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Hybrid GA and Improved CNN Algorithm for Power Plant Transformer Condition Monitoring Model

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ABSTRACT Under the general trend of smart grid development in China, it has especially importance to maintain the stability of power generation, the safety of power operation and the reliability of power supply. However, most power plants need to participate in the frequency regulation market and the power spot market, resulting in frequent load fluctuations and often unstable operating conditions of power generation equipment. In this study, a real-time monitoring method based on a hybrid Genetic Algorithm (GA) and Convolutional Neural Networks (CNN) algorithm is utilized to monitor the operation status of power transformers in power plants in real time. The GA-CNN algorithm model is proposed by analyzing the advantages and disadvantages of CNN and GA. It is proved that the accuracy of the GA-CNN is greatly improved compared with the CNN. In the recognition results, the error rate of the GA-CNN is only 1.86%, while that of the CNN is 4%; the random matrix accuracy of the predicted and actual output values of the GA-CNN model is 98.11%, and the three factors affecting the operating status of the equipment, namely temperature and humidity of the external environment and the daily power generation of the power plant, are also acceptable. The model selected for this study is able to detect abnormalities in the operating state of power transformers and provide timely feedback on changes in the external environment of the equipment.

INDEX TERMS Convolutional neural network, dissolved gas analysis in oil, genetic algorithm, GA-CNN algorithm, real-time online monitoring

I. INTRODUCTION

With the increasing complexity of the interconnection architecture of China's power grid, any small problem in the operation of the power grid may bring serious consequences, thus imposing higher requirements on the operational aspects of the power grid. In daily production operation, real-time monitoring of power transformer (PT) operating status is very important [1]. Based on the changes of the monitored parameters, timely and targeted maintenance of PT is carried out. The existing infrared thermography real-time monitoring technology, which is a periodic monitoring technology, cannot timely reflect the abnormal transformer operating condition, i.e., it is impossible to overhaul and maintain the abnormal condition [2]. In addition, the Dissolved Gas Analysis (DGA) real-time online monitoring method for PT is only for a certain period of time and does not provide feedback on the environmental parameters in which the transformer is operating [3]. To some extent, it brings instability and loss of economic efficiency for the operation of power plants or grids. In this study, a GA-CNN model is proposed to address the shortcomings of existing techniques and to combine other influencing parameters external to the transformer, such as temperature, humidity, and the daily power generation of the power plant. The CNN algorithm is utilized to establish a comprehensive real-time monitoring model of the operating condition of PT [4]. The CNN algorithm is optimized with GA for the problem that

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the CNN algorithm loses some details, resulting in low accuracy. The output of the optimal solution for the transformer operating state using the GA is used to raise the evaluation accuracy of the operating state of PTs and to complete the real-time monitoring of the transformer state in power plants [5]. The research includes three main parts. The first part illustrates the PT classification, including having the body structure of the transformer consists of internal and external faults, the faults of the constituent structures, and the parts that often produce faults. The second part is in the optimized CNN based on GA, and the GA-CNN algorithm is proposed. With the decision variable encoding as the operation object and the objective function value as the search information, the characteristics of multi-point search are used to reduce the inaccuracy of CNN neural network, and then reach to get the global optimal solution. The third part is the evaluation and diagnosis of PT operation status by GA-CNN algorithm, and the feasibility of GA-CNN algorithm and its applicability to PT operation in power plants are verified using the data set.

