID control, researchers have proposed many solutions, which can be roughly divided into the following two directions: one is to improve the structure of the conventional PID controller itself for different application sites and the other is to derive various variable structure PID control. In order to prevent the integral saturation from causing excessive system overshoot and system oscillation, the PID control strategy with integral separation is introduced. And, a PID control strategy with a dead zone is proposed to eliminate the system oscillation caused by frequent startup. For the pure lag system, Smith predictive control, PID control strategy based on ISE, ISTE, and IST2E, and other optimal evaluation indicators are proposed.

We will apply PID control based on multilayer forward network for the control of voltage-type PWM rectifiers in this work.

Backpropagation (BP) network which is the most typical feedforward neural network has been widely used in engineering fields, such as modeling and control of nonlinear systems. However, because the BP network uses the gradient descent method in the nonlinear programming method to modify the network weight coefficients, it has some problems, such as sensitivity to the initial weight coefficients, slow convergence speed, or local convergence. The essence of neural PID control based on BP network is to combine the BP network on the basis of conventional PID control and automatically adjust the parameters of the controller through the self-learning of the network. Therefore, it is inevitable that there are some defects of the BP network, which affect the performance of control strategy. To enhance the neural PID control, it is necessary to improve the BP network itself.

CPSO algorithm is a brand-new intelligent optimization algorithm. It is proposed based on swarm intelligence and chaos theory. It has the characteristics of group collaborative search, fast convergence speed, strong global optimization ability, and wide application range. CPSO algorithms are usually applied to the training of the initial weight coefficients of the BP network, and the strong local optimization ability of the BP algorithm is combined with the strong global optimization ability of the CPSO algorithm. These can effectively enhance the convergence speed and accuracy of the BP network. In this work, we use the CPSO algorithm to optimize the initial weight coefficients of the neural PID controller and apply the CPSO neural PID control to the DC voltage control of the voltage-type PWM rectifier.

3. Method

The particle swarm optimization (PSO) algorithm is a new evolutionary algorithm based on swarm intelligence theory, which is proposed to simulate the behavior of birds in the

process of foraging and migration. Each bird is abstracted as a particle without volume and mass to represent a feasible solution of the problem. The search space of the problem is compared to the flight space of the bird group. Based on the group iteration, the optimization search is guided by the cooperation and competition among the particles in the group, so that the population can find the optimal value of the problem to be solved. The PSO algorithm has the advantages of simple principle, easy implementation, parallel processing, and fast convergence speed, and it can also find the optimal solution of the problem with high probability. Moreover, it has a profound intelligent background, which is suitable for both scientific research and engineering application. The PSO algorithm is a research hotspot in many fields and has been widely used in function optimization, pattern recognition and classification, signal processing, neural network training, robot technology, and other fields. Among them, the production scheduling research based on particle swarm optimization belongs to the current international frontier topic. Aiming at the control problem of the three-phase voltage-source PWM rectifier, we introduce the chaos particle swarm optimization algorithm and BP neural network model, which effectively improves the control effect of rectifiers.

3.1. Mathematical Model of the Three-Phase Voltage-Source PWM Rectifier. Figure 1 shows the system structure of the three-phase voltage-source PWM rectifier. In this figure, L is the inductance connecting the reactance, R is the internal resistance connecting the reactance, i_a , i_b , and i_c are the power supply current, V_c is the output voltage of the DC side, and C is the DC filter capacitor at the output end.

From the mathematical model of the three-phase voltage-source PWM rectifier, the state average model in the d-q synchronous rotating coordinate system can be obtained as shown in

$$\begin{bmatrix} i_d \\ i_q \\ V_c \end{bmatrix}_{\text{avg}} = \begin{pmatrix} -\frac{R}{L} & \omega & -\frac{S_d}{C} \\ -\omega & -\frac{R}{L} & -\frac{S_q}{C} \\ \frac{S_d}{C} & \frac{S_q}{C} & 0 \end{pmatrix} \begin{bmatrix} i_d \\ i_q \\ V_c \end{bmatrix} + \begin{pmatrix} \frac{1}{L} & 0 & 0 \\ 0 & \frac{1}{L} & 0 \\ 0 & 0 & -\frac{1}{C} \end{pmatrix} \begin{bmatrix} e_d \\ e_q \\ i_0 \end{bmatrix}. \quad (1)$$

From equation (1), the first-order approximate linear model of rectifier can be obtained as follows:

$$\frac{dV_c}{dt} = \frac{(S_d i_d + S_q i_q - i_0)}{C}, \quad (2)$$

where S_d and S_q are the control rates of d-axis and q-axis, respectively.

