Currency exchange rate prediction using wavelet network

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Abstract

Currency exchange rates prediction is one of the most important applications of modern time series prediction. The currency rates are inherently noisy, and chaotic. There is no complete information that could be obtained from the history of the past behavior of currency exchange rate markets to fully capture the dependency between the future exchange rates and that of the past. In this paper , the currency exchange rate prediction problem is studied and a new proposed currency exchange rate prediction scheme based on using wavelet network is presented. The proposed scheme is tested and results are compared with other known methods. Different cases are considered.

1- Introduction

Exchange rates prediction is one of the challenging applications of modern time series prediction. The rates are inherently noisy, non-stationary and chaotic [1, 2]. These characteristics suggest that there is no complete information that could be obtained from the past behavior of such markets to fully capture the dependency between the future exchange rates and that of the past. One general assumption is made in such cases is that the historical data incorporate all those behavior. As a result, the historical data is the major player in the prediction process. Although the well-known conventional prediction techniques provide predictions, for many stable forecasting systems, of acceptable quality, these techniques seem inappropriate for non-stationary and chaotic system such as currency exchange rates, interest rates and share prices. The purpose of this paper is to investigate the use of wavelet networks based techniques for prediction of currency exchange rate. Auto-Regressive Integrated Moving Average (ARIMA) technique [3,4] has been widely used for time series prediction . However, ARIMA is developed based on the assumption that the time series being forecasted are linear and stationary [4]. The Artificial Neural

Networks, have been used for prediction and system modeling, with great applicability in time-series analysis and prediction [5-8].

In this paper, we develop a method based on using wavelet network for predicting currency exchange rates. Wavelet neural networks combine the theory of wavelets and neural networks into one. A wavelet neural network generally consists of a feed-forward neural network, with one hidden layer, whose activation functions are drawn from an orthonormal wavelet family.

One applications of wavelet neural networks is that of function estimation. Given a series of observed values of a function, a wavelet network can be trained to learn the composition of that function, and hence calculate an expected value for a given input.

2- Wavelet Network

The structure of a wavelet neural network is very similar to that of a feed-forward neural network, taking one or more inputs, with one hidden layer and whose output layer consists of one or more linear combiners or summers(see Figure 1). The hidden layer consists of neurons, whose activation functions are drawn from a wavelet basis. These wavelet neurons are usually referred to as wavelons.

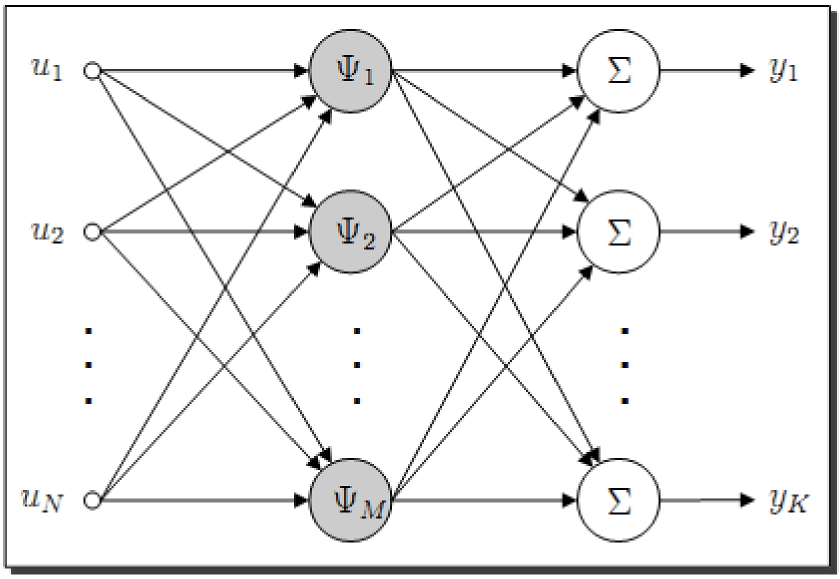


Figure (1): Structure of a Wavelet Neural Network

There are two main approaches to creating wavelet neural networks. In the first the wavelet and the neural network processing are performed separately. The input signal is first decomposed using some wavelet basis by the neurons in the hidden layer. The wavelet coefficients are then output to one or more summers whose input weights are modified in accordance with some learning algorithm. The second type combines the two theories.