II. RELATED WORKS

As the growth of information technology, the usage of smart grid technology in daily production and life has gradually become more popular and more intelligent in condition monitoring, and some experts have carried out many related researches in smart condition monitoring technology. Chen Z et al. proposed a Temporal Convolutional Network (TCN) based RUL prediction model to improve the accuracy of deep neural network parameters. The performance of this prediction model is validated by C-MAPSS dataset. The outcomes showed that the proposed GA-TCN reduced 7.9% to 27.13% and 27.87% to 78.69% in assessment indexes of root mean square error and score function, respectively [6]. This prediction model’s accuracy has been improved to a large extent and has practical applications. Kaleli and Akola improved the exhaust gas emissions and fuel consumption by designing an electromechanical exhaust gas recirculation (EGR) cooling system that is different from the conventional system. With a grid search method, the hyperparameters of the best model were decided. It was proved that the Gaussian process regression model outperforms other ML models based on the error prediction of NOx and BSFC. Compared with the conventional EGR cooling method, this study demonstrated that the proposed ML-GA-based system reduced 13.6% (NEDC)-9.88% (WLTP) and 2.57% (NEX)-1.89% (WLTP) under NEDC and WLTP conditions, respectively [7]. Zhu et al. proposed an attention mechanism and GA based LSTM model. The structure of the model and data selection parameters were optimized by GA, and the time series memory and processing capability of the model were utilized to predict global horizontal irradiance and direct normal irradiance after 5, 10 and 15 minutes. The lab outcomes showed that the prediction effectiveness of the model was below 19% for all three predicted illumination levels, effectively improving the prediction accuracy [8]. Moslemi et al. designed a single-legged robot similar to the human leg anatomy. To make the simulation more precise, the physical characteristics of the environment need to be defined in detail and ground contact and friction models need to be developed. After this, joint motions are designed and referred to make the robot jump in the vertical direction, with toe joint stiffness playing a dominant role in the jump height. A GA is then applied to optimize the jump height [9]. Xia et al. proposed a clutch control strategy to promote the shift quality. The strategy well avoids power cycling by analyzing the variation of transmission torque and the relationship between the speed of the active and driven discs of the shift clutch. Hybrid particle swarm optimization with GA solves the problem that basic particle swarm optimization often converges to a locally optimal solution. Simulation results show that the raised control strategy perfectly avoids power cycling during gear shifting and improves the shift quality [10].

With the development of information technology, intelligent algorithms are gradually being used in various fields of analysis, providing objective and effective data for evaluation and analysis in various fields. Ma Q et al. designed a method that combines the discrete wavelet transform (DWT) with time-convolutional network and particle swarm optimization-based support vector regression. The method will use the discrete network wavelet model to decompose the traction load into sub-series, and then select the TCN model to predict the low and medium frequency series with the frequency difference of various series. Experimental results show that this method has higher prediction accuracy [11]. Ding et al. proposed an algorithm for calculating the degree of blade icing, which works out the same points between unlabeled data and icing data as labels for the class imbalance problem. The final predictions are then obtained by pooling the predictions of all temporal convolutional network models. Using actual monitoring and data collection which were collected from a wind farm in northern China, the raised model was proved and the results showed that the algorithm is very beneficial for improving the detection accuracy [12]. Vinolin and Sucharitha presented a study of deep convolutional neural networks based on Taylor rider optimization algorithm for detecting spliced images. The aim is to be able to distinguish effectively between forged and original images. Among the forged images, stitched images involving human faces are a great threat to information security. Therefore, this research can detect the stitched-out forged images. The results show that the maximum accuracy, true positive and negative rates of the method for the dataset are 99.23%, 98.96% and 96.67%, respectively. The proposed method improves the detection accuracy in contrast to the previous methods [13].

In summary, the real-time monitoring of PT operating parameters of the power plant is critical in daily production operations. Due to the fault points in the operation of PTs, it is impossible to determine their fault types and fault points in time, leading to timely and targeted maintenance of transformers. The GA-CNN algorithm proposed in this study can provide timely feedback, which can effectively detect fault points, overhaul and maintain them, and improve the economic efficiency of production life.

III. POWER TRANSFORMER CONDITION MONITORING MODEL ESTABLISHMENT

A. FAULT CLASSIFICATION OF POWER TRANSFORMERS

PTs are subject to a variety of faults caused by fluctuations in load on the generation side and in the power network during long-term operation, as well as by environmental and other equipment factors. Screening whether a PT is in operating condition requires a comprehensive assessment based on multiple factors and cannot be determined from a single point of real-time data. Transformers in the power network are in an abnormal state, which will cause serious accidents if not judged and overhauled in time. The types of PT failures occurring are roughly divided into five. The percentage of their occurrence is displayed in Table 1.

