Reliability Testing Model of Micro Grid Soc Droop Control Based on Convolutional Neural Network

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Abstract. In order to avoid the fatigue operation of microgrid and ensure the application reliability of equipment components, a reliability detection model of micro grid soc droop control based on convolutional neural network is proposed. The convolutional neural network architecture is constructed. By defining small target parameters, the real-time tracking of target samples is realized, and the micro grid charging state operation target is identified. Improve the polarity detection conditions of capacitor equipment, according to the data acquisition and calibration processing results, match the micro grid operation data with the detection template, and achieve the design of micro grid soc droop control reliability detection model based on convolutional neural network. Comparative experimental results: under the effect of the convolutional neural network detection model, when the fatigue curve value reaches 0.18, the indicator device will flash abnormally, which can avoid the fatigue operation state of the microgrid, and has a prominent role in ensuring the reliability of the application of the micro grid soc droop control.

Keywords: Convolutional Neural Network · Micro grid soc droop control · Reliability Testing · Small Target Object · Target Tracking · Capacitance Polarity · Data Calibration · Detection Template

1 Introduction

Convolutional neural network (CNN) is a type of deep feedforward neural network that utilizes convolutional calculations. It is regarded as one of the prominent algorithms in the field of deep learning. CNN is capable of representation and learning, and it can classify input information in a translation-invariant manner through its hierarchical structure. Because of this property, it is often referred to as a "translation-invariant artificial neural network". The input layer of a CNN can process multi-dimensional data. In the case of a one-dimensional CNN, the input layer receives one-dimensional or two-dimensional arrays, where one-dimensional arrays typically represent time or spectrum samples. A two-dimensional array may contain multiple channels. For a two-dimensional CNN, the input layer receives a two-dimensional or three-dimensional array. As for a three-dimensional CNN, the input layer receives a four-dimensional array [1].

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Due to the widespread application of CNNs in the field of computer vision, many studies assume the presence of three-dimensional input data, which consist of two-dimensional pixel points and RGB channels on a plane. The hidden layers of a CNN usually consist of convolutional layers, pooling layers, and fully connected layers. In more modern algorithms, complex structures such as inception modules and residual blocks may be used. However, convolutional and pooling layers are common and unique to CNNs. The convolutional layer contains weight coefficients in its convolution kernel, whereas the pooling layer does not. Therefore, the pooling layer is not considered as an independent layer. The application of CNNs in reliability detection of microgrid SOC droop control holds great significance.

A microgrid refers to a compact power generation and distribution system consisting of distributed generation, energy storage devices, energy conversion devices, loads, monitoring and protection devices, among others. Its purpose is to enable the flexible and efficient utilization of distributed generation and address challenges related to connecting numerous distributed generation sources in various forms to the grid. The advancement and expansion of microgrids can greatly facilitate the integration of distributed power generation and renewable energy on a large scale, providing reliable and diverse energy supply to loads. Microgrids play a crucial role in enabling active distribution networks and facilitating the transition from traditional power grids to smart grids. With the increasing demands of social development, the complexity of microgrid SOC droop control is growing, necessitating SOC droop control devices that possess traits such as reliability, fast response, low power consumption, lightweight, compact size, and cost-effectiveness. In the context of microgrids, compactness leads to higher integration capability, shorter response times enable faster computing speeds, and higher transmission frequencies accommodate larger amounts of information transfer. This research proposes a convolutional neural network-based reliability detection model for microgrid SOC droop control. The proposed method aims to prevent fatigue operation of microgrids and ensures high reliability in SOC droop control for microgrids.

2 Target Recognition of Micro Grid Soc Droop Control

The construction of the micro grid soc droop control reliability detection model is based on the micro grid operation target recognition, with the support of the convolutional neural network architecture, to solve the small target definition expression, so as to achieve accurate tracking of the micro grid soc droop control operation target.

