



Harmonic current control strategy of DC distribution network based on deep learning algorithm

Yufang Chen^{*}, Wei Han

College of Engineering, Inner Mongolia Minzu University, Tongliao 028000, Inner Mongolia, China

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ABSTRACT

In today's power grid configuration system, due to the unique advantages of high efficiency, strong power supply capacity, and good energy utilization, DC distribution network gradually replaced AC distribution and became a more popular distribution system. However, the harmonic current control method in the DC distribution network often cannot keep up with the performance requirements of the entire power system. The design of the DC distribution network structure, the selection and matching of current control methods, which has a significant impact on the healthy operation of the entire system. Traditional current control methods often cannot take into account both quality and efficiency in current effect, and in recent years, current control methods have been difficult to innovate. Aiming at the above problems, this paper combines PI control and repetitive control and optimizes on this basis, and creatively proposes a new harmonic current control strategy. And based on deep learning related algorithms, a convolutional neural network model that is more in line with the current control concept is selected to build, and ADMM algorithm is introduced to improve the model. Experiments show that the accuracy of the optimized deep residual convolutional neural network model can reach up to 93.1%, the minimum value in error control is 0.06, which well meets the needs of the current control strategy.

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1. Introduction

Deep learning is a semi-theoretical and semi-empirical modeling method that uses mathematical knowledge and computer

algorithms to build an overall architecture, combined with as much training data as possible and the large-scale computing power of computers to adjust internal parameters and approach the problem goal as much as possible. From the results, the performance of deep learning is very good, and his learning ability is very strong. The neural network of deep learning has a large number of layers and a wide width. In theory, it can be mapped to any function, so it can solve very complex problems. Deep

^{*} Corresponding author.

E-mail addresses: tlcyf@imn.edu.cn (Y. Chen), dr_wan@163.com (W. Han).

learning is highly data-dependent, and the larger the amount of data, the better its performance. The DC distribution network is relative to the AC distribution network. It provides the load with a DC bus. The DC load can be directly powered by the DC bus, while the AC load needs to be powered by the inverter device. If the proportion of the DC load in the load is larger, DC power distribution will have greater advantages. The DC distribution network has small line loss, high reliability, no need for phase frequency control, and strong ability to accept distributed power sources. This paper studies the control strategy of harmonic current in DC distribution network based on deep learning algorithm.

In the actual urban power system, due to the increase in user demand and other reasons, the system load will continue to increase, which will lead to a decline in the quality of the power system, and eventually lead to various current power supply problems. In this case, the DC distribution network has become the best choice for the power supply system due to its strong supply capacity and ultra-high efficiency. The rapid development of DC transmission technology and the stable optimization of related structures have made no major changes in the structural composition of the DC distribution network. Based on this background, in order to further optimize the entire power system and promote better performance, it is necessary to optimize the harmonic current control. Today's current control has also been proposed by many theories, and the corresponding optimal control technology is also emerging one after another. However, the core part of the current control theory has not been innovated in a targeted manner. The traditional harmonic current control strategy has gradually failed to meet the technical requirements of the system. Therefore, it is necessary to carry out creative optimization on the basis of the original harmonic current control technology, and at the same time, it needs to be proved by scientific practice. In this paper, deep learning related technologies are used to construct a control strategy to improve the feasibility of harmonic current control.

This paper combines the traditional current control technology and optimizes it on this basis, creatively proposes a harmonic current control strategy under the DC distribution network, and uses a scientific algorithm for experimental verification. The innovations of this paper are: (1) The harmonic current control strategy is optimized by combining PI control technology and repetitive control technology, and the current control performance of the strategy is improved. (2) The ADMM algorithm is introduced to improve the convolutional neural network model based on the deep learning algorithm, which improves the overall accuracy of the algorithm and reduces the error well.

2. Related work

A good harmonic current control strategy plays an important role in the detection of current and the healthy operation of the entire power grid system. In terms of current control, the concept innovation is very fast, and the research space is huge. In recent years, many scholars have conducted a lot of research in this area. Among them: Scholar Liu K and his team first compared the performance of several traditional parallel modules and summarized their advantages and disadvantages, and based on this, they proposed a harmonic current control strategy with comprehensive filtering function. The strategy is based on double loops, and has good enhancements in system stability and control response time. Finally, the efficiency of the strategy is verified by simulation experiments (Liu et al., 2019). Li G combined with the quadratic evaluation method to propose an optimized harmonic current control strategy, and applied it to the controller-related direction of electric vehicle. The results show that the proposed strategy has obvious advantages in dynamic response (Li et al.,

2019). In order to improve the calculation speed and improve the performance of the algorithm, Wang L and his team proposed an innovative harmonic current control strategy. And he also developed a mathematical model to eliminate the negative influence of traditional detectors on the acquisition of current, and finally proved the feasibility of this strategy through experiments (Wang et al., 2018). Nie C analyzed the advantages and disadvantages of parallel converters applied in the power field, and then in order to solve its influence on the deterioration of compensation performance caused by harmonic currents, a control strategy of the enhanced version of harmonic currents was proposed. This strategy can be used to adjust the optimal output position of harmonic currents (Nie et al., 2017). Dehkordi N M et al. proposed a reliable nonlinear harmonic current control strategy for the defects of fuzzy filter parameter setting and uneven load configuration. And he also put it in MATLAB for simulation experiments to prove the efficacy of the strategy (Dehkordi et al., 2017). The above research provides a good theoretical help for the concept innovation of harmonic current control, and can also well broaden the development direction of the current control field. However, the above research does not propose a truly efficient current control method in the actual operating environment, and the simulation samples used are too few. This makes the ideas presented in the above studies unsupported by scientific methods.

