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Chaotic Time Series Prediction of Echo State Network Based on Memristor †

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Summary

In this paper, we proposed a new echo state network (ESN) model, namely echo state network based on memristor (memristor-ESN). It improve the memory function of the reservoir and the prediction performance of the ESN. In the memristor-ESN, memristor is used to replace the synapses between neurons in the reservoir of echo state network. In the prediction of chaotic time series, we compare the classical echo state network with the echo state network based on memristor. Simulations are conducted to verify the prediction accuracy and prediction performance of the memristor-ESN.

KEYWORDS:
neural network; echo state network; memristor; chaotic time series prediction

1 | INTRODUCTION

Artificial neural network (ANN) is a mathematical model based on the basic principle of neural network in biology. After understanding and abstracting the structure of human brain and the response mechanism of external stimuli, it simulates the processing mechanism of complex information of human brain's neural system on the basis of network topology knowledge[1]. Echo state network (ESN) is a kind of recurrent neural network, which was proposed by Jaeger et al.[2]. It includes learning and prediction process, and composed of input neuron, reservoir and output neuron.

The connection weights of neurons in the reservoir have memory effect on the data related to time[3,4,5]. In the existing researches, Cui et al. have widely discussed the structure of reservoir[6]. Han et al. and Bianchi et al. optimized the performance of echo state network from the point of view of reservoir calculation and dynamics[7]. Sun et al. proposed the deep belief echo state network, which embeds a regression layer into the learning mechanism of the network. It can significantly improve the short-term memory ability, but it deepens the complexity of the network[8]. When echo state network solves practical problems, because the reservoir of echo state network is randomly generated, it will still affect the memory performance and network prediction performance of reservoir[9,10,11,12,13]. Memristor is a kind of device with its own resistance state storage function[14]. Researchers have introduced the characteristics of memristor into the neural network model, and the existing studies have shown that the resistance memory characteristics of memristor are very similar to the synaptic function of neurons[15,16].

Based on the above analysis, in order to improve the memory function of the reservoir and the prediction performance of the ESN, we proposes a new echo state network model, namely echo state network based on memristor (memristor-ESN).

The remaining of this paper is given as follows. Section 2 gives the algorithm description of echo state network based on memristor. Section 3 setups numerical simulation experiment. Section 4 gives the numerical simulation experimental results. Section 5 gives the conclusions.

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2 | ALGORITHM DESCRIPTION OF ECHO STATE NETWORK BASED ON MEMRISTOR

In order to better describe the echo state network based on memristor, we first introduce the relevant knowledge of memristor model. Then, we introduce the model of echo state network based on memristor (memristor-ESN).

2.1 | Introduction of Memristor

According to the memristor model proposed by HP Laboratory (as shown in Figure 1)[17], we have

$$M = \frac{d\varphi}{dq}$$

Among them, $M$is the resistance of the memristor (also known as its memristor),φ is the magnetic flux, defined $\varphi(t) = \int_{-\infty}^{t} v(t)d(t)$ by the formula.

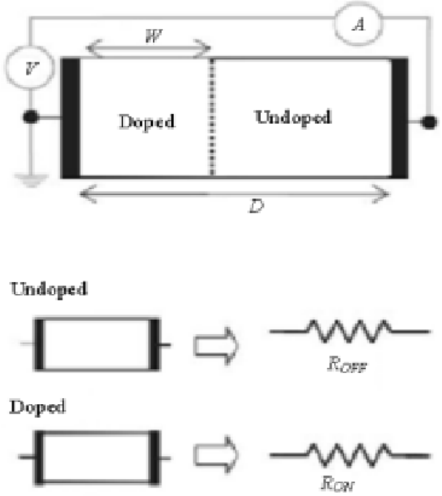

FIGURE 1 simplified circuit of memristor.

