RBF Network-Based Chaotic Time Series Predictionand Its Application in IRAN stock market

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Abstract: The stock market is a chaotic dynamic system. We apply the RBF network-based chaotic time series prediction on the stock market exchange rate in Iran. We apply the RBF network and phase space reconstruction to find the optimal embedding dimension in the Iran stock market from the point view of forecasting. We find that the optimal embedding dimension is 10. Finally, we use the optimal embedding dimension to implement the prediction.
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Introduction

A chaotic system is a relatively complex behaviorthrough the deterministic dynamics of nonlinearsystems. Deterministic laws make the orbits of the system attracted to a complex higher-dimensional subset called a strange attractor. The chaotic system is sensitivity to initial conditions; points that are arbitrarily close initially become exponentially further apart with increasing time, leading to the amplification of very small perturbations into global uncertainties. As a result it is not possible to make accurate long termpredictions. The importance of studying chaoticbehavior lies in the fact that chaotic behavior is much more widespread, and may even be the norm in the real world. Scheindman and Lebaron, Frank and Stengos found the chaotic behavior in financial market such as stock market, foreign exchange markets and futures market [1]-[2]. Chaotic time series prediction becomes an extremely important research area and obtains widespread application [3]-[4]. The phase space reconstruction and embedding theorem proposed by Takens supply the theory foundation for nonlinear time series prediction [5]. In the phase space reconstructed artificial neural networks can deal with the mapping relations between the current situation and future situation to implement the chaotic time series prediction.BP (back propagation) neural network is universally applied in nonlinear prediction. Since BP neural network encounters local minimum, slow convergence speed and convergence instability, the shortcomings should be overcome by application of other new method. Radial basis function network is a special type of feed-forward neural network. It has received considerable attention recently due to its universal approximation properties and simple parameter estimation in the field of interpolation regression and classification [6]-[7]. Due to its nonlinear approximation properties, RBF network is able to fit the training data in multidimensional space. As a direct consequence, RBF's properties made them attractive for complex prediction in nonlinear dynamics systems of financial market [8]. In this paper we will apply the RBF networkbased chaotic time series prediction to the Iran Stock market in Iran The paper is structured as follows: in section 2 we describe the method of chaotic time series prediction based on RBF network. In section 3 we apply the method to the foreign exchange market, and obtain the optimal embedding dimension in China exchange market. Section 4 gives the conclusion.

2. Radial basis function networks

The architecture of RBF network is simple and consists of one hidden layer. The hidden layer is composed of a number of kernel nodes with kernel activation functions. The output of network is simply a weighted linear summation of the kernel functions as

$$f(x) = \sum j = 1 M W_i \cdot K_i(x) = \sum i \;\; = 1 M W_i \cdot \psi(\|x - C_i\|) \qquad (1)$$

Where $x \in R^n$ is the input vector, M is the number of kernel nodes in the hidden layer, w_i ($1 \leq i \leq$ M) is the vector of weights from the i the kernel node to the output nodes$\|.\|$ is the Euclidean distance, and k is a radial symmetric kernel function. A Gaussian function, ψ, is normally chosen as kernel function. The vectors C_i represent the locations of the kernel functions in R^n. The RBF models can be considered as a particular case of the state-dependent deterministic models with the property combining both global and local modeling capabilities [1] as follows:

$$x_{t+1} = \sum i = 1MW_i \cdot X_i(x_t) = \sum i = 1MW_i \cdot \psi(\|x_t - C_i\|) \quad (2)$$

Where $x_t=(x_t,\ldots,x_{t-m+1})$ denotes the state vector at time t and represents a state of the system which may be thought of as a point in phase space and m is the embedding dimension of the embedding space. It can be seen that the RBFs establish a partition of the embedding space into regions in each of which it is possible to approximate the dynamics with a kernel function. The number of regions corresponds to the number of the hidden nodes in the RBF network. The vectors ci represent the locations of the kernel functions in the state space. The w_i expansion coefficients define the contribution of each kernel function to the global dynamics.

When we deal with observable from a dynamical system, the measured time series can be embedded in an m-dimensional state space using Takens' time-delay method [8] where m is the embedding dimension of the embedding space. Takens [4] proved that for the time series x_t, there is a smooth map $f: R^m \rightarrow R^n$, such that $x_{t+1}=f(x_t)$ under the condition $m \geq 2n+1$, where n is the dimension of the manifold containing the underlying attractor. However, Takens' embedding theorem does not provide a constructive method for determining f. From the universal approximation capability of the RBF network, it follows that a neural network can be constructed to approximate f to any degree of accuracy.