In view of the lack of scientific methods applied to the harmonic current control strategy in the above research, deep learning related algorithms can be used to solve the problem. Deep learning algorithms can be used to solve practical problems in many fields such as image processing, which has attracted many scholars to conduct in-depth research on deep learning algorithms. Among them, scholars Ping L and others reviewed the successful cases of deep learning applied in various fields, and then expounded the disadvantages of deep learning in actual operation. Then two problems and corresponding solutions for applying deep learning to the dataset were proposed, and the security of the two schemes was finally proved (Ping et al., 2017). Jian Y et al. made a creative discussion on the convolutional neural network model in deep learning, and introduced deep learning technology into it according to the characteristics of digital image technology. The constructed deep learning structure is very different from the structure and function of the traditional visual algorithm model. Finally, the performance of the model is further improved by combining with the technology of selecting channels (Jian et al., 2017). Scholar Pan B et al. analyzed the advantages and disadvantages of deep learning related technologies applied to the field of image classification. In order to solve the problem that deep learning consumes a lot of resources, a streamlined deep learning model is originally proposed. This model can be used to maintain experimental results at high accuracy levels with little resource consumption (Pan et al., 2017). He H reviewed the commonly used tools for evaluating channel-related data, and specifically combined deep learning techniques to deal with the relatively difficult situation of evaluating channel-related data in large-scale experimental environments (He et al., 2018). Araque O et al. had well analyzed and discussed the common deep learning-based sentiment factor assessment methods. And he also proposed a variety of methods such as classification and integration technology to further improve the performance of deep learning, and compared the performance of the method model with the traditional deep learning model (Araque et al., 2017). The above research on deep learning has greatly enriched the relevant knowledge framework of deep learning, and provided valuable experimental data for improving deep learning theory. However, the performance of the algorithm accuracy and error control used in the above research is difficult to support the overall demand of the DC power distribution system, and it will be slightly weak in maintaining the normal operation of the system.

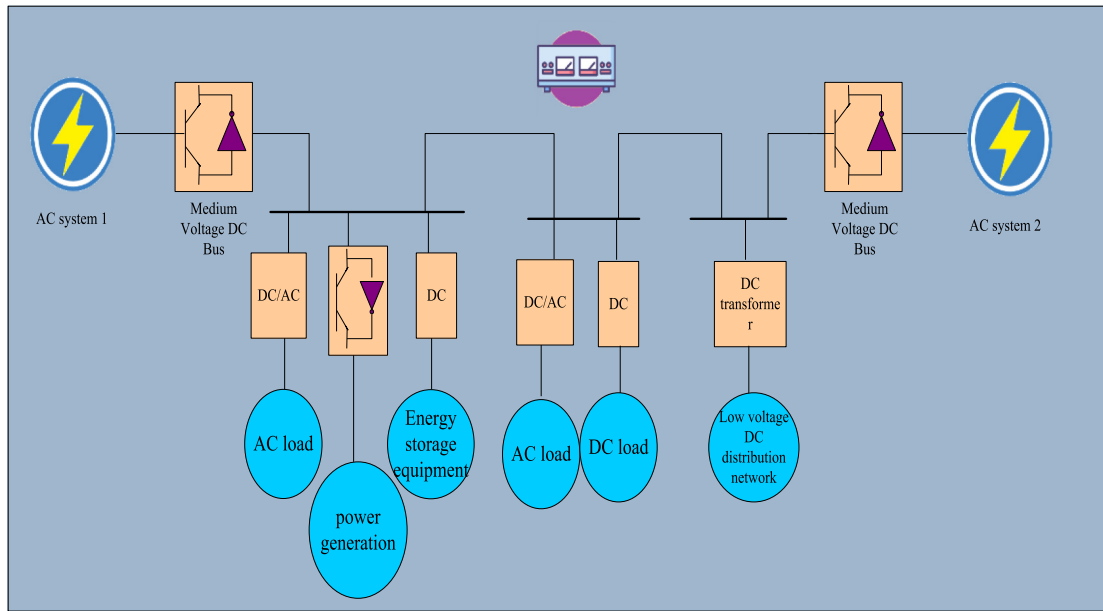


Fig. 1. Structure of two-terminal DC distribution network.

3. Construction of current control strategy based on deep learning

3.1. Harmonic current control strategy of DC distribution network

Under the background of the rapid development of the power system and the continuous expansion of the overall layout of the power grid, the AC power distribution system is becoming more and more difficult to support the high-load operation of the entire power grid. The AC power distribution network is difficult to meet the electricity demand of urban residents, and the widely implemented distributed systems use AC power distribution to waste a lot of energy loss and other AC power distribution problems frequently occur (Lv et al., 2020). In this case, the DC distribution network with higher efficiency, stronger power supply capacity, and better energy utilization rate is a better choice for urban electricity consumption. Based on this, this paper discusses the optimization of the current control function of the DC distribution network (Guo, 2020; Xiangyu et al., 2022). Among them, in order to better understand the actual situation of the current and optimize various control strategies, it is necessary to build a perfect and reasonable structure of the DC distribution network. The structure of the DC distribution network designed in this paper is shown in Fig. 1.

It can be seen from Fig. 1 that the structure of the DC distribution network proposed in this paper is a structure in which two converter stations are connected to both ends of the power grid. In this way, the two converter stations are connected in parallel. This structure has become the focus of current research on DC distribution networks due to its advantages of high power conversion efficiency and reliable power supply system. The current control strategy proposed in this paper is also based on this structure. Other commonly used structures are the ring structure and the radial structure, but they are not comparable to the overall performance of the two-end structure.

After determining the structure of the DC distribution network, it is necessary to determine the control methods and related strategies for harmonic currents. In fact, in the current power grid development, the structure of the distribution network has not changed much. However, the current control strategy has a great potential to be tapped. According to the advantages and disadvantages of traditional control methods, this

paper proposes a combination of two control methods. First, Fig. 2 shows the specific structure of PI control (Laoprom and Tunyasirut, 2020).

Fig. 2 shows the control flow trend in PI control, which is a good demonstration of the relationship and conversion method between digital controller and analog control. J_p represents the relative composition proportion, which can be converted into a digital representation of PI control by means of relative discrete (Apte et al., 2019; Hamdy et al., 2018). PI control technology is a control method with relatively simple components and relatively stable overall operation, so it has the largest audience in the field of current control. In this paper, it is combined with the repetitive control method to control the current of the DC distribution network in the whole process. The relevant structure and functions of the repetitive controller are shown in Fig. 3.

In the parameters of Fig. 3, the function of x^{-M} is to delay the running time by one cycle process, which can be used to calculate the cumulative value of all error points in different cycle time periods for the signal representing the size of the error. $Q(x)$ is a constant coefficient, its value limit is that it must be less than 1, which is often used to indicate the stability of the system. X^j can freely control and adjust the leading or lagging properties of the entire system according to the actual situation, making the control process more stable. J_s represents the enhanced intensity expression achieved throughout the control process, and $T(x)$ is a compensatory function that makes the system more precise. The repetitive control process is extremely powerful because of the role of these parameters. The biggest advantage of the repetitive process is its unique memory function. It is proposed based on the assumption that the current release process exhibits cyclic repeatability. Combining the repeat process with the advantages of the PI process described above will lead to an unprecedented enhancement of the overall harmonic current control capability.

