

Time Series Prediction Using Emotional Neural Networks

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Abstract— Time series forecasting is important in many fields including energy management, power market, and engineering. Therefore, it is vital to introduce new algorithms that can predict time series with high accuracy. Emotional networks have recently been introduced based on emotional processes occurring in the mammalian brain. They have shown desirable numerical properties such as fast response, simple structure, learning capability, and the ability to accurately approximate and address time and complexity issues. However, their use in time-series prediction is at the primary stages. Therefore, we are inspired to use emotional models in the time-series prediction problems. Specifically, we propose to use a continuous radial basis emotional neural network (CRBENN) for time-series prediction. The normal rules of the emotional brain are used to update the network weights and the gradient descent algorithm is used to update the radial basis parameters. The proposed method is compared with two neuro and fuzzy methods in three benchmark problems. The results show the lower prediction error of the proposed method.

Index Terms— Time-series prediction, emotional neural networks, radial basis function, gradient descent algorithm.

I. INTRODUCTION

Time-series prediction is the process of establishing models based on historical data and mining the dynamic characteristics of nonlinear systems to predict future values [1],[2]. It plays a crucial role in various fields such as economy, energy load forecasting, and disease outbreak prediction. Hence, introducing powerful algorithms with acceptable accuracy in the presence of uncertainties provides valuable insights for understanding and predicting real-world dynamic phenomena. Emotional neural networks (ENNs) are a new kind of neural network (NN) based on the emotional process in the mammalian brain [3]. They have shown desirable numerical properties such as fast response, simple structure, learning ability, and robustness to uncertainties [4]. However, there are only limited works on their employment in time-series prediction. Here, we aim to evaluate the performance of emotional models as time-series predictors and evaluate their applications in forecasting some standard benchmarks.

Fuzzy systems and neural networks have illustrated promising capabilities such as approximation property and learning ability. They are employed in various decision-making and control applications such as robot control [5]-[6], COVID-19 spread control [7], and forecasting traffic congestion on the roads [8]. Additionally, because of the excellent learning ability

and uncertainty-handling property of neural networks and fuzzy systems, they are employed in various time series prediction methods. For instance, in [9], a two-stage prediction model is introduced for multivariate time series prediction based on evolutionary fuzzy cognitive maps (FCMs) enhanced by genetic algorithms. In [10], the fuzzy wavelet neural network system is developed for time series prediction. In [2], a new time-series prediction method improves the traditional long-short-term memory (LSTM) recurrent neural network, which reduces the number of network parameters. In [11], a new embedding convolutional block attention module is introduced based on a temporal convolutional network. This network is used for the prediction of chaotic time series and shows more stable training and better parallelization compared with the LSTM network and hybrid Convolutional Neural Network-LSTM (CNN-LSTM). There are also other fuzzy/neuro-based time-series forecasting methods such as fast adaptive gradient RBF (GRBF) network [12], repetitive fuzzy systems [13], second-order Takagi Sugeno Kang (TSK) fuzzy systems using Adaptive Neuro-Fuzzy Inference System (ANFIS) [14], echo state networks (ESNs) [15]–[17], and fuzzy neural networks (FNN) [18].

According to LeDoux's argumentation, emotional stimuli such as fear can bring about quick reactions, usually when there is no chance for the rational mind to process the danger [19][20]. In the emotional nervous system of mammals, there are two types of excitatory and inhibitory mechanisms. The amygdala is responsible for stimulus learning and consists of several sensory nodes and a learning input. The orbitofrontal cortex (OFC) is responsible for the inhibitory task that controls the output. Inspired by this emotional nervous system, the Brain-Emotional Learning (BEL) model is proposed by Moren and Balkenius [21] as a class of computational intelligence models that mimic the structural and functional aspects of the emotional brain. This model consists of four main parts: the amygdala, the thalamus, the sensory cortex, and OFC. The additional connection from the thalamus to the amygdala was later omitted in [22] due to harsh simulation results and would interfere with normal learning.

