Article

Prediction Model for the DC Flashover Voltage of a Composite Insulator Based on a BP Neural Network

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Abstract: To be able to predict the DC flashover characteristics of composite insulators, a four-layer BP neural network model is established with composite insulator shed structure parameters as the input. Three algorithms (gradient descent with momentum, RMSProp gradient descent, and Adam gradient descent) are applied, and the DC pollution flashover experimental data of composite insulators are used as training data. The results show that all three algorithms have good prediction capabilities. Among them, the Adam gradient descent model has the best prediction result, which can make the average prediction with an error of less than 4% and a maximum error of less than 8%, so these results can provide a reference for the design of composite insulators in DC voltage and product performance verifications.

Keywords: composite insulator; DC flashover performance; shed optimization; BP neural network

1. Introduction

Composite insulators have become the main solution for the external insulation problem of transmission projects. According to incomplete statistics, more than 10 million composite insulators have been used in the Chinese Power Grid [1–3]. However, there is still no unified standard for the shape design of composite insulators at this time. Vendors often manufacture a variety of products with different shed structural parameters based on the project requirements for creepage distance or insulation distance and the limitations of their own molds. However, existing studies have shown that shed parameters have a significant impact on the pollution flashover characteristics of composite insulators. By simulating the meteorological environment in an artificial climate chamber, some researchers have used composite insulators with different shed combinations to evaluate their external insulation characteristics by conducting artificial pollution flashover experiments. The results showed that although the creepage distance of composite insulators had increased, the pollution flashover voltage did not increase significantly [4,5]. Furthermore, the test results also showed that depending on the shed combination of composite insulators, the maximum difference in flashover voltage per unit insulation height can be 24.9% [6]. Other scholars have also concluded that the shape of composite insulators has a greater influence on their insulation performance than creepage distance [7].

The influence of the shed configurations of composite insulators varies in different operating environments: For instance, the icing state of the insulator will be distinct due to different shed structures, which will affect the insulation performance of the insulator under icing conditions [8]. Moreover, in rainy conditions, some studies used the finite element analysis method to illustrate how the shed parameters dominate the electric field distribution along the insulator surface [9].

Consequently, under the same insulation distance, products with different shed parameters will have different insulation properties. Therefore, in order to improve the performance of composite insulators, during the design process it is important to select appropriate shed combinations and parameters according to their working environment.

The traditional optimization method of shed parameters starts by designing a variety of test products with different parameters, then the vendor will change the mold to produce these test products, followed by the use of an artificial pollution test to compare the pollution flashover voltage of these test products. Products with better pollution flashover performances will be selected. However, this method has a high cost and a long research period, which is not suitable for large-scale implementation.

As a machine learning method that has emerged in recent years, neural networks have been widely used in external insulation-related research. Some studies have established convolutional neural network models to automatically locate and classify insulator defects on transmission lines. The detection precision of these models can reach more than 90% [10,11]. By analyzing a large number of leakage current data obtained by monitoring devices on operating insulators, some researchers built a BP neural network model to fit the distribution of leakage current. It has been shown that this model can reliably predict the leakage current on the insulator surface [12,13]. It is worth mentioning that a neural network algorithm also was applied to predict the flashover performance of external insulation equipment. Most training data were obtained by performing experiments in high-voltage laboratories where the operating weather and environment could be simulated artificially. The results demonstrated the ability of the proposed neural network to predict the required parameters with considerable accuracy [14]. Furthermore, the application of deep learning in the design of composite insulators' profiles has also been reported [15]. Studies quantified the related influencing factors including equivalent salt deposit density, shed diameter, shed spacing, etc., in DC flashover experiments, and built an artificial neural network model to analyze the effect of these factors on the flashover voltages.

