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Prediction of Electrostatic Discharge Signal Based on Improved Echo State Network

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ABSTRACT

Electrostatic discharge (ESD) can power loss and internal damage of power equipment, and also interferes with the normal operation of other equipment. How to accurately predict the ESD signal is of great significance to the stable operation of power equipment. Therefore, the ESD signal prediction will be carried out. The ESD signal is predicted by the improved deep echo state network, which solves the problems of the weak ability of traditional ESN to map the high dimension and the complexity of updating the weight of the reserve pool of ESN, and reduces the error in the prediction, and has a strong ability to identify the ESD signal. This paper improves the weight collection mode of deep echo state network. Unlike deep echo state network, which collects all the state weights of the reserve pool, this paper only collects the state weights of the reserve pool at the last layer for output weight calculation, so as to reduce the influence of useless features and reduce the prediction error. Finally, the experimental results are compared with other networks, and the results show that the improved ESN has the best performance.

1. Introduction

Electrostatic Discharge (ESD, Electrostatic Discharge) refers to the partial or complete disappearance of Electrostatic charge on the charged body due to ionization of the dielectric when the field strength around the charged body exceeds the insulation breakdown field strength of the surrounding medium (Liu Shanghe 1999). It is widely found in uHV power transmission (Liu Shoubao et al. 2018), high-speed rail transportation (Dong Haiyan et al. 2019), high-speed aircraft (Liu Shanghe et al. 2013), satellites and spacecraft (Liu Shanghe et al. 2014; Hu Xiaofeng et al. 2019). On the one hand, ESD, as a typical hazard source, will not only cause damage and energy loss of electronic equipment, and bring security risks to system operation, but also produce electromagnetic radiation, which makes the space electromagnetic environment worse, and cause unintentional electromagnetic interference to broadcasting, navigation, communication and other frequency equipment. On the other hand, ESD is also a kind of available electromagnetic signal, which is of great value for the spatial location of electrostatic discharge power supply, system status monitoring and fault diagnosis, such as insulation failure location of power system, off-line fault location of high-speed bow network, passive detection of aircraft and soft fault diagnosis of spacecraft, etc. Therefore, it is of great significance to study the identification and prediction of electrostatic discharge signals for eliminating electrostatic hazards and extracting useful information (Hu Xiaofeng et al. 2015).

Electrostatic discharge radiation signal is a non-stationary signal with strong singularity (Hu Xiaofeng et al. 2018). In engineering applications, the signal to noise ratio of electrostatic discharge radiation obtained by electromagnetic testing system is often low, and even submerged in background noise, periodic or random interference signals, such as communication, broadcasting, vehicle spark plugs discharge and electronic switch radiation signals, etc. At present, conventional electrostatic discharge signal detection algorithms represented by wavelet denoising method, adaptive digital filtering method and Fourier frequency domain transform method are difficult to break through the limit of signal-to-noise ratio (Liu Weidong et al. 2017). With the continuous development of artificial intelligence, recognition and prediction methods based on deep learning (Zhou Xin et al. 2019) are expected to break through this difficult problem.

With the development of relevant technology industry in China, the research of deep learning combined with all kinds of signal prediction is also carried out. Esn is applied in wireless communication signal prediction (Ren Haipeng et al. 2019), lower limb surface emG signal prediction (Xiong Ming 2020) and mobile communication traffic (Peng Yu et al. 2010). Long and short-term memory neural network is applied to predict the time series of theft crime (Yan Jinghua 2020) and Wiener degradation process series (Shi Guorong et al. 2020).

For electrostatic discharge signal prediction, the deep learning method is seldom used. This paper hopes to provide a new idea for electrostatic discharge prediction by using deep learning method. In this paper, an improved deep echo state network is proposed, and

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experiments show that it has better ability to recognize electrostatic discharge signals. The electrostatic discharge signal data set used in this paper is collected at different times in the same experimental environment, without considering the electrode structure characteristics (radius of curvature) that will affect the shape of the waveform. The data collected are basically similar in amplitude and waveform.

2. Improved Deep Echo State Network(IDESN)

2.1 Echo state network (ESN)

Echo state network (Peng Yu et al. 2010) is mainly divided into three parts in structure: input layer, reserve pool layer and output layer, and these three parts are connected with each other by connection weights. Figure 1-1 shows the esn structure.