The relationship between voltage and current is as follows:

$$v(t) = (R_{ON}\frac{w(t)}{D} + R_{OFF}(1 - \frac{w(t)}{D}))i(t)$$

Where $\frac{w(t)}{D}$ is the equivalent state variable. In the memristor model proposed by HP lab, state variable $w(t)$ is a function of current $i(t)$, that is,$\frac{dw(t)}{dt} = \mu_v \frac{R_{ON}}{D} i(t)$. The relationship between charge q and magnetic flux $\varphi(t)$ is as follows:

$$\varphi(t) = R_{OFF}(q(t)(1 + \frac{w_0}{D}(\frac{R_{ON}}{R_{OFF}} - 1)) - \frac{\mu_v R_{ON}}{2D^2}(1 - \frac{R_{ON}}{R_{OFF}})q^2(t)) + \varphi_0$$

Therefore, the mathematical model of memristor is as follows:

$$M = \frac{d\varphi}{dq} = R_{OFF}((1 + \frac{w_0}{D}(\frac{R_{ON}}{R_{OFF}} - 1)) - \frac{\mu_v R_{ON}}{2D^2}(1 - \frac{R_{ON}}{R_{OFF}})q(t))$$

Memristor reflects the characteristics of hysteresis loop, which is similar to the characteristics of neurons in human brain, as shown in Fig. 2. It is pointed out that memristor bridge computer can realize the weights of 0, negative and positive synapses, which can be used to simulate the operation of synapses[17]. In the research of artificial neural network, when memristor is used to replace synapse, a neural network model based on memristor can be created. In this paper, we use a simplified memristor model, which has been used in many studies[18,19], as shown in Fig. 3.

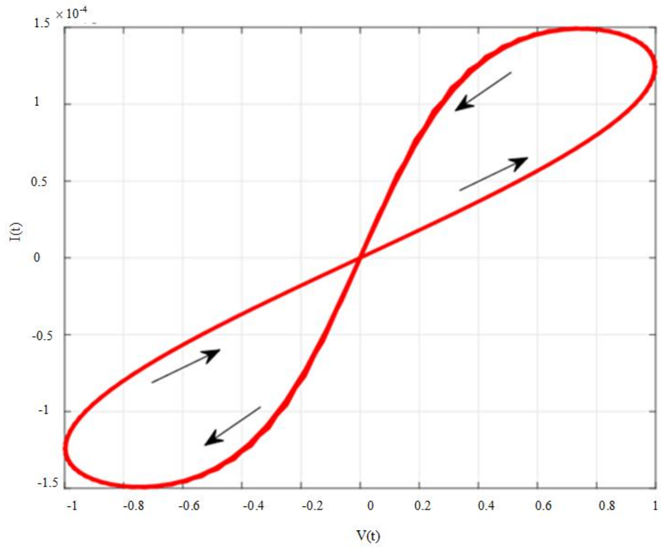

FIGURE 2 characteristic diagram of memristor

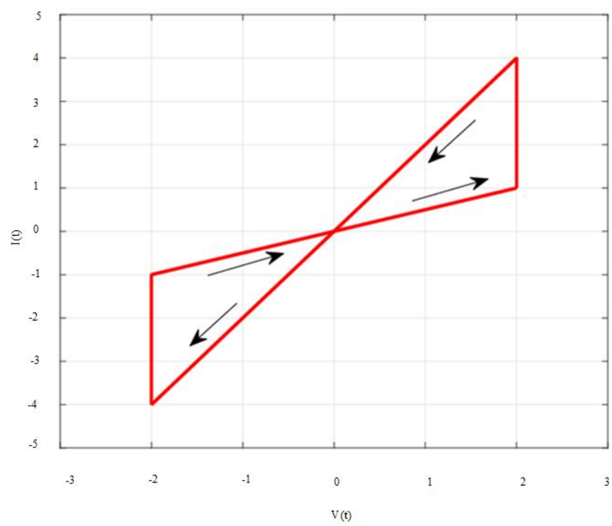

FIGURE 3 Simplified Memristor model

The simplified memristor mathematical model is as follows:

$$M_1(v(t)), |v(t)| \leq T$$
$$M_2(v(t)), |v(t)| > T \tag{1}$$

Where $M(v(t))$ is the memristor value, T is the switching jump, $M_1(v(t))$ and $M_2(v(t))$ is the bounded function.