The ENNs address the time and complexity issues associated with computational intelligence models such as neuro/fuzzy methods [23]. Hence, until now, emotional models have been widely used in many areas of control and decision-making, showing simplicity, a low computational burden, fast response to changes, and higher accuracy. For instance, they are

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employed for a predictive alert system [24], aerospace launch vehicles during atmospheric flight [25], controlling nonlinear systems [26], electrically heated micro-heat exchangers [27], and pattern recognition problems [28].

Different kinds of emotional neural networks are also suggested. For instance, in [29] a prototype-incorporated emotional neural network is introduced, which includes both the prototype- and adaptive-learning theories into a unified framework. In [30], a hybrid genetic algorithm-emotional artificial neural network (GA-EANN) is designed and applied in water quality index modeling. The method resulted in a higher performance compared with two competing approaches. In [31], a limbic-based artificial emotional neural network (LiAENN) is presented and demonstrates a higher accuracy than other applied emotional networks in pattern recognition problems, facial detection, and emotion recognition. Finally, the study in [32], presents a control system based on an evolutionary emotional neural network for active power filters to improve power quality.

Recently, few studies have used emotional models for time-series forecasting. In [33], the authors designed a winner-take-all emotional neural network (WTAENN) approach with universal approximation property. They use it for a wide variety of problems, including function approximation, face recognition, and time series problems. In [34], the authors present an emotionally inspired architecture for chaotic time series prediction that consists of one recurrent and two feed-forward adaptive neuro-fuzzy networks. This model is investigated to predict space storms. In [35], a network is introduced that uses the radial basis emotional neural network (RBENN) in [36] based on adaptive inertia weight comprehensive learning and particle swarm optimization algorithm. The model is then investigated in time series prediction and a real wastewater treatment system. In [37], the Neo-Fuzzy integrated Adaptive Decayed Brain Emotional Learning (NF-ADBEL) network is presented. This network is capable of predicting online time series with shorter update intervals and offers features such as fast learning, accuracy, simplicity, and less computational complexity.

Few of the works have investigated mathematical properties of the emotional models such as the universal approximation property and the continuity and differentiability of the network. For example, the approximation property is proved for WTAENN [25] based on a multi-layered perceptron. Also, the radial basis emotional neural network (RBENN) [28] follows the approximation property based on WTAENN. However, both WTAENN and RBENN have discrete outputs. In [4], the Continuous Radial Basis Emotional Neural Network (CRBENN) is designed, which approximates the characteristics of the Radial Basis Function Neural Networks (RBFNN). It also provides the continuity and differentiation of the output related to the network weights inherited from the RBFNNs.

Therefore, we aim to evaluate the emotional models' capabilities in prediction problems and propose to use the previously established CRBENN for time-series prediction. The weights of the amygdala and OFC are updated using the ordinary laws of emotional networks. The amygdala update

rules also include a forgetting factor. The parameters of the RBFs (centers and the standard deviation) are updated using the gradient-descent algorithm. The work is among the few studies that use emotional models for time-series forecasting. In particular, CRBENN has not yet been incorporated for time-series forecasting problems. The proposed method is evaluated on three time-series forecasting problems, and the results show lower prediction error compared to the two neuro and fuzzy approaches.

The rest of the paper is organized as follows: Section II introduces the preliminaries on CRBENN. Time-series prediction method using CRBENN is presented in Section III. Simulation results are provided in Section IV. Finally, conclusions are drawn in Section V.

II. THE STRUCTURE OF CRBENN

In this section, CRBENN is briefly described. The overall structure of CRBENN is shown in Fig. 1. As can be seen, CRBENN has four main subsystems: the thalamus, the amygdala, the sensory cortex, and OFC. The input first enters the thalamus, where the main functions are constructed, as follows:

$$\varphi_j = \exp\left(-\left[\frac{(x - \mu_j)^2}{\sigma_j^2}\right]\right), \quad j = 1, \dots, k \quad (1)$$

Where $\underline{x} \in \mathbb{R}^n$ is the input vector, σ_j and $\mu_j \in \mathbb{R}^n$ are the corresponding smoothing factor and mean of the j^{th} neuron, respectively, and $k \in \mathbb{N}$ denotes the total number of nodes.