TABLE I
STATISTICS ON THE PROPORTION OF FAULT TYPES IN POWER TRANSFORMERS

Fault Type	Number of units	proportion
overheat fault	231	54%
High energy discharge fault	59	17.93%
Overheating and high-energy discharge faults	38	10.57%
Spark discharge fault	23	6.79%
Damping or partial discharge	9	2.15%

As can be seen from Table 1, common faults of transformers can be classified in three ways. First, the body structure of the transformer can be divided into internal faults and external faults. Internal faults are manifested as abnormalities in the core, insulating oil, magnetic circuit and other structural aspects. External faults are manifested as phase shorts and ground shorts on the transformer bushing and lead-in line. Second, from the transformer's composition structure can be divided into winding failure, auxiliary equipment failure, filling failure and transformer core failure. Finally, from the different parts of the fault generation, it is divided into equipment insulation, core insulation, bushing faults, and tap changer faults [14]. Among them, overheating faults are one of the most common faults that, in addition to affecting the daily operation of the transformer, also affect the operation of the generator set, thus causing significant fluctuations in the power grid, as shown in Figure 1.

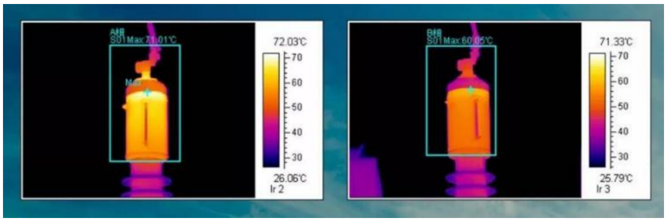

FIGURE 1. **Power transformer overheat fault.**

Figure 1 represents a bushing overheating fault in a PT. The overheating of metal parts is caused by the superposition of various current interactions such as operating current and circulating current generated by the operation of the PT in daily operation. In addition, the insulation failure of PT is also a common type of fault. PT insulation part of the excellent is to determine whether the PT indicators can meet the standard, in the long-term operation of the safety. Insulation part of the problem, lightly affect the operation of the generator set, serious impact on the power plant and the safety of the power grid, resulting in great economic losses, as shown in Figure 2.

FIGURE 2. **Insulation faults in power transformers.**

Figure 2 represents the insulation failure of a PT. Temperature, humidity, oil protection and overvoltage are the principal issues leading to transformer insulation failure. If a PT fails, it is very easy to cause paralysis of the power system and affect the normal power supply of the power system, thus causing serious economic impact. In addition to the above common types of transformer failure, there are other internal and external factors caused by the PT failure. Failure to perform timely maintenance and repair during prolonged operation leads to a reduction in insulation performance and increases the risk of transformer failure [15]. The classification of PT fault types, as well as the statistics of the types with high frequency, provide reliable and effective characteristic parameters for this study, which establishes a real-time monitoring model of the PT operating condition.

B. OPTIMIZATION OF CNN NEURAL NETWORKS BY GA

The most commonly used methods for evaluating the operating condition of transformers are infrared thermal imaging temperature measurement and oil chromatography analysis by DGA real-time online monitoring devices. However, both of them have significant limitations. The former is a periodic inspection method, which cannot reflect the real-time operating status of the transformer, while the latter is a condition assessment of the equipment's interior only, which cannot reflect the exterior with other operating conditions. Therefore, this study uses a hybrid of GA and CNN algorithms for transformer condition assessment. The CNN is used to evaluate the transformer operating status, and its structure is shown in Figure 3.

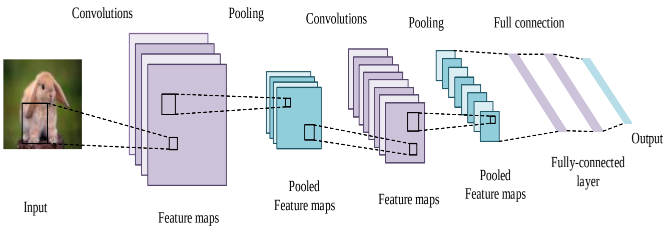

FIGURE 3. CNN network structure.