2.2 | Model Framework

The core structure of echo state network is a reservoir which is randomly generated and remains unchanged. The reservoir contains a large number of sparsely connected neurons, which contains the running state of the system and has memory function. We improve the classical echo state network. As shown in Fig. 4, we use memristors to connect neurons in the reservoir. So memristors replace the synapses in the reservoir. Memristor has memory function. It has only one value at a certain time.

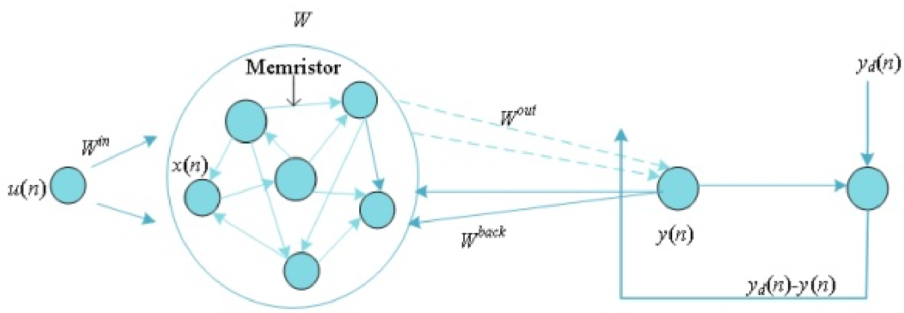

FIGURE 4 echo state network model based on memristor

Therefore, at a certain time, there is only one synaptic weight in the reservoir. We set the value range of synaptic weight in the reservoir as (0,1). At sampling time, the update equation and output equation of the echo state network based on memristor are as follows,

$$x(n+1) = tanh(W^{in}u(n+1) + Wx(n) + \upsilon(n)) \tag{2}$$

$$y(n+1) = W^{out}x(n+1) \tag{3}$$

Among them, the internal connection weight W is the $r \times r$ b-dimensional matrix, the input connection weight W^{in} is the $r \times k$ d-dimensional matrix, $\upsilon(n)$ is the noise vector, and the hyperbolic tangent (tanh) function is the activation function. Formula (3) is the output formula of single output network, and the connection weight W^{out} of output neurons is $l \times r$ b-dimensional matrix. W^{out} is adjusted by linear regression formula $W^{out} = y_d X^{-1}$. $y(n)$ is the output of the network, which is created by the internal neuron activation signal $x(n)$ and the trained W^{out} .

3 | NUMERICAL SIMULATION EXPERIMENT SETUP

3.1 | Numerical Simulation Experiment Data

The simulation tool is matlab software. In the prediction of classical chaotic time series, data sets are generated by two typical chaotic systems determined by differential equations. Two typical chaotic systems are Rössler system and Chen system. The following describes the related contents of the two chaotic systems and the initialization settings of the echo state network.

3.1.1 | Chen chaotic system

The equation of Chen chaotic system is presented as

$$\dot{z}_1 = a(z_2 - z_1)$$
$$\dot{z}_2 = (c - a)z_1 - z_1 z_3 + cz_2$$
$$\dot{z}_3 = z_1 z_2 - bz_3$$

where a, b and c are the parameters, and z_1, z_2, z_3 are the states of this system. When $a = 35$, $b = 3$, $c = 28$, this system is in a chaotic state. We select the parameter values of Chen chaotic system as $a = 35$, $b = 3$, $c = 28$ to simulate. We use the trajectory of the first coordinate z_1 for training and testing of ESN.

The method of network initialization is as follows: we create a random network with 1000 neurons which spectral radius is 1.7 and sparsity is 0.02. Gaussian white noise is 1×10^{-5} dBW.

3.1.2 | Rössler chaotic system

The equation of Rössler System is given as follows

$$\dot{z}_1 = -z_2 - z_3$$

$$\dot{z}_2 = z_1 + az_2$$
$$\dot{z}_3 = b - cz_3 + z_1 z_3$$

where a, b and c are the parameters, and z_1, z_2 and z_3 are the states of this system. When $a = 0.2$, $b = 0.2$ and $c = 5.7$, the Rössler system is in a chaotic state. We select the values of Rössler system parameters as $a = 0.2$, $b = 0.2$ and $c = 5.7$ to simulate. We use only the trajectory of the first coordinate z_1 for training and testing in ESN.