The sensory cortex then receives vector input from the thalamus and distributes it into the amygdala and OFC. The outputs of the amygdala and OFC are calculated through the sensory cortex path as (2) and (3), respectively:

$$E_a = \sum_{j=1}^k v_j \varphi_j = \underline{v}^T \underline{\varphi}, \quad (2)$$

$$E_o = \sum_{j=1}^k w_j \varphi_j = \underline{w}^T \underline{\varphi}, \quad (3)$$

where v_j ($j = 1, \dots, k$) is the weight of the j^{th} node in the amygdala and w_j ($j = 1, \dots, k$) is the weight of the j^{th} node in OFC. The weight vectors are denoted as $\underline{v} = [v_1, v_2, \dots, v_k]^T \in \mathbb{R}^k$ and $\underline{w} = [w_1, w_2, \dots, w_k]^T \in \mathbb{R}^k$ and $\underline{\varphi} = [\varphi_1, \varphi_2, \dots, \varphi_k]^T \in \mathbb{R}^k$ is the vector of radial basis functions. As can be seen, in CRBENN the amygdala does not have the extra thalamic connection of RBENN in [28] and both the amygdala and OFC have the same number of nodes.

The output of CRBENN is calculated as follows:

$$E = E_a - E_o. \quad (4)$$

This subtraction implements the inhibitory task of OFC in preventing the inappropriate responses of the amygdala. Using (2) and (3), the output of CRBENN, is calculated as follows:

$$E = \sum_{j=1}^k v_j \varphi_j - \sum_{j=1}^k w_j \varphi_j = \sum_{j=1}^k (v_j - w_j) \varphi_j \quad (5)$$

$$= \underline{v}^T \underline{\varphi} - \underline{w}^T \underline{\varphi}.$$

Remark 1 [4]: CRBENN has the universal approximation property, which states that for a given $\varepsilon \in \mathbb{R}$ and a sufficiently large number k , any smooth nonlinear function $f(x): \mathbb{R}^n \rightarrow \mathbb{R}$ on the compact set $\Omega \in \mathbb{R}^n$, there exists the ideal CRBENN weights $\underline{v}^* \in \mathbb{R}^k$ and $\underline{w}^* \in \mathbb{R}^k$ such that:

$$f(x) = \underline{v}^{*T} \underline{\varphi} - \underline{w}^{*T} \underline{\varphi} + \varepsilon. \quad (6)$$

The universal approximation property of CRBENN is easily established using the similar property of RBF networks. This proof is not limited to a specific kernel function and includes any symmetric radial basis kernel that can be considered as a Thalamus node [4].

Remark 2: The CRBENN has some properties that distinguish it from the ordinary RBF networks. First, CRBENN has two paths from the input to the output. One is through the sensory cortex to the OFC and the other is through the amygdala. The amygdala indeed reacts to the input signal, while OFC, functioning as an inhibitor, eliminates the unsuitable portion of the response. The OFC exclusively processes mapped data and adjusts its weights in a manner akin to RBFNN. The situation differs for the Amygdala. There exists a limitation on the adaptation rules governing the weights of the amygdala, requiring them to remain non-decreasing. These differences lead CRBENN to have a higher level of accuracy compared to RBFNN as is stated for similar emotional networks in [31][23]. CRBENN also omits the extra connection from the thalamus to the amygdala because of the harsh results reported in [22] resulting in a continuous and differentiable output of CRBENN concerning the weights.

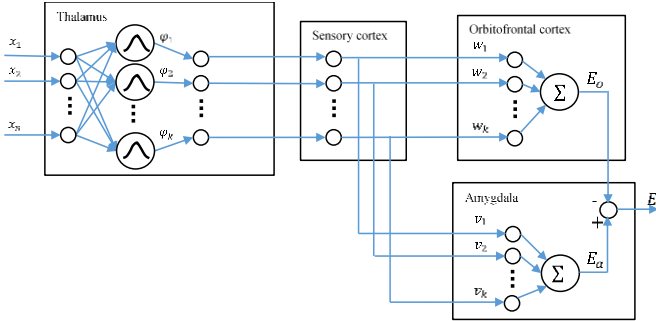


Fig. 1. The structure of CRBENN [4].

