Prediction of Power System Load Using Echo State Network Based on Dropconnect Method

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***Abstract*—The application of artificial intelligence makes the power system more intelligent. Load forecasting has always been one of the main problems faced by the power system. The paper proposes an echo state network based on Dropconnect method for predicting power system load. This method subtly changes neuronal connection, optimizes connection structure of reservoir neurons, and improves efficiency of load forecasting in power system, ensuring stable operation of power system. For validation effectiveness of proposed method, the paper compared its predictive performance for rail transit power systems with classical ESN, Dropout ESN, and Dropconnect ESN from three aspects. At the same time, a comparison was made between the predictions of time series generated by Mackey-Glass system. The simulation results show Dropconnect ESN has better performance in load predictive task of rail transit power systems.**

Keywords—artificial intelligence, echo state networks, Dropconnect, load forecasting

I. Introduction

Artificial intelligence has a wide range of applications in the power system, enabling it to operate more efficiently and intelligently. It not only improves the reliability, safety of the system, but also promotes the effective integration of renewable energy [1-3].

Among them, using neural network technology to predict power system load has important practical significance and application value. Neural networks have the ability to handle complex nonlinear relationships. The load of the power system is influenced by various factors, and neural networks can learn these complex patterns from historical data to improve the accuracy of load forecasting [4-7]. Echo state network(ESN) is commonly used to predict time series data. The randomly generated reservoir structure and weights to some extent affect the network's characterization of power system load data [8]. Due to the fact that the connections between neurons are usually randomly generated in the reservoir, the sparsity of connections affects the computational efficiency and dynamic characteristics of the reservoir. Therefore, reasonable sparsification of the reservoir is beneficial for improving the performance of the entire network.

In our previous work, we introduced the Dropout method into the reservoir and sparsified the structure of the reservoir in ESN[9]. Dropout randomly discards the output of the entire neuron. This method has a coarser granularity because it affects the entire neuron, and all connections are simultaneously discarded or retained. In this paper, we introduce the Dropconnect method into the reservoir to achieve finer granularity sparsity of the ESN structure. By implementing a more rational sparse reservoir structure, predictive performance and accuracy of entire network can be improved when predicting power system data. Dropconnect randomly discards the weight connections of each neuron. Specifically, each connection (i.e. weight) has a certain probability of being set to zero. This approach has finer granularity because it only affects individual weights, rather than the entire neuron. Partial connections of a neuron can be discarded, while other connections can still be retained and used. The Dropconnect method can control the complexity of the network more finely, and the randomization of weights can prevent model overfitting at a finer level, which can lead to better model performance in some cases.

Support vector regression and binary nonlinear fitting regression models are predicted total electricity[10], a fuzzy time-matching method predicting carriage load[11]. Although many studies used different methods for load forecasting, they are all relatively traditional methods. In recent years, echo state networks have shown better predictive ability in processing time series data. Although these studies have made structural improvements to ESN, they have also increased the network's reservoir and complexity[12-14] . Therefore, we propose a novel ESN that improves predictive performance of network without increasing its complexity.

II. Background Introduction

A. Dropconnect

Dropconnect method is a promotion of Dropout [15], which is similar to Dropout in that it introduces dynamic sparsity in the model. The difference is that sparsity of Dropconnect method is in the weight, and each connection can be deleted with probability p, rather than every output unit[16].

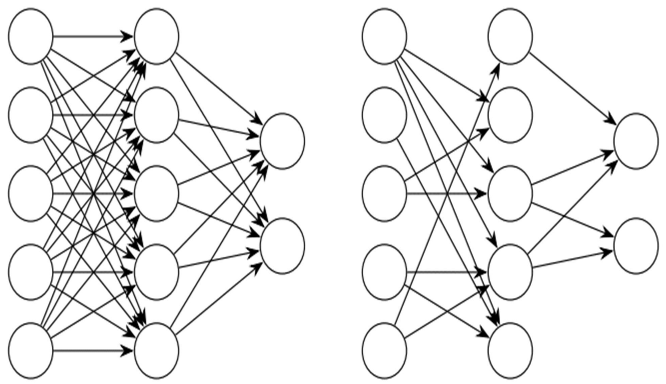

Fig.1 An example of dropconnect. The weights of the network on the right have dropped with probability p.

