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RESEARCH ARTICLE

Real-Time Monitoring Method for Thyristor Losses in Ultra High Voltage Converter Station Based on Wavelet Optimized GA-BP Neural Network

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ABSTRACT As the core equipment for AC/DC conversion in ultra-high voltage direct current (UHVDC) transmission systems, thyristor converter valves are the main source of losses in converter stations. However, it is difficult to directly measure the actual thyristor losses in UHVDC converter stations, and the existing loss calculation methods have many shortcomings, lacking accuracy and real-time performance. In this paper, a real-time monitoring method for thyristor losses in UHVDC stations based on wavelet optimized genetic algorithm-backpropagation (GA-BP) neural network is proposed. Firstly, wavelet transform is used to remove high-frequency noise from thyristor test data and extract features from the original signal. Then, genetic algorithm is used to optimize the initial weights and biases of the BP neural network, and a loss calculation model is constructed through dataset training. Finally, combined with the electromagnetic transient operating point, real-time monitoring of thyristor losses is achieved. Through PSCAD-MATLAB interactive interface simulation verification, this method can obtain real-time power consumption curves of thyristors based on changes in operating conditions. Moreover, compared to traditional fitting algorithms and standard neural networks, the wavelet optimized GA-BP neural network has the advantages of fewer iterations and higher fitting accuracy.

INDEX TERMS UHVDC, converter station, thyristor, energy consumption calculation, real-time monitoring, wavelet transform, GA-BP neural network.

I. INTRODUCTION

Ultra-high voltage direct current (UHVDC) transmission systems enable long-distance and large-capacity power transmission, which is of great significance for energy supply, grid stability, and economic development. Due to the large transmission capacity of the UHVDC transmission line, its absolute losses are relatively large, and they are directly included in the project construction cost. It is particularly important to determine the composition and distribution of system losses [1], [2]. The main sources of losses in the UHVDC transmission system are transmission lines, thyristor valves, converter transformers, AC and DC filters, etc. Above all, the thyristor converter valve is the main source of losses in the UHVDC converter station [3], [4]. It is difficult to determine the distribution of power loss of the main energy-consuming components represented by the thyristor converter valves, which poses a serious challenge for the study of loss reduction in UHVDC transmission systems.

For the monitoring of thyristor loss, IEEE and IEC develop several standards, which provide for the commissioning of high voltage direct current converter stations and the power

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loss of major components [5], [6]. Relevant scholars have modeled the UHVDC system and built a UHVDC system simulation model based on transient simulation software such as PSCAD/EMTDC and RT-LAB real-time simulation software [7], [8], [9], [10], [11]. They also carried out a more complete analysis of the control strategy and dynamic characteristics of the UHVDC system [12], [13], [14]. For the thyristor converter valve, Y. Lou put forward the simulation calculation method of thyristor converter valve loss by establishing a high-precision simulation model of the thyristor and saturation reactor and successfully calculated the loss of the main components in the converter valve of the Ximeng converter station under the rated condition [15]. But its refined model has the drawbacks of low simulation efficiency and complex model modification. P. A. Gbadega and A. K. Saha studied the verification, determination, and calculation of the total loss of the thyristor valve in UHVDC converter stations and established the loss calculation model of the thyristor valve in detail based on the theoretical calculation method [16], [17]. But its calculation accuracy is not high and some of the parameters required for the calculation are difficult to be obtained in the different types of thyristors. In recent years, data-driven modeling methods based on massive data have developed rapidly [18], [19], [20], [21], and artificial intelligence algorithms are widely used in electrical engineering fields such as power equipment fault diagnosis, load forecasting, power system optimization, etc. [22], [23], [24]. In the field of UHVDC transmission, C. Liu proposed a new method based on the combination of wavelet transform and wavelet neural network for commutation fault diagnosis, and the simulation experimental data showed that its diagnostic speed is fast and the recognition accuracy is high [25]. However, the method fails to realize real-time diagnosis of the system operation, and the relevant artificial intelligence algorithms are rarely used in thyristor loss monitoring.

At present, scholars have almost perfected the accurate modeling and operation control strategies of the UHVDC system, but there is relatively little research on the system loss, especially the thyristor valve losses. There are still some shortcomings in the existing research. On the one hand, the existing thyristor valve theoretical calculation method is difficult to obtain some of the parameters, lacks accuracy, and is difficult to achieve real-time monitoring of loss. On the other hand, the refinement of the transient model has high complexity, and low simulation efficiency, which is difficult to accurately reflect the real-time loss under the influence of multiple elements. In addition, data-driven artificial intelligence algorithms are advanced, but they have not been applied in the research of thyristor loss monitoring.

The purpose of this paper is to propose a real-time monitoring method of thyristor loss in UHVDC converter station based on wavelet optimized genetic algorithm-backpropagation (GA-BP) neural network algorithm to accurately calculate the thyristor loss and display it in real-time in response to the above problems. In section II, the traditional thyristor theoretical calculation method is introduced. Based on the wavelet optimized GA-BP neural network algorithm the system architecture of real-time monitoring and the modeling of the UHVDC system is explained in section III. The implementation of the proposed algorithm is elaborated in section IV. In section V, the proposed real-time monitoring method is validated based on the simulation model and compared with other neural networks and traditional algorithms. Finally, conclusions are drawn in section VI.

II. THEORETICAL CALCULATION METHOD

For each thyristor, it can be roughly divided into four states according to the characterization of its turn-on process, conduction state, turn-off process, and blocking state. Since there is almost no current flow during the thyristor blocking state, the blocking state loss of the thyristor valve mainly depends on the other components of the valve group, which is not discussed in the study of this paper. Therefore, the theoretical calculation of thyristor loss is presented below through turn-on process loss, conduction state loss, and turn-off process loss [6].