2.1 Convolutional Neural Network Architecture

When compared to traditional neural networks, convolutional neural networks (CNNs) include a convolutional layer for feature extraction and a downsampling layer to maintain spatial consistency. In CNNs, the convolution layer is typically connected to the input layer and extracts information from the input image. The intermediate layers of the network consist of alternating convolution and downsampling layers. The output layer usually leverages label information and adopts supervised training methods to achieve network convergence. In addition to their distinct structure, CNNs utilize weight sharing among neurons in the same plane to reduce computational complexity. Different convolution kernels are used to extract diverse features.

The original information is transformed according to the network input requirements, and the connected convolution layer single neuron is connected to the local sample area of the input information. By sensing the different response behaviors in the digital sub area, the underlying features in the neural node structure, such as points, edges and corners, can be extracted. It approximates the application mechanism of neural networks. From the current development, computers obtain input data samples through neural nodes. The perception of information is from the motion of points to edges, and different textures and shapes are perceived through the motion of edges [2]. Convolution networks use different subunits to generate feature maps corresponding to such features through these features. The complete convolutional neural network architecture is shown in Fig. 1.

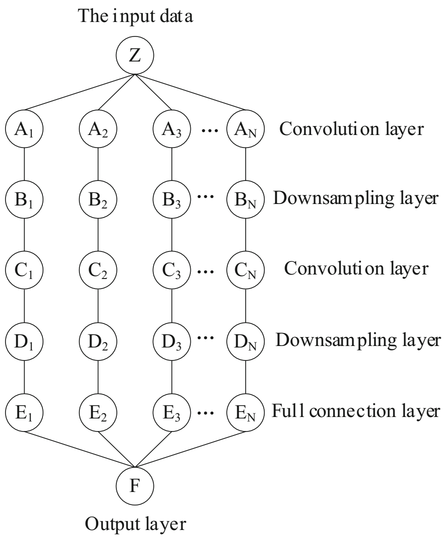

Fig. 1. Convolutional neural network architecture

Convolutional neural network is deep feed-forward neural network that incorporate convolution calculations. They possess representation learning capabilities and classify input information based on their hierarchical structure. By sharing convolution kernel parameters in the hidden layers and utilizing sparse inter-layer connections, CNNs efficiently capture features while minimizing computation requirements. A convolution layer obtains four types of data information from multiple convolution kernel nodes. When the convolution kernel convolutes the data samples in turn, the response value of the lowest convolution kernel reaches the maximum, and the corresponding features are extracted. If there is no relative position change in the features, the spatial position relationship is extracted from the data samples by convolution check during the convolution process to ensure the invariance of the spatial position. The down sampling layer is connected with the convolution layer in turn, and each convolution layer is connected with a down sampling layer. The down-sampling layer is a down-sampling process. The sampling frequency is less than twice the maximum frequency of the signal. The nearest neighbor method is mainly used, and the down-sampling is usually performed at the receiver side. After the digital down conversion at the receiver, the sampling rate of the signal is still high and the data volume is large. Therefore, under the premise of ensuring the Nyquist sampling theorem, down-sampling the signal with high sampling rate can reduce the sampling frequency and the amount of computation. Downsampling the feature samples generated by the convolution layer is equivalent to the network node performing fuzzy processing on the data samples of the previous layer. When the information parameters are slightly displaced, the eight possible motion directions before downsampling change to three possible motion directions, which greatly reduces the sensitivity of the network to the displacement of the target information parameters [3]. After that, the convolution layer and the downsampling layer are connected alternately, so that more features can be learned through training.

Let $e_{\min}$ denote the minimum value of the information parameter of the data sample, $\chi_{\min}$ denotes the convolution coefficient based on the parameter index $e_{\min}$, $e_{\max}$ denotes the maximum value of the information parameter of the data sample, $\chi_{\max}$ denotes the convolution coefficient based on the parameter index $e_{\max}$, α denotes the coding coefficient of the neural node, and δ denotes the hierarchical coefficient of the convolutional neural network architecture. By combining the above physical quantities, the connection expression of the convolutional neural network system can be defined as:

$$E = \frac{\frac{1}{\delta}\sum_{\alpha=1}^{+\infty}\sqrt{\left(e_{\max}^2 - e_{\min}^2\right)}}{\left|\chi_{\max} - \chi_{\min}\right|^2} \tag{1}$$

In the convolutional neural network, each neuron can sense the local information of the input data sample, and remove the convolutional neural nodes from the same convolutional kernel, and each convolutional kernel shares the same weight parameter. Thus, while extracting the local features of data samples, the number of parameters in the training process of convolutional neural network is greatly reduced.