3. Chaotic time series prediction

If we find the embedding dimension$m$, according to the method of phase space reconstruction, we can reconstruct an m-dimensional phase space from the time series $\{p_i\}$.Let the vector of the phase space marked as $P_{(t)}=(P_t, P_{t-\tau}, P_{t-2\tau}, \ldots, P_{t-(m-1)\tau})$. And there exists a smooth function F: $R^m \rightarrow R^m$, satisfying F $(P_t) = P_{t+1}$.We can infer from F a function f: $R^m \rightarrow R$, satisfying $P_{t+1}= f(P_t)$. As a result choosing the embedding dimension m is very important, with which we can predict P_{t+1} from the history data. Takens considered that the sufficient condition for embedding dimension is m>=2d+1. However, too large embedding dimension needs more observations and complex computation. If m is too large, chaotic data add redundancy and degrade the performance of many algorithms. It is more difficult to separate the deterministic system from the signal noises in observations [10]. As a result if the original attractor has dimension d, then an embedding dimension of m=2d+1 will be adequate for reconstructing the attractor. We apply RBF network to find the optimal embedding dimension. We construct a RBF network to fit the nonlinear function f^, which can approximate $f_{\text{precisely}}$. Take $P_{t+1}=(P_t, P_{t-\tau}, P_{t-2\tau}, \ldots, P_{t-(m-1)\tau})+\varepsilon_t$. Through the training of the network with the sample, we can obtain different ε with different dimension m. The noise ε will diminish with m increases. Then we can obtain the optimal m when ε_t is minimal.

4. Application to chaotic time series prediction

In this section, the performance of the proposed scheme is given for predicting the chaotic time series that have appeared in the literature. The normalized mean-square error (NMSE) is used as a performance index for measuring the quality of prediction and is the root mean square error divided by the standard deviation of the time series. The exponentially recursive least-square (RLS) algorithm [13] is employed to estimate the contribution of each kernel function to the global dynamics (i.e., w_i). The exponential weighting factor is assigned value 1. To start the recursion of the RLS algorithm, the weight vector is set to the null vector and the initial value of the correlation matrix is assigned to have $1.0\times10{-}9I$ where I is the identity matrix.

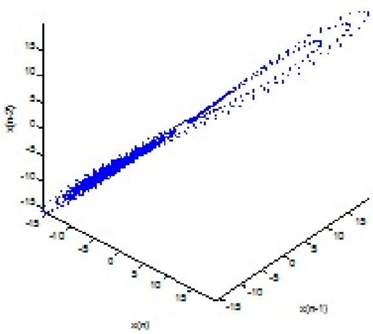
5. The Lorenz Attractor—chaotic time series

In this section, the feasibility of the proposed scheme is examined through modeling and predicting the Lorenz Attractor

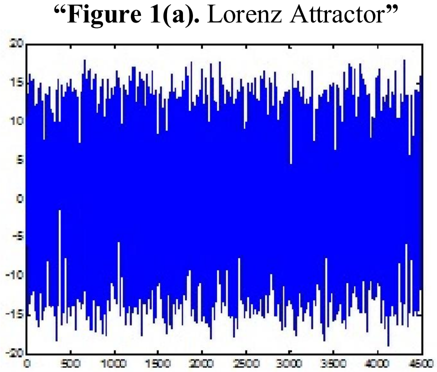
$$\frac{dx(t)}{dt} = -\sigma_L x(t) + \sigma_L y(t)$$
$$\frac{dy(t)}{dt} = r_L x(t) - y(t) + x(t)z(t)$$
$$\frac{dz(t)}{dt} = -b_L z(t) + x(t)y(t)$$

In [14], the RBF network was employed to approximate the Lorenz Attractor. They used the k-means algorithm for the purpose of center selection, the heuristic P-nearest neighbor for determining of smoothing factor, and the least-mean-square (LMS) for computing the weights of kernel functions. The 1000 data points were used for training and 500 points for testing. They reported achieving an error rate of 0.27% with six Gaussian units. In [10], a sequential approximation algorithm for generating the RBF network has been proposed and the performance of the proposed algorithm has been shown on predicting the Lorenz Attractor. They reported an error rate as low as 0.111% with seven Gaussian units, 100 training samples, and 500 testing points. A recurrent perceptron structure has been employed to model the Lorenz Attractor [8]. In this work, the perception refers to a recursive adaptive filter with an arbitrary output function. The objective function is similar to Akaike's minimum information theoretical criterion estimate. They reported a NMSE as low as 0.32% for 100 samples. Moreover, their investigations showed that an error rate as low as 0.15% can be found by a single hidden layer feed-forward network with 15 hidden units using backpropagation learning algorithm.