In conclusion, in order to further demonstrate the value of the data obtained from the artificial pollution test, building a neural network model is a forward-looking and effective method, which can save the test cost and time while improving the intelligence level of the external insulation design of the power grid. For this purpose, this paper establishes a four-layer backpropagation (BP) neural network that takes composite insulator shed structure parameters as the inputs, with the DC pollution flashover voltage per insulation distance and the DC pollution flashover voltage per creepage distance as the outputs. The DC pollution flashover voltage of composite insulators was predicted using gradient descent with momentum, RMSProp gradient descent, and Adam gradient descent. The most suitable algorithm was selected to build a neural network model based on the prediction results. Finally, the trained model is used to predict and analyze the influence of different shed structure parameters on the DC pollution flashover voltage of composite insulators. This work shows that neural networks have preferable prediction capabilities for the flashover voltages of composite insulators, and can provide a reference for the design of insulator shed parameters of favorable engineering application value.
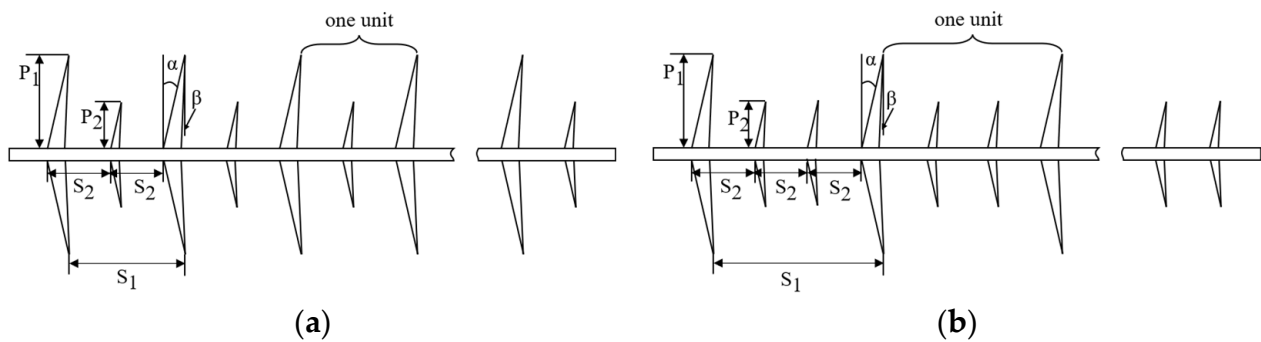
2. Methods

2.1. Data Set

Under the requirements for certain insulation distances and creepage distances, composite insulator vendors can produce composite insulators with different shed parameters according to their own molds. Currently, composite insulators with large/small shed combinations and large/small/small shed combinations are used widely in existing artificial pollution tests, so this article summarizes the pollution test results of 29 types of composite insulators with different combinations of large/small shed parameters, and 23 types of composite insulators with different large/small/small shed parameter combinations. The experimental data were used as the training and testing data set of the BP neural network. The experimental parameters of the artificial pollution test are shown in Table 1: ρ_{ESDD} is the equivalent salt deposit density of the insulator surface contamination; ρ_{NSDD} is the nonsoluble deposit density of the insulator surface contamination; and temperature and humidity are the experimental environments.

Table 1. Experimental parameters of artificial pollution test.

ρ_{ESDD} (mg/cm^2)	ρ_{NSDD} (mg/cm^2)	Temperature (°C)	Humidity
0.1	0.6	20~30	30~50%

The composite insulator structure of two different shed combination modes is shown in Figure 1, where P_1 is the radius of the large shed, P_2 is the radius of the small shed, S_1 is the distance between two large sheds, S_2 is the distance between two adjacent sheds, α is the up-shed angle, and β is the down-shed angle. Settings: $\alpha = 12°$, $\beta = 7°$, P_1–$P_2 \geq 20$ mm, $S_1 \geq 80$ mm (large/small) or $S_1 \geq 90$ mm (large/small/small).

Figure 1. Shed structure: (**a**) large/small; and (**b**) large/small/small.