2.2 Small Target Definition

The definition of small targets can be categorized into relative size and absolute size definitions. Relative size is determined based on the width and height of the original data sample space. Small targets are typically considered to have dimensions less than or equal to one tenth of the width and height of the original space. Convolutional neural networks are a type of multi-layer perceptron in artificial neural networks. Neurons in CNNs are interconnected and responsible for information transmission, resembling the visual cortex in animals. Each individual cortical neuron responds to stimuli within its receptive field. As there is overlap between the receptive fields of different neurons, they collectively cover the entire data sample space [4]. Currently, small target detection algorithms based on CNNs aim to strike a balance between speed and accuracy by sacrificing a small degree of accuracy.

Let r_1, r_2, r_3 represent three unequal sample accuracy parameters, and the inequality conditions of $r_1 \geq 1$, $r_2 \geq 1$, $r_3 \geq 1$ and are satisfied at the same time. $\hat{R}$ represents the overlapping characteristics of the data samples, ε represents the repetition parameter, w_{r_1} represents the absolute target based on the accuracy parameter r_1, w_{r_2} represents the absolute target based on the accuracy parameter r_2, and w_{r_3} represents the absolute target based on the accuracy parameter r_3. With the support of the above physical quantities, the solution result of the small target transition condition can be expressed as:

$$q = \frac{\sum_{\varepsilon=1}^{+\infty} \left| E \times \hat{R} \right|^2}{\sqrt{\frac{w_{r_1}+w_{r_2}+w_{r_3}}{w_{r_1}\times w_{r_2}\times w_{r_3}}}\,\Bigg|} \tag{2}$$

Small target objects perform two key functions within the convolutional neural network. Firstly, they classify based on the combination of different detailed features extracted from the convolutional layer. Secondly, they effectively mitigate the impact of feature position shifts on classification, acting as a classifier in this regard.

The presence of small target objects affects various parameters of the model, including the total number of layers in the fully connected layer, the number of neurons in each individual fully connected layer, and the activation function. When the width of the small target remains unchanged, increasing the number of layers in the fully connected layer enhances the model's ability for nonlinear expression. Similarly, if the number of layers remains constant, increasing the width of the fully connected layer also strengthens the model's nonlinear expression capacity [5]. However, an excessively powerful nonlinear capacity may lead to overfitting and increased computation time. To address this issue, convolutional neural networks are employed to alleviate the occurrence of overfitting. During the forward propagation process, the introduction of neuron dropout, wherein a neuron ceases to function with a certain probability, enhances the model's generalization ability.

Set γ to represent a fitting parameter greater than zero in the convolutional neural network, and establish formula (2) to derive the definition expression of small target based on the convolutional neural network as follows:

$$Q = \frac{1 - q^{-\frac{1}{\gamma^2}}}{1 + q^{-\frac{1}{\gamma^2}}} \tag{3}$$

Batch normalization is commonly applied after the convolutional layer and before the activation layer for small target objects. In neural network training, correlations and interactions occur between connected convolutional layers, whereby changes in upper-layer parameters affect the associated lower-layer convolutional layers. As each convolutional layer produces both linear and nonlinear activation maps, these changes can be magnified with increasing depth. Consequently, adjustments in lower-layer convolutional layer parameters necessitate continuous adaptation by upper convolutional layers, resulting in a slower learning rate for the overall network model.

2.3 Target Tracking

Target tracking is used to obtain more reliable data sample features while maintaining the parameter quantity and the same receptive field. Its essence is to fill the convolution kernel. Each conventional convolution kernel can directly track and process data samples, and then each branch is connected, followed by a 1 * 1 convolution kernel to combine features under the same convolution layer feature parameter, while reducing channel parameters, forming a pattern similar to neural network perception behavior [6]. That is, the closer to the center, the higher the contribution; otherwise, the smaller the contribution. Finally, the connected characteristic parameter is multiplied by the key value. Under the condition of keeping the parameter quantity unchanged, more reliable feature parameters of data samples are generated, and the perceptual information of different convolution layers is added through the perceptual field module, so that the feature extraction network can obtain more context information.