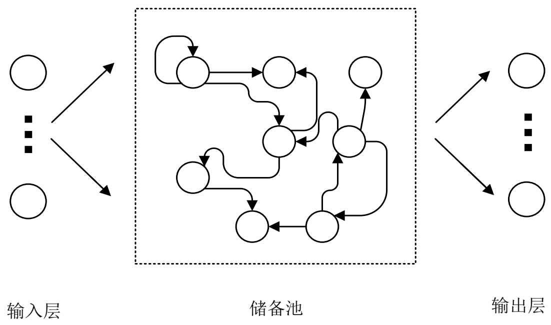

Fig.2-1 Basic structure of ESN

In order for the echo state network to possess the echo state feature, the connection weights between the input layer and the reserve pool as well as the connection weights between neurons in the reserve pool should be between (-1, 1). The reserve pool takes the output weight of the input layer at this moment as the input, and the input weight is processed by sparsely connected neurons in the reserve pool to complete the update of the state of the reserve pool. Input the collected state of the reserve pool to the output layer for weight training to complete the collection of the state of the reserve pool at this moment. After the collection of all moments is completed, the output weight is calculated to complete the network training. Its operation can be regarded as a dynamic cyclic system, and its process can be regarded as two parts: the state acquisition stage of the reserve pool and the weight calculation stage. Structurally, it has K input neurons, H internal neurons and N output neurons. Enter at time n, the values of input, internal and output units are:

$$\begin{cases} u(n) = [u_1(n), u_2(n), u_3(n), \cdots, u_K(n)]^T \\ x(n) = [x_1(n), x_2(n), x_3(n), \cdots, x_H(n)]^T \\ y(n) = [y_1(n), y_2(n), y_3(n), \cdots, y_N(n)]^T \end{cases} \quad (1)$$

In the formula 1-1, $u(n), x(n)$ and $y(n)$ represent the input signal, reserve pool state and output signal at time n respectively. The initial state of the reserve pool is set to 0, that is, $x(0) = 0$. After the input layer processes the output weight matrix w_{in}, and then the signal $u(n)$ processed by the input layer is input to the reserve pool to form the state quantity of the reserve pool at that time. Immediately after the signal input at the next moment, the current state of the reserve pool is updated through the same processing. When the input layer sends output to the reserve pool at time n+1, the current state of the reserve pool needs to be updated. The state update expression of the reserve pool in the echo state network at the n+1 moment is:

$$x(n+1) = Tanh(w_x x(n) - w_{in} u(n)) \quad (2)$$

The echo state network needs to collect the state of the reserve pool at all times to prepare for the subsequent calculation of the output weight.

According to formula 1-2, the state weights of the reserve pool at all times are calculated. Then, according to the obtained reserve pool state collected at each moment, it is put into matrix E. There is a supervision signal vector T in the output layer, and the supervision signal corresponds to the state of the reserve pool at different moments to form a training signal pair. The echo state network needs to fit the predicted value to the actual value as much as possible to minimize the difference between the predicted value and the actual value, thus obtaining the form of the output weight:

$$W_{out} = (E^T E)^{-1} E^T T \quad (3)$$

After the training of the output weights is completed, the output weights can be used to predict the next moment:

$$y(n+1) = w_{out} x(n+1) \quad (4)$$

2.1.1 Training process of ESN

Given a training sample $(x(t), y(t))$, where $t = 0,1,\cdots,n_{max}$. The learning process of esn is as follows:

1) Initialize network parameters. Determine the input connection weight matrix a_w and reserve pool connection weight W_x of the echo state network. Adjust the scaling factor a_w so that it satisfies $\rho(W) < 1$. Example Initialize the status of a reserve pool.
2) The data n in the data set is taken as input, processed by the input layer, and entered into the reserve pool layer to complete the calculation of the reserve pool status weight of the input data through formula 1-2.
3) Set the remaining data in the data set as the supervision signal T of the echo state network.
4) The output weights are calculated according to formula 1-3. After all the training of output weights is completed, the model construction of echo state network is completed.
5) Re-input the output layer, input the predicted data at the next moment, and get the network output value.