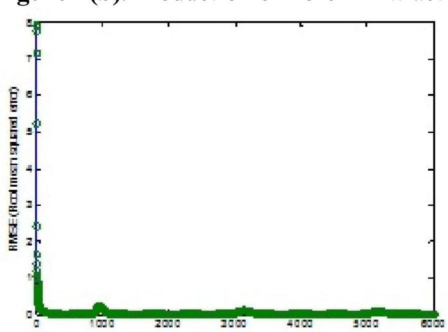
In this work, the 1000 data points of the Lorenz Attractor are used for scaling the attractor and estimating the expansion coefficient (i.e., w_i) and subsequent 1000 data points used for testing. Fig. 1(a) shows the Lorenz attractor. Fig. 1(b) shows 4000 samples product from Lorenz Attractor. In this work, the embedding dimension is chosen to have the value 2. The number of kernel neurons is obtained by specifying the scaling parameter over the scaling region. Fig. 1(c) present RMSE‘s result from prediction of Lorenz attractor.



“Figure 1(a). Lorenz Attractor”



“Figure 1(b). Production of Lorenz Attractor”



“Figure 1(c). RMSE from prediction of Lorenz Attractor”

6. Prediction of Euro & pound and Mark than RIAL

The foreign exchange market is the largest and most liquid of the financial markets. Foreign exchange rates are amongst the most important economic indices in the international monetary markets. The forecasting of them poses many theoretical and experimental challenges.Foreign exchange rates are affected by many highly correlated economic, political and even psychological factors. The interaction of these factors is in a very complex fashion. Therefore, to forecast the changes of foreign exchange rates is generally very difficult. Researchers and practitioners have been striving for an explanation of the movement of exchange rates. Thus, various kinds of forecasting methods have been developed by many researchers and experts. Technical and fundamental analyses are the basic and major forecasting methodologies which are in popular use in financial forecasting. Like many other economic time series, Forex has its own trend, cycle, season, and irregularity. Thus to identify, model, extrapolate and recombine these patterns and to give Forex forecasting is the major challenge. We apply the chaotic time series prediction based on RBF network to the foreign exchange market in IRAN.We take the IRAN Rial as basic exchange rate. In the following empirical studies, we use the daily rate from 2000 to 2008. We take two steps.

In the first step, we apply the RBF network and phase space reconstruction to find the optimal embedding dimension. In the second step, we use the optimal embedding dimension to implement the prediction.Table(1) shows pound prediction for MSE, RMSE, MAE,MAPE and AVE DIR for 1,2,3,4 days ahead

6.1.Euro prediction

In this section, we will predict Euro exchange market than Rial. Fig(2) shows prediction for 4days ahead. Table(1) shows prediction for MSE,RMSE, MAE,MAPE and AVE DIR for 1,2,3,4 days ahead

Figure 2. Prediction for 4days ahead with RBF network for Euro”

Table 1: Prediction for 1,2,3,4 days for Euro

	RBF						
	win	Step	MSE	RMSE	MAE	MAPE	Ave DIR
Euro	3	1	7.84e-006	0.0028	0.0019	0.2767	76.4331
Euro	3	2	2.24e-005	0.0047	0.0033	0.4795	71.9745
Euro	3	3	4.00e-005	0.0063	0.0046	0.6665	70.4883
Euro	3	4	5.97e-005	0.0077	0.0060	0.8625	70.4883
Euro	4	1	9.59e-006	0.0031	0.0022	0.3131	76.4331
Euro	4	2	2.74e-005	0.0052	0.0037	0.5342	71.5499
Euro	4	3	4.86e-005	0.0070	0.0053	0.7677	70.4883
Euro	4	4	7.44e-005	0.0086	0.0068	0.9830	70.2760
Euro	5	1	1.17e-005	0.0034	0.0024	0.3479	76.2208
Euro	5	2	3.26e-005	0.0057	0.0042	0.6013	71.7622
Euro	5	3	5.85e-005	0.0077	0.0060	0.8627	69.4268
Euro	5	4	9.18e-005	0.0096	0.0076	1.0965	69.8514

6.2.Pound prediction

In this section, we will predict pound exchange market than Rial. Fig(3) shows prediction for 4days ahead. Table(2) shows prediction for MSE,RMSE, MAE,MAPE and AVE DIR for 1,2,3,4 days ahead for pound.