By connecting the prediction layers, the high-level semantic information and the low-level semantic information can be better integrated. Because compared with the low-level semantic information, the deeper convolutional neural network can detect more semantic information, and these semantic information are translation invariant, which is more effective for the detection of target categories. The larger the target weight, the more similar the area represented by the representative particles and the area tracking the target. However, after many iterations, the weights of most particles will become small, the weights of a few particles will become large, and the variance of the weights will continue to increase, resulting in difficulty in convergence, that is, the degradation phenomenon in convolutional neural networks.

Let β denote the degradation behavior coefficient of the data sample, i denote the initial assignment of the particle weight, φ denotes the number of iterative transmission of the data sample in the convolutional neural network, ΔT denotes the single execution time of the iterative transmission instruction, $\dot{W}$ denotes the iterative characteristics of the data sample to be processed, the inequality condition of $\dot{W} \neq 0$ is always true, ϕ denotes the convergence index, and I denotes the translation vector of the data sample. With the support of the above physical quantities, the degradation performance intensity can be expressed as:

$$u = \frac{\beta\left(\sum_{i=1}^{+\infty} Q^{-\frac{1}{|\varphi|}} \times \frac{1}{|\Delta T| \times \dot{W}}\right)}{\phi \times \left(1 - I^2\right)} \tag{4}$$

On the basis of formula (4), let p_1, p_2 denote the operating parameters of two randomly selected micro grid soc droop control, and the value conditions of $p_1 > 0$, $p_2 > 0$, $p_1 \neq p_2$, $\tilde{y}$ denotes the fluctuation characteristic index of the data sample in the convolutional neural network space, and y' denotes the fluctuation coefficient.

The target tracking expression of micro grid soc droop control operation data based on convolutional neural network is:

$$U = \frac{O \times \frac{u}{|p_1 - p_2|^2}}{\sum_{-\infty}^{+\infty} y' \times \tilde{y}} \tag{5}$$

When degradation occurs, resampling is performed according to the weight of the current particle. Particles with too low weight are eliminated, and more particles are regenerated through particles with high weight. The tracking method of shape matching represents the target by the shape of the target in the data sample, and tracks the target similar to template matching by calculating the difference between the candidate target shape template and the tracking target shape template. Because the target shape needs to be modeled, it is more suitable for tracking the operation data of micro grid soc droop control.

3 Reliability Detection of Micro Grid Soc Droop Control

With the support of convolutional neural network, according to the processing flow of capacitance equipment polarity detection, data acquisition and calibration, detection template matching, the design and application of micro grid soc droop control reliability detection model are completed.

3.1 Polarity Detection of Capacitor Equipment

After the target recognition of micro grid soc droop control is completed, the electrolytic capacitor equipment is positioned and the polarity of the electrolytic capacitor is detected. The polarity organization of most electrolytic capacitors is white fan-shaped area, which is very different from the color of other places. By processing the operating data samples of electrolytic capacitors through threshold segmentation, it is possible to judge whether electrolytic capacitor elements are defective according to the metal characteristics of the middle circular white area, and then complete the accurate detection of the polarity of capacitor equipment according to the polarity relationship between the edge area and the core capacitance. The specific detection principle is shown in Fig. 2.

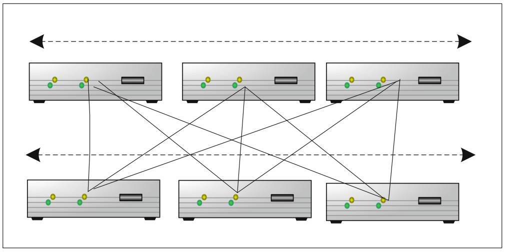

Fig. 2. Polarity detection principle of capacitor equipment

In the polarity detection device shown in Fig. 2, the display screen can display different values according to the specific charging conditions of the capacitive devices. Generally speaking, the detection result of the positively charged capacitive devices is positive, and the detection result of the negatively charged capacitive devices is negative. Regardless of government symbols, the larger the displayed value, the greater the current charging amount for detecting the sag control of the micro-grid soc.