In this case the translation and dilation of the wavelets along with the weights are modified in accordance with some learning algorithm. In general, the first approach is known as a wave net while the second type is known as a wavelet network[8]. The architecture of a single input single output wavelet network is shown in Figure 2. The hidden layer consists of M wavelons. The output neuron is a summer. It output a weighted sum of the wavelon

$$\mathbf{y}(\mathbf{u}) = \sum_{\mathbf{i}=1}^{\mathbf{M}} \mathbf{w_i} \psi_{\lambda_i, \mathbf{t}_i}(\mathbf{u}) + \bar{\mathbf{y}} \qquad \ldots \quad (1)$$

The output of a wavelon is given by:

$$\psi_{\lambda,\mathbf{t}}(\mathbf{u}) = \psi\left(\frac{\mathbf{u}-\mathbf{t}}{\lambda}\right)$$

The addition of the bias $\bar{\mathbf{y}}$ is for functions whose mean is non zero (since the wavelet function $\psi(u)$ is zero mean) . In a wavelet network all parameters $\bar{\mathbf{y}}$, w_i, t_i and λ_i are adjustable by some learning procedure .

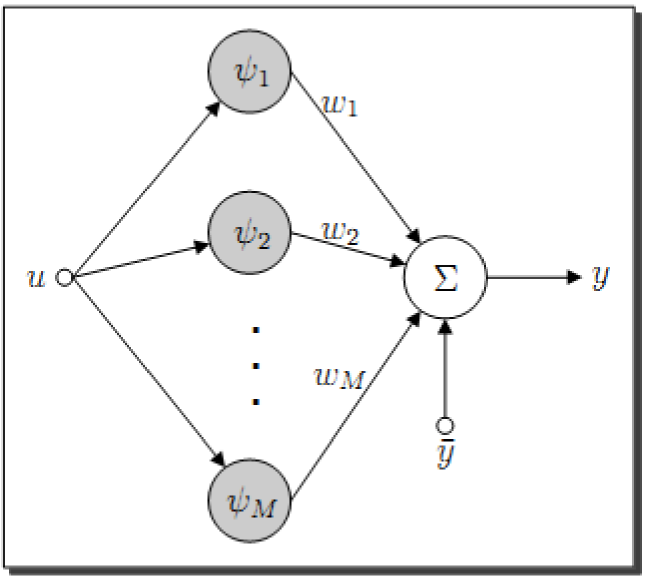


Figure (2): Wavelet Neural Network

3- Multidimensional Wavelet Network

The input in this case is a multidimensional vector and the wavelons consist of multidimensional wavelet activation functions. They will produce a non - zero output when the input vector lies within a small area of the multidimensional input space. The output of the wavelet network is one or more linear combinations of these multidimensional wavelets. Figure 3 shows the form of a wavelon . The output is expressed as:

$$y_j = \sum_{i=1}^{M} w_{i,j}\psi_i(u_1.....u_N) + \bar{y}_j \quad \text{for} \quad j = 1......k \qquad ... (2)$$

where $\bar{\mathbf{y}}_j$ is needed to deal with functions of non zero mean

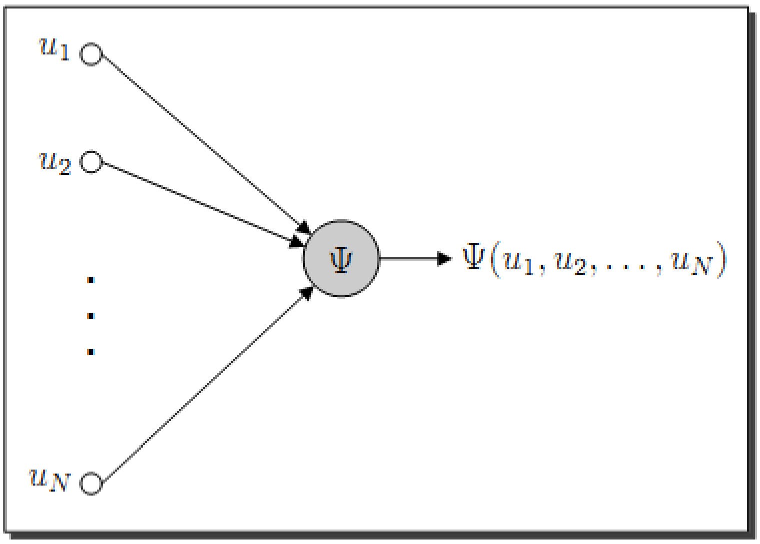


Figure (3): A Wavelet Neuron with a Multidimensional Wavelet Activation Function

The input - output mapping of the network is defined as:

$$\mathbf{y}(\mathbf{u}) = \sum_{i=1}^{M} \mathbf{w}_i \Psi_i(\mathbf{u}) + \bar{\mathbf{y}} \quad \text{where} \quad \begin{cases} \mathbf{y} = (y_1, \ldots, y_K) \\ \mathbf{w}_i = (w_{i1}, \ldots, w_{iK}) \\ \mathbf{u} = (u_1, \ldots, u_N) \\ \bar{\mathbf{y}} = (\bar{y}_1, \ldots, \bar{y}_K) \end{cases}$$

One application of wavelet networks is function approximation . In[8] an algorithm for adjusting the network parameters for the one- dimensional case. Learning is per formed from a random sample of observed input - output pairs using of gradient type algorithm for the learning.

The parameters $\bar{\mathbf{y}}$, w_i's, t_i's and λ_i's should be formed into one vector θ. Now $y_\theta(u)$ refers to the wavelet network, expressed in (4) with parameter vector θ.

$$\mathbf{y}_{\theta}(\mathbf{u}) = \sum \mathbf{w}_{\mathbf{i}} \psi\left(\frac{\mathbf{u}-\mathbf{t}_{\mathbf{i}}}{\lambda_{\mathbf{i}}}\right) + \bar{\mathbf{y}} \quad .... \quad (3)$$

The objective function to be minimized is then

$$C(\theta) = \frac{1}{2} \mathrm{E}\{(y_{\theta}(u) - f(u))^2\}.$$

The minimization is performed using a gradient algorithm. This recursively modifies θ, after each sample pair $\{u_k, f(u_k)\}$, in the opposite direction of the gradient of

$$c(\theta, u_k, f(u_k)) = \frac{1}{2}(y_{\theta}(u_k) - f(u_k))^2.$$

The gradient for each parameter of θ can be found by calculating the partial derivatives of $c(\theta, u_k, f(u_k))$ as follows:

$$\frac{\partial c}{\partial \bar{y}} = e_k$$

$$\frac{\partial c}{\partial w_i} = e_k \psi(z_{ki})$$

$$\frac{\partial c}{\partial t_i} = -e_k w_i \frac{1}{\lambda_i} \psi'(z_{ki})$$

$$\frac{\partial c}{\partial \lambda_i} = -e_k w_i \left(\frac{u_k - t_i}{\lambda_i^2}\right) \psi'(z_{ki})$$

where $e_k = y_{\theta}(u_k) - f(u_k)$, $z_{ki} = \frac{u_k - t_i}{\lambda_i}$ and $\psi'(z) = \frac{d\psi(z)}{dz}$.

To implement this algorithm , a learning rate value and the number of learning iterations need to be chosen . The learning rate γ ∈ (0,1] determines how fast the algorithm attempts to converge. The gradients for each parameter are multiplied by γ before being used to modify that parameter . The learning iterations determine how many times the training data should be fed through the learning process.

4- proposed scheme

Time series analysis is used as a method for currency exchange rate prediction. A time series x(1), ... , x(k) are used to predict the value x(k+1) . The inputs to the network are chosen as the previous k values x(1), x(2), ..., x(k) and the output will be the predicted value x(k+1).

In this section we present the proposed wavelet network scheme for solving the prediction problem . The network has k input unit and one output as shown in figure(4). The k past currency rate values are used as input to the network to predict the next (the k+1) currency rate value.