2.2. Data Preprocessing

When inputting data into the neural network, to prevent the gradient explosion phenomenon caused by the large difference in the magnitude of the input data range [16], P_1, P_2, and S_1 can be normalized based on Equation (1), and the training of the neural network can also be accelerated.

$$x = 0.1 + 0.8\frac{(x - x_{min})}{(x_{max} - x_{min})} \tag{1}$$

In Equation (1), x is the input sample data of P_1, P_2, and S_1, x_{min} is the minimum value of the sample data, and x_{max} is the maximum value of the sample data. The input of the neural network can be fixed in the range of 0.1 and 0.9 after normalization.

The DC pollution flashover voltage data of composite insulators are also normalized for comparison. One group of composite insulator pollution flashover experimental data results are selected from the sample as a baseline, U_{0H} is the pollution flashover voltage per unit insulation distance, and voltage per unit creepage distance, U_{0C}, is the pollution flashover voltage per unit creepage distance. The result is normalized by Equation (2):

$$\begin{cases} K_1 = \frac{U_{xH}}{U_{0H}} \\ K_2 = \frac{U_{xC}}{U_{0C}} \end{cases} \tag{2}$$

where K_1 is the per-unit value of pollution flashover voltage of the composite insulators with different shed structure parameters (U_{xH} and U_{0H}) in the sample, K_2 is the per-unit value of pollution flashover voltage creepage distance of the composite insulators with different shed structure parameters (U_{xC} and U_{0C}).

2.3. BP Neural Network Model

A four-layer BP neural network model was established, with large shed extension P_1, small shed extension P_2, large shed spacing S_1, and large and small shed combination mode variable C_{shed} as inputs, and K_1 and K_2 as outputs. Among them, C_{shed} is used to digitize the combination of large and small sheds to convert them into a form that is easy to use by machine learning algorithms. When $C_{shed} = 0$, the input is the shed data of the

"big/small shed" combination, and when $C_{shed} = 1$, the input is the shed data of the "big shed/small/small shed" combination.

The structure of the four-layer BP neural network is shown in Figure 2, including the input layer, hidden layer 1, hidden layer 2, and output layer. Compared with the three-layer BP neural network with a single hidden layer, the network with two hidden layers can better fit the output with the input. The number of neurons in the hidden layer is set to nine according to the empirical equation 2N + 1 (N is the number of neurons in the input layer) [17].
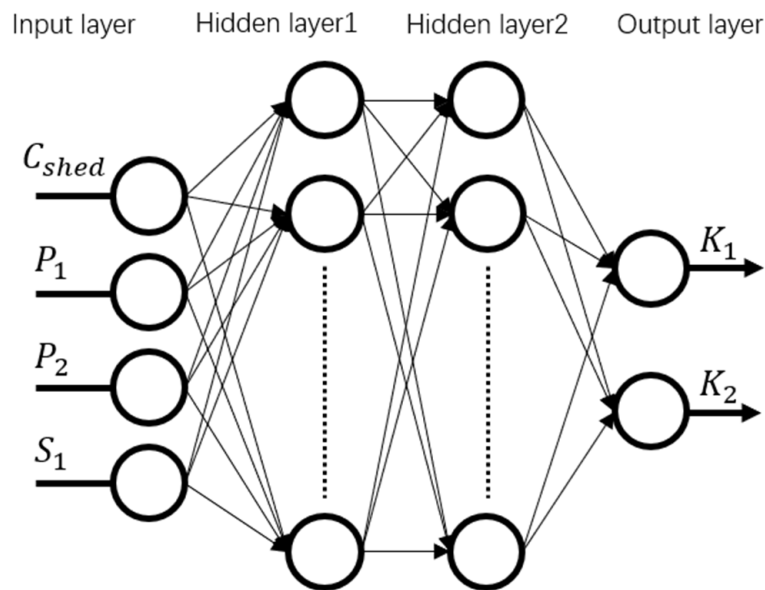

Figure 2. The neural network structure.

The ReLU function is selected as the activation function of the neuron, and the equation is shown in Equation (3).

$$\text{Relu}(x) = \begin{cases} x & x > 0 \\ 0 & x \leq 0 \end{cases} \tag{3}$$

Compared with the traditional sigmoid activation function, the ReLU function will avoid the disappearance of the gradient during the network training process, and the ReLU function has a faster calculation speed and convergence speed [18].