The method of network initialization is as follows: we create a random network with 1000 neurons which spectral radius is 1.6 and sparsity is 0.02. Gaussian white noise is 1×10^{-8} dBW .

3.2 | Evaluation Criteria

To predict the time series generated by chaotic system, there be error between the generated value and the actual value, which is called prediction error. A reasonable evaluation index can evaluate the prediction effect of the algorithm. In order to evaluate the prediction performance, we use normalized root mean square error (MRMSE) to measure the prediction accuracy.The mathematical description is as follows,

$$NRMSE = (\sum_{j=1}^{k}(d_j(8000) - y_j(8000))^2/k\sigma^2)^{1/2} \tag{4}$$

Where k is the length of the test sample. d_j and y_j are the actual test output and the expected output in the test phase respectively. And σ^2 is the variance of the expected output.

4 | MAIN RESULTS

This section discusses the experimental results of chaotic time series prediction based on memristor-ESN. By adjusting the parameters in the reservoir, the prediction results of memristor-ESN and classical ESN are compared from three aspects of prediction performance, NRMSE and parameter analysis.

4.1 | Analysis of Prediction Performance

We will analyze the prediction steps of classical echo state network and memristor-ESN for time series, and compare the prediction performance of the two algorithms.

4.1.1 | Time series generated by Chen system

Figure 5 shows the comparison between the classical echo state network prediction time series generated by Chen system and that generated by Chen system. The weights of the classical echo state network reservoir are generated randomly. The abscissa represents prediction steps, and the ordinate represents the predicted value. With "x" the marked red curve represents the prediction curve of classical echo state network to the time series generated by Chen system. The blue curve marked with "*" represents the curve of time series generated by Chen system. It can be seen from Fig. 5 that the first 15 steps of the classical echo state network prediction are consistent with the time series generated by Chen system, but prediction steps behind are not consistent with the time series generated by Chen system.

Figure 6 shows the comparison of the echo state network based on memristor to the time series generated by the Chen system when the weight of synapses in the reservoir is 0.6 or 0.4, compared with the time series generated by Chen system. Where the horizontal coordinates represent the predicting steps and the vertical coordinates represent the predicted values. With "x" the marked red curve represents a predictive curve of the time series generated by the Chen system based on the memristor-ESN when the weight of the synaptic connection in the reservoir is 0.6 or 0.4. The blue curve marked with "*" represents the curve of the time series generated by the Chen system. As can be seen in Fig. 6, the predicted values are almost identical in the range of 0 to 89 steps.Therefore, compared with the prediction effect of classical echo state network on time series generated by Chen system (Fig. 5), the memristor-ESN has a better prediction effect on time series generated by Chen system.

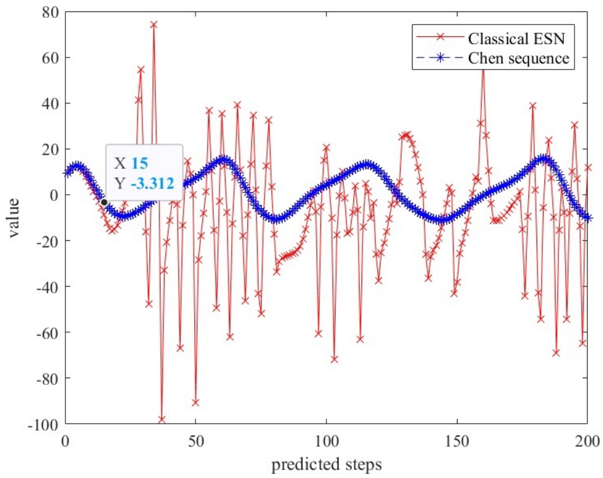

FIGURE 5 Time series curve generated by Chen system predicted by classical echo state network, in which the weights of synapses in the reservoir are randomly generated