From Figure 3, CNNs are different from CNNs in that the neurons of each layer are prepared in width, height, and depth [16]. CNNs mainly consist of two parts, forward extraction and backward propagation optimization, and are a multilayer perceptron that can mine local features and thus recognize images with high accuracy. The algorithm is trained for CNN under the condition of that the initial learning rate is 0.01 and the formula for its iteration is shown in equation (1).

$$learning\_rate_{n+1} = \frac{learning\_rate_n}{1+0.2*learning\_rate_n} \tag{1}$$

In equation (1), $learning\_rate_{n+1}$ is the learning rate of the next round and $learning\_rate_n$ is the learning rate of the current round. In addition, the error function is the sum of squared differences, which is calculated as shown in Eq. (2).

$$loss = \frac{1}{B} * \sum_{k}^{B} (\sum_{i}^{C} (pred_i^k - label_i^k)) \tag{2}$$

In equation (2), *loss* is the error of the current mini batch, a mini batch with B graphs and a total of C nodes, $pred_i^k$ is the coordinates of the node on the ik graph, and $label_i^k$ is the real coordinates of the i node on the k graph. Compared with conventional neural networks, it is possible to reduce the training parameters and thus the computational cost by sharing parameters. The input data is convolved in the convolution layer to extract the features, and after moving the convolution kernel to obtain different results, the whole feature set is finally obtained. The output formula of the 1D convolution is shown in equation (3).

$$C_{cn} = f(X * W_{cn} + b_{cn}) \tag{3}$$

In equation (3), f means the activation function of the convolutional layer, X the output data, W_{cn} the weights of the convolutional kernel, and b_{cn} the bias of the convolutional kernel. The fully connected layer is considered as a feature classifier, usually *Soft* max classifier, which maps the output to a normalized probability distribution and outputs the confidence level. The expression is shown in equation (4).

$$p(x)_i = \frac{e^{z_i}}{\sum_k e^{z_i}}, \quad i = 1, 2, \mathrm{K}, k \tag{4}$$

In equation (4), k means the amount of classifications and z_i denotes the output value of the last layer of neurons that are not activated. The model needs to be trained to optimize the network parameters to prevent the underfitting or overfitting phenomenon. The surrogate function is a calculation of the error between the predicted result and the actual classification, and the cross-entropy loss function is commonly used, whose expression is shown in Eq.

$$H(p,q) = -\sum_x p(x) \log q(x) \tag{5}$$

In equation (5), $p(x)$ is the definition of the target distribution and $q(x)$ is the definition of the prediction distribution. The backpropagation algorithm is the key to the optimization of the neural network parameters, which is an optimization algorithm update by biasing the objective function and then measuring the error between the output and the target, i.e., the sensitivity with respect to the parameters, and the error calculation formula is shown in equation (6).

$$\delta^{l-1} = \frac{\partial J}{\partial z^{l-1}} = \frac{\partial J}{\partial z^l} \frac{\partial z^l}{\partial z^{l-1}} = \delta^l \frac{\partial z^l}{\partial z^{l-1}} \frac{\partial a^{l-1}}{\partial z^{l-1}} \tag{6}$$

In equation (6), δ^l is the error of the target function J to z^l. Since CNN neural networks lose some details when extracting features, there are inaccuracies. In contrast, GA is a kind of genetic law that simulates the biological world by imitating the biological evolution process. The core of the GA is that the optimal individuals are screened in each generation until the genetic process is terminated and the optimal individuals in the original sample are screened [17]. With the decision variable encoding as the operation object and the objective function value as the search information, the characteristics of multi-point search are used to cut down the inaccuracy of the CNN and subsequently reach to get the global optimal solution (GOS). The algorithm flow is shown in Figure 4.

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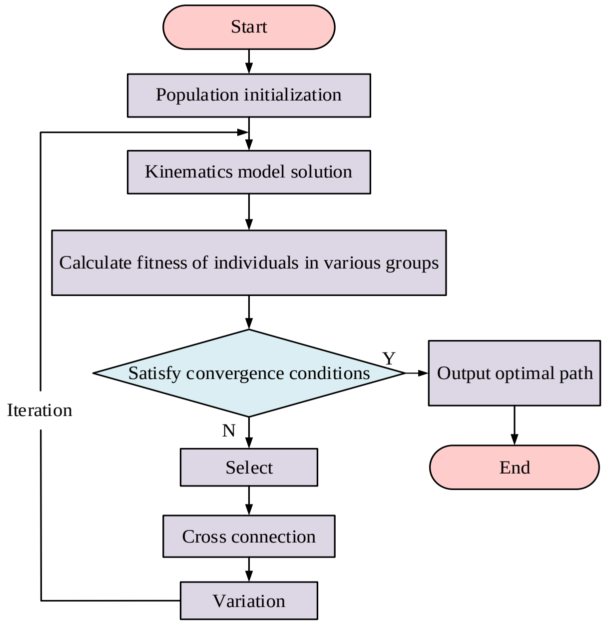

FIGURE 4. GA flowchart.