2.4. BP Algorithm

The predicted value ŷ is calculated through the forward propagation link, which is used as the input of the loss function Equation (4) together with the actual value y.

$$\text{loss} = \frac{1}{m} \sum_{i=0}^{m} (y^{(i)} - \hat{y}^{(i)})^2 \tag{4}$$

where m is the number of samples, and $\hat{y}^{(i)}$ and $y^{(i)}$ represent the predicted value and actual value of the i-th sample, respectively. The calculated loss is the Mean Squared Error (MSE) value of the predicted value and the actual value.

The BP of the neural network is used to obtain the gradient of the weights of each layer based on taking the derivative of the weights of each layer of the network through the loss function. The weights of each layer of the network are then updated according to the gradient and the learning rate of the network, as shown in Equation (5) (standard gradient descent):

$$\begin{cases} dW^{(n)} = \frac{\partial \text{loss}}{\partial W^{(n)}} \\ W^{(n)} = W^{(n)} - \alpha dW^{(n)} \end{cases} \tag{5}$$

where $W^{(n)}$ represents the weight of the n-th layer of the network, $dW^{(n)}$ represents the calculated gradient of the n-th layer of the network, and α is the learning rate of the network. As the number of neural network training iterations increases, the network weights will be adjusted, the loss function will gradually converge, and the predicted value $\hat{y}$ will move closer to the actual value y.

For the neural network model, different algorithms in the BP will affect the performance of the neural network, e.g., the convergence speed and the accuracy of the prediction. Common optimization algorithms include mini-batch [19], gradient descent with momentum, RMSProp (Root mean square propagation) gradient descent, and Adam gradient descent [20]. The mini-batch algorithm is used in the case of a large amount of data, and will not be discussed in this article. This paper compares the results of three algorithms: gradient descent with momentum, RMSProp gradient descent, and Adam gradient descent. The principles of the three algorithms are discussed below:

1. The gradient descent with momentum algorithm updates the weights after taking the exponentially weighted average of the gradient dW calculated by Equation (5). As shown in Equation (6), compared with the standard gradient descent, the gradient descent with momentum method can reduce the swing in the gradient descent process and increase the convergence speed.

$$\begin{cases} v_{dW(n)} = \beta v_{dw(n)} + (1 - \beta)dW^{(n)} \\ W^{(n)} = W^{(n)} - \alpha dv_{dW(n)} \end{cases} \tag{6}$$

where $v_{dW(n)}$ is the exponentially weighted average of the gradient $dW^{(n)}$, β is an adjustable hyperparameter, and α is the learning rate. $v_{dW(n)}$ includes the result of the previous BP process and the gradient calculated by the current BP process. $v_{dW(n)}$ is used to update the network weight $W^{(n)}$ to avoid the vibration of the $W^{(n)}$ value. In this way, the loss function can converge faster.

2. The RMSProp gradient descent algorithm calculates the exponentially weighted average of the gradient square and then updates the weights based on the learning rate, gradient, and exponentially weighted average. The equation is shown in Equation (7).

$$\begin{cases} S_{dW(n)} = \beta S_{dW(n)} + (1 - \beta)\left(dW^{(n)}\right)^2 \\ W^{(n)} = W^{(n)} - \alpha \frac{dW^{(n)}}{\sqrt{S_{dW}} + \varepsilon} \end{cases} \tag{7}$$

where $S_{dW(n)}$ is the exponentially weighted average of the square of the gradient $dW^{(n)}$, β is an adjustable hyperparameter, α is the learning rate of the network, ε is a small real number to set the denominator to a nonzero value. As can be seen from Equation (7), when $S_{dW(n)}$ is large, the update speed of weight $W^{(n)}$ is slow because s is in the denominator. When $S_{dW(n)}$ is small, the update speed of weight $W^{(n)}$ is fast. RMSProp can obtain faster learning progress of weights in the gentle parameter set, reduce the oscillation of weights in the steep parameter set, and speed up the learning speed of the neural network.