3.2. Convolutional neural network construction

In order to better describe the harmonic current variation curve under the DC distribution network and optimize the scientific application of the control strategy, the convolutional neural network model under deep learning is used in this paper to construct the relevant links of harmonic current control. The

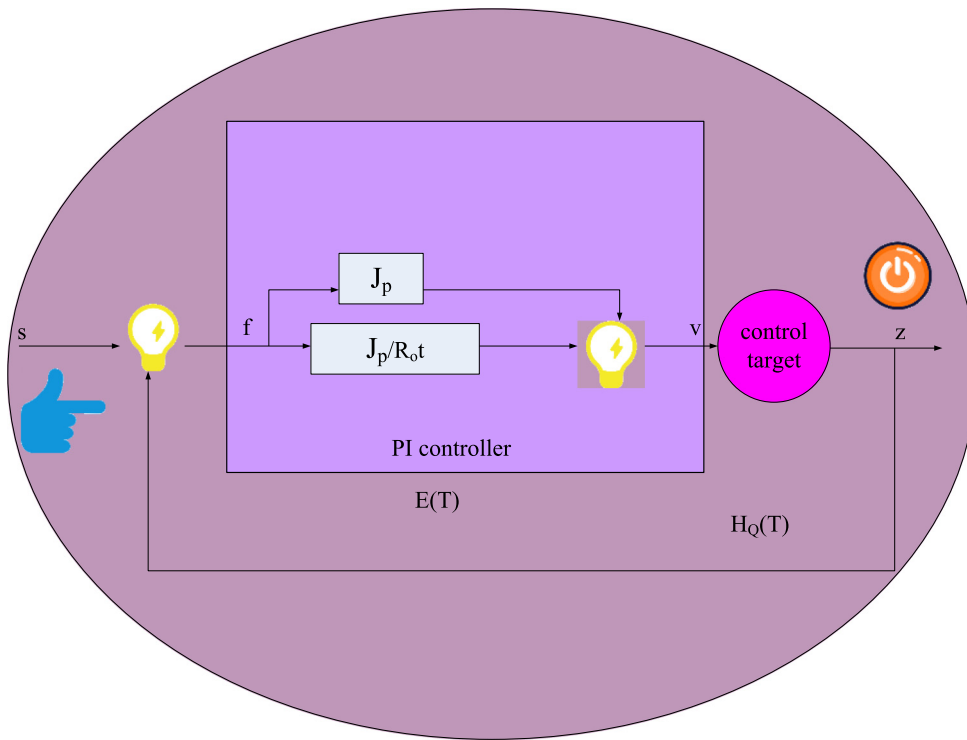


Fig. 2. Composition figure of PI controller.

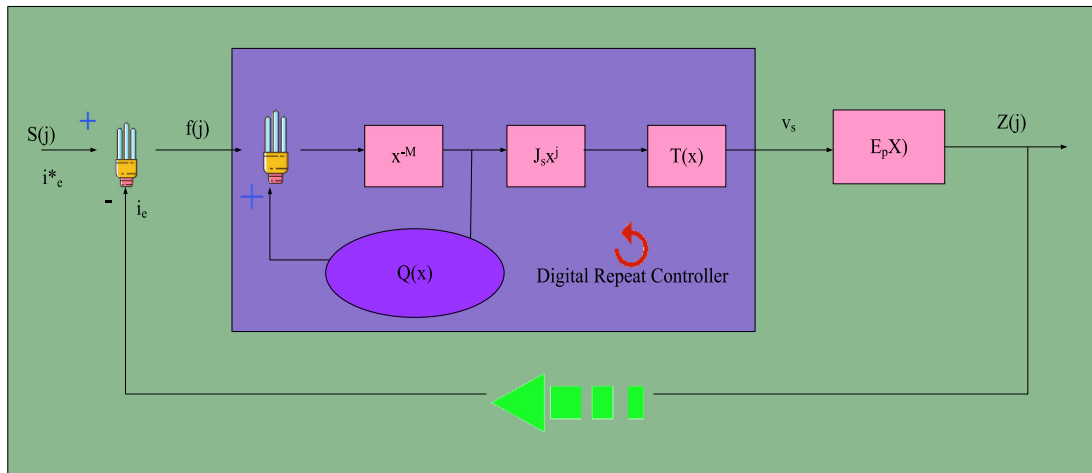


Fig. 3. Repetitive controller composition figure.

convolutional neural network model is divided into a three-layer structure (Ren et al., 2017), they are the input layer, the convolution layer and the pooling layer, respectively, and the specific structure is shown in Fig. 4.

In Fig. 4, the convolutional neural network model is divided into three layers: the layer structure used in the output process, the layer structure used in the convolution process, and the layer structure used in the aggregation process. These three layers constitute the main operation process of the entire algorithm. The convolutional layer is one of the most important parts of the convolutional neural network, which is mainly used to obtain the data information of the previous layer (Kuo, 2017). Through the convolution kernel and the assignment of mathematical operation rules, relevant operations are performed on the output data that has passed the mapping area to make it the same size as the original data.

In the convolutional layer, before selecting a suitable function with activation function to perform the band filtering operation, it is necessary to learn the relationship corresponding to the features of the previous layer (Wang et al., 2017). The composition of the convolutional layer can be expressed by Formula (1):

$$y_p = \int \prod_{i=0}^{l-1} \prod_{h=0}^{N_i} (j_{hi,p} * y_{h,p-1} + c_{i,p}) \quad (1)$$

In Formula (1), y_p represents the feature correspondence display figure of the p th layer of the convolutional layer. Change the resolution of the figure by a downsampling function to impose strict limits on the number of features that can be increased or decreased, at the same time, the size of the corresponding area in the input process can also be increased, and the feature corresponding relationship display figure can be displayed by