A. TURN-ON PROCESS LOSS

The turn-on process loss component of a thyristor is the product of the rapidly rising current and the rapidly falling voltage drop during its conduction. This voltage drop greatly exceeds the ideal thyristor conduction state voltage.

$$P_{thy1} = N_t \times f \times \int_0^{t_1} [u_B(t) - u_A(t)] \times i(t)dt \tag{1}$$

where, N_t is the number of thyristors in series with a single valve; f is the AC frequency. t_1 is the turn-on process time, which can be calculated by $t_1 = (2\pi/3 + \mu)/2\pi f$; $u_B(t)$ is the instantaneous conduction state voltage of the thyristor; $u_A(t)$ is the average value of the instantaneous conduction state voltage drop of the thyristor under the same conditions; $i(t)$ is the instantaneous current flowing through the thyristor.

B. CONDUCTION STATE LOSS

The conduction state loss component of a thyristor theoretically corresponds to the product of conduction state current and conduction state voltage. When the DC current is well smooth, the theoretical calculation of its conduction state loss applies equation (2); while equation (3) is used instead provided that the RMS (Root Mean Square) value of the DC side harmonic currents exceeds 5% of the DC component.

$$P_{thy2a} = \frac{N_t \times I_d}{3} \times \left[U_0 + R_0 \times I_d \times (\frac{2\pi - \mu}{2\pi}) \right] \tag{2}$$

$$P_{thy2b} = \frac{N_t \times I_d \times U_0}{3} + \frac{N_t \times R_0}{3} \times (I_d^2 + \sum_{n=12}^{48} I_n^2) \times (\frac{2\pi - \mu}{2\pi}) \tag{3}$$

where, I_d is the DC current; μ is the commutation angle; U_0 is the current-independent part of the thyristor mean conduction state voltage; R_0 is the resistance that determines the slope of the thyristor mean conduction state characteristic; I_n is the RMS value of the n-th harmonic current of the DC bridge.

C. TURN-OFF PROCESS LOSS

The turn-off process loss component of a thyristor is generated by the reverse recovery current flowing through the thyristor during the turn-off process. The value of the reverse recovery current is usually characterized by the reverse recovery charge.

$$P_{thy3} = Q_{rr} \times f \times \sqrt{2} \times U_{V0} \times \sin(\alpha + \mu + 2\pi f \times t_0) \tag{4}$$

where, Q_{rr} is the average value of the thyristor storage charge; U_{V0} is the RMS value of the no-load line voltage on the valve side of the converter transformer without harmonics; α is the trigger angle; t_0 is the reverse recovery time, which can be calculated by $t_0 = \sqrt{Q_{rr}/(di/dt)_{i=0}}$.

The total thyristor loss during system operation is the sum of the above components:

$$P_{thy} = \sum_{i=1}^{3} P_{thyi} \tag{5}$$

III. ARCHITECTURE OF THE REAL-TIME THYRISTOR LOSS MONITORING SYSTEM

The theoretical calculation method of thyristor described in the previous section is a common calculation method for converter stations, which is universal but lacks calculation accuracy for different actual UHVDC systems. At the same time, it is difficult to obtain some data such as $u_A(t)$ and $u_B(t)$ in the datasheet of thyristor, and the key parameters of different types of thyristors are different, which brings certain difficulties to the theoretical calculation method.

Aiming at the problem of thyristor loss monitoring, this paper intends to propose a new method of data-driven real-time monitoring. Based on the wavelet optimized GA-BP neural network algorithm, an accurate loss calculation model can be established through massive thyristor test data. At this time, it is only necessary to provide data such as the operating point of the system to analyze and calculate, and then the loss calculation results with high accuracy can be derived. To realize the real-time monitoring of loss, this paper adopts the idea of combining electromagnetic transient and numerical calculation. Firstly, the PSCAD simulation model of the UHVDC transmission system is established. And then, the BP neural network training is carried out by MATLAB to form the loss calculation model. Finally, the operating point data of the system is obtained through the PSCAD simulation model, and the real-time monitoring of the loss is realized based on the interactive interface [26], [27]. The architecture of the real-time thyristor loss monitoring system is shown in Fig. 1.

An electromagnetic transient simulation model in PSCAD based on an actual UHVDC transmission system is established in this paper, whose structure is schematically shown in Fig. 2.

As shown in Fig. 2, the UHVDC transmission system is mainly composed of thyristor valves, converter transformers, AC filter bank, DC filter bank, DC smoothing reactor, etc. The UHVDC transmission system model uses the basic control method. The constant DC current control method is applied on the rectifier side which makes the DC current constant by the change of the trigger angle α. The constant γ-angle control method is deployed on the inverter side to make the thyristor's arc extinguishing angle γ not less than the minimum arc extinguishing angle avoiding the phase change failure. At the same time, the rectifier side also has the minimum trigger angle limitation control, and the inverter side also has the current error control (CEC) and voltage-dependent current order limiter (VDCOL).

Based on the operating point obtained from the UHVDC transmission model, PSCAD interacts with MATLAB, which realizes real-time monitoring and visualization through the loss calculation algorithm. The algorithm is elaborated thoroughly in the following section.