In Figure 4, algorithm's core is composed of three parts, selection, crossover and variation, and the core parameters are parameter encoding, initial population setting, fitness function design, operational mode setting and parameter setting for the genetic process [18]. In the deriving the GOS using GAs, there are different data types, and some of them are not applicable to GAs. Therefore, these data types that are not applicable to the algorithm are converted to applicable data types by coding. In this study binary encoding is used for the encoding setup of the algorithm. Assuming that the length of a set of codes has k bits, the total number of codes is 2^k, and the formula for calculating the true gap between two adjacent codes is shown in equation (7).

$$\delta = \frac{U_{\max} - U_{\min}}{2^k - 1} \tag{7}$$

In Eq. (7), the gap δ is the precision of this binary code. For any binary code, the true solution corresponding to the code can be known, and its calculation formula is shown in equation (8).

$$x = U_{\min} + \left(\sum_{i=1}^{k} z_i \bullet 2^{i-1} \right) \bullet \frac{U_{\max} - U_{\min}}{2^k - 1} \tag{8}$$

In equation (8), X denotes the binary encoding and $X = z_k z_{k-1} \cdots z_2 z_1$ is the encoding. Both the binary encoding method and decoding method are relatively simple; encoding is a discretization of the original data information, and decoding is a reverse operation. Due to the small number of codes, crossover and mutation operations are relatively convenient. In GAs, the degree of adaptation of this scheme in the optimization process is evaluated by setting an adaptation criterion so that the scheme's has a high degree of adaptability [19]. The whole process of the GA is global optimization, so the model of the algorithm is divided into two main types, one for solving the maximum value and the other for solving the minimum value. The formula for the transformation process is shown in equation (9).

$$F(x) = \begin{cases} f(x) + C_{\min}, & f(x) + C_{\min} > 0 \\ 0, & f(x) + C_{\min} \le 0 \end{cases} \tag{9}$$

In equation (9), *f(x)* is the target function value, *F(x)* is the adaptation evaluation function, and $C_{\min}$ represents a smaller number. If the minimum value is solved, the formula of the conversion process is shown in Eq. (10).

$$F(x) = \begin{cases} C_{\max} - f(x), & C_{\max} - f(x) > 0 \\ 0, & C_{\max} - f(x) \le 0 \end{cases} \tag{10}$$

In equation (10), $C_{\max}$ denotes a larger number. All of the above are general expressions of the adaptation evaluation function. Individuals with advantageous weights with larger values can have a greater probability of participating in the next step of the operation. Individuals with disadvantage have smaller weight values and can have a smaller probability of participating in the next step of the operation, which may also eliminate them. Therefore, to increase the probability of the dominant individuals to participate in the next step of the operation process, a selection operator needs to be designed to automatically select the individuals. The formula for calculating the probability of each of its individuals to participate in the next step of the genetic operation is shown in equation (11).

$$P_i = \frac{F_i}{\sum_{i=1}^{D} F_i}, \quad (i = 1, 2, \ldots, D) \tag{11}$$

In equation (11), D means the population size, F_i means the fitness of an individual, and P_i indicates the probability that an individual will be chosen to participate in the next genetic operation. GAs can solve problems from a global perspective and filter the best individuals and search for the dominant individuals in the population under a certain degree [20]. Its self-learning capability also makes it a better solution for complex nonlinear problems. The fitness function of the GA can raise the accuracy of the CNN as a way to get the GOS. Therefore, the optimization of CNN neural network by GA is designed and its basic algorithm flow is shown in Figure 5.