B. Dropconnect ESN

Figure 2 shows Dropconnect ESN model . W^{in} is the input matrice, W^{out} is the input matrice , and W^{back} is the feedback connection weight matrices. In the reservoir, the dashed line are the randomly blocked synapses. Randomly blocks some synapses in reservoir, and the synapses stop working with a certain probability.

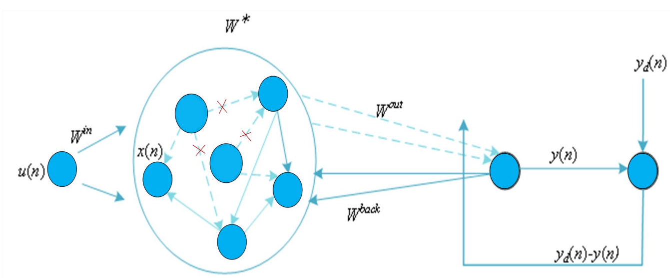

Fig.2 Dropconnect ESN

The output equation of Dropconnect ESN and update equation of Dropconnect ESN are as follows at sampling time n,

$$x(n+1) = \tanh(W^* x(n) + W^{back} y(n) + v(n)) \qquad (1)$$

$$y(n+1) = W^{out} x(n+1) \qquad (2)$$

Among them, W^* is the internal weight matrix of the reservoir. $v(n)$ is the noise . $W^* = \mathrm{p}W$.

C. Basic configuration of simulation verification scenarios

The QingDao rail transit operation scenario of Line 11 is used for simulation verification scenario.

D. ROC curve

In binary classification of machine learning, ROC curve used evaluation indicator. When distribution of positive samples test set changes and negative samples test set changes, the ROC curve remains unchanged. Because there will be class imbalances in data set. There are far more negative samples than positive samples. In test data, the distribution of negative samples and positive samples may also constantly change over time.

E. NEMSE

NRMSE described as follows:

$$NRMSE = \left(\sum_{j=1}^{k} (d_j(8000) - y_j(8000))^2 / k\sigma^2\right)^{1/2} \quad (3)$$

Among them, k represents test sample length , d_j represent the actual test output, and y_j represent expected output (predicted value of network) during the testing phase, and σ^2 represents expected output variance.

III. EXPERIMENTAL SETUP

In Dropconnect echo state network, there are 800 neurons in the reservoir, trains steps are 10000 , and tests steps are 300. The noise is set to 0.01.

A. rail transit simulation power load data

In the experiment, JetBrains PyCharm 2022.3.2 was used as the simulation tool. There are 15000 simulation data, which are based on power load data in rail transit.

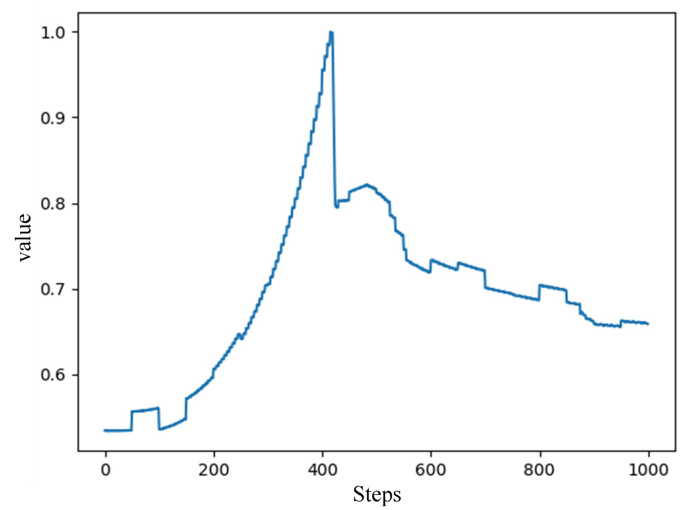

Fig.3 Power Data Diagram

B. time series data generated by Mackey-Glass system

In time series prediction task, Mackey-Glass(MG) time series has nonlinear characteristics and is one of benchmark problems.