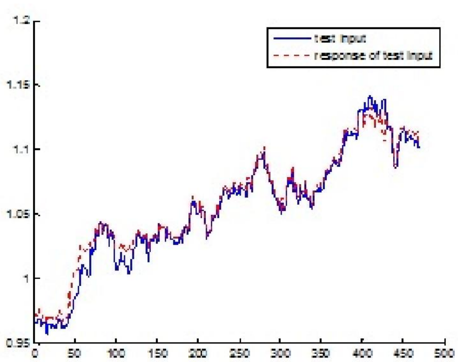


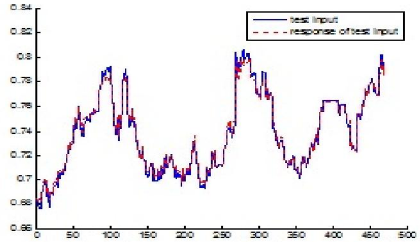
Figure 3. Prediction for 4days ahead with RBF network for pound"

Table 2: Prediction for 1,2,3,4 days for pound

	RBF						
	win	Step	MSE	RMSE	MAE	MAPE	Ave DIR
Pound	3	1	7.68e-006	0.0028	0.0017	0.16	72.82
Pound	3	2	1.88e-005	0.0043	0.0029	0.27	71.33
Pound	3	3	3.30e-005	0.0057	0.0039	0.37	72.61
Pound	3	4	5.36e-005	0.0073	0.0052	0.49	72.61
Pound	4	1	8.89e-006	0.0030	0.0018	0.17	71.54
Pound	4	2	2.28e-005	0.0048	0.0031	0.30	73.24
Pound	4	3	4.58e-005	0.0068	0.0046	0.43	72.82
Pound	4	4	7.01e-005	0.0084	0.0061	0.58	71.12
Pound	5	1	1.07e-005	0.0033	0.0020	0.19	70.06
Pound	5	2	2.88e-005	0.0054	0.0035	0.33	72.61
Pound	5	3	5.64e-005	0.0075	0.0052	0.50	72.18
Pound	5	4	8.81e-005	0.0094	0.0070	0.67	71.33

6.3.Mark prediction

In this section, we will predict Mark exchange market than Rial. Fig(4) shows prediction for 4days ahead. Table(3) shows prediction for MSE,RMSE, MAE,MAPE and AVE DIR for 1,2,3,4 days ahead for mark.



"**Figure 4.** Prediction for 1days ahead with RBF network for mark"

Table 3: Prediction for 1,2,3,4 days for mark

	RBF						
	win	Step	MSE	RMSE	MAE	MAPE	Ave DIR
Mark	3	1	8.53e-006	0.0029	0.0022	0.29	70.27
Mark	3	2	3.65e-005	0.0060	0.0045	0.60	67.30
Mark	3	3	8.16e-005	0.0090	0.0070	0.93	66.24
Mark	3	4	1.34e-004	0.0116	0.0095	1.27	62.20
Mark	4	1	1.19e-005	0.0035	0.0025	0.34	70.27
Mark	4	2	4.94e-005	0.0070	0.0053	0.70	66.24
Mark	4	3	1.04e-004	0.0102	0.0082	1.10	63.69
Mark	4	4	1.63e-004	0.0128	0.0109	1.46	59.66
Mark	5	1	1.60e-005	0.0040	0.0029	0.39	68.78
Mark	5	2	6.35e-005	0.0080	0.0061	0.81	66.02
Mark	5	3	1.27e-004	0.0113	0.0093	1.25	61.57
Mark	5	4	1.93e-004	0.0139	0.0124	1.66	58.59

7. Conclusion

Progresses in calculation tools in recent decades have provided us with the possibility of utilizing theories based on existence of certain or chaotic non-linear patterns. Chaotic theory with more through study of specifications of complicated behavior and data that seem to be random, tryto recognize order and pattern governing them and use them for predictability future trend in short term. Nowadays this knowledge with the help of data behavior analysis has provided the base of structural changes in future performance prediction. In this article with reviewing the concepts of this theory and testing for knowing chaos existence, we have examineda case study. Results obtained from this study shows existence of complex chaotic behavior in foreign exchange rate market in Iran. We can say data have big degree freedom in their behavior and shows random like behavior.

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