After the prediction, all the error values between the predicted value and the actual value of the echo state network are calculated, and then all the error squares are added to obtain the mean square error of the predicted value and the actual value. The mean square error is used to measure the performance of the echo state network. The closer the value is to 0, the better the performance is. The mean square error is defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (5)$$

$$\begin{cases} u(n) = [u_1(n), u_2(n), u_3(n), \cdots, u_K(n)]^T \\ x(n) = [x_1(n), x_2(n), x_3(n), \cdots, x_H(n)]^T \\ y(n) = [y_1(n), y_2(n), y_3(n), \cdots, y_N(n)]^T \end{cases} \quad (1\text{-}1)$$

2.1.2 ESN Features

The characteristic of echo state is the basis of many advantages of echo state network, which determines the performance of echo state network. Echo state characteristic is a special property of echo state network, that is, the input weight W_{in}, the connection weight matrix of each neuron in the reserve pool W_x and the feedback connection matrix W_{back} satisfy a certain relationship. The relation satisfied by these weights is not universal, that is to say, the characteristics of echo state network are different in different data sets. Therefore, the echo state characteristics require its input weight W_{in}, the connection weight matrix of each neuron in the reserve pool W_x and the feedback connection matrix W_{back} to be tightly concentrated in a training sample. The echo state properties are defined as follows.

Definition 1-1: when the echo state network is not trained W_{in}, W_x and W_{back}, input data $u(n)$ and prediction data $y(n)$ come from compact set U and D respectively. In this case, (W_{in}, W_x, W_{back}) about compact sets U and D have echo state characteristics. All the state matrices $x(n)$ and $x'(n)$ input $u(n)$ satisfy equations 1-6. Then $x(n) = x'(n)$。

$$\begin{aligned} x(n+1) &= f(W_{in}u(n) + W_x x(n) \\ &\quad + W_{back}y(n)) \\ x'(n+1) &= f(W_{in}u(n) + W_x x'(n) \\ &\quad + W_{back}y(n)) \end{aligned} \tag{6}$$

It $x(n) = x'(n)$ can be seen that after the echo state network runs for a long time, the reserve pool state matrix W_x is closely related to the echo state characteristics. That is, when the network runs for a long time, if it does not meet the echo state characteristics, W_x may increase or decrease infinitely, which will lead to invalid training. But at present, no theory can make it clear that (W_{in},W_x, W_{back}) can satisfy the necessary and sufficient conditions of echo state. Jaeger gives a general condition for an ESN with echo state characteristics: the maximum singular value of the matrix composed of the connection weights of each neuron in the reserve pool is less than 1.

In this paper, reserve pool size, sparsity, input scaling factor and spectral radius are initially set as 100, 0.05, 0.5 and 0.5. Then start to fix the other 3 values and change the remaining value to find the optimal situation.

In the later part of the experiment, the echo state network is used to identify electrostatic discharge signals. According to the error performance of each key parameter, the key parameters of the echo state network are set as follows: the scale of the reserve pool is 100, the sparsity is 0.02, the scaling factor is 0.5, and the spectral radius is 0.7. These parameters are also used in the deep echo state network and the improved deep echo state network.

Although the echo state network successfully overcomes the bottleneck in the training process of the traditional recursive neural network, there are still many problems in the echo state network :(1) there are large-scale sparsely connected neurons in the reserve pool, and the network state will be unstable due to completely random connections; (2) In the application, the extraction ability of high-dimensional data is very poor, and there are collinearity problems in the echo state network, which leads to the occurrence of abnormal solutions in the training process; (3) shallow echo state network in order to be more come up to solve the problem of high-dimensional mapping, the structure of single reserve pool can only increase the structure of the network, along with the network structure of gradually increased, the reserve pool of invalid connection will be more and more, this caused a lot of useless calculations, greatly reduces the computing performance and generalization ability of network, improve the computational complexity. By improving these shortcomings, the calculation error can be effectively reduced and the calculation efficiency can be improved.

2.2 Deep echo state network (Deep-ESN)

The main idea of deep echo network is to increase the number of reserve pools. Data is input from the input layer, and then goes through different levels of abstraction representation of each layer of reserve pool, and finally output. The process can be seen as the bottom reserve pool effectively abstracts and extracts the features of key information and sends them to the top. In addition, there is no connection from the top to the next layer in the upward transfer process of the bottom layer, that is, the connection can only be positive and irreversible.