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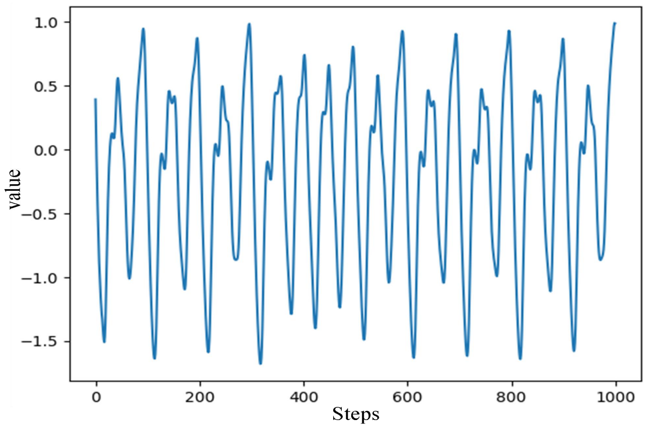

Fig.4 data of time series

IV. EXPERIMENTAL RESULT

A. *Experimental results of load data for rail transit power system*

1) predicted steps

For the prediction steps of rail transit load data, fig. 5 shows the comparison between the Dropconnect ESN proposed in this paper and the classical ESN and Dropout ESN. Among them, in the prediction of rail transit load data, the load data curve of rail transit is green line. The Dropconnect ESN prediction curve is the red line. The classical ESN predictive curve is the blue line . The Dropout ESN predictive curve is the black line. The Dropconnect ESN predictve curve is closer to load data curve in the 300 steps predictive range .

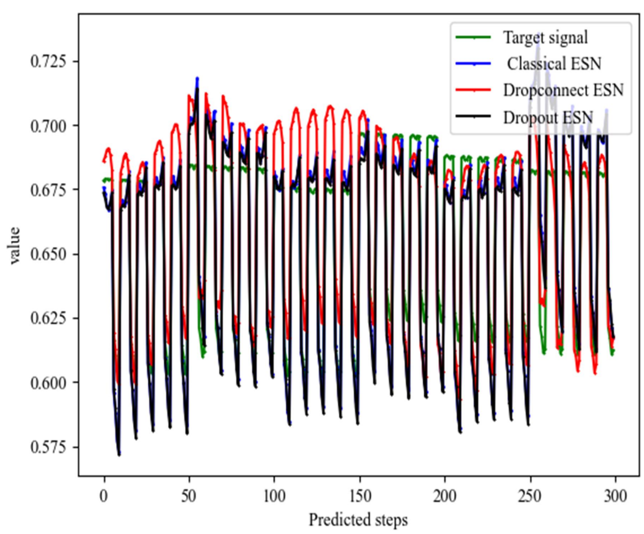

Fig. 5 predicted steps of rail transit load data

2) ROC curves

In the prediction of rail transit load, Fig.6 shows the ROC curves of classical ESN， curves of Dropout ESN and curves of Dropconnect ESN. In the fig.6 , the ROC curves of Dropconnect ESN is the orange line. The ROC curves of classical ESN is the blue line. The red line represents the ROC curves of Dropout ESN. Dropconnect ESN ROC curve is closer to the upper left than that of classical ESN and Dropout ESN. It shows that Dropconnect ESN classify numerical values more accurately and has higher predictive performance compared to classical ESN and Dropout ESN.