IV. WAVELET OPTIMIZED GA-BP NEURAL NETWORK

A. OVERALL ALGORITHM FLOW

BP neural network is a common artificial neural network model that approximates complex nonlinear functional relationships consisting of one or more layers of neurons. It is trained and learned by a backpropagation algorithm, including an input layer, a hidden layer, and an output layer, as shown in Fig. 3.

It calculates the error between the predicted output and the desired output and adjusts the weights and biases in the network according to the error so that the output of the network gradually approaches the desired output. The error function and the amount of adjustment of the weights and biases are given in the following equation.

$$e = \frac{1}{2}\sum_{k=1}^{l}(d_k - o_k)^2 \tag{6}$$

$$\Delta w = -\eta \frac{\partial e}{\partial w} \tag{7}$$

$$\Delta b = -\eta \frac{\partial e}{\partial b} \tag{8}$$

where, e is the output error; d_k is the desired output; o_k is the output layer output; w is the weight; and b is the bias.

For the thyristor loss which is affected by multiple factors such as trigger angle, commutation angle, DC current, junction temperature, etc., the BP neural network can be trained to obtain an accurate loss calculation model by fitting the complex functional relationship between the loss and the influencing factors. However, the standard BP neural network has certain defects. On the one hand, it does not have a pre-processing process for the data input. The massive test data is very likely to produce some high-frequency noise or contradictory data due to various reasons, which will have a

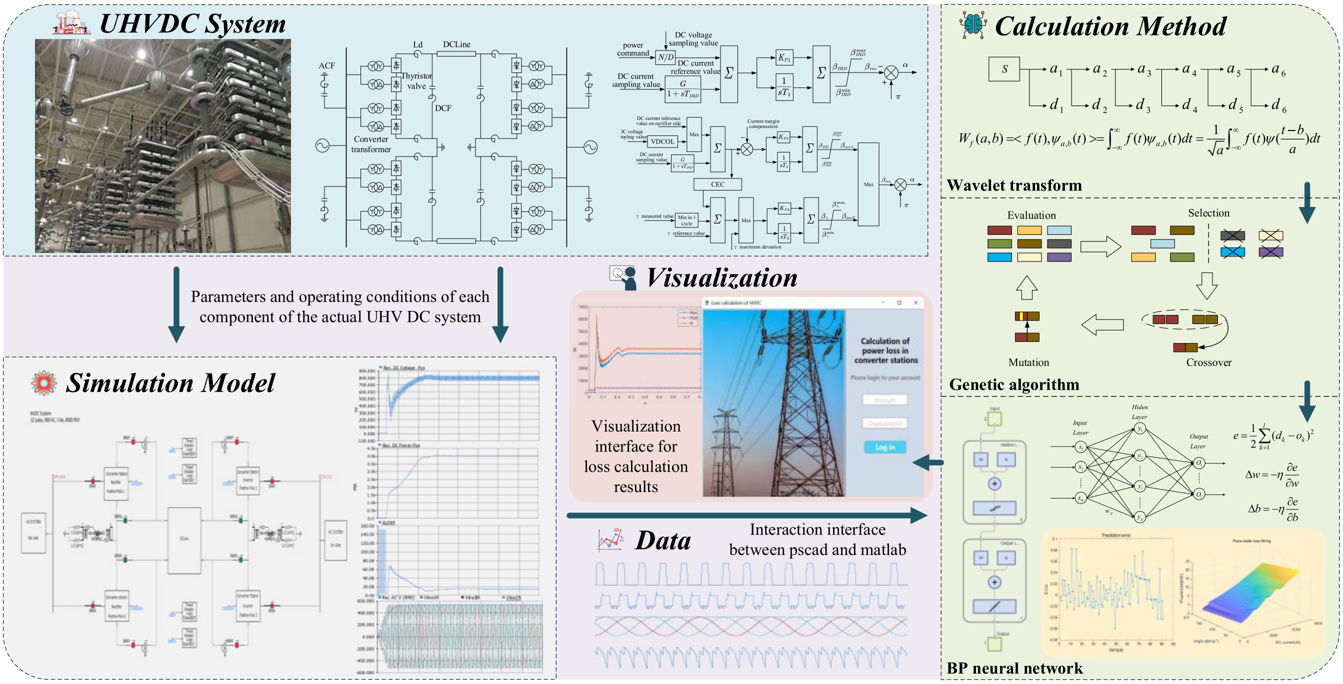

FIGURE 1. Real-time thyristor loss monitoring architecture based on wavelet optimized GA-BP neural network algorithm.

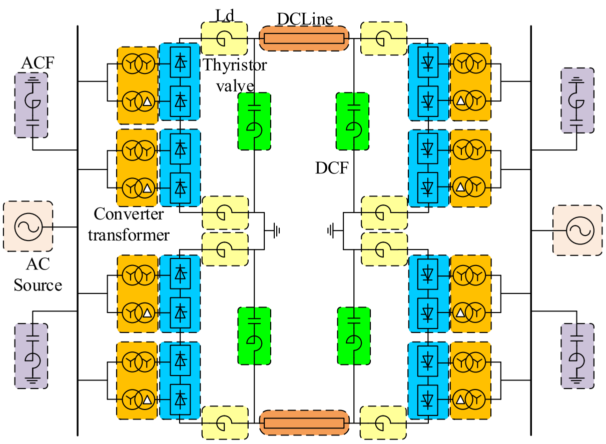

FIGURE 2. Schematic diagram of the structure of ultra-high voltage direct current transmission system.

certain impact on the model accuracy. On the other hand, the training of the BP algorithm is very sensitive to the selection of the initial weights and biases, and different initial values may lead to different training results. In addition, the training process uses the gradient descent method to minimize the error function, while this may lead the network to fall into the local optimal solution and not achieve the global optimal solution. Consequently, some optimization of the algorithm is required to achieve the desired results of the calculation model.