Based on the idea of deep echo state network, it is improved. An encoder layer is added to the reserve pool layer instead of just the reserve pool, which is located before the reserve pool of the last layer. In this way, the high-dimensional mapping of the reserve pool can be converted into a low-dimensional mapping, so as to achieve the effect of feature compression. The reserve pool will extract the key information features more clearly, but it is inevitably mixed with other noise influence. Encoders are used to map these high-dimensional information to low-dimensional information, so as to extract features again and compress the noise again. After compression, the noise becomes smaller, and the small ones can be ignored in front of features. After the encoder operation is completed, the key information features are passed through the last layer reserve pool again to change the low-dimensional mapping into high-dimensional mapping, making the features more prominent.

After the structure improvement of deep echo state network is completed, the collection of reserve pool state weight will be improved. Traditional deep echo state network collects the reserve pool state weight of all layers, but this paper will only collect the reserve pool state weight of the last layer. Figure 1-2 shows the improved deep echo state network.

2.3 Improved deep echo state network

(1) The input layer inputs the data into the improved deep echo state network through the input layer, and the external incoming data is recorded as $u(n)$, $u(n) \in R^{M\times 1}$. M is the dimension value of input data, which mainly plays a decisive role in the number of neurons in the input layer. Input data $u(n)$ is weighted by input layer through calculation of input layer, and the weighted input data becomes $W_{in}^1 u(n)$ $W_{in}^1 \in R^{N_1\times M}$, is the weight of input layer, and N_1 is the number of neurons in the first reserve pool. In this paper, the number of neurons in all reserve pools is set to 100.

(2) The biggest difference between the echo state network and the deep echo state network at the reserve pool layer is the state update mode of the reserve pool. The state update of the traditional ESN reserve pool is shown in Formula 1-7. W is the connection weight matrix of each neuron in the $N \times N$ reserve pool, F (•) is the activation function, and $y(n-1)$ is the network output value of the previous state. W_{back} is the feedback connection between neurons in the reserve pool and neurons in the output layer, which is an $N \times L$ matrix.

The reserve pool update mode of deep echo state network is formula 1-8.

$$\begin{aligned} \mathrm{x(n)} &= \mathrm{Wx(n-1) + f(W_{in}u(n))} \\ &\quad + \mathrm{W_{back}y(n-1)} \end{aligned} \tag{7}$$

$$\begin{aligned} \mathrm{x_l(n)} &= \mathrm{W^l x_l(n-1) + f(W_{in}^l z_l(n))} \\ &\quad + \mathrm{R_l x_l(n-1)} \end{aligned} \tag{8}$$

In Formula 1-9, the state of reserve pool at Layer L is $x_l(n)$. W_{in}^l is the input weight of the reserve pool at layer l. Setting W_{in}^l can represent the input weight outside the reserve pool and the input weight of the reserve pool. Therefore, W_{in}^l must meet formula 1-9. The weight of the reserve pool at layer L is W^l, $W^l \in R^{N_l\times N_l}$, where N_l is the number of neurons in the reserve pool.

$z(n)$ must meet formula 1-10, which is equal to 1 is the external input $u(n)$, and greater than 1 is the output of the reserve pool at the previous layer is the input of the next layer.

$$W_{in}^{l} \in \begin{cases} R^{N_l \times N_{l-1}} & l > 1 \\ R^{N_l \times Nu(n)} & l = 1 \end{cases} \quad (9)$$

$$z_l(n) = \begin{cases} x_{l-1}(n) & l > 1 \\ u(n) & l = 1 \end{cases} \quad (10)$$

The first layer on the reserve pool will l a status value $x_l(n)$, after reserve pool weighted sum with weighted input results, again after activation function to obtain a new status value, which will be the first reserve pool in l layer status updates, namely will $x_l(n)$ of the state after the operation to obtain new reserve pool $x_l(n+1)$. The updated weight of the reserve pool at layer l will be used as the input of the reserve pool at the next layer (l+1). After $W_{in}^{l+1} \in R^{N_l \times N_{l+1}}$, the previous state $x_{l+1}(n)$ of layer l+1 will be summed up with the received weighted value of the previous layer, and then it will enter the activation function processing. The status update of the reserve pool at layer L +1 is complete. Repeat until the state of the last reserve pool is updated. The reserve pool state of the last layer is $x_L(n) \in R^{N_L \times 1}$, where N_L is the number of neurons in the final layer of the deep echo state network, so the total number of neurons is $N = N_1 + N_2 + \cdots + N_L$.