III. TIME-SERIES PREDICTION USING CRBENN

a. Preliminaries

A time series is a sequence of data points collected over successive time intervals. It represents the evolution of a variable or phenomenon over time.

Let $x(i)$ ($i = 1, 2, 3, \dots$) be the time series generated by the appropriate equation. Given $x(i - n + 1)$, $x(i - n + 2)$, \dots , $x(i)$, where n is a positive integer, the task is to determine a mapping from $[x(i - n + 1), x(i - n +$

$2), \dots, x(i)] \in \mathbb{R}^n$ to $[x(i + 1)] \in \mathbb{R}$. Therefore, the input vector to the emotional network can be represented as:

$$\underline{x} = [x(i - n + 1), x(i - n + 2), \dots, x(i)]^T. \quad (7)$$

b. Adaptive rules for CRBENN parameters

Here, the updated rules are made for CRBENN parameters. The first update rules of the emotional brain are used for the network weights (i.e., amygdala and OFC), and the gradient-descent algorithm is used for the RBFs parameter in the thalamus.

The updated rules of the amygdala also include a forgetting factor based on [30]. Hence, the learning rules for the amygdala and OFC weights are considered respectively as follows:

$$v_j(i + 1) = (1 - \gamma)v_j(i) + \alpha \max(x(i) - E_a(i), 0) \varphi_j, \quad (8)$$

$$j = 1, 2, \dots, k,$$

$$w_j(i + 1) = w_j(i) + \beta(E(i) - x(i)) \varphi_j, \quad (9)$$

$$j = 1, 2, \dots, k,$$

where α and β are the learning rates and γ is a small positive constant indicating the forgetting factor that happens in the amygdala [38]. The terms $E(i)$ and $x(i)$ represent the output of CRBENN and the desire value of time-series in the previous step, respectively. Note that in (7) the max operator causes the monotonic learning of the basic update rules of the emotional brain.

The gradient-descent algorithm also updates the mean and the standard deviation of the RBFs in (1). First, the error is defined as follows:

$$e(i) = \frac{1}{2}(E(i) - x(i))^2. \quad (10)$$

Using the chain rules in partial derivative, the update rules are attained as follows:

$$\mu_j(i + 1) = \mu_j(i) - \lambda_1(E(i) - x(i)) \left(v_j(i) - w_j(i) \right) \varphi_j \frac{2(x(i) - \mu_j(i))}{\sigma_j^2(i)}, \quad j = 1, 2, \dots, k, \quad (11)$$

$$\sigma_j(i + 1) = \sigma_j(i) - \lambda_2(E(i) - x(i)) \left(v_j(i) - w_j(i) \right) \varphi_j \frac{2(x(i) - \mu_j(i))^2}{\sigma_j^3(i)}, \quad j = 1, 2, \dots, k, \quad (12)$$

where λ_1 and λ_2 are the learning rates of the mean and smoothing factor, respectively.

IV. SIMULATION RESULTS

In this section, we evaluate the performance of the proposed method on three time-series forecasting problems: sinusoidal, Mackey–Glass, and Lorenz time series. The proposed method is compared with RBFNN-based and fuzzy-based methods. Similar to the proposed method, RBFNN and fuzzy parameters are updated using the gradient-descent algorithm. We use the Mean Squared Error (MSE) index as the measurement criterion, which is calculated as follows:

$$MSE = \frac{1}{N} \sum_{i=1}^N (T(i) - E(i))^2, \quad (13)$$

where N shows the number of samples. Also, T and E indicate the target value and predicted value of the network, respectively. For a fair comparison, all experiments are programmed in MATLAB R2013a by using a PC with Intel(R) Core(TM) i3-2330M CPU @ 2.20GHz and 10 GB RAM.