In this paper, a wavelet optimized GA-BP neural network algorithm is proposed. Wavelet transform is used to remove high-frequency noise from thyristor test data and extract features from the original signal. Then, genetic algorithm is used to optimize the initial weights and biases of the BP neural network, and a loss calculation model is constructed through

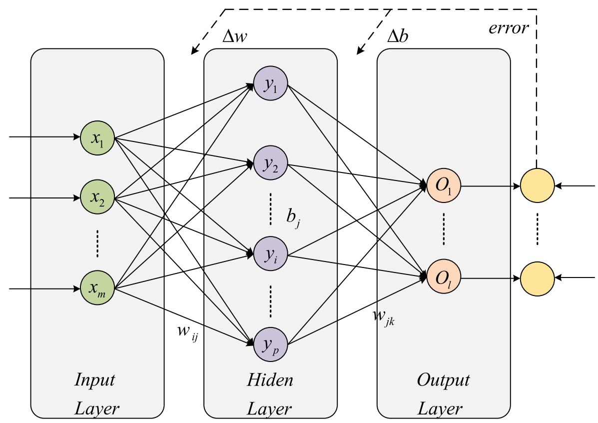

FIGURE 3. BP neural network structure diagram.

dataset training Fig. 4 shows the flow block diagram of the algorithm.

B. WAVELET TRANSFORM

Wavelet transform is a multi-scale analysis method that decomposes a signal into wavelet functions of different scales and frequencies. The wavelet function can be selected according to the frequency and time domain characteristics of the signal, which can effectively deal with high-frequency noise in the signal.

The continuous wavelet transform is defined as:

$$\begin{aligned} W_f(a,b) &= < f(t), \psi_{a,b}(t) > \\ &= \int_{-\infty}^{\infty} f(t)\psi_{a,b}(t)dt \\ &= \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-b}{a}\right)dt \end{aligned} \tag{9}$$

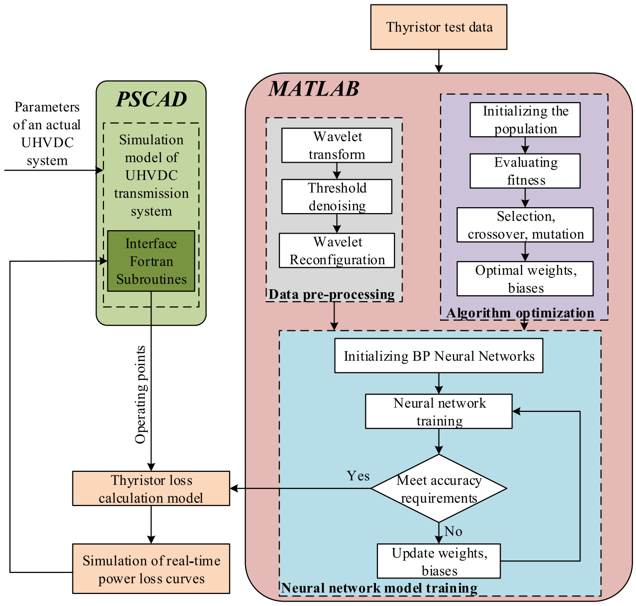

FIGURE 4. Wavelet optimized GA-BP neural network algorithm.

where, $f(t)$ is the original signal; $\psi_{a,b}$ is the wavelet function, commonly used wavelet function such as Haar, Daubechies, Symlets, Coiflets, etc., and each wavelet function corresponds to a different frequency and time domain resolution characteristics; a is the scale factor, used to adjust the frequency and width of the wavelet function; b is the displacement factor, used for the translation of the wavelet basis function in the position of the time axis.

In practical applications, discrete signals are often processed. By discretizing the scale and displacement of basic wavelets, a discrete wavelet transform can be obtained:

$$W_f(m,n) = 2^{-m/2}\sum_{t=0}^{T} f(t)\psi(\frac{t-n2^m}{2^m}) \tag{10}$$

where, $a = 2^m$ and $b = n2^m$.

Considering that there are few data dimensions obtained that affect the loss of thyristors, the test data samples in the article are relatively simple. To reduce algorithm complexity, Haar wavelet, one of the earliest wavelet functions proposed, is selected to improve computational efficiency while maintaining high accuracy. And although its performance is not optimal compared to other wavelet functions, it is simple to calculate and still effective in practical applications.

$$\psi(t) = \begin{cases} 1 & (0 \leq \text{t}<0.5) \\ -1 & (0.5 \leq \text{t}<1) \\ 0 & (t < 0, t \geq 1) \end{cases} \tag{11}$$

In this case, $\psi_{a,b}$ can be expressed as:

$$\psi_{a,b}(t) = 2^{a/2}\psi(2^a t - b) \tag{12}$$

According to the spectral characteristics of the signal and the characteristics of the noise, select the appropriate threshold function to threshold the wavelet function, set the noise coefficient to zero or make corrections, and obtain the denoised signal through wavelet reconstruction.

$$f(t) = \frac{1}{C_\psi}\int_0^\infty \int_{-\infty}^\infty W_f(a,b)\cdot\frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})dadb \tag{13}$$

where, C_ψ is the constant of the wavelet function.

The test data extracted by wavelet denoising can be trained by BP neural network.