3. Adam gradient descent is a combination of gradient descent with momentum and RMSProp gradient descent. It is one of the most effective algorithms for training neural networks. The algorithm is shown in Equation (8).

$$\begin{cases} S_{dW(n)} = \beta S_{dW(n)} + (1 - \beta)\left(dW^{(n)}\right)^2 \\ W^{(n)} = W^{(n)} - \alpha \frac{dW^{(n)}}{\sqrt{S_{dW}} + \varepsilon} \end{cases} \tag{8}$$

where $v_{dW(n)}$ is the exponentially weighted average of the gradient, $S_{dW(n)}$ is the exponentially weighted average of the square of the gradient, β_1 and β_2 are adjustable hyperparameters, α is the learning rate of the network, and ε is a small real number

that prevents the denominator from being 0. Adam algorithm has the advantages of fast convergence speeds and good learning results. It can avoid the loss of learning rate and the loss of function oscillation.

3. BP Neural Network Model Training and Prediction Results

This paper builds a BP neural network model based on the Python and Tensorflow deep learning framework. Three different algorithms were used, gradient descent with momentum, RMSProp gradient descent, and Adam gradient descent. Fifty-two sets of data were divided into 2 sets, of which 42 sets of data were used as the training set, and 10 sets of data were the test values. The parameter settings for data training are shown in Table 2.

Table 2. Network parameters.

Gradient Descent Algorithm	Train Epochs	Learning Rate α	Hyperparameter
Momentum	50	0.01	B = 0.9
RMSProp	50	0.01	B = 0.9 and $\varepsilon = 10^{-7}$
Adam	50	0.01	$\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\varepsilon = 10^{-7}$

The loss function curve obtained based on the BP neural network model established in this paper for the three algorithms is shown in Figure 3. The result shows that under the data set conditions of this paper, the convergence speed of the three loss function curves has no obvious difference. The loss function tends to converge after about 20 training sets, and the Adam gradient descent algorithm obtains the smoothest model loss function curve.
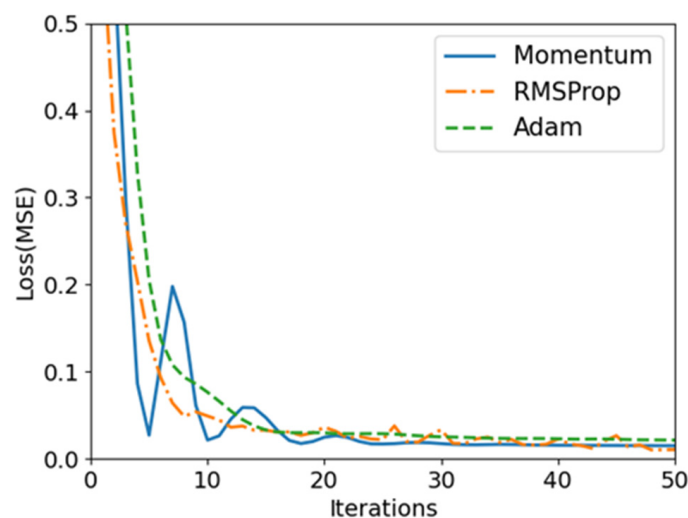

Figure 3. Loss function curves.

The 10 sets of test data were inputted into the trained BP neural network model, and the comparison between the predicted value of the model and the actual value under three different gradient descent algorithms is shown in Figure 4.