FIGURE 1: Model of the voltage-source PWM rectifier.

3.2. Sliding Mode Variable Structure Control of PWM Rectifiers. The three-phase PWM rectifier shown in Figure 1 is a nonlinear and strong coupling system. When the system adopts direct voltage control, it is a nonminimum phase system and thus is often controlled by voltage and current double loops. The control objective of the voltage loop is to make the output voltage stable and have fast response to input voltage fluctuation and output load disturbance. This can generate reference instruction current for the current loop. If the error between the reference value and the actual value is taken as the state variable of the system, $e_{Vc} = V_{\text{cref}} - V_c$, $e_w = w_{\text{ref}} - w$, then equation (2) can be converted as follows:

$$\frac{de_{Vc}}{dt} = e_w. \quad (3)$$

By tracking the given value $V_{\text{cref}} = V_c$ with the output voltage and combining with equation (3), the sliding mode surface $S(e_{Vc}, e_w, t)$ satisfying the robustness of the closed-loop system is obtained as follows:

$$S(e_{Vc}, e_w, t) = k_1 e_{Vc} + k_2 e_w = 0, \quad (4)$$

where k_1 and k_2 are the gain values used in the model to make the system meet the expected dynamic characteristics and remain stable. When the feedback error is taken into account, the switching function of the sliding surface is as follows:

$$S(e_{Vc}, e_w, t) = k_1 e_{Vc} + k_2 \frac{de_{Vc}}{dt} = e_{Vc} + \beta \cdot \frac{de_{Vc}}{dt} = 0, \quad (5)$$

where β is a parameter related to the first-order response time constant of the output voltage V_c , $\beta = k_2/k_1$, where $\beta > 0$. This switching function is the main control mode of the voltage loop of the nonlinear system. If the d-axis voltage $e_d = \sqrt{3} \cdot V_{\text{rms}}$ and S_d is a constant value in steady state and the output voltage completely tracks the reference voltage $V_c = V_{\text{cref}}$, then equation (5) can be converted as follows:

$$S_d = \left[i_0 - S_q i_{q\text{ref}} + C \left(\frac{de_{Vc}}{dt} \right) \right] \cdot i_{\text{dref}}^{-1}. \quad (6)$$

When $C(dV_{\text{cref}}/dt) = 0$ in steady state and there is power balance at both ends of the rectifier, equation (6) can be simplified as

$$S_d \approx \frac{e_d - Ri_d}{V_c} = \frac{\sqrt{3}V_{rms} - Ri_d}{V_c}. \quad (7)$$

Substituting equation (7) into equation (6), we can get the following results:

$$S = \left[(V_{cref} - V_c) + \beta \cdot \frac{dV_{cref}}{dt} + \frac{\beta}{C} i_0 \right] \times \frac{CV_c}{\beta(\sqrt{3}V_{rms} - Ri_d)} - i_d. \quad (8)$$

The reference value of d-axis current can be obtained from the following equation:

$$i_{dref} = \left[(V_{cref} - V_c) + \beta \cdot \frac{dV_{cref}}{dt} + \frac{\beta}{C} i_0 \right] \times \frac{CV_c}{\beta(\sqrt{3}V_{rms} - Ri_d)}. \quad (9)$$

Combining equation (9) and $i_{qref} = 0$, the reference value of output current of the voltage outer loop which meets the requirements of output voltage and input unit power factor can be obtained. This reference value is used as the input command of the current inner loop, and the current loop completes the fast tracking of reference current.

3.3. Chaos Particle Swarm Optimization Neural PID Control Strategy. The structure of CPSO neural PID control system is shown in Figure 2. As can be seen from the figure, the system mainly includes CPSO algorithm offline optimization module, BP network module, and PID control module. The meanings of variables in this figure are as follows: $r(k)$ is the system input at k time, $e(k)$ is the system error at k time, $\Delta e(k)$ is the system error variation at k time, $u(k)$ is the controller output at k time, $y(k)$ is the system output at k time, W_i is the initial weight coefficient matrix assigned to the BP network after CPSO algorithm optimization, and $k_p(k)$, $k_i(k)$, and $k_d(k)$ are the PID controller proportion, integral, and weight coefficient matrix set by the BP network at k time differential parameters, respectively.