If the data sample is occluded, the modulus of the gradient vector of the information parameter in this area will be very small, and the inner product of the template gradient vector corresponding to it will be a very small value, and the impact on the total can be ignored; If there is confusion in the data sample, the modulus of the gradient vector of the corresponding template in this area will be very small, and the influence of their inner product on the total can be ignored. However, this does not mean that the similarity measure of the formula can meet the changes in the reliability of micro grid soc droop control [7]. This is because the modulus of the gradient vector has the following relationship with the reliability parameter: when the total number of data samples is large, the modulus of the gradient vector is small; When the total number of data samples is small, the modulus of the gradient vector is large.

According to the simultaneous formula (5), the polarity detection expression of the capacitor device is:

$$P = \frac{f\left(A^2 - 1\right) - \overline{A}^2}{\sqrt[t]{U^2}} \times \frac{\sum_{-\infty}^{+\infty} s \times s'}{S_{\max}^2 - S_{\min}^2} \tag{6}$$

In the formula, f represents the polarity discrimination condition of the electrical signal parameter, A represents the total storage amount of the data sample, $\overline{A}$ represents the output average value of the data sample in the unit detection period, s represents the random value of the similarity index, s' represents the supplementary explanation condition of the coefficient s, $S_{\min}$ represents the minimum value of the polarity constraint parameter, and $S_{\max}$ represents the maximum value of the polarity constraint parameter.

Although the template matching algorithm based on convolutional neural network relies on similarity measures, the similarity measures it considers are different from the template matching of micro grid soc droop control reliability data. It considers the gradient vector of data samples in the template. And the obtained matching position is determined by calculating the sum and minimum of the inner product of the gradient vector, so it has superior stability and reliability.

3.2 Data Acquisition and Calibration

In the aspect of target detection, the algorithms used are convolutional neural network based methods and reliability modeling methods. The region recommendation is a two-stage method, that is, the candidate region evaluation method is used to generate potential micro grid soc droop control operation data package files, and then the classifier is used to identify these data files and classify the required target objects. When building the micro grid soc droop control reliability detection model, the traditional image processing method has made some achievements, effectively promoting the development and application of the defect detection system, but there are also complex detection processes [8]. With the breakthrough of convolutional neural network technology in data processing, data analysis and other aspects, using convolutional neural network to collect and calibrate the operation data of micro grid soc droop control has become the main research direction.

In the manufacturing process of micro grid soc droop control, there will be various types of defects. The previous detection methods usually use manual vision or traditional image processing methods. Although these methods have achieved certain results, they still have great shortcomings. With the rise of convolutional neural network technology, various target detection models have achieved good results in the field of reliability detection. Inspired by this, convolutional neural network is used to detect target samples in the process of designing micro grid soc droop control. In the research object, the electrolytic capacitor is taken as the detection object. In the selection of network structure, a multi-layer network cycle structure of neural network nodes is designed to enhance the feature extraction ability of the network, and good results are achieved in the detection of electrolytic capacitor.

The reliability detection model for microgrid SOC droop control is fundamentally based on the gradient descent method, aiming to optimize the objective function, which is the square of the discrepancy between the expected and actual output of the entire network [9, 10]. Structurally, the convolutional neural network consists of an input layer, hidden layer(s), and an output layer. The number of nodes in the input and output layers can be determined based on the size of the input feature vector and the number of classification categories. Unlike the input-output layer, the hidden layer(s) does not directly connect with the input or output layers. However, changes in its state have an impact on the relationship between the input and output, allowing for customization as needed.

Let $l_1, l_2, \cdots, l_n$ and 1 represent the value taking results of n non-zero micro grid soc droop control operation data samples, and the definition formula is as follows:

$$\begin{cases} l_1 = \dfrac{\lambda_1}{1+g_1} \\ l_2 = \dfrac{\lambda_2}{1+g_2} \\ \vdots \\ l_n = \dfrac{\lambda_n}{1+g_n} \end{cases} \tag{7}$$

In the formula, $\lambda_1, \lambda_2, \cdots, \lambda_n$ represent the collection coefficients of n randomly selected data samples, and the inequality condition of $\lambda_1 \neq \lambda_2 \neq \cdots \neq \lambda_n$ is always true, and $g_1, g_2 \cdots, g_n$ represent the calibration indicators of n data samples, whose values belong to the numerical range of $[1, +\infty)$, and the above physics is established simultaneously.