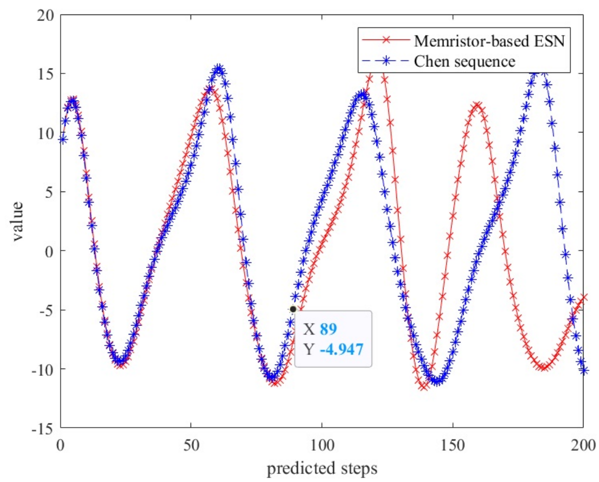

FIGURE 6 Time series curve generated by Chen system predicted by memristor-ESN, where the weight of synapses in the reservoir is 0.6 or 0.4

4.1.2 | Time series generated by Rössler system

Figure 7 shows the comparison between the time series generated by Rössler system predicted by classical ESN and that generated by Rössler system. The weights of classical ESN reservoir are randomly generated. The abscissa represents the number of prediction steps and the ordinate represents the predicted value. The red curve with "x" the mark represents the prediction curve of classical ESN to the time series generated by Rössler system, and the blue curve with "*" mark represents the time series curve generated by Rössler system. As can be seen from Fig. 7, in the range of 0 to 39 prediction steps, the values of the two lines are consistent.

Figure 8 shows the comparison between the time series generated by Rössler system and the time series predicted based on the memristor-ESN by Rossler system when the weight of synapses in the reservoir is 0.1 or 0.9. The abscissa represents the prediction steps and the ordinate represents the predicted value. The red curve with "x" the mark represents the prediction curve of the time series generated by Rössler system based on the memristor-ESN when the weight of synaptic connection in the reservoir is 0.1 or 0.9, and the blue curve with "*" mark represents the curve of the time series generated by Rössler system. As can be seen from Fig. 8, in the range of 0 to 165 prediction steps, the values of the two lines are consistent. Therefore, compared

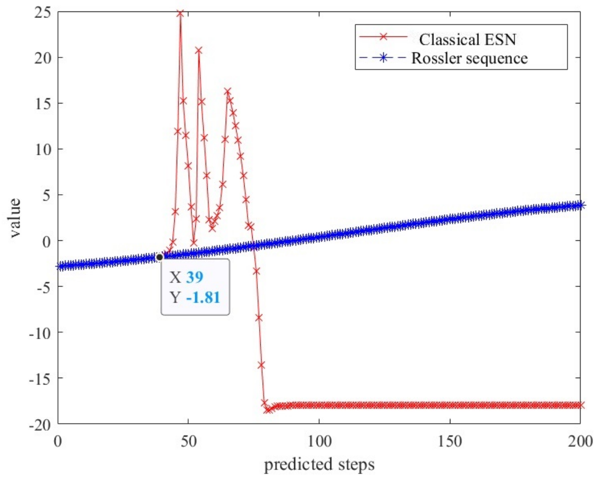

FIGURE 7 Time series generated by Rössler system predicted by classical echo state network, where the weights of synapses in the reservoir are randomly generated

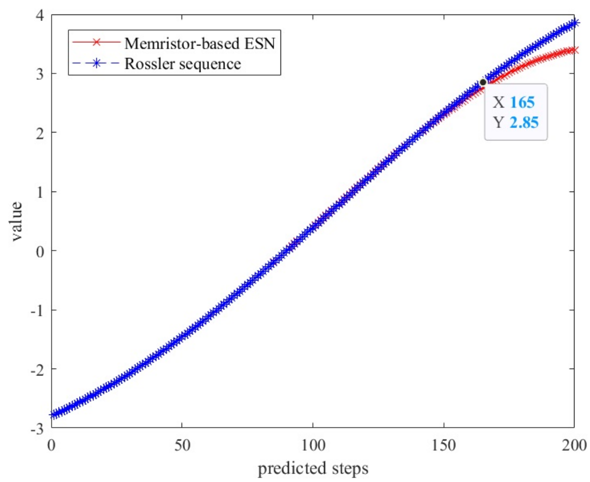

FIGURE 8 The graph predicts the time series generated based on the memristor-ESN by Rössler system, where the weight of synapses in the reservoir is 0.1 or 0.9