C. GENETIC ALGORITHM

Genetic algorithm is a guided stochastic search method for solving optimization problems, which has a strong ability for global search and global optimization. Aiming at the defects of the BP algorithm, which is easy to fall into local optimum, it can be used to optimize its initial weights and biases, accelerate the convergence speed of the network, and improve the prediction accuracy of the model.

The wavelet optimized GA-BP algorithm searches for the optimal combination of neural network weights and biases to minimize the loss function through the genetic algorithm. The elements of the genetic algorithm include population initialization, evaluation of fitness, selection operation, crossover operation, and mutation operation.

The initial population is first randomly generated $P = \{p1, p1, \ldots, pn\}$, where pi denotes the i-th individual, including the weights and biases of the neural network.

Next, each individual is applied to the neural network. The output of the neural network and the value of its loss function $L(pi)$ are calculated, and the value of the loss function is converted to the value of the fitness function $F(pi)$ to obtain the fitness of each individual.

$$F(pi) = k\left(\sum_{i=1}^{n} abs(y_i - o_i)\right) \tag{14}$$

where, n is the number of network output nodes; y_i is the desired output of the i-th node of the BP neural network; o_i is the predicted output of the i-th node; and k is the coefficient.

The selection operation uses the roulette method, and the probability of selection $P(pi)$ for each individual is calculated based on the fitness values as follows:

$$f(pi) = k/F(pi) \tag{15}$$

$$P(pi) = \frac{f(pi)}{\sum_{i=1}^{N} f(pi)} \tag{16}$$

where, k is the coefficient; N is the population size.

The crossover operation adopts the real number crossover method. The k-th chromosome a_k and the lth chromosome a_l are crossed at the jth position, and the crossover operation is performed as follows:

$$\begin{cases} a_{kj} = a_{kj}(1-b) + a_{lj}b \\ a_{lj} = a_{lj}(1-b) + a_{kj}b \end{cases} \tag{17}$$

where, b is a random number between [0,1].

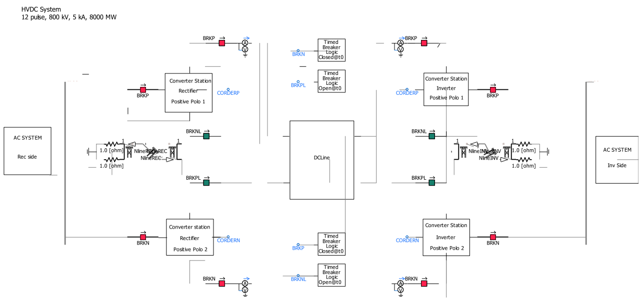

FIGURE 5. PSCAD simulation model of UHVDC transmission system.

The mutation operation is to select the j-th gene of the ith individual for mutation:

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) \cdot f(g) & r > 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) \cdot f(g) & r \leq 0.5 \end{cases} \tag{18}$$

where, $a_{\max}$ is the upper bound of the gene a_{ij}; $a_{\min}$ is the lower bound of the gene a_{ij}; $f(g) = m(1 - g/G_{\max})^2$, m is a random number, g is the current iteration number, $G_{\max}$ is the maximum evolution number; r is a random number between [1, 0].

Finally, a new population $P' = \{m1, m1, \ldots, mn\}$ is constructed, which includes the individuals obtained through crossover and mutation as described above. The fitness of the individuals is improved by selection, crossover, and mutation operations to produce new weights and biases. Such an evolution process will continue until the fitness requirement is satisfied. And then the new weights and biases will be given to the BP neural network to realize the global optimization of the network.

V. CASE ANALYSIS AND VERIFICATION

A. PSCAD-MATLAB JOINT SIMULATION VERIFICATION

The proposed real-time monitoring method for thyristor loss in ultra-high voltage converter stations based on wavelet optimized GA-BP neural network will be verified by joint simulation through the PSCAD-MATLAB interactive interface. This paper performs a study based on a ±800 kV/5 kA UHVDC transmission line from Northwest China to Central China, whose relevant operating parameters are shown in Table 1, and the PSCAD simulation model is constructed in Fig. 5.

Based on MATLAB, the proposed wavelet optimized GA-BP neural network algorithm program is written, and the neural network is trained to establish the thyristor loss calculation model through massive thyristor test data. Finally, the PSCAD-MATLAB interactive interface setting is carried out.

In this experiment, the simulation duration is set to 0.8 s, and the UHVDC system works in the double great ground return line operation mode to start the joint simulation. The voltage, current, and monopole delivered power of the UHVDC transmission system are shown in Fig. 6 which

TABLE 1. Operational parameters of the UHVDC transmission system.

Item	Rectifier Side	Inverter Side
Rated capacity/MW	4000	4000
DC voltage/kV	800	800
DC current/A	5000	5000
AC voltage/kV	525	525
Ideal no-load DC voltage/kV	236.2	227
Trigger angle/° (electrical angle)	15	15
Arc extinguishing angle/° (electrical angle)	/	19.5

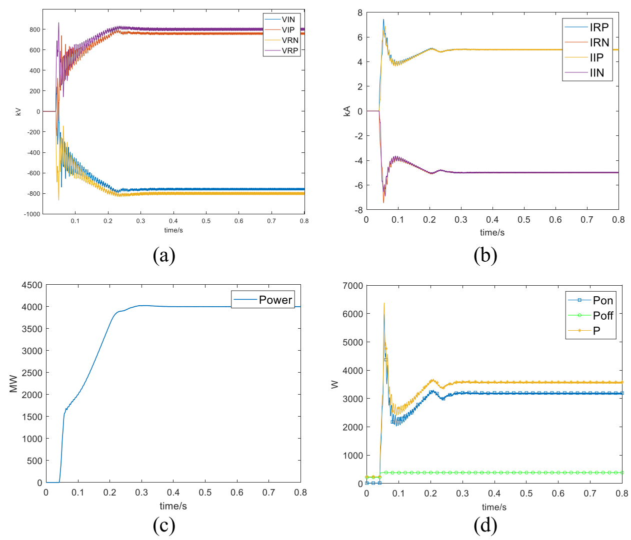

FIGURE 6. Simulation results (a) Bipolar DC voltage (b) Bipolar DC current (c) Monopole power delivered in rectifier station (d) Single thyristor power loss.

correspond to the operating parameters of ±800 kV/5 kA and 4000 MW.