A. Example 1: a sinusoidal time-series example

In this example, the predictive capability of the proposed system is investigated by identifying the nonlinear dynamics system as follows:

$$y(i+1) = 0.3y(i) + 0.6y(i-1) + g[u(i)], \quad (14)$$

where the unknown function $g[u(i)]$ is defined as:

$$g(u) = 0.6 \sin(\pi u) + 0.3 \sin(3\pi u) + 0.1 \sin(5\pi u), \quad (15)$$

and u is defined as:

$$u(i) = \sin \frac{2\pi i}{200}. \quad (16)$$

For this example, we take 1000 data samples, 70% of which are used for the training and the remaining 30% for the testing. Also, $y(i)$ and $y(i-1)$ are used to predict the value $y(i+2)$. The parameters of CRBENN are set at $k = 10$, $\beta = 0.001$, $\gamma = 0.001$, $\alpha = 0.025$, $\lambda_1 = 0.06$, and $\lambda_2 = 0.001$. The initial values are $\underline{w}(0) = 0$, $\underline{v}(0) = 0$, and $\sigma_j(0) = 1$. Also, $\mu_j(0)$ is evenly spaced in $[0,1]$ for all the nodes. All the corresponding parameters of the fuzzy-based and RBFNN-based methods are set the same as CRBENN for a fair comparison. The number of fuzzy sets in each dimension is set to 3 so there are $3^2=9$ fuzzy rules.

The outputs of CRBENN and the competing methods for step 200 to step 1000 are shown in Fig. 2. It can be seen that CRBENN has better accuracy than the fuzzy and RBFNN-based methods. As shown by the absolute testing errors in Fig. 3, CRBENN has the lowest error. In addition, the MSE is presented in Table I, which shows the lowest training and testing errors of the proposed method.

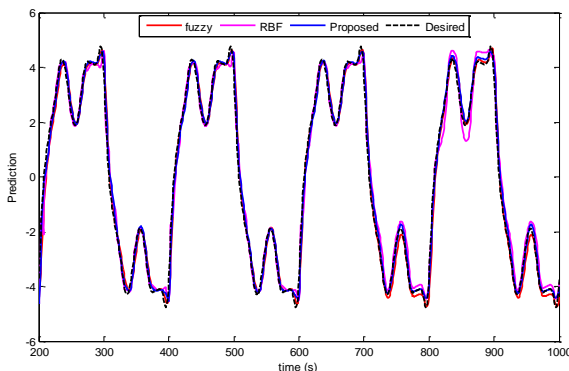


Fig. 2. (a) A sinusoidal time-series prediction

TABLE I
the Results of Mse for the Proposed Method and the Competing Approaches. Bold Numbers Show Better Performance.

Case \ Method	Fuzzy		RBF-based		Proposed (CRBENN)	
	train	test	train	test	train	test
Example 1	0.351	0.1013	0.3029	0.1787	0.2771	0.0686
Example 2	0.0213	0.002	0.009	0.0046	0.0076	8.96e-4
Example 3	2.69	1.244	1.650	1.874	1.462	0.945

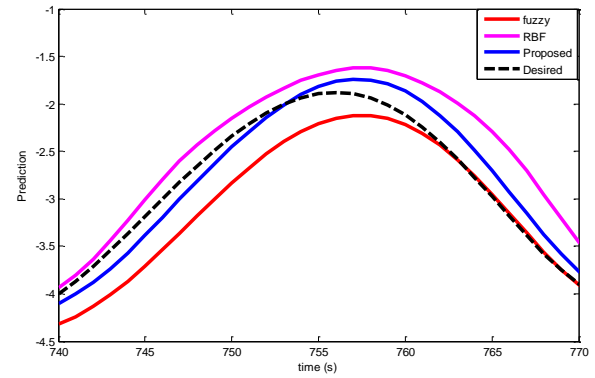


Fig. 2. (b) The zoom view of Fig. 2 (a)

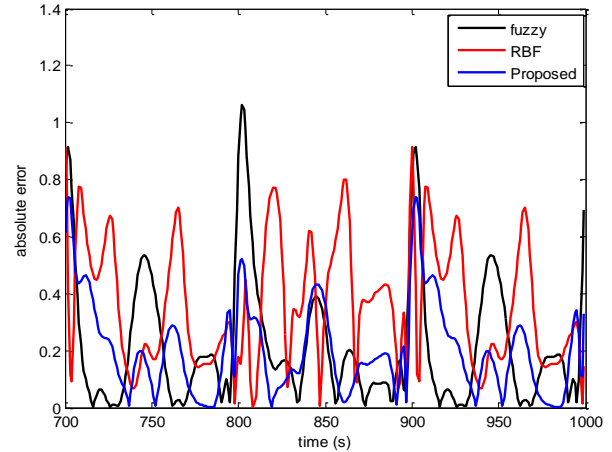


Fig. 3. The absolute error of the testing of the nonlinear dynamics system

B. Example 2: Mackey-glass time-series

One of the standard benchmark models to evaluate the performance of prediction algorithms is the Mackey-glass time series. The series can be defined as follows:

$$\frac{dx(t)}{dt} = \frac{ax(t-\tau)}{b+x^{10}(t-\tau)} - cx(t), \quad (17)$$

Where $a = 0.2$, $\tau = 20$, $b = 1$, and $c = 0.1$. When $\tau > 17$, the equation shows the chaotic behavior. In this experiment, $\tau = 20$ and the total number of data points generated is 1000. We used 70% of the data for the training and the remaining data for testing to validate the identified model. Here, $y(i)$ and $y(i-1)$ are used to predict the value of $y(i+2)$. The parameters of CRBENN are determined by trial and error to achieve the best

output for prediction. They are set at $k = 10$, $\beta = 0.0015$, $\gamma = 0.1$, $\alpha = 0.015$, $\lambda_1 = 0.02$, and $\lambda_2 = 0.025$. The initial conditions are $\underline{w}(0) = 0$, $\underline{v}(0) = 0$, and $\sigma_j(0) = 1$. The centers $\mu_j(0)$ are evenly spaced in $[0,1]$ for all the nodes. The fuzzy and RBFNN-based methods are constructed the same way with the same similar parameters. The fuzzy sets in each dimension are 3, hence there are $3^2=9$ fuzzy rules.

To demonstrate the prediction performance of CRBENN, the outputs of fuzzy test data, RBFNN, and the proposed method are compared and shown in Fig. 4. The absolute prediction error is also shown in Fig. 5. As can be seen, the proposed method has higher accuracy than the fuzzy-based and RBFNN-based methods. Moreover, the resulting MSE in Table I shows a higher test accuracy for the proposed methods.

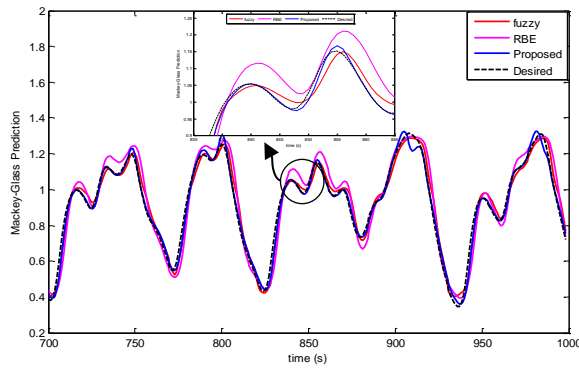


Fig. 4. Prediction of Mackey-Glass time-series

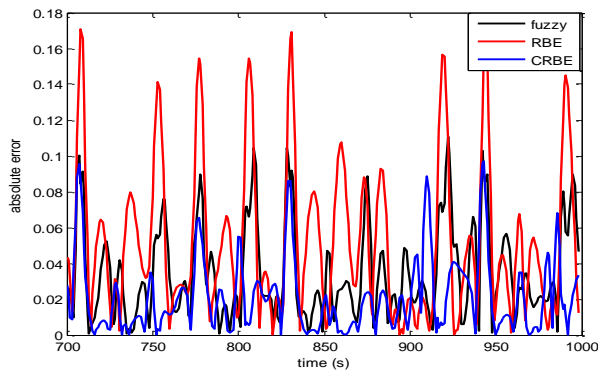


Fig. 5. The absolute error of the testing of the Mackey-Glass time-series

C. Example 3: Lorenz time-series

The Lorenz time series is generated by solving the following equations:

$$\begin{cases} \frac{dx}{dt} = a(-x(l) + y(l)) \\ \frac{dy}{dt} = bx(l) - x(l)z(l) - y(l). \\ \frac{dz}{dt} = -cz(l) + x(l)y(l) \end{cases} \quad (18)$$

The parameters are set to the standard values $a = 10$, $b = 28$, and $c = 8/3$. Solutions to this system of three differential equations exhibit a sensitive dependence on initial conditions, which is the characteristic of chaotic dynamics. The initial values are set to $x(1) = 3$, $y(1) = 2$, and $z(1) = 1$.