with the prediction effect of classical ESN on the time series generated by Rössler system (Fig. 7), the memristor-ESN has a better prediction effect on the time series generated by Rössler system. We analyze the prediction performance of classical ESN and memristor-ESN for time series, and compare the prediction results of the two networks. The experimental results show that the prediction performance of memristor-ESN is better than that of ESN in the time series generated by Chen system and Rössler system.

4.2 | Prediction Accuracy Analysis of NRMSE

We will analyze the relationship between each step of the classical ESN and the memristor-ESN prediction and its corresponding NRMSE in the time series generated by Chen system and Rössler system. We will compare the classical ESN with the memristor-ESN.

4.2.1 | Time series generated by Chen system

Figure 9 shows the relationship between each step of the classical ESN and the memristor-ESN prediction and its corresponding NRMSE. We compare the classical ESN with the memristor-ESN proposed in this paper, and intercept the first ten steps of the prediction results of the time series generated by Chen system. The synaptic weight of the memristor-ESN reservoir is 0.1 or 0.9, and the synaptic weight of the classical ESN reservoir is random. In Fig. 9, the abscissa represents the number of prediction steps (in this experiment, the first ten steps of the time series prediction results generated by Chen system are taken), and the ordinate represents the value of NRMSE corresponding to the first ten steps. The two lines in the figure are the contrast curves between the classical ESN and the memristor-ESN. The red curve marked with "o" indicates the relationship between each step of the classical ESN prediction and its corresponding NRMSE. The blue curve marked with "*" indicates the relationship between each step of prediction based on memristor-ESN and its corresponding NRMSE.

It can be seen from Fig. 9 that the red curve marked with "o" in the figure is higher than the blue curve, that is, the corresponding NRMSE of the classical ESN is larger than that of the memristor-ESN. Therefore, in the prediction of time series generated by Chen system, the prediction error of memristor-ESN is less than that of classical ESN, that is, the prediction performance of memristor-ESN is higher than that of classical ESN.

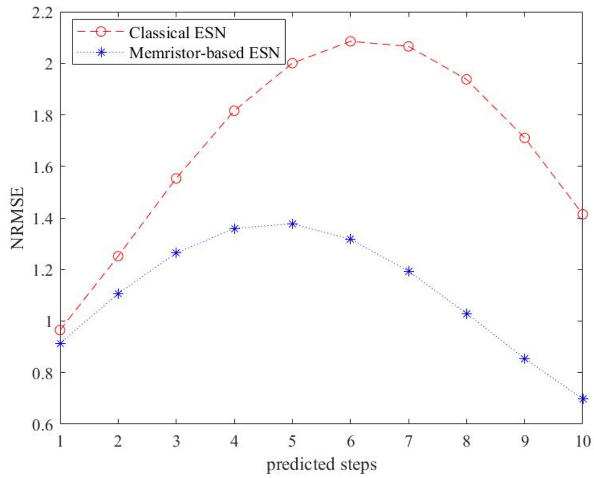

FIGURE 9 The time series generated by Chen system are predicted, and the relationship between each step predicted by classical ESN and memristor-ESN and its corresponding NRMSE is shown. The weight of synapses in memristor-ESN reservoir is 0.1 or 0.9.

4.2.2 | Time series generated by Rössler system

In Fig. 10, the abscissa represents the prediction steps (in this experiment, the first ten steps of the time series prediction results generated by Rössler system are taken), and the ordinate represents the NRMSE corresponding to each step of network prediction. The two lines in the figure are the contrast curves between the classical ESN and memristor-ESN. The red curve marked with "o" indicates the relationship between each step of the classical ESN prediction and its corresponding NRMSE . The blue curve marked with "*" indicates the relationship between each step of memristor-ESN prediction and its corresponding NRMSE.