As can be seen from Figure 4, the flashover voltage per unit insulation height K_1 and flashover voltage per unit creepage distance K_2 are predicted by the gradient descent with the momentum algorithm. The maximum errors are about 11.4% and 16.8%, and the average errors are about 6.1% and 6.8%. For the RMSProp gradient descent algorithm, the maximum errors for K_1 and K_2 are about 7.8% and 9.0%, and the average errors are about 3.4% and 5.1%, respectively. For the Adam gradient descent algorithm, the maximum errors for the predicted K_1 and K_2 are about 5.3% and 7.3%, and the average errors are about 2.1% and 3.4%. The comparison results are shown in Figure 5.
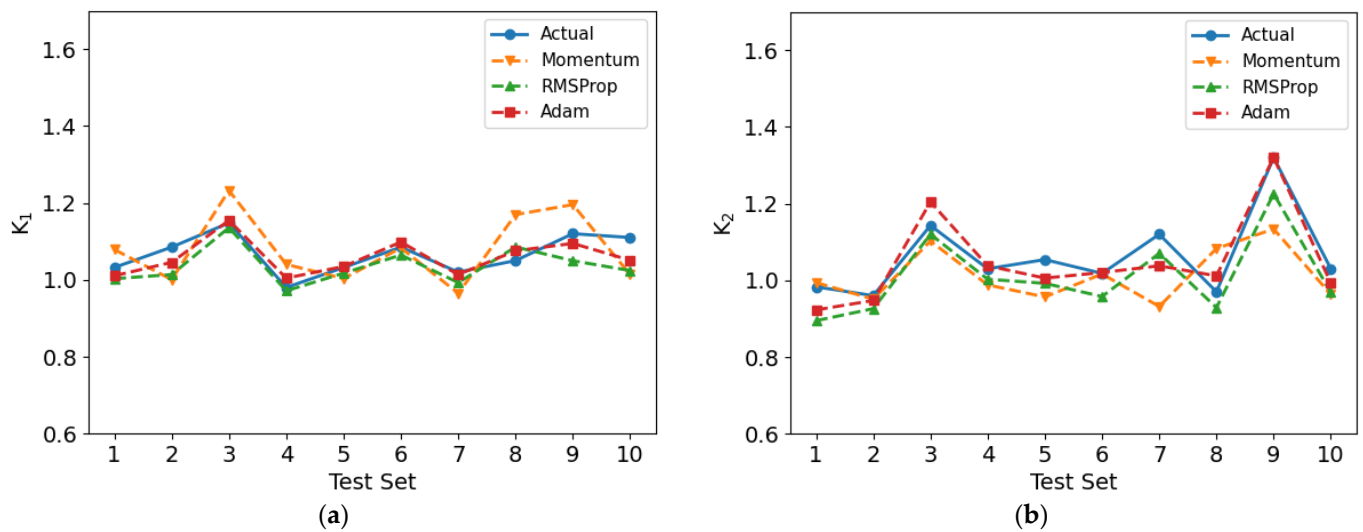
Figure 4. The predicted and actual values of the test set of the model. (**a**) Predicted and actual values of K_1; and (**b**) Predicted and actual values of K_2.
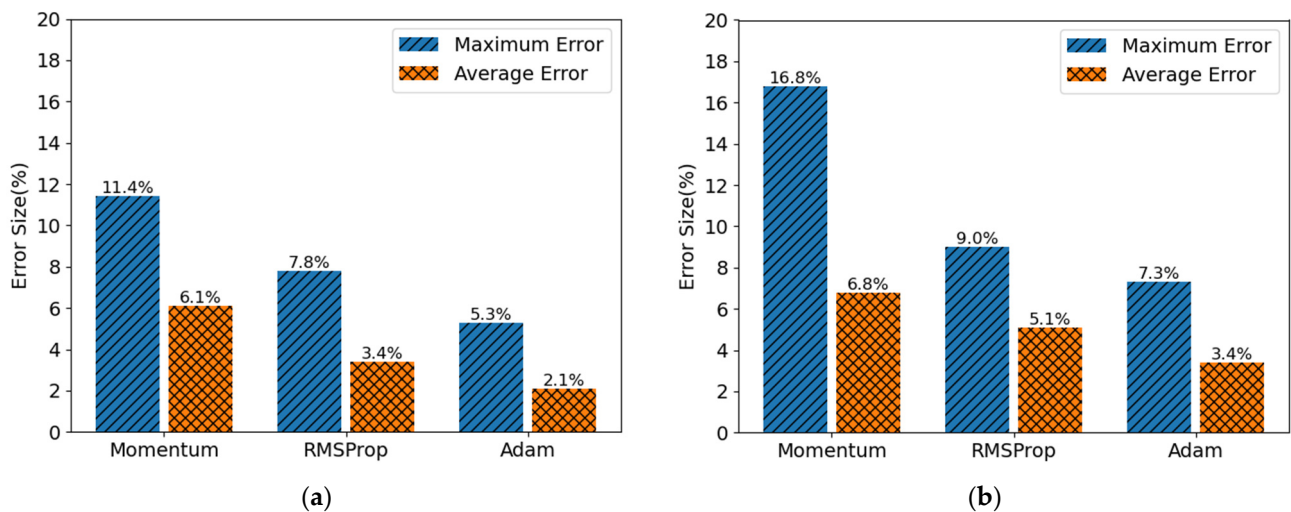