The encoder layer is added before the reserve pool of the last layer, and the encoding process is formula 1-11 and 1-12, where $\mathcal{T}$ is the unsupervised dimension reduction tool of the decoder. $x_{enc}(n)$ is the encoding value, f_{enc} is the activation function of the encoder, and $W_{enc}x(n)$ is the encoding weight, which is used to encode the state information of the upper layer reserve pool. After the coding is completed, the coding result becomes the input of the last layer reserve pool, as shown in Formula 1-13.

$$x_{enc}(n) = \mathcal{T}(x(n)) \quad (11)$$

$$\mathcal{T}(x(n)) = f_{enc}(W_{enc}x(n)) \quad (12)$$

$$x_{in}(n+1) = x_{enc}(n) \quad (13)$$

The output weight calculation of the traditional deep echo state network is shown in Formula 1-15. In Formula 1-15, T is the supervised signal matrix, E^{-1} is the pseudo inverse of matrix E, which stores the state of the reserve pool at a certain time, and the supervised matrix T corresponds to the supervised signal at the same time in E.

$$W_{out} = E^{-1}T \quad (15)$$

Different from the output weight calculation of traditional deep echo state network, this paper only collects the state of the reserve pool at the last layer $x_L(n)$. The state collection of the reserve pool is shown in Formula 1-16, and the weight output formula is shown in Formula 1-17.

$$\hat{E}(n) = [x_L(n)] \quad (16)$$

$$\hat{W}_{out} = \hat{E}^{-1}T \quad (17)$$

(4) Prediction The improved deep echo state network only collects the state of the last layer of the reserve pool during prediction, and carries out prediction output based on the collected state, namely

$$y(n) = W_{out}[x_L(n)]^T \quad (18)$$

Figure 1-2 shows the structure of the improved deep echo state network.