Figure 10 shows the relationship between each step of the classical ESN and the memristor-ESN prediction proposed in this paper and its corresponding NRMSE. We compare the classical ESN with the memristor-ESN proposed in this paper, and intercept the first ten steps of the prediction results of the time series generated by Rössler system. The synaptic weight of the memristor-ESN reservoir is 0.4 or 0.6, and the synaptic weight of the classical ESN reservoir is random. It can be seen from Fig. 10 that the red curve marked with "o" is higher than the blue curve marked with "*", that is, the corresponding NRMSE of the classical ESN is larger than that of the memristor-ESN. Therefore, in the prediction of time series generated by Rössler system, the prediction error of memristor-ESN is less than that of classical ESN, that is, the prediction performance of memristor-ESN is higher than that of classical ESN.

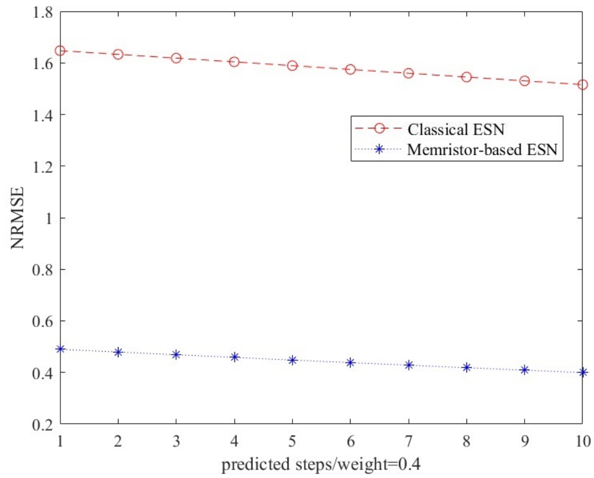

FIGURE 10 The time series generated by Rössler system are predicted, and the relationship between each step predicted by classical ESN and memristor-ESN and its corresponding NRMSE is shown. The weight of synapses in memristor-ESN reservoir is 0.4 or 0.6.

In the prediction of time series generated by Chen system and Rössler system by classical ESN and memristor-ESN, we analyze the relationship between each step of prediction and its corresponding NRMSE, and compare the classical ESN with memristor-ESN. The experimental results show that the prediction error of memristor-ESN is less than that of classical ESN, that is, the prediction accuracy of memristor-ESN is higher than that of classical ESN.

4.3 | Parameter Analysis

We will verify the relationship between the synaptic weights in the reservoir and NRMSE, and compare the classical ESN with the memristor-ESN. In the reservoir of classical ESN, the weights are randomly selected.

4.3.1 | Time series generated by Chen system

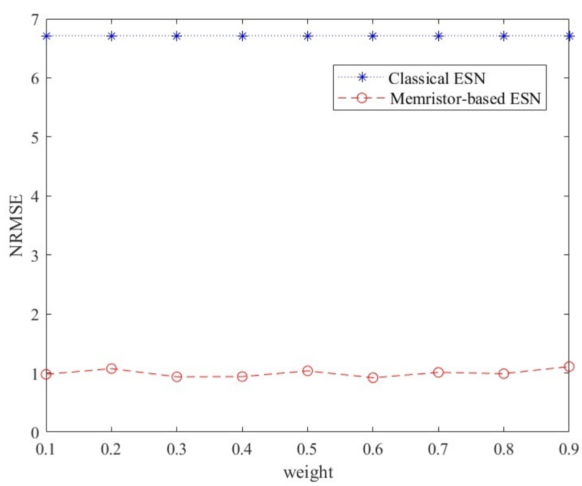

FIGURE 11 The relationship between synaptic weight of reservoir and NRMSE, when the classical ESN and the memristor-ESN predict the time series generated by Chen system

Figure 11 shows the relationship between the synaptic weights of the reservoir and NRMSE. The abscissa represents the weight, and the ordinate represents the NRMSE when the prediction steps is 200. The blue curve marked with "*" indicates the relationship between the weights in the reservoir of classical ESN and NRMSE (the weights in the reservoir of classical ESN are randomly generated) when predicting the time series generated by Chen system. The red curve marked with "o" indicates the relationship between the weights of memristor-ESN and NRMSE (the weights of reservoir are 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9 respectively) when predicting the time series generated by Chen system. It can be seen from Fig. 11 that the NRMSE corresponding to the memristor-ESN is smaller than that of the classical ESN. The experimental results in Fig. 11 show that the prediction error of the memristor-ESN is less than that of the classical ESN, and its prediction accuracy is higher than that of the classical ESN.