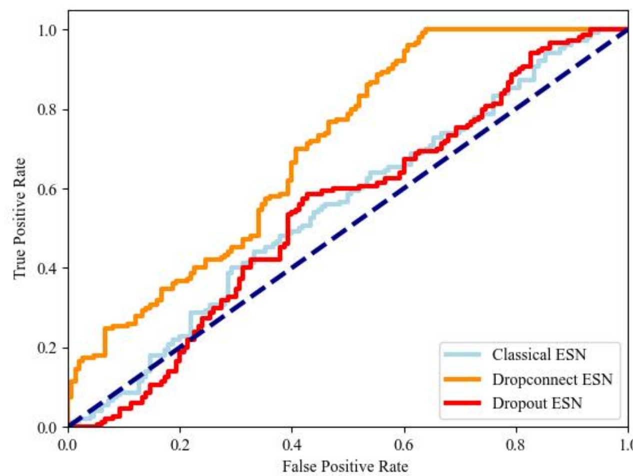

Fig.6 the curves of ROC

3) predicted accuracy

In the prediction of rail transit load, fig.7 shows the relationship between predictive steps and NRMSE, compares echo state network based on Dropconnect method, Dropout ESN, and classical ESN. In the fig.7 , the abscissa is the predictive steps, y-axis is the NRMSE. Blue curve represents the change in NRMSE as the number of prediction steps increases in classical ESN prediction. Green curve is change in NRMSE as prediction steps increases in prediction of echo state network based on Dropconnect method. The red curve represents the change in NRMSE as prediction steps increases in prediction of echo state network based on the Dropout method.

From the fig.7 , it can be seen that the NRMSE value of ESN based on Dropconnect method has been lower than the NRMSE value of classical ESN and Dropout ESN. The prediction error of echo state network based on Dropconnect method is lower than that of the classical ESN and Dropout ESN. Its predictive performance is higher than that of the classical ESN and Dropout ESN.

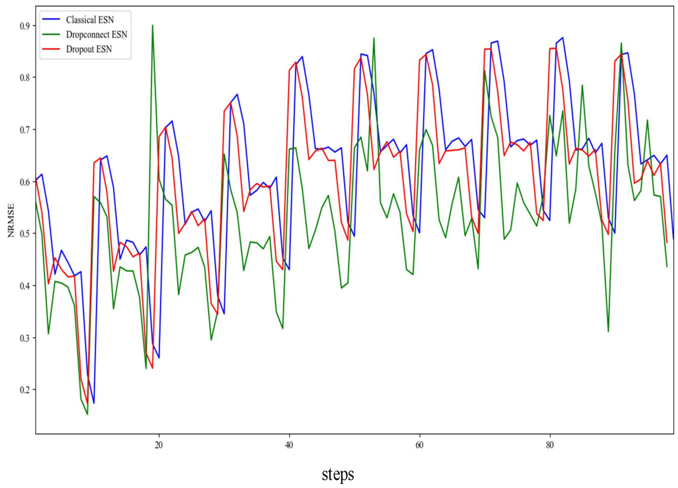

Fig.7 predicted accuracy

B. *time series data generated by Mackey-Glass system*

1) *predicted steps*

For the predicted steps of time series data generated by Mackey-Glass system, in fig.8, it shows the comparison between the Dropconnect ESN proposed in this paper and the classical ESN and Dropout ESN. Among them, the Dropconnect ESN predictive curve is red line. The predictive curve of classical ESN is blue line. The Dropout ESN predictive curve is black line. The curve of time series data is green line. The Dropconnect ESN predictive curve is closer to the real time series data in the 300 steps predicted range.

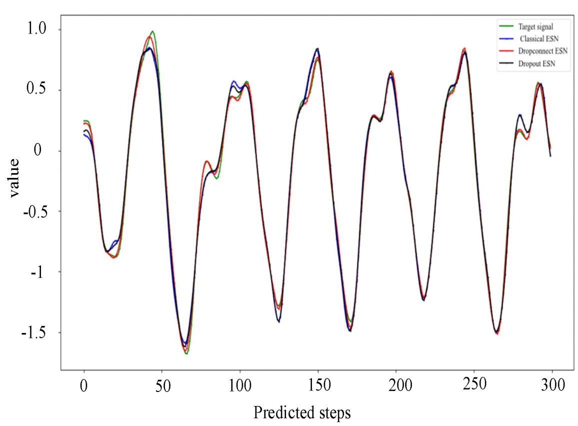

Fig.8 predicted steps of time series data

2) *ROC curve*

When predicting the time series data generated by the Mackey-Glass system, Fig.9 shows the ROC curves of classical ESN， curves of Dropout ESN and curves of Dropconnect ESN. In the fig.9, the orange line is ROC curves of Dropconnect ESN. The blue line represents the ROC curves of classical ESN. The red line is ROC curves of Dropout ESN. ROC curve of Dropconnect ESN is closer to the upper left than that of classical ESN and Dropout ESN. It shows that Dropconnect ESN classify numerical values more accurately and has higher predictive performance compared to classical ESN and Dropout ESN.