On the basis of formula (7), select a data sample defect value parameter $\hat{d}$, which is required $\hat{d}$ to be not less than the natural number "1". In conjunction with formula (6), calculate the collection and calibration processing expression of the operation data of micro grid soc droop control as follows:

$$D = \frac{\hat{d} \times P}{\sqrt{l_1^2 + l_2^2 + \cdots + l_n^2}} \tag{8}$$

The data acquisition and calibration principle greatly reduces the number of data samples in the convolutional neural network by using local connection, weight sharing, multi-core convolution and pooling, so that the number of layers of the network can become deeper and the features can be extracted implicitly. Convolution nodes are mainly used to identify data sample parameters with distortion invariance. The so-called distortion invariance means that the original expression content of data will not be changed after displacement, scaling and other operations. Figuratively speaking, convolution neural networks do not have separate steps and processes to extract features like traditional methods. It implicitly learns from training data sets. In addition, convolution neural networks can learn in parallel, This is also a bright spot.

3.3 Detection Template Matching

Detection template matching is to achieve the purpose of classifying data, that is, to obtain a set of usable weights of the perceptron, and to randomly initialize the weights of the perceptron. The role of using the perceptron is to hope that the desired output can be classified through the judgment of the weights of the perceptron. For the output of each training sample, the weight of the perceptron can be adjusted by constantly calculating the difference between the output and the label, Through many times of training, the purpose of correct classification can be achieved. The process is shown in the following formula:

Template marking coefficient:

$$k = \sqrt{\frac{\eta \times \overline{\overline{H}}^2 - \sqrt{j_1^2 + j_2^2 + \cdots + j_n^2}}{D}} \tag{9}$$

where, η represents the transmission efficiency of the operation data of micro grid soc droop control in the convolutional neural network, and its value belongs to the numerical range, $\overline{\overline{H}}$ represents the secondary value of the average value of the operation data samples, and $j_1, j_2, \cdots, j_n$ respectively represent the detection parameters corresponding to $l_1, l_2, \cdots, l_n$, and.

Matching characteristics between operation data of micro grid soc droop control and convolutional neural network:

$$\varpi = \frac{\mu \times |\Delta J|}{k} \tag{10}$$

In the formula, ΔJ represents the accumulated amount of data samples in the unit detection interval of the convolutional neural network, and μ represents the sample matching coefficient.

On the basis of formula (9) and formula (10), let $V_{\min}$ represent the minimum value of the reliability definition parameter, $V_{\max}$ represent the maximum value of the reliability definition parameter, $\tilde{b}$ represent the data sample extraction parameter based on convolutional neural network, and κ represent the detection coefficient.

The matching expression of reliability detection template of micro grid soc droop control operation data based on convolutional neural network is:

$$M = \sum_{-\infty}^{+\infty} (\varpi \times k)^2 \times \frac{\kappa \times \left| V_{\max}^2 - V_{\min}^2 \right|}{1 - \tilde{b}^2} \tag{11}$$

The reliability detection model of micro grid soc droop control based on convolutional neural network is a lightweight algorithm for fast detection of small targets. It is different from many current complex feature extraction framework algorithms in that it uses a lightweight skeleton network [11, 12]. Through data acquisition, calibration expressions and feature fusion results, the detection accuracy is increased and the detection effect of small target parameters of micro grid soc droop control is further enhanced under the premise of sacrificing a few speeds. Through the expression of feature fusion, the problem of insufficient information interaction between different convolution layers is solved.

4 Case Analysis

To assess the practical significance of the reliability detection model for microgrid SOC droop control based on convolutional neural networks, a series of comparative experiments have been designed.

