Where L is the number of implied layer nodes to be set; n, m are the number of nodes in the input and output layers, respectively; c is a constant value between 1 and 10. is a constant value between 1 and 10.

According to equation (10) the trade-off optimum can determine the nodes of the hidden layer number. The network learning rate is set to 0.05, the training error is chosen to be 1× The hidden layer activation function tensing, the output activation function purelin, and weights and thresholds are obtained by genetic algorithm The optimization is done by genetic algorithm.

5.2. Inspection cost forecast analysis

To test the prediction accuracy of maintenance costs, three methods for prediction analysis, and verify each model through prediction effect evaluation effectiveness.

(1) The traditional deep neural network algorithm is used for prediction.

(2) Using GA-deep neural network algorithm based on genetic algorithm to improve algorithm for prediction.

(3) K-fold cross-validation was used to pre-process the training data, and then the GA-deep neural network was used for prediction. (3) K-fold cross-validation is used to pre-process the training data, and then the GA-deep neural network algorithm is used to make predictions.

The results and relative errors of the three different methods for the training of maintenance and operation cost data are shown in the table below. The results and relative errors of the training are shown in Tables 1 and 2. Taking the 2017-year data, for example, the maintenance cost in 2017 is 55.83.7 million the traditional deep prediction is 58.1976 million yuan, and the GA-deep the prediction result is 56.88.921 million yuan, and the prediction result of K-fold-GA-deep is 5.527.372 million yuan.

The relative errors of the three methods are 0.040 70, 0.018 84 and 0.010 09, respectively. The relative errors of the three methods are 0.040 70, 0.018 84 and 0.010 09, respectively. The K-fold-GA-deep method is the best, with a relative error of only 1.009%. 1.009%, while the relative error of the traditional deep prediction is larger, reaching 4.070%. The relative error of the traditional deep prediction value is larger, reaching 4.070%, which indicates that the prediction effect of this method is not good.

Table 1: Trainging reusltls of the operation and mintenance cost data by three methods

Yeah	**Groundtruth**	**Preditictions**		
		deep	GA-deep	K-fold_GA-deep
2015	3877.0	3893.673	3943.525	3874.328
2016	4404.0	4444.600	4339.355	4397.532
2017	5604.4	5423.453	5556.078	5631.609
2018	5583.7	5810.976	5688.921	5527.372
2019	6529.2	6385.458	6473.004	6591.704
2020	7457.9	7511.336	7408.192	7429.191

Table 2: Relative errors of three methods of forecasting results

Yeah	**Relative errors**		
	deep	GA-deep	K-fold_GA-deep
2015	0.004300	0.01716	0.00067
2016	0.009219	0.01468	0.00147
2017	0.032290	0.00862	0.00486
2018	0.040700	0.01884	0.01009
2019	0.022150	0.00861	0.00957
2020	0.007165	0.00299	0.00385

The comprehensive evaluation index data of the training effects of the different models constructed As shown in Table 2, it can be seen that the K-fold-GA-deep prediction models of MAPE and RMSE are 38.063 800 and 0.005 087, respectively. It can be visualized that the comprehensive evaluation indexes with K-fold-GA-deep method the minimum error of the comprehensive evaluation indexes of the K-fold-GA-deep method indicates that the model constructed by this method is suitable for this city. The model constructed by this method is suitable for predicting the maintenance and operation cost of this city, and the effect is good. The results are good.

6. Conclusion

For the problem of allocated cost of maintenance of constructed UHV substation equipment, firstly, the historical data are processed, and the true value of the historical maintenance cost data is imputed according to the analysis and collation of UHV substation maintenance financial entries; to avoid the traditional deep neural network will fall into local optimum, then the training data are K-fold processed, and the deep improved by genetic algorithm is used neural network to predict UHV substation maintenance costs. Conclusions are drawn from the study.

(1) The process of collecting historical data of UHV substation operation and maintenance overhaul costs is difficult, and the relevant overhaul costs are obtained by analyzing and organizing the financial entries of UHV substation engineering overhaul, and processing the data in horizontal and vertical directions to ensure the real reliability of the obtained data. And analyze the various constituent factors affecting UHV substation overhaul operation and maintenance costs and use them as prediction input of the model.

(2) When training the deep neural network on the original data, K-fold cross-validation can better ensure the accuracy of the prediction model and avoid the phenomenon of overfitting.

(3) The K-fold-GA-deep neural network model is used to predict the future maintenance allocation costs of constructed UHV substations. Through the training and prediction of typical municipal UHV substation maintenance cost data, it is known that the model can accurately predict the future maintenance costs. In the case of large fluctuation of maintenance cost every year, this method can be used to get the maintenance allocation value more accurately, which can provide reference for the grid to allocate maintenance cost to UHV substations.

Acknowledgement

This work is supported by Science and Technology Program of State Grid Corporation of China(5500-202224139A-1-1-ZN).

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