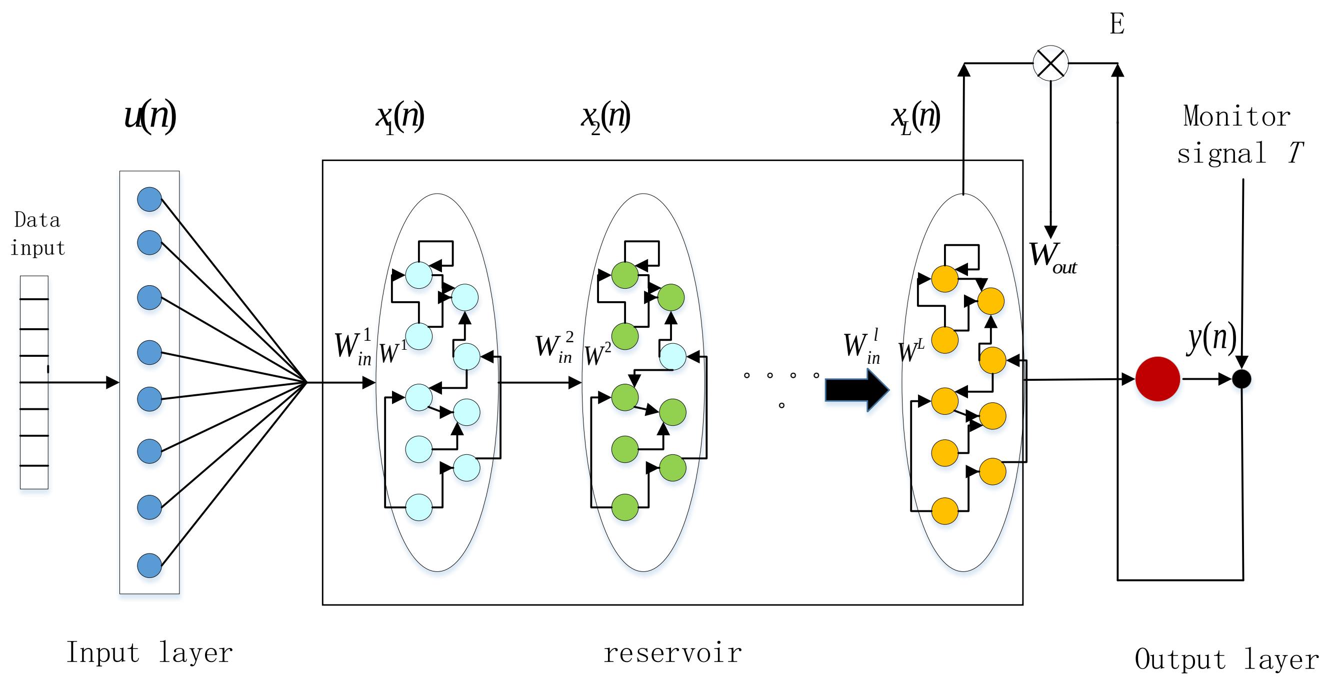

Figure 2-2 Improved deep echo state network structure

3. Experimental Part

3.1 Performance comparison of different ESN algorithms

This section compares the advantages and disadvantages of ESN, deep-ESN, and improved deep-ESN in electrostatic discharge signal detection. The data set was trained with 9 data pieces and tested with 1 data piece. Each piece of data has 2,600 sets of information. The results were obtained by means of single step training.

Single-step training refers to the input bit, output is its next bit, put in the training, prediction is to predict the next bit of the original data.

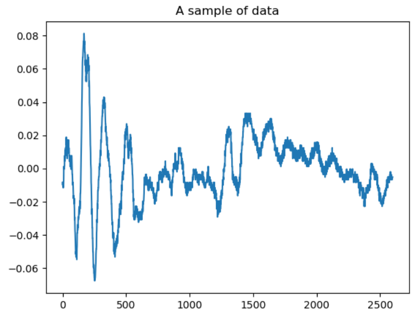

Fig.3-1 Single step data

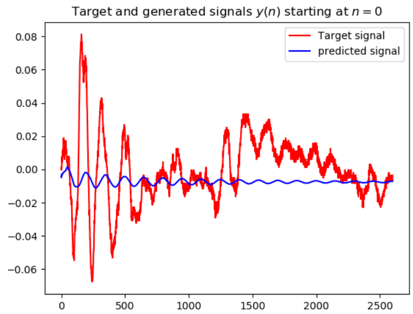

Fig. 3-2 ESN single step

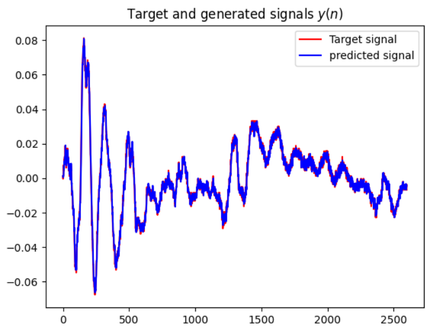

Fig.3-3 Deep-ESN Single Step

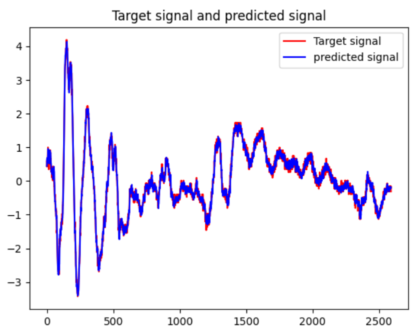

Fig.3-4 IDESN Single Step

The original test data is shown as 3-1. The final test results are obtained after training verification. Figure 2-2, 2-3 and 2-4 respectively show the test results of echo state network, deep echo state network and improved deep echo state network. Table 2-1 Results of single-step experiment

Table 3-1 Single step experiment results

Network name	MSE	Training Time(s)	Test Time (s)
ESN	0.00042237	0.4409597	0.090621
Deep-ESN	0.00000650	0.237620354	0.03556728
IDESN	0.00000507	2.79874349	0.52212644

Table 2-1 shows the MSE value, training time and verification time of the training results.

It can be seen that the improved echo state network has the best effect and the smallest error. Training time and training time are relatively long, but still in the acceptable range.