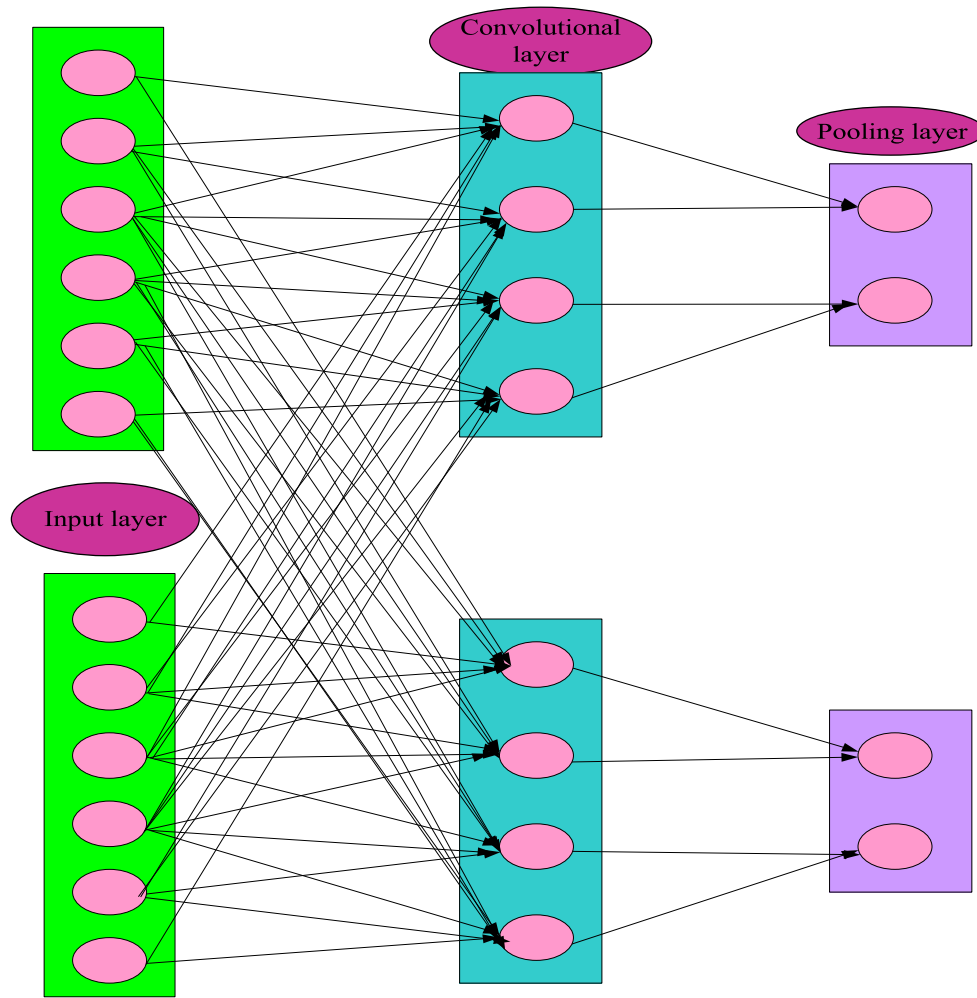


Fig. 4. Convolutional neural network model.

Formula (2):

$$y_p = \prod_{i=0}^{I-1} \int \chi_{i,p} \text{down_s}(y_{i,p-1}) - c_{i,p} \quad (2)$$

Among them, χ represents the weight of the downward sampling process, and $\text{down_s}()$ represents the function expression of the downward sampling. Then, the feature correspondences are divided into squares with side length a that do not affect each other, the feature representations in each square are averaged, and each feature correspondence is reduced by a factor element of a .

By tiling the feature correspondence display figure with two-dimensional space to make it one-dimensional, the figure is represented as the input of the structural layer with the fully connected property:

$$y_p = \int (\varphi_{p-1} y_{p-1} - c_{p-1}) \quad (3)$$

In Formula (3), φ_p represents the attribute parameter of the input weight, and c_p represents the offset. Typically, convolutional layers are max-pooling layers, which reduce the size of feature maps by dividing them into blocks and replacing the entire block with its maximum value (Zhao and Kumar, 2017).

3.3. Deep residual convolutional neural network construction

In harmonic current prediction and control, the data $z \in \mathbb{R}^{N \times 1}$ is modeled by evaluating it to obtain a Poisson random variable

with no dependence. The averaged value $\bar{z} \in \mathbb{R}^{N \times 1}$ of this variable has a certain relationship to the unpredictable image $z \in \mathbb{R}^{M \times 1}$ after the affine transformation process:

$$\bar{z} = Qz + t + s \quad (4)$$

Among them, $Q \in \mathbb{R}^{N \times M}$ is the matrix used to calculate the probabilities, and Q_{ih} represents the probability that the detector arranged in i calculates the probability of a particle released by voxel h that transmits electromagnetic interactions. $t \in \mathbb{R}^{N \times 1}$ is the estimated value of scattered events, and $s \in \mathbb{R}^{N \times 1}$ is the estimated value of random events. N is the number of lines spent in the response phase, and M is used to represent the pixel size scale of the entire image space (Yang et al., 2019). The log-likelihood function is shown in Formula (5):

$$K(z|y) = \sum_{i=1}^N z_i \log \bar{z}_i - \log z_i! \quad (5)$$

The maximum likelihood estimate of the unpredictable image y can be obtained by Formula (6):

$$\hat{y} = \arg \max_y K(z|y) \quad (6)$$

Among them, the value range of y is $y \geq 0$. Through the above derivation, the unpredictable image y can be constructed in a nonlinear way:

$$y = f(\beta) \quad (7)$$

Among them, $f: \mathfrak{R} \rightarrow \mathfrak{R}$ represents the corresponding relationship of the neural network, and β represents the transmission value during the input process of the neural network.

With this representation, the harmonic current prediction information can be constructed based on the framework of using the existing relevant parameters and data to explore the neural network in advance and incorporating the results into an iterative feedback process (Yuan et al., 2019). Then replace the representation in Formula (7) with the reconstructed network structure above, so that the system model initially created in Formula (4) can be redesigned as:

$$\bar{z} = Qf(\beta) + t + s \quad (8)$$

The maximum likelihood estimate for an unpredictable image y can be expressed as:

$$\hat{y} = f(\hat{\beta}) \quad (9)$$

$$\hat{\beta} = \arg \max K(z|\beta) \quad (10)$$

Among them, $\beta \geq 0$, because the model is constructed in a nonlinear way, the target form pursued in Formula (10) cannot be easily obtained, and it can be converted into the restricted form in Formula (11):

$$\begin{aligned} \max K(z|y) \\ t.r. y = f(\beta) \end{aligned} \quad (11)$$

For the restricted form shown in Formula (11), it must be optimized to solve the restriction problem. In this paper, the augmented Lagrangian formula is used to solve this problem. The formula is as follows:

$$K_{\eta} = K(z|y) - \frac{\eta}{2} \|y - f(\beta) + \gamma\|^2 + \frac{\eta}{2} \|\gamma\|^2 \quad (12)$$