The process of CPSO offline optimization algorithm is as follows:

- (1) The group size m of particles and the dimension d of search space are determined, where d is equal to the number of parameters to be optimized by the BP network, i.e., the dimension of the vector formed by cascade weight coefficients of the BP network.
- (2) Taking the vector composed of cascade weight coefficients of the BP network as the position vector of particles, the position vector of the i ($i = 1, 2, \dots, m$) particle is $x_i = [x_{i1}, x_{i2}, \dots, x_{id}]$.
- (3) Initializing algorithm parameters, the CPSO algorithm starts offline optimization and updates inertia weight factor w .
- (4) The population fitness variance δ^2 of particles is calculated, and it judges whether the particle converges prematurely. If it converges prematurely, only chaos search is performed on the global optimal value of the particle.

- (5) It is judged whether the algorithm reaches the maximum number of iterations or meets the convergence condition. If the condition is met, the algorithm will end. Otherwise, it skips to (3) and continues the iteration until the end condition is met.

After the offline optimization of CPSO algorithm, the elements in the global optimal value P_g are arranged and combined as the initial weight coefficient matrix W_i of the BP network and then the PID parameters are adjusted in real time by the BP network to control the system.

BP neural PID control is composed of BP network and PID control. The number of nodes in the input layer of the BP network depends on the characteristics and requirements of the controlled object, and the number of nodes in the output layer is usually set as 3. In this work, the input vector is defined as $I(k) = [r(k), y(k), e(k), 1]^T$, and the output vector $O(k) = [k_p(k), k_i(k), k_d(k)]^T$. The symmetric sigmoid function is selected as the neuron activation function in the hidden layer of the network, and the nonnegative sigmoid function with contraction ability as shown in the following equation is selected as the output layer activation function:

$$g(x) = \lambda \frac{e^x}{e^x - e^{-x}}, \quad (10)$$

where λ is a scale coefficient, and the range of PID parameter can be adjusted. In BP neural PID control, the BP neural network uses the gradient descent method to modify connection weight coefficient. Neural PID control uses the nonlinear mapping ability and self-learning ability of the neural network on the basis of the running state of the system to automatically adjust the parameters of the PID controller and achieve the optimization requirements of a certain performance index of the system.

The nonlinear and strong coupling characteristics of the PWM rectifier make it difficult to design its controller. In view of the fact that the PWM rectifier is a nonlinear system, the application of nonlinear control theory or the intelligent control method to study the PWM rectifier has become a research hotspot of scholars. It is the most important control target of voltage-source PWM rectifiers such that the DC voltage follows the given value quickly and smoothly. In order to improve the control effect of DC voltage, CPSO neural PID control is introduced into the control of DC voltage of the rectifier. According to the operation state of the system, the best combination of PID control is realized through the self-learning of the controller by using the nonlinear expression ability of the neural network to ensure that the DC voltage of the rectifier can track the given value smoothly.

4. Experiments and Results

Based on MATLAB/Simulink platform, the CPSO neural PID controller model is built as shown in Figure 3. All the experiments are conducted on a Windows 10 operating system with 8 GB RAM and an Intel Core i7 processor with 3.60 GHz. The method is implemented using the MATLAB R2018b Win64.

FIGURE 2: Structure of CPSO neural PID control system.

4.1. PID Control Experiment. The controller is simulated and applied to the VFDPC system of the rectifier based on SVPWM. The parameters are $U_m = 300$ V, $\omega = 314$ rad/s, $U_{dcr} = 600$ V, $l = 8$ mh, and $C = 500$ μ F. The settings of the CPSO algorithm and BP network are shown in Table 1. T_{max} is the maximum number of iterations of the CPSO algorithm, N is the number of chaotic iterations, and S_N is the structure of the network. It should be noted that ‘-’ in Table 1 means the parameter is related to the corresponding model.

When $t = 0$ s, the rectifier operates at rated power; when $t = 0.1$ s, the load is suddenly applied and the rectifier operates at 1.4 times of rated power; when $t = 0.2$ s, the rectifier changes to the inverter condition and feeds back electric energy from the DC side to the grid. The simulation results are shown in Figure 4.

As can be seen from Figure 4, the DC voltage overshoot of the PWM rectifier based on CPSO neural PID control is 25.8% and the regulation time is 0.026 s. This means that after about one power frequency cycle adjustment, the DC voltage can follow the given value. When the load is suddenly disturbed, the DC voltage can quickly recover to the given value with strong anti-interference performance. When the system turns to inverter condition, the overshoot of DC voltage is small.

As can be seen from Figure 5, after 0.026 s regulation, the power supply voltage and AC current are in the same phase and the system operates under the condition of unit power factor. At 0.2 s time, when the rectifier turns to the inverter condition, the rectifier can also adjust the power factor to -1 in time according to the requirements of system control.