3.2 Comparison between the improved ESN and other network experiments

In this paper, three networks (CNN, GRU and LSTM respectively to achieve time series prediction) are compared with the improved deep echo state network. They are LSTM (Hochreiter et al. 1997), GATED cyclic unit (GRU)(Cho et al. 2014) and the combination of LSTM and convolutional Neural network (CNN)(Donahue et al. 2017). LSTM shows strong processing ability of time series in the field of prediction. According to Cho,et al., GRU is a new generation of recurrent neural network and can also be regarded as a variant of LSTM. In the literature (Donahue et al. 2017), the combination of LSTM and CNN can make the study of spatial and temporal features more complete.

The time series prediction algorithm used in this experiment comes from CNN, GRU and LSTM respectively. At the beginning, the data set used is a time series data set made by the author of the brief book. After modifying the code, it is changed to the electrostatic signal recognition data set required in this experiment: Table 2-2 shows the MSE value, training time and verification time of single-step training results.

Table 3-2 MSE value of single-step training results, time spent in training and time spent in verification

Network name	MSE	Training Time(s)	Test Time(s)
LSTM	0.00000897	183.103199	0.4346263
GRU	0.00001276	179.25335	0.4063620
LSTM&&CNN	0.00000884	128.517474	0.2683994
IDESN	0.00000507	2.79874349	0.52212644

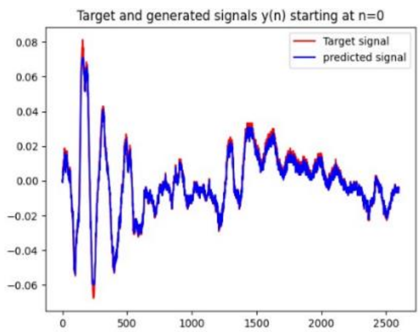

Fig.3-5 LSTM Single Step

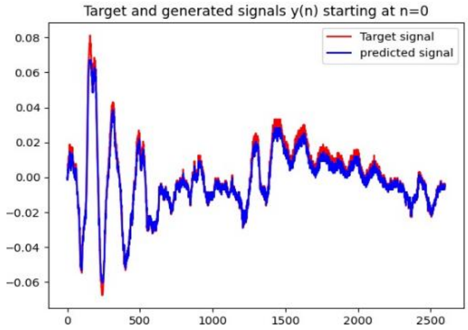

Fig.3-6 GRU Single Step

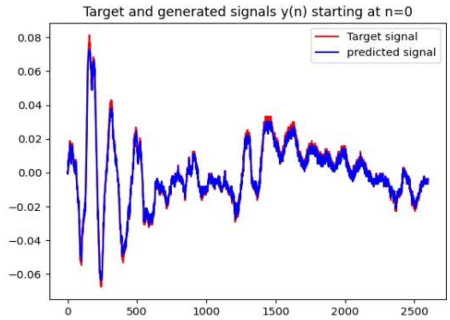

Fig.3-7 LSTM&&CNN Single Step

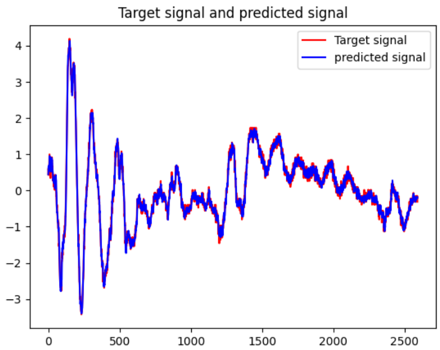

Fig.3-8 IDESN Single Step

After these comparative experiments, we can see that the best MSE value of the three networks suitable for time series recognition is 0.00000884, namely LSTM&&CNN, for the recognition of characteristic electrostatic discharge signals. However, compared with the improved deep echo state network, the error is larger.

3.3 Test the results of other data sets

After testing other data sets, it can be known that these networks are true and effective to the data set of this experiment. Only the trained data sets can be predicted, but not the untrained data sets. Table 2-3 lists the results.

Table 3-3 Results of 2600 groups of original test data and other data

Network name	original data MSE	Other data MSE
ESN	0.00037804	0.02506966
Deep-ESN	0.00004259	0.02095871
LSTM	0.00017752	0.02543872
GRU	0.00018129	0.02548696
LSTM&&CNN	0.00017880	0.02527457
IDESN	0.00002351	0.02280255

4. Conclusion

In this paper, the method of electrostatic discharge signal prediction is designed, which can effectively reduce the prediction error. It provides a feasible direction for electrostatic discharge signal prediction.