4.3.2 | Time series generated by Rössler system

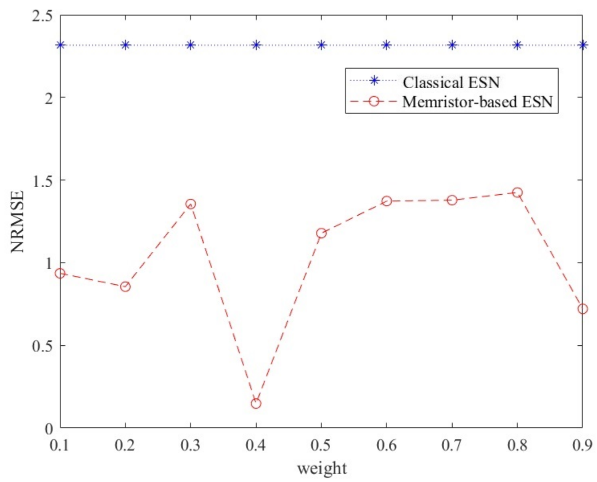

FIGURE 12 The relationship between synaptic weight of reservoir and NRMSE, when the classical ESN and the memristor-ESN predict the time series generated by Rössler system

Figure 12 shows the relationship between the synaptic weights and NRMSE of the reservoir of classical ESN and the memristor-ESN. The abscissa represents the weight, and the ordinate represents the NRMSE when the prediction steps is 200. The blue curve marked with "*" indicates the relationship between the weights in the reservoir of classical ESN and NRMSE (the weights in the reservoir of classical ESN are randomly generated) when predicting the time series generated by Rössler system. The red curve marked with "o" indicates the relationship between the weights of memristor-ESN and NRMSE (the weights of reservoir are 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9 respectively) when predicting the time series generated by Rössler system. It can be seen from Fig. 12 that the NRMSE corresponding to the memristor-ESN is smaller than that of the classical ESN. The experimental results in Fig. 12 show that the prediction error of the memristor-ESN is less than that of the classical ESN, and its prediction accuracy is higher than that of the classical ESN.

We analyze the relationship between the synaptic weights of reservoir and NRMSE, and compare the classical ESN with the memristor-ESN. The experimental results show that the prediction error of memristor-ESN is less than that of classical ESN in the prediction of time series generated by Chen system and Rössler system, that is, the prediction performance of memristor-ESN is higher than that of classical ESN.

5 | CONCLUSIONS

In this paper, memristor-ESN is proposed to solve the problem that the randomness of the reservoir of classical ESN affects the memory ability and prediction effect of the network. In this paper, memristor is used to replace the synapses in the reservoir of classical ESN, which further optimizes the structure of the reservoir and improves the memory ability of the connecting synapses in the reservoir and the prediction efficiency of the ESN. In this paper, memristor-ESN is applied to the prediction of chaotic time series. By adjusting the weights of synapses in the reservoir, the performance of memristor-ESN and classical ESN is compared from three aspects. First, we compare the prediction performance. Then, when the synaptic weights in the reservoir take different values, we intercept the first ten steps of the prediction results and analyze the relationship between the prediction steps and the corresponding NRMSE. Finally, we analyze the relationship between the synaptic weights in the reservoir and NRMSE. The experimental results show that the prediction error of memristor-ESN is less than that of classical ESN, that is, its prediction performance is higher than that of classical ESN.

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Author contributions

X. Mu and L. Li wrote the paper. H. Peng, S. Pan and S. Li modified the paper.

Conflict of interest

The authors declare no potential conflict of interests.

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