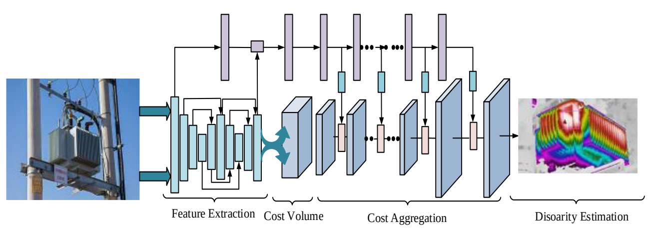

FIGURE 5. GA-CNN algorithm process.

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For under this algorithm flow, the key parameters setting of GA-CNN algorithm and its operation mode are designed as follows. Initialize the number within the population as P, set the variation probability, weights and the threshold value. The individual fitness is calculated, and the formula of its selection operator probability is shown in equation (12).

$$P_i = \frac{f_i}{\sum_{i=1}^{N} f_i} \tag{12}$$

To this, the square of the error signal is added and used to test the suitable degree value, which is calculated as shown in equation (13).

$$E(i) = \sum_{p}\sum_{k}(V_k - T_k)^2 \tag{13}$$

In equation (13), i = 1, 2,..., N denotes the amount of chromosomes, p = 1, 2,..., l infers the number of learning samples, k = 1, 2,..., m means the amount of nodes in the output layer, V_k denotes the network output signal, and T_k is the actual value. In response to the limitations and inaccuracies of CNN neural networks, a GA-CNN algorithm model with GA optimized CNN neural network is developed to evaluate the operating condition of PTs.

IV. GA-CNN ALGORITHM TO EVALUATE AND DIAGNOSE THE OPERATION STATUS OF POWER TRANSFORMERS

PTs' operation condition of four units in this power plant was evaluated and diagnosed, and the 600 sets of samples involved in the network training were normalized and a random number matrix was created based on the number of original samples. The data were normalized uniformly, while the CNN neural network was then initialized and set up. Finally, the following results were obtained through the training, learning, and testing of the network, and the results are shown in Figure 6.

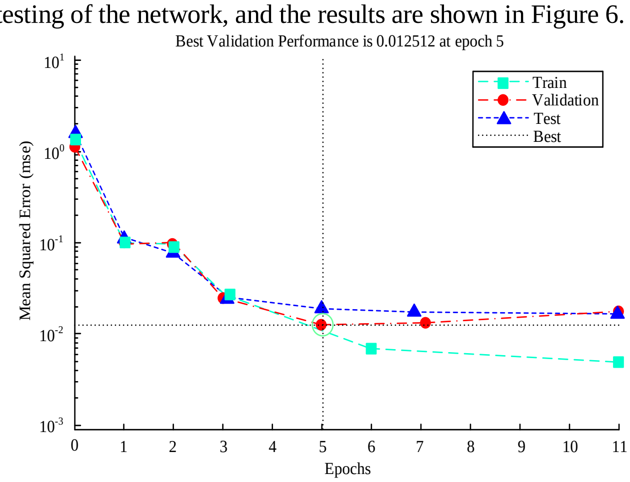

FIGURE 6. **CNN neural network training error results.**

From Figure 6, the error results of the training sample, the learning sample and the test sample are the same at the initialization. With the amount of iterations increases, the error results of the training samples gradually reduce, and after 6 iterations, the trend of decreasing error results slows down. The error of the test sample also reduce with the rising of the amount of iterations, and after 7 iterations, the error results tend to level off. However, the error of the overall sample verification decreases from the initial to 5 iterations, and tends to increase after 5 iterations. And the training of CNN is shown in Figure 7.