Figure 5. Comparison of model prediction results. (**a**) Prediction error for K_1; and (**b**) Prediction error for K_2.

From the results in Figure 5, it can be found that the average error for the prediction results of the flashover resistance of composite insulators by the three neural networks is smaller than 7%. Due to the small number of data sets, there is no significant difference in the convergence speed of the loss function during the training of different models. Among the three algorithms, the Adam gradient descent algorithm has the best performance. Not only does it have a smoother loss function curve, but the error between the final output predicted value and the actual value is also relatively low. Given that there is a certain error in the artificial flashover experiment itself, it demonstrates that the BP neural network model using the Adam gradient descent algorithm has a better prediction of the flashover resistance of composite insulators.

SVM (support vector machine) is using commonly in machine learning. To prove the superiority of the neural network model, we used the data set established in this paper for training and used SVM to build a model. The comparison between the SVM and neural network is shown in Table 3. It can be seen that the prediction accuracy of neural networks using the Adam algorithm is much higher than for SVM.

Table 3. Model accuracy.

Model	Value	Average Accuracy
SVM	K_1	92.1%
	K_2	89.7%
Neural Network with Adam	K_1	97.9%
	K_2	96.6%

4. Discussion and Prospect

The neural network model used in this paper has a good prediction accuracy, which is acceptable in engineering applications. This method is simple and efficient to implement, which is the main reason why this model been chosen. Admittedly, there are other methods that can further improve the prediction effect (accuracy) of the model, such as making more improvements to the algorithm, or combining neural network and other commonly used optimization algorithms (e.g. the Ant Colony). However, due to the small number of data sets, the model has the possibility of over-fitting. The main way to improve the robustness of the model is to increase the number of data sets, even if there is a certain possibility that the accuracy of the model will be reduced. Specifically, it is difficult to obtain the data of insulator pollution flashover voltage, so the existing research is carried out under the condition of small amount of data. In the future, algorithms for small data sets will be the focus of research in this field.

With the rapid development of deep learning technology, more work related to the application in HVDC system would be carried out in the future. At present, some achievements in the field of computer vision have been applied, including the use of various CNN models for intelligent identification of equipment features or defects with good results. Moreover, it is believed that an intelligent platform that can monitor the operation of HVDC system in real time and online will soon be widely applied and promoted. This achievement would further improve the digital level of power system and significantly facilitating the establishment of a new energy system. The digital twinning of HVDC system is also a feasible research direction in the future.

5. Conclusions

Three types of four-layer BP neural network models using different gradient descent algorithms were established. The neural network was trained with data for the insulator DC pollution flashover experiment as the input. The results proved that gradient descent with momentum, RMSProp gradient descent, and Adam gradient descent can all predict the pollution flashover characteristics of composite insulators to a certain level.

Among the three neural network models, it was found that the Adam gradient descent model had the best prediction effect. The average error was only about 4%, and the maximum errors were smaller than 8%. This can provide a reference for the design of composite insulator shed structures. There is still room for further optimization of the model given that there were only a few data sets available for the training of the neural networks.

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Conflicts of Interest: The authors declare no conflict of interest.

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