Then Formula (12) is solved by ADMM algorithm, ADMM algorithm is a widely used optimization method for constraint problems in machine learning, and this process can be divided into three repeated feedback processes:

$$y^{m+1} = \arg_y \max K(z|y) - \frac{\eta}{2} \|y - f(\beta^m) + \gamma^m\|^2 \quad (13)$$

$$\beta^{m+1} = \arg_{\beta} \max K(z|y) - \frac{\eta}{2} \|y - f(\beta^m) + \gamma^m\|^2 \quad (14)$$

$$\gamma^{m+1} = \gamma^m + y^{m+1} - f(\beta^{m+1}) \quad (15)$$

For the penalized reconstruction problem presented by Formula (13), it can be improved by optimizing the transfer method. Since the y in $K(z|y)$ are coupled together, a function $P_K(y|y^m)$ for surrogate loss can be created for $K(z|y)$ as follows:

$$P_K(y|y^m) = \sum_{h=1}^{m_h} q_h(\hat{y}_{h,EM}^{m+1} \log y_h - y_h) \quad (16)$$

Among them, $q_h = \sum_{i=1}^{m_i} q_{ih}$ and $\hat{y}_{h,EM}^{m+1}$ are obtained from Formula (17):

$$\hat{y}_{h,EM}^{m+1} = \frac{y_h^m}{q_h} \sum_{i=1}^{m_i} q_{ih} \frac{z_i}{[Qy^m]_i + t_i + s_i} \quad (17)$$

The function $P_K(y|y^m)$ used for the substitution loss must satisfy the requirements of the following two formulas (Wu et al., 2017):

$$P_K(y; y^m) - P_K(y^m; y^m) \leq K(z; y) - K(z; y^m) \quad (18)$$

$$\nabla P_K(y^m; y^m) = \nabla K(z; y^m) \quad (19)$$

After the function $P_K(y|y^m)$ is obtained, the problem presented by Formula (13) can be optimized step by step. For pixel h , the

objective function of Formula (13) for the substitution loss is expressed as:

$$Q(y_h|y^m) = q_h(\hat{y}_{h,EM}^{m+1} \log y_h - y_h) - \frac{\eta}{2} [y_h - f(\beta_h^m) + \gamma_h^m]^2 \quad (20)$$

After maximizing Formula (20), the determined updateable formula of pixel h can be calculated as:

$$\begin{aligned} y_h^{m+1} = \frac{1}{2} [f(\beta_h^m) - \gamma_h^m - q_h/\eta] \\ + \sqrt{(f(\beta_h^m) - \gamma_h^m - q_h/\eta)^2 + 4\hat{y}_{h,EM}^{m+1} q_h/\eta} \end{aligned} \quad (21)$$

Formula (14) embodies a nonlinear least squares problem, and the gradient of the sought function with respect to the input β can be calculated. Since it is difficult to calculate the matrix representation of the target form pursued by the algorithm relative to the input attributes in the current experimental environment, this paper will take the following approach instead:

$$\beta_h^{m+1} = [\beta_h^m - \chi \sum_{n=1}^M \frac{\partial f(\beta_h^m)_n}{\partial \beta_h} [f(\beta_h^m)_n - y_n^{m+1} - \gamma_n^m]]_+ \quad (22)$$

Among them, χ represents the step size. Since all the relevant attributes of the input process in the algorithm model are non-negative, it is necessary to add non-negative constraints to the input β in the proposed network model. In the practical application of this paper, χ has only numerical value, but no actual directional attribute, so the target form pursued in Formula (14) can exist in a monotonically decreasing trend. Since the intensity of the input process in the entire neural network model is limited to a certain interval, as long as the value of χ is reasonable, χ can be applied to different data sets. At the same time, in order to speed up the convergence speed, in Formula (14), this paper will use the Nesterov momentum method to optimize the convergence speed. In actual operation, this paper will repeat the feedback process for Formula (13) once, and then repeat the feedback process for Formula (14) five times, and assign a reasonable initial value to β to prevent falling into the local minimum problem.

Through the above process, solving the optimization constraint problem through the ADMM algorithm will make the overall performance of the improved deep residual convolutional neural network more significantly improved compared to the convolutional neural network.

4. Deep learning applied to harmonic current control strategy

4.1. Application of harmonic current control strategy

In order to test the feasibility and scientificity of the harmonic current control strategy proposed in this paper under the DC distribution network, this paper conducts a comprehensive detection and analysis of the main performance of the harmonic current. The first is for the performance of harmonic frequencies under different J_p values. The power frequency standard generally used internationally is 50 Hz. When analyzing the Bode plot under different J_p values, the harmonics within the 4th and 8th orders can be selected as the comparison. This paper selects the harmonic frequencies of 200 Hz and 400 Hz to conduct a comparative experiment. The results are shown in Table 1.

In Table 1, in the process of increasing the value of J_p from 0.1 to 1.5, the amplitudes of the two frequencies both increased, while when the value of J_p increased from 1.5 to 4, the amplitudes showed a slight downward trend. This also means that the probability of system fluctuations in this interval has been significantly enhanced; and the phase of the system is positively correlated with the J_p value. Among them, the increase of the

Table 1
Bode plot analysis results at different J_p values.

J_p value	Harmonic (200 Hz)		Harmonic (400 Hz)	
	Amplitude (dB)	Phase (°)	Amplitude (dB)	Phase (°)
0.1	0.4387	−62.3263	0.3221	−67.8996
0.3	0.8251	−39.2687	0.6891	−50.0058
0.7	0.9845	−18.6625	0.9586	−23.9089
1.5	1.0172	−9.349	1.0197	−14.2316
4	1.0069	−3.5691	1.0128	−4.7783

Table 2
Relationship between output results and PI parameters within 1200 Hz.

P	400	550	700	850	1000	1150
I						
5	17.44	17.51	17.58	17.63	17.74	17.83
6	16.18	16.31	16.39	16.38	16.46	16.51
7	15.22	15.25	15.31	15.36	15.47	15.52
8	14.21	14.29	14.37	14.44	14.58	14.7
9	13.33	13.42	13.55	13.64	13.82	13.98
10	12.44	12.58	12.77	12.91	13.14	13.32

Table 3
Relationship between output results and PI parameters within 11 000 Hz.