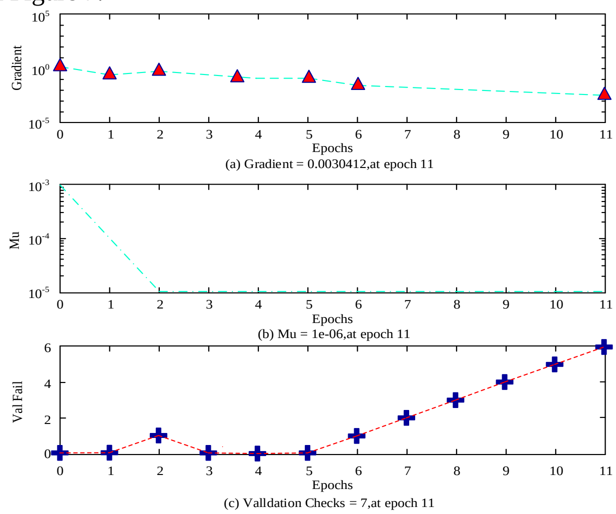

FIGURE 7. **Training situation of CNN neural network.**

From Figure 7, the training of CNN neural network gradually improves with the rising of the number of iterations. Among them, the slope shows an overall trend of decreasing with the increase of iterations. The validation sample tends to be flat before 5 iterations as the number of iterations increases, and shows an overall increasing trend after 5 iterations. Besides, the regression of CNN training results is shown in Figure 8.

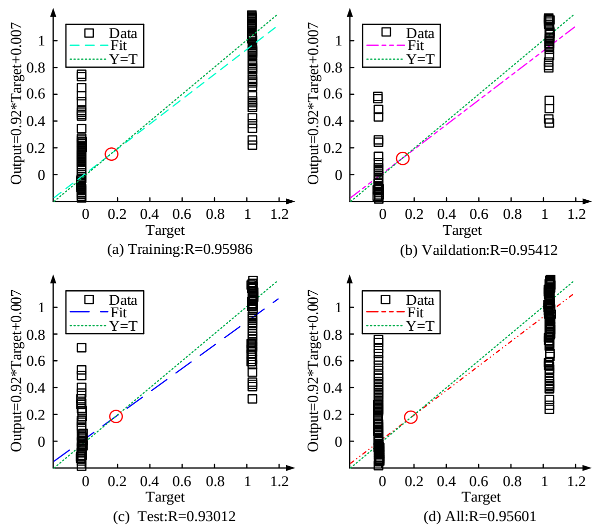

FIGURE 8. **Regression graph of CNN neural network training results.**

From Figure 8, the accuracy of the training sample, the test sample, and the validation sample are all above 93%, and the

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accuracy of the full sample data is above 96%. The actual output values of the three input samples are acceptable and all have some relevance in for the evaluation of the operating condition of PTs. The network output values are 0.95986, 0.95412, 0.93012 and 0.95601, which prove that the input sample data of CNN neural network is correlated with the operation of PT. However, the inaccuracy of the CNN algorithm itself makes its evaluation and analysis of the operation status of PTs inaccurate. To improve the accuracy of the output results and avoid the local optimal solutions that appear in the CNN to realize the GOS, the GA-CNN algorithm is used to evaluate and diagnose the operation status of the PT. The optimization results of the GA are expressed in Figure 9.

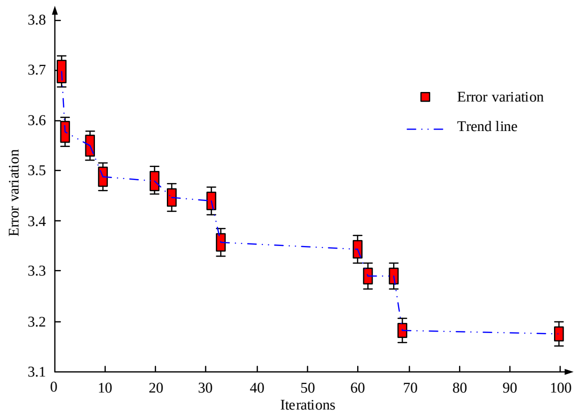

FIGURE 9. Trend of error changes in GA-CNN algorithm.

From Figure 9, the error of the GA-CNN is gradually decreasing as the amount of iterations raises. At the initial time, the error value is 3.71, and the first steady state appears around 33 iterations. And the error tends to decrease again when the iterations reach 60. Until about 67 iterations, the variation of the error starts to level off. The training accuracy of GA-CNN is promoted in contrast with that of CNN neural network. The superiority of the GA-CNN algorithm can also be seen from the established random number matrix, the results of which are shown in Figure 10.