4.1 Environment Construction

X7R capacitive element is selected as the experimental object (as shown in Fig. 3), placed in the experimental circuit as shown in Fig. 4, closed the connecting switch, and recorded the numerical changes of relevant index parameters.

Based on Fig. 3, the capacitor material identified as X7R is known as a temperature-stabilized ceramic capacitor. X7R capacitors exhibit a 15% change in capacity when exposed to temperatures ranging from -55 °C to 125 °C. It is important to note that the capacitance change in X7R capacitors is nonlinear under these conditions. Moreover, the capacitance of X7R capacitors can vary based on voltage and frequency conditions, as well as change over time at a rate of approximately 5% every 10 years. These capacitors find common use in industrial applications that have lower requirements, where the acceptable capacity change is dependent on voltage variation.

In order to avoid the influence of other interference conditions on the experimental results, when replacing the detection model, the indication of the experimental equipment must be returned to the initial state.

4.2 Experimental Procedure

The specific process of this experiment is as follows:

(1) Use the reliability detection model of micro grid soc droop control based on convolutional neural network to control stc-12c5a equipment, close the control switch, and record the numerical change of fatigue value index within the given experimental time;

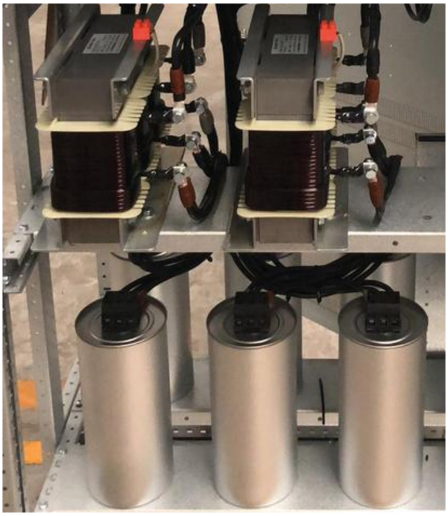

Fig. 3. X7R capacitance

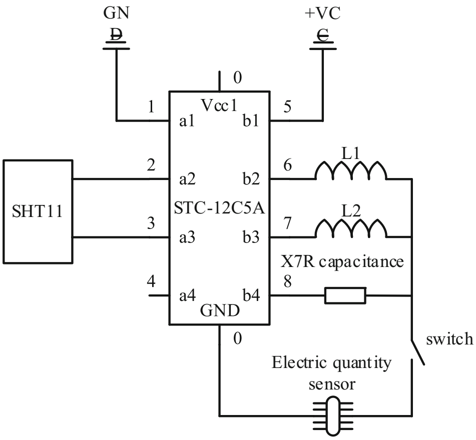

Fig. 4. Experimental circuit

(2) Reset the indication of the experimental equipment to zero to make it present the state before the experiment;
(3) Control the stc-12c5a equipment with the detection model based on the small fundamental wave algorithm and the detection model based on the traditional neural network, repeat the above experimental steps again, and record the numerical change of the fatigue value index;
(4) Compare the recorded experimental data and summarize the experimental rules;

The following table records the specific models of relevant experimental equipment (Table 1).

Table 1. Selection of experimental equipment

Equipment / parameters	Model / value
Micro grid soc droop control	X7R capacitive element
Main control element	Stc-12c5a equipment
Electric quantity sensor	Electric quantity sensor
Motor	SHT11
Connecting wires	Twisted pair
Rated voltage	220V
Rated current	Up to 35.7A
Circuit internal resistance	$9.7 \times 107\Omega$

During the experiment, all experimental equipment were directly controlled by stc-12c5a equipment elements.

4.3 Results and Discussion

The fatigue curve can reflect the fatigue operation state of the microgrid, and can be used to describe the application reliability of the selected equipment components. Without considering other interference conditions, the lower the value level of the fatigue curve, the lower the operating fatigue level of the micro grid soc droop control, that is, the stronger the application reliability of the selected equipment components.

The Fig. 5 reflects the specific numerical changes of fatigue curve under the action of convolutional neural network detection model, small fundamental wave algorithm detection model and traditional neural network detection model.