In this paper, an improved deep echo state network is proposed. The encoder added to the reserve pool of deep echo state network converts the high-dimensional mapping to the low-dimensional mapping, which makes the feature more prominent and reduces the computational complexity. The collection of state weights of reserve pools in deep echo state network is also modified. Experiments show that the improved network has good performance. However, certain problems were also found in the study. The echo state characteristic of echo state network is the key attribute for it to process nonlinear signal, but there is no strict theoretical basis for echo state characteristic, so the generalization ability of echo state network is limited. It is of great significance for the development of echo state network to explore the necessary and sufficient conditions of echo state characteristics.

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References

Liu Shanghe. Electrostatic Theory and Protection [M]. Electrostatic Theory and protection, 1999.

Liu SHOUbao, HUANG Fucheng, Yu Shifeng, et al. Study on overvoltage of UHV DC grounding line [J]. High Voltage Technology, 2018, 7): 2410-7.

Dong H Y, Zhang Y P, Dou J M, et al. Numerical analysis of fouling characteristics of wrist arm insulators of a new catenary system [J]. High Voltage Technology, 2019, 045(007): 2267-75.

Liu S H, ZHU L, WEI M, et al. Research on remote detection technology of corona discharge radiation signal [J]. High Voltage Technology, 2013, 12): 2845-51.

Liu Shanghe, DU Zhaoheng, HU Xiaofeng, et al. Electrostatic charging mechanism analysis and experimental study of aero-engine exhaust gas [J]. High Voltage Technology, 2014, 40(9): 2678-84.

Hu Xiaofeng, Zhang Jianping, Xu Bin. High Power Laser and Particle Beams, 2019, 031(010): 6-14.

Hu X F, Liu W D, Zhang Y, et al. Detection and localization of space discharge radiation pulse [J]. High Power Laser and Particle Beams, 2015, 27(10): 128-33.

Hu XIAO-feng, LIU Wei-dong, WANG Lei, et al. Time delay estimation method of generalized cross-correlation corona discharge radiation signal [J]. High Power Laser and Particle Beams, 2018, 30(001): 50-4.

Liu W D, Liu S H, HU X F, et al. An aperiodic weak local discharge power detection method based on cross-correlation information accumulation [J]. High Voltage Technology, 2017, 03): 966-72.

Zhou Xin, He Xiaoxin, Zheng Changwen. Radio Signal Recognition based on Image Deep Learning [J]. Communications Journal, 2019, 040(007): 114-25.

Ren HAI-peng, Yin Hui-ping, BAI Chao, et al. A Method for predicting future signals of wireless communication based on echo state network [M]. 2019.

Xiong Ming. Prediction algorithm of lower limb surface EMG signal based on ESN. Journal of Beijing Information Science and Technology University: Natural Science, 2020, 2): 15-20.

Peng Yu, Wang Jianmin, Peng Xiyuan. Research on time Series Prediction method based on echo state Network [J]. Acta Electronica Sinica, 2010, 38(B02): 148-54.

Yan Jinghua hou. Study on time Series Prediction of theft crime based on LSTM Network [J]. Data Analysis and Knowledge Discovery, 2020, V. 4; No.47(11): 88-95.

Shi GUorong, Dai Hongde, Dai Shaowu, et al. Time Series prediction based on long short-term memory network [J]. Instrument Technology, 2020, No.370(02): 28-30+3.

Respectively with CNN, GRU helped and LSTM implementation time series prediction [OL]. HTTP: / / https://www.jianshu.com/p/9133900e7e66.

HOCHREITER S, #XFC, SCHMIDHUBER R A. Long Short-Term Memory [J]. Neural Computation, 1997,

CHO K, MERRIENBOER B V, GULCEHRE C, et al. Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation [J]. Computer Science, 2014,

DONAHUE J, HENDRICKS L A, ROHRBACH M, et al. Long-term Recurrent Convolutional Networks for Visual Recognition and Description; proceedings of the IEEE Transactions on Pattern Analysis & Machine Intelligence, F, 2017 [C].

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