P	400	550	700	850	1000	1150
I						
5	19.39	19.46	19.54	19.56	19.75	19.79
6	18.21	18.31	18.46	18.48	18.55	18.71
7	17.49	17.55	17.61	17.64	17.76	17.83
8	16.92	16.97	17.13	17.17	17.21	17.2
9	16.88	16.95	17.15	17.21	17.44	17.58
10	17.86	17.82	17.99	18.44	18.81	19.02

phase is the highest in the initial growth stage of the value of J_p , and the growth trend of the phase becomes more stable as the value goes on. When the value of J_p tends to 4, the phase even approaches 0°. On the whole, the strategy proposed in this paper needs to improve the stability of the system as much as possible by reducing the overall gain of the system when the value of J_p is greater than 1.5.

In addition, since the PI parameter has an important influence on the total harmonic part of the input process signal in the entire power grid that is more than the output process signal. In this paper, the parameter value of PI is changed to explore the specific impact results, and two different cases of low amplitude and high amplitude are used for research. The influence results in the low amplitude 1200 Hz are shown in Table 2.

As can be seen from Table 2, when the P parameter remains unchanged, the change of the size of the I parameter has no great influence on the output result of the input process signal in the entire power grid that is more than the total harmonic part of the output process signal. The largest increase occurs in the interval where P is 10 and I increases from 400 to 1150, and the final output increase is only 0.88%. When the I parameter remains unchanged, the overall output result is negatively correlated with the P parameter. The larger the P parameter, the smaller the output result. Contrasted with this is the relationship between the output results and the PI parameters in the high amplitude 11 000 Hz, the results are shown in Table 3.

Table 3 shows that when the P parameter remains unchanged, the impact of the change of the I parameter on the test results is similar to that in Table 2, and the increase and decrease of the test results in each interval are very small. While the I parameter remains unchanged and the P parameter increases, the test results show a trend of first falling and then rising. When the P value is 8 or 9, there will be a lowest test result. Combining the results of Tables 2 and 3, the I parameter has little to do with the output result that the input process signal in the entire power grid is

Table 4
Relationship of output results to repetitive control enhancement strength.

Coefficient	1200 Hz	11 000 Hz	Difference
0.15	5.59%	11.86%	6.27%
0.3	3.98%	10.29%	6.31%
0.45	3.12%	9.45%	6.33%
0.6	2.23%	9.19%	6.96%
0.7	2.01%	8.77%	6.76%
0.8	1.93%	8.71%	6.78%
0.9	2.11%	8.58%	6.47%
1	2.37%	8.75%	6.38%

more than the total harmonic part of the output process signal. For the value of P, it is more appropriate to take an intermediate value such as 8 or 9, which will have a better effect on the output of the entire harmonic current.

After exploring the influence of the PI parameters on the input process signal more than the total harmonic part of the output process signal, this paper also explores the effect of the repeated control process coefficient on the result, as shown in Table 4.

The results in Table 4 show that with the increase of the repetitive control enhancement strength, the output results at both amplitudes show a situation of first decreasing and then increasing. Among them, the minimum value is 1.93% when the enhancement strength is 0.8 in the low amplitude 1200 Hz, and the minimum output result is 8.58% when the enhancement strength is 0.9 in the high amplitude 11 000 Hz. The difference between the high-amplitude and low-amplitude output results is the reflection of the degree of fluctuation under the DC current. The data in the table shows that the overall difference is basically maintained between 6.2% and 7%, without much fluctuation, and the degree of fluctuation will not have too much influence due to the change of the repeated control enhancement intensity.

This paper also conducts a simulation experiment on the actual situation of the output current under the optimized harmonic current control strategy. The fluctuation degree of the current is shown in Fig. 5.

In Fig. 5, under the optimized control strategy operation combined with two common control methods in this paper, the overall output current situation presents an efficient and stable state. Compared with the traditional harmonic current control method, the control strategy in this paper has an absolute advantage in stability.

4.2. Convolutional neural network applications

This paper compares the accuracy of the convolutional neural network with the traditional algorithm, and explores the practicability and superiority of the convolutional neural network in the electric power field. The feedback experiment of 100 times of exchange substitution is carried out using the relevant samples of current prediction under the DC distribution network, and the final experimental results are shown in Fig. 6.

The results in Fig. 6 show that in the total 100 repeated feedback experiments, the experimental sample accuracy under the convolutional neural network is superior to the traditional algorithm in all stages. Among them, after 70 repetitions of feedback, the sample accuracy of the convolutional neural network was maintained at more than 90%, and the highest value reached 93.6%. However, the accuracy performance of the traditional algorithm in the whole stage is not ideal, and the best accuracy performance is only 81.1%. The lowest accuracy of the convolutional neural network is 69.2% of the initial stage, which is 7.7% ahead of the lowest value of the traditional algorithm. It can be seen from this that the harmonic current control under the DC distribution network is realized by the convolutional neural network correlation model, which can meet the requirements of better accuracy.

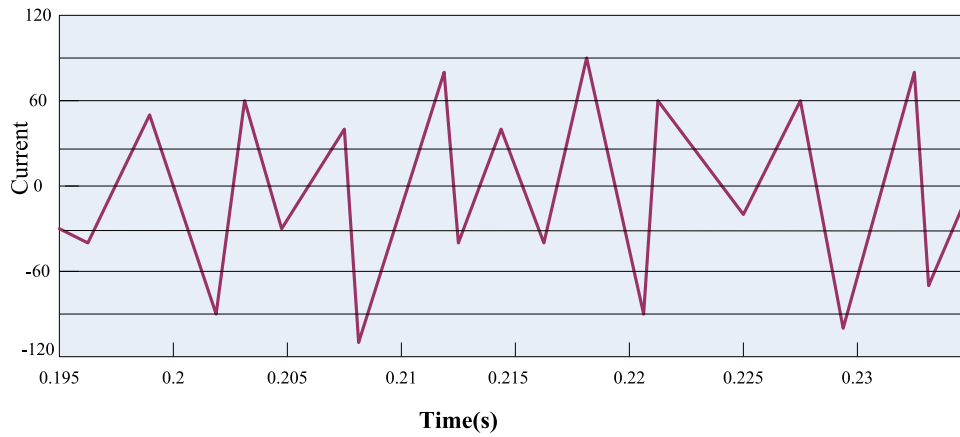


Fig. 5. Output current waveform under optimized current control strategy.