It can be seen from the analysis of Fig. 5 that the standard value of fatigue index shows a trend of increase and re stabilization. During the whole experiment, the maximum value reaches 0.24; Under the action of the detection model based on convolutional neural network, the fatigue curve also maintains a numerical change state of first increasing and then stabilizing, but its maximum value can only reach 0.17, which is lower than the standard maximum value; Under the action of the detection model based on the small fundamental wave algorithm, the change trend of the fatigue curve is consistent with the standard curve, and its maximum value reaches 0.22, which is also lower than the standard maximum value; Under the action of the traditional neural network detection model, the change value of the fatigue curve is also consistent with the standard curve, but its average level is high, and the maximum value reaches 0.25, which is higher than the standard maximum value. The reason is that the designed model transforms the original information according to the network input requirements, and the single neuron of the convolution layer connected with it is connected with the local sample area of the input information. By sensing the different response behaviors in the digital sub-area, the underlying features in the neural node structure can be extracted. To that extent, clothing is conducive to effectively control the value level of fatigue index and ensure the application reliability of equipment components.

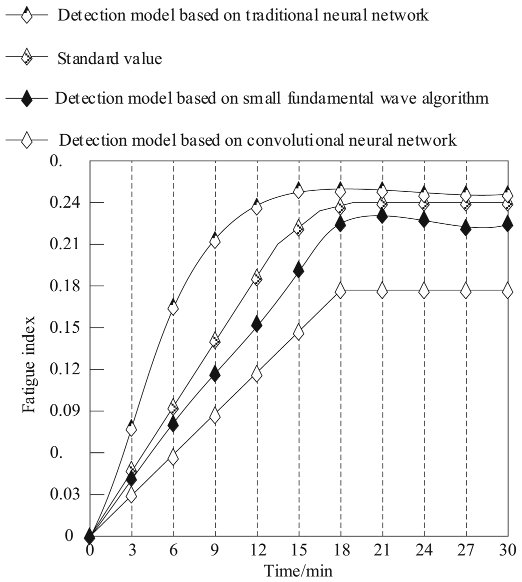

Fig. 5. Fatigue curve

To sum up, the conclusion of this experiment is:

(1) Small fundamental algorithm based detection model and traditional neural network based detection model have limited control ability for fatigue index, which cannot effectively solve the fatigue operation problem of micro grid soc droop control;
(2) The inspection model based on convolutional neural network can effectively control the value level of fatigue index, avoid the fatigue operation state of micro-grid, and play a promoting role in ensuring the application reliability of equipment components.

5 Conclusion

This paper studies the reliability detection model of micro grid soc droop control based on convolutional neural network, and focuses on the application of convolutional neural network technology in the reliability detection of micro grid soc droop control. The main research results are as follows:

(1) The traditional defect detection methods are investigated, and the specific methods used in defect detection are introduced.
(2) The micro grid equipment detection based on convolutional neural network is realized. The proposed polarity detection results are used to expand the data space. Experiments based on the detection template matching standard show that the data expansion improves the classification performance and classification ability of the convolutional neural network.

(3) The reliability of micro grid soc droop control operation data is determined by using data acquisition and calibration expressions, and then the convolutional neural network is used to correlate the completed data sample parameters, so as to maximize the integrity of the information to be detected.

A lot of research has been carried out on the reliability detection algorithm of micro grid soc droop control based on convolutional neural network. The classification method of micro grid equipment defects and the detection method of basic micro grid equipment have been studied respectively, but there are still many deficiencies that need to be further studied and improved, as follows:

(1) In terms of data set expansion, further research can be carried out to expand the data set by strengthening the cooperation of industry, university and research projects, or continue to expand the data set through data expansion methods. For micro grid equipment data, further improvement can be made on the basis of convolutional neural network structure, and preprocessing operations can be added at the input of the network to expand the diversity of generated samples.
(2) Only the experimental research of theoretical algorithm is carried out, which can further expand the application research and better transform the research content into productivity.
(3) Based on the micro grid soc droop control equipment, we have made in-depth research, and can continue to expand the types of micro grid components, such as chip defects, resistance defects, inductance defects, etc., which can be taken as the research direction, to further expand the application value of convolutional neural network in the establishment of micro grid equipment reliability detection model.

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