Figure 6 shows that the total harmonic distortion rate of a-phase current is 1.20%. Compared with the traditional PID control system, the performance of the system is improved.

In order to further prove the superiority of CPSO neural PID control, BP neural PID control and PSO Neural PID control are used to simulate the DC voltage control of the

voltage-source PWM rectifier. The parameters of BP neural PID control and PSO neural PID control are the same as CPSO neural PID control. Under the same simulation conditions, the simulation results of several control methods are shown in Table 2.

In Table 2, $\sigma\%$ is the overshoot of DC voltage in the startup phase of the system, t_{s1} is the DC voltage regulation time, t_{s2} is the time to adjust the power factor of the rectifier from 0 to 1, e_{ss} is the maximum steady-state error of DC voltage when the system is in steady state, and i_{THD} is the total harmonic distortion rate of a-phase current on the grid side. Because the simple BP neural PID control has no CPSO algorithm to optimize the initial weight coefficient, the response result shows instability and randomness. In the experiment, we select the average value of the 10 results to compare.

Comprehensive evaluation of the performance indicators in Table 2 shows that both original and optimized BP neural PID control have achieved better control effect than traditional PID control, because BP neural PID control belongs to the category of intelligent control with the characteristic of self-learning and self-adaptability. Compared with other control methods, CPSO neural PID control achieves the best control effect, which shows that the performance of the controller can be effectively improved by offline training of the initial weight coefficient of the BP neural PID controller with intelligent optimization algorithm and assigning the reasonable initial weight coefficient to the BP network. Table 2 shows the effectiveness and superiority of applying CPSO neural PM control to the voltage-source PWM rectifier.

4.2. Discussion. According to the performance of our method presented in Section 4.1, the BP neural PID control has achieved better control effect than the traditional PID control, because the BP neural PID control belongs to the

FIGURE 3: Simulation model diagram of the CPSO-BP-PID controller.

TABLE 1: Parameter setting of the CPSO algorithm and BP network.

	d	m	C_1	C_2	$T_{\max}$	N	δ	η	S_N
CPSO	44	30	1.5	1.5	200	500	-	-	-
BP	-	-	-	-	-	-	0.25	0.05	4-5-3

FIGURE 4: Current-voltage response curve.

category of intelligent control and has self-learning and self-adaptability. Compared with other control methods, CPSO neural PID control has achieved the best control effect. It shows that the initial weight coefficient of the BP neural PID controller can be trained offline through the intelligent optimization algorithm and the reasonable initial weight coefficient can be assigned to the BP network, which can effectively improve the performance of the controller. There are two issues that need to be further studied:

FIGURE 5: Response curve of the power factor of the current device.

FIGURE 6: Response of the PWM rectifier based on CPSO neural PID control.

TABLE 2: Comparison of simulation results of several control methods.

Control method	Performance index				
	σ (%)	t_{s1} (s)	t_{s2} (s)	e_{ss} (V)	i_{THD} (%)
PID [15]	43.5	0.040	0.030	4.1	1.37
Neural PID [16]	34.1	0.037	0.036	5.5	1.41
PSO neural PID [17]	26.5	0.028	0.023	2.3	1.23
CPSO neural PID [18]	25.8	0.026	0.022	2.3	1.20

- (1) We have studied the modeling and optimal control of PWM rectifiers under pure resistive load and three-phase power grid ideal conditions. The characteristics of PWM rectifiers under resistive or inductive load and power grid nonideal conditions can be further considered.
- (2) The time complexity of intelligent PID control algorithm and the real-time performance of system control need to be coordinated.

5. Conclusions

In this work, a CPSO neural PID controller is designed and applied to the control of DC voltage of voltage-source PWM rectifiers. Firstly, the structure, principle and main function modules of the controller are introduced. Then, we describe the application of the controller in the voltage-source PWM rectifier. Finally, a simulation model is built based on MATLAB/Simulink. The feasibility and superiority of applying CPSO neural PID control to DC voltage control of voltage-source PWM rectifiers are verified by simulation and comparison of results.

Abbreviations

PWM: Pulse width modulation
 IGBT: Gate bipolar transistor
 DPC: Direct power control
 CPSO: Chaos particle swarm optimization
 APF: Active power filter
 BP: Backpropagation
 UPFC: Unified power flow control
 SVG: Static var generator
 SMES: Superconducting magnetic energy storage
 HVDC: High voltage direct current
 ED: Electrical driver
 PSO: Particle swarm optimization
 PID: Proportion integral differential.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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