The parameters of CRBENN are determined by trial and

error to optimize the predicted output. Hence, the parameters are set at $k = 10$, $\beta = 0.001$, $\gamma = 0.0075$, $\alpha = 0.025$, $\lambda_1 = 0.1$, and $\lambda_2 = 0.005$. The initial values are $\underline{w}(0) = 0$, $\underline{v}(0) = 0$, and $\sigma_j(0) = 1$. The centers $\mu_j(0)$ are evenly spaced in $[0,1]$ for all the nodes. The number of data samples for this prediction is 1000. Here, $y(i)$ and $y(i - 1)$ are used to predict the value $y(i + 2)$. The data is split into two parts: 700 points are used for training and the remaining 300 for assessing the generalization capability of the network. For a fair comparison, all the parameters of all methods are chosen the same. There are 3 fuzzy sets in each dimension with $3^2=9$ fuzzy rules.

The test data results in Fig. 6 show that CRBENN is more accurate than other methods. As shown in Fig. 7, the absolute test error of CRBENN is lower than that of competing approaches. Due to the many errors in the initial steps of the training, for a better comparison, the training errors for computing MSE in Table I are calculated from step 200 to step 700. In addition, based on the data in Table I, CRBENN shows the lowest errors in training and testing compared to the other methods. This suggests that CRBENN may provide more accurate and reliable forecasts when applied to time series prediction problems.

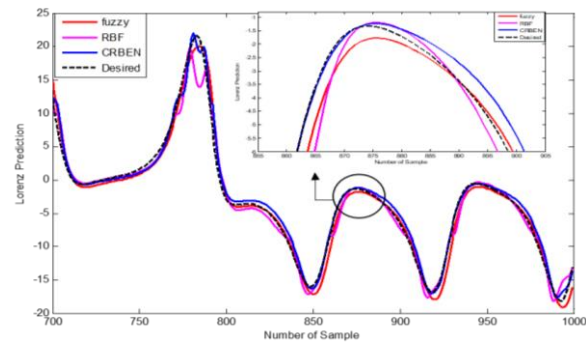


Fig. 6. Prediction of the Lorenz time series.

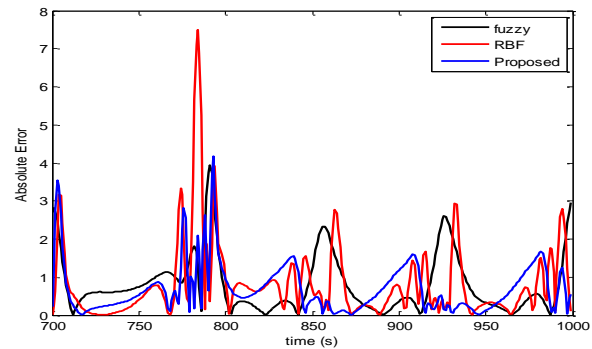


Fig. 7. The absolute error of the testing of Lorenz time-series

V. CONCLUSION

With the emergence of the information age and a large volume of data, the use of new methods to predict and analyze data is more important than before. Time-series forecasting plays a fundamental role in various real-world engineering applications. The promising features of emotional models, such as fast response, simple structure, and the ability to accurately approximate and address time and complexity issues inspired us to utilize the emotional neural networks in time-series

prediction problems. Hence, we use CRBENN for time-series prediction. Network weights are updated using the basic emotion laws. The RBF parameters in the thalamus are updated using the gradient descent algorithm. Then, the proposed method is evaluated on the prediction of three time-series problems and shows lesser training and testing errors compared to the two fuzzy and neuro approaches. However, the number of nodes in the network is fixed and must be determined through trial and error, which can affect the network's performance. Therefore, we hope that appropriate methods such as self-organizing structures to select the appropriate number of nodes for the network will be investigated in future works.

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