The simulation model of the UHVDC system operates under the rated operating conditions, and from the three figures (a), (b), and (c) above, the voltage, current, and power are consistent with the actual system, namely ±800 kV/5 kA and 4000 MW. As a result, the PSCAD simulation model is greatly close to the actual system, and the operating point data obtained from the simulation are valid. The loss monitoring needs the operating point data of the PSCAD transient simulation model, which is transferred to MATLAB through the interactive interface, and then the real-time loss monitoring results are output from the loss calculation model based on the wavelet optimized GA-BP neural network algorithm. From the real-time power loss diagram of a single thyristor in the rectifier station, it can be seen that the thyristor loss can be calculated and displayed in real-time as the voltage and current of the UHVDC system change. Under the steady state condition, the thyristor turn-off loss is about 386 W, the thyristor conduction loss is about 3186 W, and the approximate total thyristor loss is about 3572 W. The thyristor single valve of this UHVDC system consists of 60 thyristors connected in series, which results in a single-valve thyristor conduction loss of 180.44 kW and a turn-off loss of 20.73 kW. The result is similar to its theoretical calculations of 173 kW and 23.19 kW, and the effectiveness of the proposed method is verified. From the joint simulation experiments, it can be concluded that the real-time thyristor loss monitoring method of the UHVDC converter station based on wavelet optimized GA-BP neural network algorithm proposed in this paper can operate perfectly, and the strategy has both real-time and accuracy, which is helpful for the accurate calculation of the loss of the actual UHVDC transmission system.

B. COMPARISON OF ALGORITHMS

1) THE RESULTS OF THE PROPOSED ALGORITHM

To verify the effectiveness of the proposed wavelet optimized GA-BP neural network algorithm, the test data of a certain model of the thyristor is taken as an example for experimental analysis. A total of 404 test data samples are selected for the algorithm, and each sample data contains two input variables (trigger angle, conduction current) and one output variable (average conduction power), with 80% of the samples taken as the training data and 20% of the samples taken as the test data. In this experiment, a 2-5-1 neural network structure is used, with a genetic algorithm population size of 20, 50 evolutionary generations, a maximum number of 1000 iterations of the neural network, and an objective error of 0.001. To evaluate its performance, Epoch, MSE, RMSE, R^2, and MAE are selected as evaluation indexes. Epoch is the number of neural network training and other indexes are expressed as follows.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{19}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{20}$$

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{21}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{22}$$

The model training results are shown in Fig. 7 and Fig. 8. It can be shown in the results that the proposed algorithm is extremely accurate and efficient.

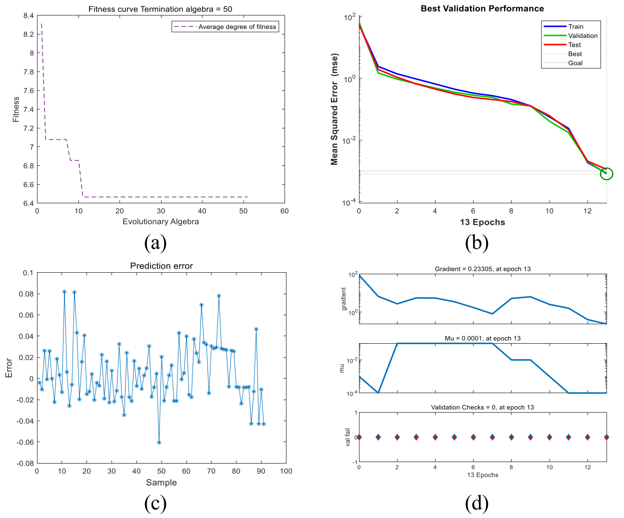

FIGURE 7. Experiment results (a) Number of evolutionary generations (b) Algorithm performance (c) Prediction error (d) Training state.

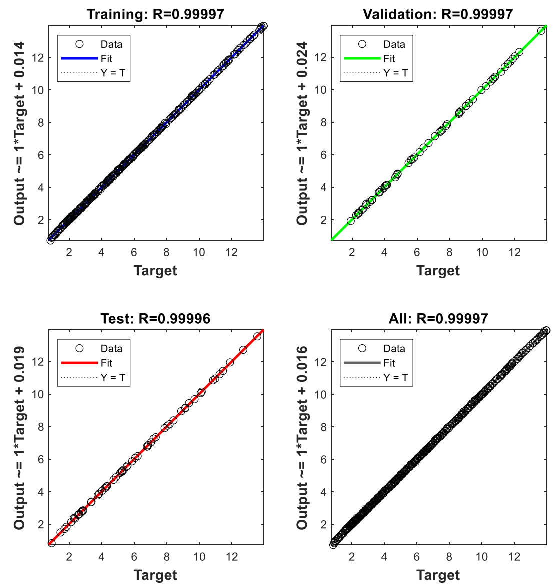

FIGURE 8. Algorithm goodness of fit: R-squared.