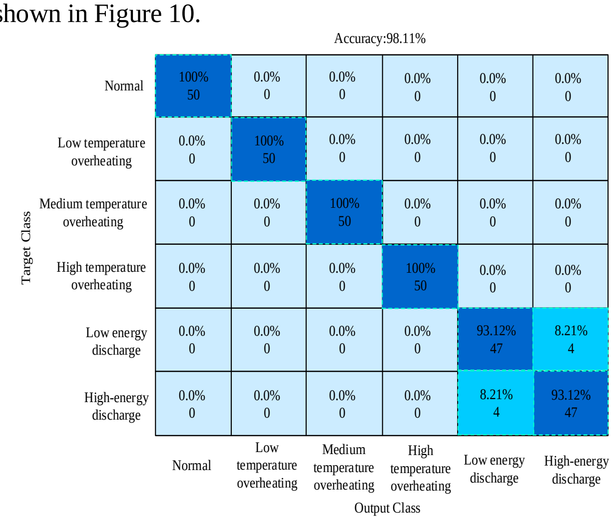

FIGURE 10. GA-CNN algorithm prediction value and actual output value matrix.

From Figure 10, the accuracy of the predicted value of the GA-CNN with respect to the actual output value is 98.11%. The environment's temperature and humidity throughout the operation of the PT and the daily power generation of the generator set, the input sample data of these three factors, have some correlation on the operating status of the PT. However, it can be concluded from the matrix data that these three factors affecting the operating state of the equipment are acceptable. And the error results between the predicted and actual values of GA-CNN algorithm are shown in Figure 11.

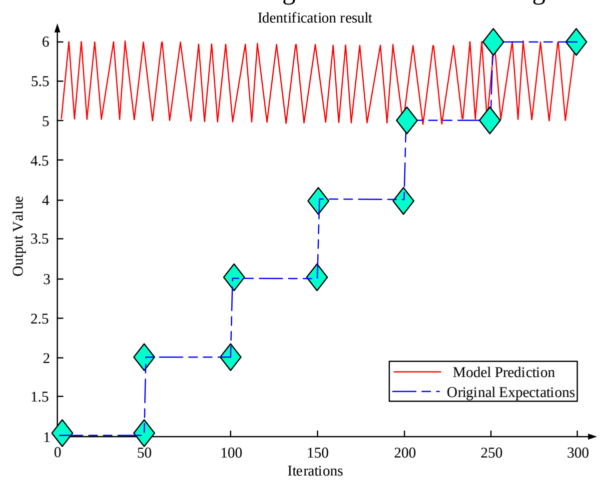

FIGURE 11. Error between predicted and actual values using GA-CNN algorithm.

From Figure 11, it can be seen that in the diagnostic test for evaluating the operating condition of PTs, and then combined with Figure 10, it can be concluded that the error rate of GA-CNN algorithm is only 1.86%, while the error rate of CNN neural network is 4%. The output accuracy after optimization of CNN with GA has a large improvement, and the scheme and data of this study are of certain application value.

V. CONCLUSION

The importance of real-time monitoring of the operating status of PTs in the daily work should not be underestimated. The traditional infrared thermal imaging monitoring is a regular monitoring method, which is not easy to be found in time when the operating condition is abnormal. The DGA real-time online monitoring device can detect the abnormal operation status in time, but it is not able to do timely feedback on the changes of the external environment of the equipment, which has certain limitations. The minimum value of convergence error is 0.012512. The accuracy of training, testing and validation samples is above 93%, and the accuracy of all samples is above 96%. The final MSE output of the network is 0.012512. However, considering the accuracy of the CNN needs to be promoted, this study uses GA to optimize the CNN neural network and establishes the GA-CNN algorithm model to evaluate and analyze the operation conditions of PTs. The accuracy of the GA-CNN algorithm is improved compared with that of the CNN. The accuracy in the random matrix of predicted and actual output values of the GA-CNN algorithm is 98.11%, and all three factors affecting the operation status of the device are acceptable. In the final recognition results, the error rate of the GA-CNN algorithm is only 1.86%, while the error rate of the CNN neural network is 4%. This shows that the optimization of CNN neural network with GA has a large improvement in the output accuracy. Although this study has provided a more accurate assessment of the operation status of PTs, there are still some limitations. For the abnormal operation of transformers, how to effectively overhaul and improve the efficiency of production work are to be further analyzed and studied.

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