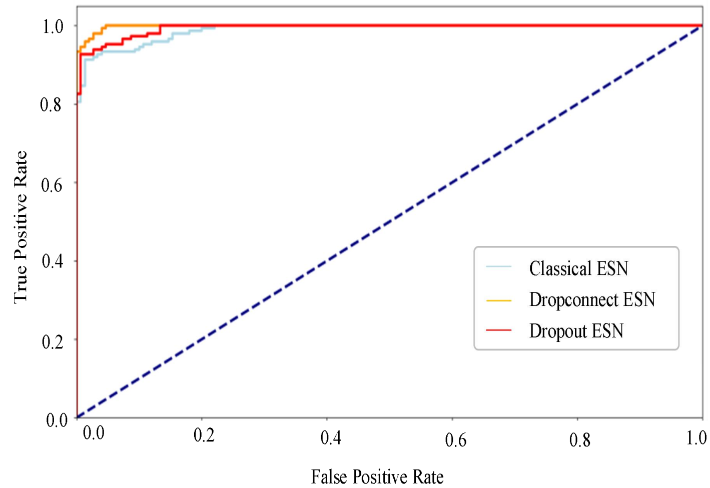

Fig.9 the curves of ROC

3) *predicted accuracy*

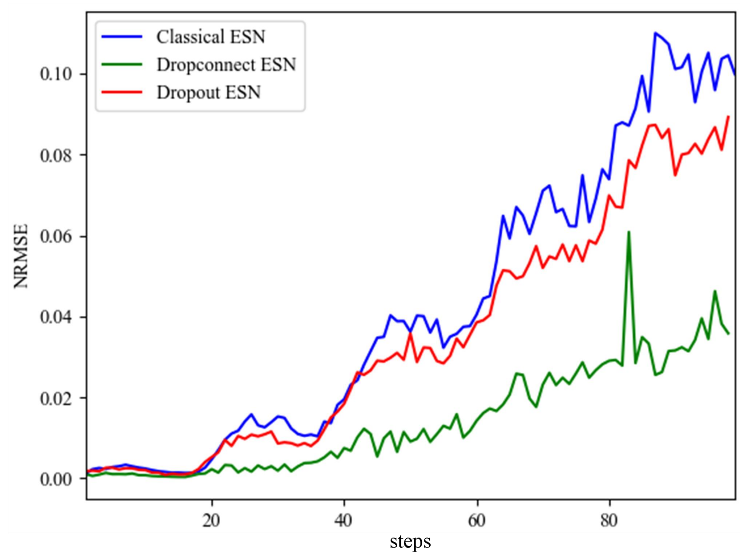

Fig.10 predicted accuracy

In predicting time series data generated by Mackey-Glass system, the fig.10 shows that relationship between predicted steps and NRMSE, and compares the ESN based on Dropconnect method, dropout ESN, and classical ESN. In the fig.10, the abscissa is predictive steps, y-axis is the NRMSE. Blue curve represents the change in NRMSE as the number of prediction steps increases in the classical ESN prediction. Green curve is the change in NRMSE as predictive steps increases in prediction of ESN based on Dropconnect method. The red curve represents the change in NRMSE as predictive steps increases in prediction of ESN based on Dropout method.

From the fig.10 , it can be seen that the NRMSE value of ESN based on Dropconnect method has been lower than the NRMSE value of classical ESN and Dropout ESN. Predictive error of ESN based on Dropconnect method is lower than that of classical ESN and Dropout ESN. Its predictive performance is higher than that of classical ESN and Dropout ESN.

V. Conclusion

In order to predict the load of the power system, ensure its reliability and safety, and enable it to operate more intelligently, this paper applies artificial intelligence technology to the power system. The paper proposes a new ESN, Dropconnect ESN, and applies it to load predictive task of rail transit. To verify the effectiveness, the paper compared predictive performance of Dropconnect ESN with classical ESN and Dropout ESN from three aspects. At the same time, three methods were compared from three aspects in series data generated by Mackey-Glass system. The experimental results show that Dropconnect ESN has high accuracy in predicting load of rail transit, and effectiveness of proposed method in rail transit power system load prediction is demonstrated. In future work, we will adopt different artificial intelligence technologies to solve the problems in the power system of rail transit.

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