2) COMPARISON WITH CONVENTIONAL ALGORITHMS

This paper is based on a data-driven approach to calculate thyristor loss, which is essentially data fitting of complex functional relationships between multiple inputs and outputs. Traditional fitting algorithms, unlike artificial intelligence algorithms, are usually based on statistical and mathematical principles to fit given data.

The least squares method is one of the most common traditional fitting algorithms that determines the best-fit curve by minimizing the sum of squares of the errors between the data points and the fitted function, and it is applicable to both linear and nonlinear function fitting. For a given data sample, the sum of squares of errors for each data point is:

$$S = \sum_{i=1}^{m}|f(x_i) - y_i|^2 \tag{23}$$

For polynomial fitting by the least squares method, the coefficients of the optimal function should be set to minimize the sum of the squares of the errors. Thus, for the optimal function, the partial derivatives of the sum of the squared errors concerning each polynomial coefficient θ_j should be

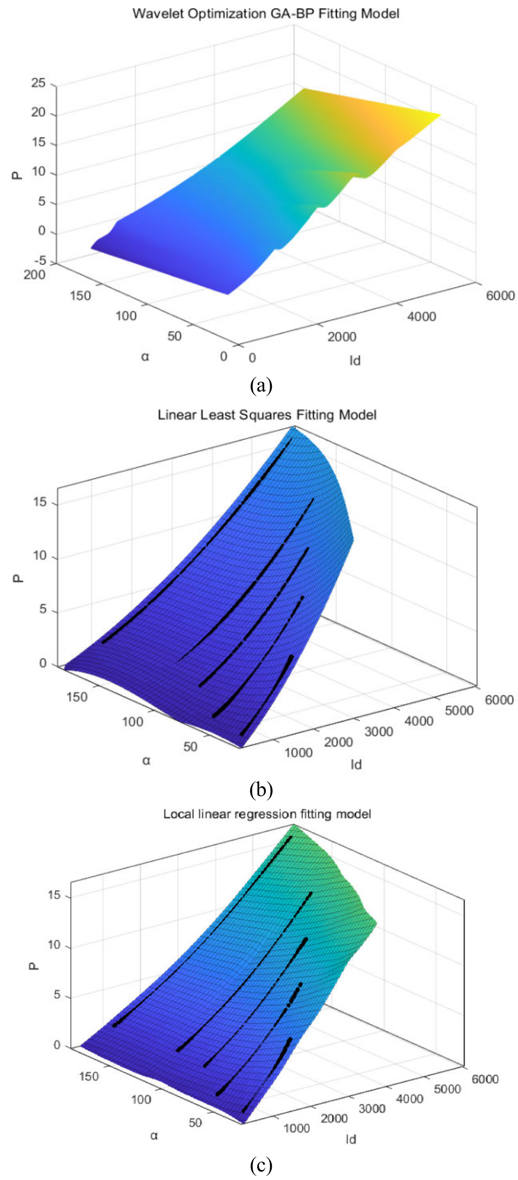

FIGURE 9. The proposed algorithm and traditional algorithm fitting model.

satisfied:

$$\frac{\partial S}{\partial \theta_j} = \sum_{i=1}^{m} \left[2 \left(\theta_0 + \theta_1 x_i + \theta_2 x_i^2 + \cdots + \theta_n x_i^n - y_i \right) x_i^j \right] = 0 \tag{24}$$

The fitting function is obtained by solving each polynomial coefficient by constructing a matrix. In addition to this, the local linear regression method is also selected as a traditional fitting algorithm to compare with the proposed algorithm. The traditional fitting algorithm program is written, and the experiment results are as bellow. Fig. 9 shows the fitting model of the proposed algorithm and the traditional algorithm, and the related comparison results are shown in Table 2.

TABLE 2. Comparison results with conventional fitting algorithms.

Algorithm	MSE	MAE	RMSE	R²
Linear least squares	0.0055462	0.2791	0.0745	0.99961
Local linear regression	0.0032149	0.1944	0.0567	0.99977
Wavelet optimized GA-BP neural network algorithm	**0.0007672**	**0.0218**	**0.0277**	**0.99997**

The above experiments are conducted by comparing the MSE, MAE, RMSE, and R^2 of the traditional fitting algorithm and the proposed wavelet optimized GA-BP neural network algorithm. In terms of the fitting model, the proposed algorithm has a better performance whose fitting data is more complete and smoother. The proposed algorithm outperforms the traditional fitting algorithm in all performance indexes. Compared with the fitting effect of the least squares method, the MSE, RMSE, and MAE of the proposed algorithm decreased by 86.2%, 62.8%, and 20.5%, respectively, and the R^2 increased by 0.036%, which indicates that the computational accuracy was significantly improved. The fitting effect of local linear regression is similar to that of the least squares method. Due to the limited data resources, and only two input variables (theoretically, the thyristor loss is affected by multiple factors such as trigger angle, DC current, junction temperature, commutation angle, etc.), the traditional fitting algorithm is still practical in the case of simple data distribution, so that the proposed algorithm has limited room for improvement in some performance indexes. It can be concluded that the wavelet optimized GA-BP neural network algorithm improves significantly compared with the traditional algorithm, and its effect is more obvious when the data volume is more and more complex.

3) COMPARISON WITH OTHER BP NEURAL NETWORK ALGORITHMS

The proposed algorithm is also compared horizontally with other BP neural network algorithms. For the data preprocessing session of wavelet transform and the initial value optimization session of the genetic algorithm, the experiments are divided into four groups here, which are labeled as No.1 to No.4. Compare their performance indexes through neural network model training, and the comparison results are shown in Table 3 and Fig. 10.