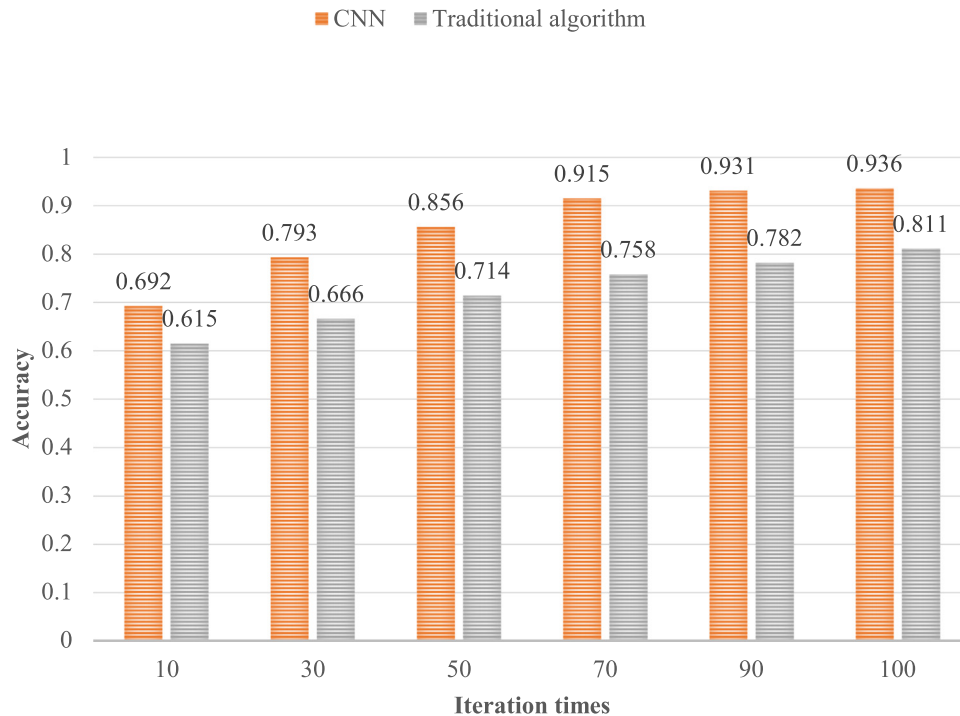


Fig. 6. Comparison of data mining accuracy between two algorithms.

4.3. Deep residual convolutional neural network applications

In order to explore the comprehensive performance of the optimized deep residual convolutional neural network proposed in this paper and its operating effect in the actual environment, this paper designs and analyzes the two main performances of the algorithm model, namely error and accuracy, and related experiments. The influence degree of the penalty parameter η in the algorithm construction in this paper is experimentally demonstrated. Fig. 7 shows the curve representation of the log-likelihood formula of η under different values:

It can be concluded from Fig. 7 that if an appropriate value of η is selected, the entire log-likelihood formula curve will rise relatively smoothly with the continuous increase of the number of repeated feedbacks. Among them, only when η is set to $1e5$, the curve will show a downward trend in the middle of the experimental process, and the curve trend in other values is in line with the expected effect. From a comprehensive comparison, when the value of η is $5e6$, the performance of the entire model is the best.

In the error performance evaluation experiment of the algorithm model proposed in this paper, this paper selects a total of 3000 samples related to DC current control as the experimental object. The mean square error of the optimization algorithm model proposed in this paper is compared with the traditional convolutional neural network model, and the comparison results are shown in Fig. 8.

Fig. 8 shows that from the initial stage of the experiment to the end of the experiment, the deep residual convolutional neural network model has been in the leading position in terms of control error. The two models have maintained a gap of more than 0.1 error. Among them, the optimization algorithm model in this paper has always maintained a high level of error control performance after 500 samples, and the error is well maintained below 0.12. The convolutional neural network model has only a minimum value of 0.18 in the error control. Obviously, the optimization algorithm model proposed in this paper has an absolute advantage in error control.

In addition, this paper also selects the same samples in the above experiments to compare the accuracy of the algorithm.

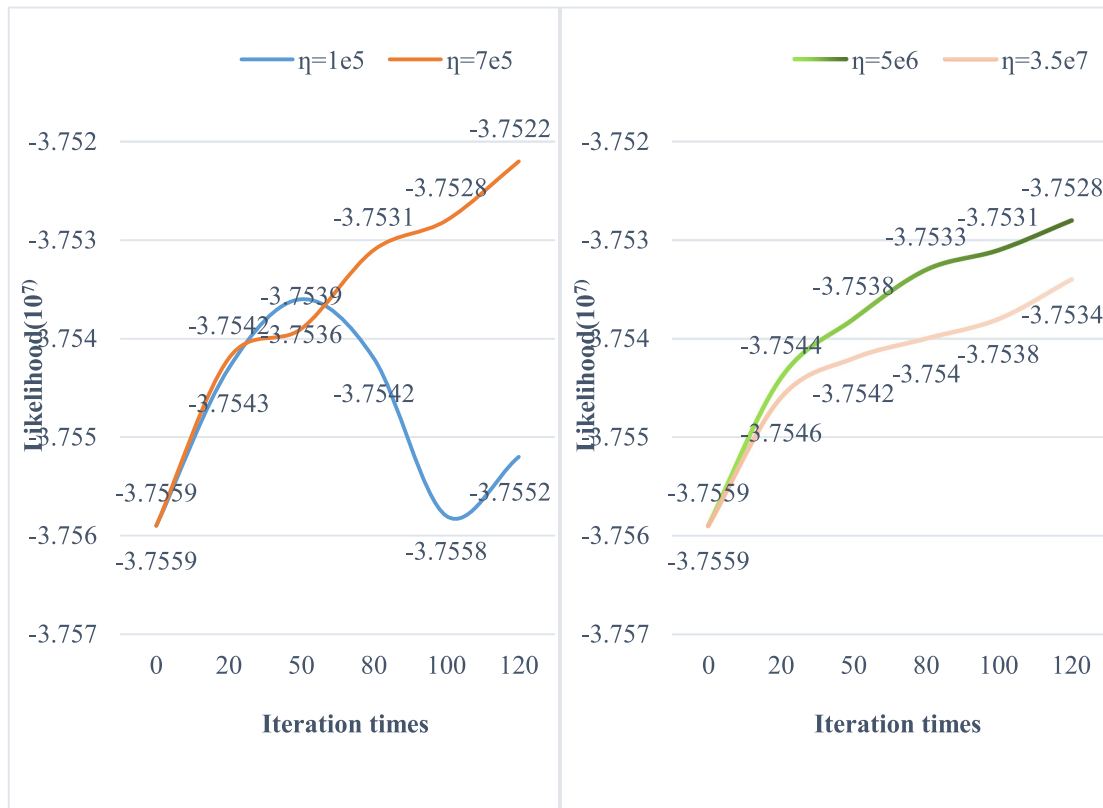


Fig. 7. Effect of penalty parameters.