Comparison results show that the wavelet optimized GA-BP neural network algorithm outperforms other BP neural network algorithms in all performance indexes. Compared with the standard BP neural network, its Epoch is reduced by 89%, and the MSE, RMSE, and MAE are reduced by 97.8%, 85.3%, and 84.6%, respectively. Similar to the results of the previous experiment, the R^2 values are slightly but not significantly improved, and these BP algorithms all have superior goodness of fit. The wavelet transform applied to the BP neural network model as data preprocessing

TABLE 3. Comparison results with bp neural network algorithms.

No.	wavelet transform	genetic algorithm	BP neural network	Epoch	MSE	MAE	RMSE	R^2
1			√	118	0.0355	0.1605	0.1885	0.99994
2	√		√	116	0.0209	0.1223	0.1447	**0.99997**
3		√	√	35	0.001232	0.0247	0.0351	0.99995
4	√	√	√	**13**	**0.0007672**	**0.0218**	**0.0277**	**0.99997**

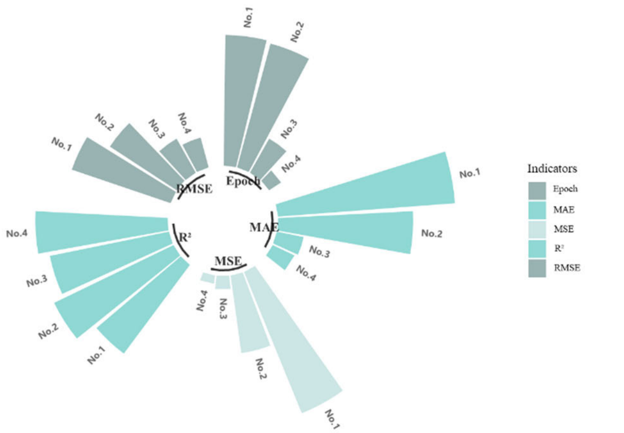

FIGURE 10. Performance comparison of BP neural network algorithms.

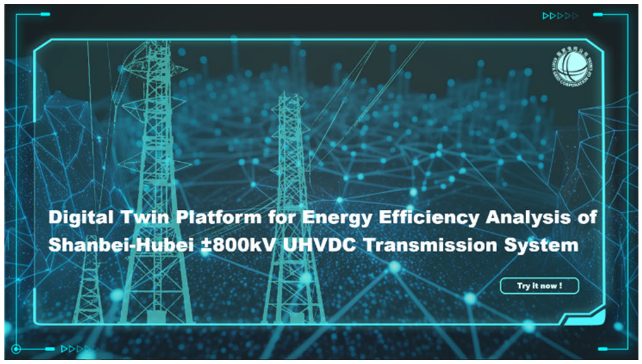

FIGURE 11. Digital twin platform for energy efficiency analysis of UHVDC transmission systems.

significantly improves these performance indexes of MSE, RMSE, and MAE so that the computational accuracy is improved compared to the BP neural network model without this link. Meanwhile, the genetic algorithm is applied to the initial weights and biases optimization of the BP neural network model to avoid falling into the local optimum. From the experiment results after adding the genetic algorithm for optimization, its Epoch has been significantly reduced, which indicates that the computational efficiency has been greatly improved and the computational accuracy has been improved slightly. In summary, compared with other BP neural network algorithms, the wavelet optimized GA-BP neural network algorithm proposed in this paper has the advantages of fewer iterations, higher computational efficiency, and higher fitting accuracy.

VI. CONCLUSION

The UHVDC transmission system has a huge transmission capacity, with large absolute loss during operation, and the loss of the thyristor is difficult to be obtained. Given this problem, this paper proposes a real-time monitoring method for thyristor loss in UHVDC converter station based on the wavelet optimized GA-BP neural network algorithm. Firstly, the PSCAD simulation model of the UHVDC transmission system is built based on the actual system. Secondly, the wavelet optimized GA-BP neural network algorithm is proposed, and based on the test data of the thyristor, the thyristor loss calculation model is trained and built. Finally, the joint simulation through the PSCAD-MATLAB interactive interface verifies that it can run perfectly to calculate the loss of the UHVDC transmission system in real-time. The real-time monitoring method for thyristor loss has been embedded into a digital twin system for energy efficiency calculation and analysis, and Fig. 11 shows a screenshot of the digital twin platform software.

The method proposed in this paper has significant advantages and implications:

(1) The proposed wavelet optimized GA-BP neural network algorithm has fewer iterations, high computational efficiency, and high fitting accuracy. Compared with the traditional fitting algorithm, its MSE, RMSE, and MAE decreased by 86.2%, 62.8%, and 20.5%, respectively, and R^2 increased by 0.036%. Compared with the standard BP neural network algorithm, its Epoch was reduced by 89%, and its MSE, RMSE, and MAE were reduced by 97.8%, 85.3%, and 84.6%, respectively.

(2) The proposed method solves the problems of existing theoretical methods and simulation models for calculating thyristor loss. It takes into account real-time monitoring and high accuracy, and the loss results can be displayed in real-time along with the changes of the working conditions of the simulation model. Furthermore, the artificial intelligence algorithm is used to fill the gaps in the field of thyristor loss monitoring, and the accuracy of the calculation model is higher.

(3) The loss calculation and distribution of the main loss source thyristor in the UHVDC converter station are

determined to provide an effective basis for the further study of the loss distribution and loss reduction technology of the UHVDC transmission system.

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