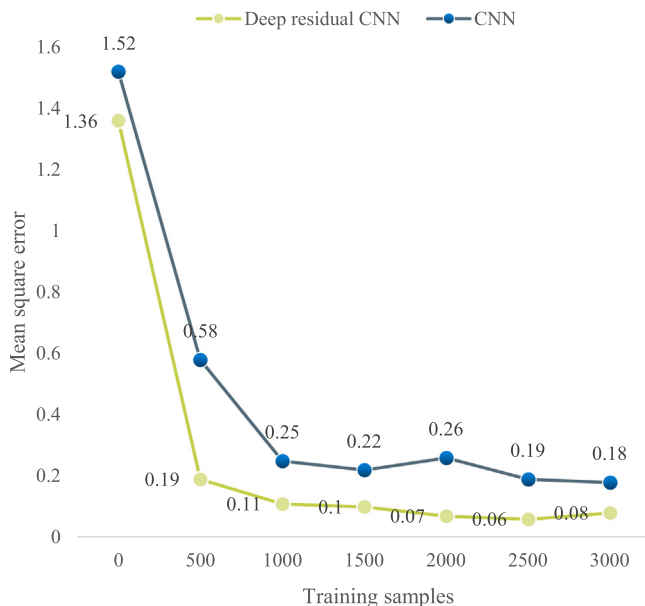


Fig. 8. Comparison of error performance of two algorithms.

In order to ensure the reliability of the experimental data, this paper will carry out two comparative experiments under the same environment, and increase the number of iterations to 1200 times to consider the performance of the whole process. The results are shown in Fig. 9.

In the data display in Fig. 9, the accuracy of the two algorithms in the two experiments gradually increased with the superposition of the repeated feedback times, but the increase of the deep

residual convolutional neural network model was significantly higher. And the accuracy is even stabilized at more than 90% after more than 1000 repeated feedback times, and the accuracy can reach up to 93.1%, which is a great optimization compared to the traditional algorithm. The highest accuracy performance of the corresponding convolutional neural network model is only 86.2%, and the accuracy performance is relatively mediocre throughout the experimental stage. In the two comparison experiments, the accuracy changes of the two algorithms are roughly the same, and the experimental data is only within 2% deviation, which fully proves the reliability of the experiment.

5. Conclusions

Now that the development and optimization of the structure of the DC distribution network has become stable, how to improve the harmonic current control method to enhance the system performance is an important breakthrough in power system research. In this paper, combining the advantages of the commonly used PI control and repetitive control techniques, a more efficient harmonic current control strategy is proposed. The strategy is based on the convolutional neural network model under the deep learning algorithm, and ADMM algorithm is introduced on the model to solve the constraint problem. The final constructed deep residual convolutional neural network model can better complete the tasks of improving accuracy and error control on the basis of the original. The experimental accuracy is stable at more than 90% for a long time, and the highest value reaches 93.1%. It is very suitable for the actual operation requirements of the harmonic current control strategy, and shows good performance in current prediction and current control. Although the algorithm in this paper has a very good breakthrough in accuracy, the difference between the accuracy of the algorithm in the initial stage and the accuracy in the later stage is large, so

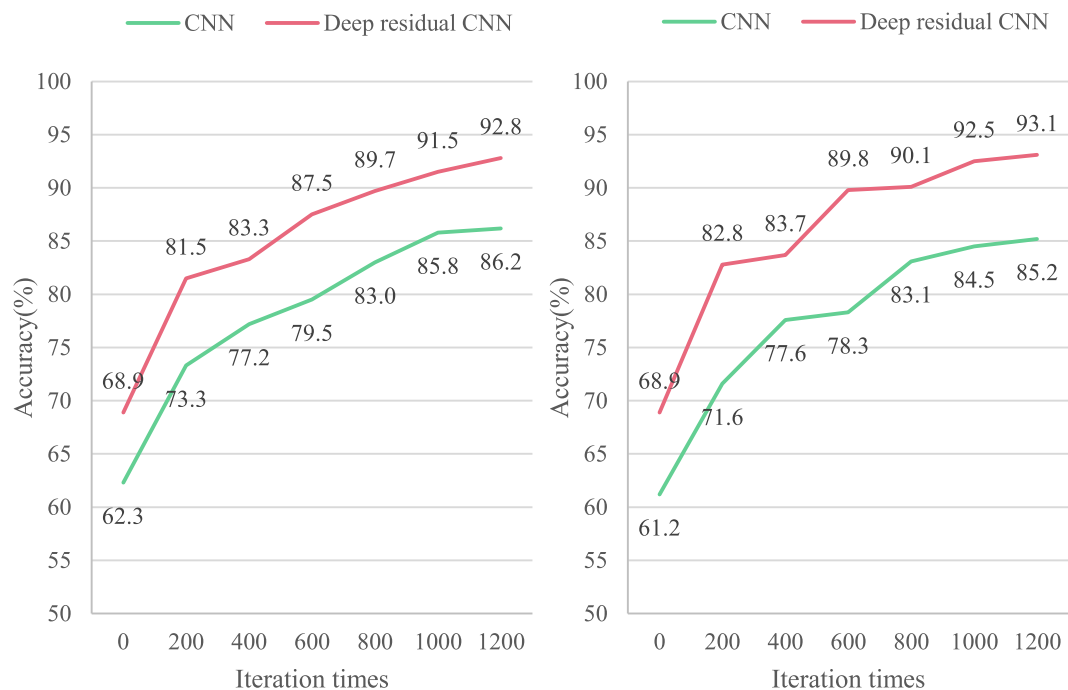


Fig. 9. Two comparisons of the accuracy performance of the two algorithms.

this paper will make improvements in the overall stability of the accuracy in the follow-up work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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