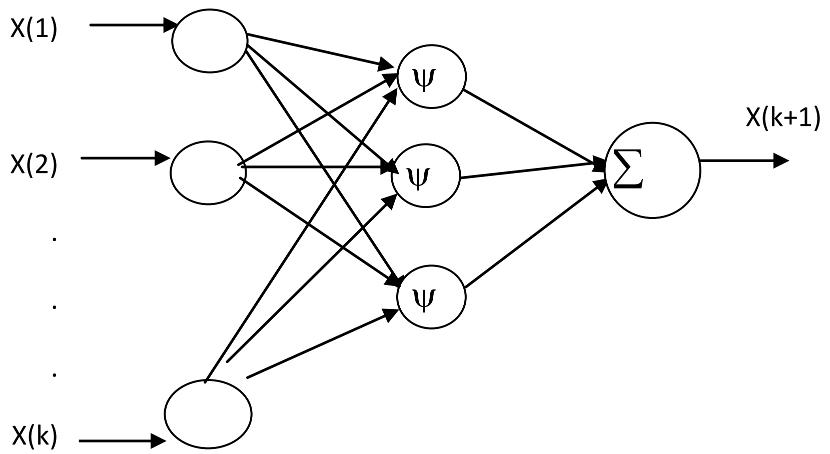


Figure (4): proposed wavelet network

5- Simulation result

The data set contains weekly averaged exchange rates between two main currencies - the British pound and US dollar – in the period from 31 December 1979 to 26 December 1983. The first 110 data points are considered [9]. The data are normalized to values in the range between 0 and 1 using the formula. The proposed wavelet network scheme shown in Figure (4) is used for currency exchange rate prediction . two cases are considered.

1- A wavelet network with three input(k=3) and one output as shown in figure(4). It has three input units (each time three consecutive exchange rates are used as inputs to the network to produce a prediction for the fourth exchange rate).
2- A wavelet network with four input(k=4) and one output as shown in figure(4).It has four input neurons (each time four consecutive exchange rates are used as inputs to the network to produce a prediction for the fifth exchange rate).

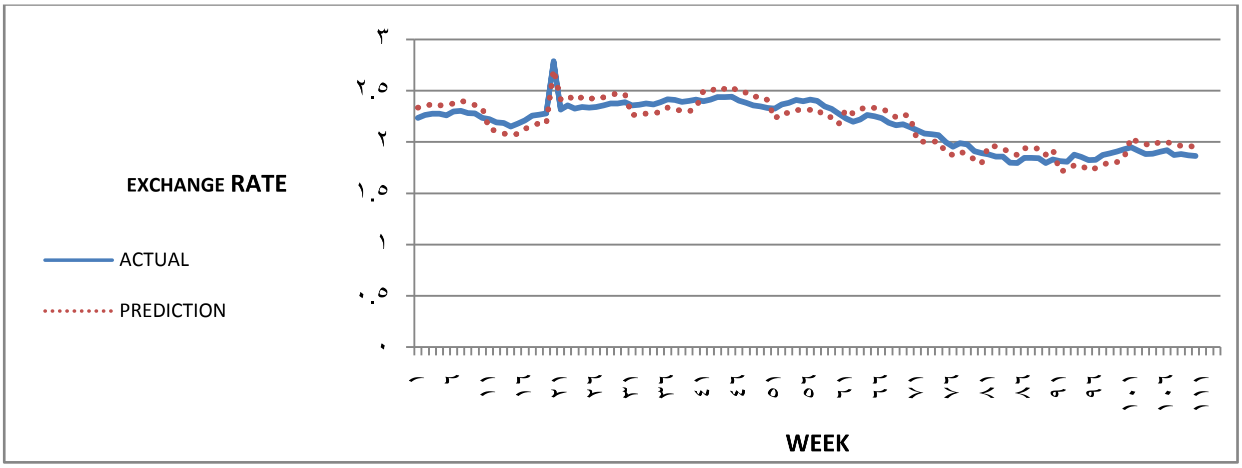
The data set is divided into two groups: training group and testing group. The gradient algorithm is used as a learning algorithm. For the 110 data items, the first 100 data are used as training group. The remaining 10 data are used for testing the trained network to unseen data.

The wavelet network in both cases are trained for 500 epochs with 0.4 learning rate. Three Rasp2 wavelet functions are used ($\mathbf{f(t)} = \frac{\tau\cos(\tau)}{\tau^2+1}$ where $\tau = \frac{\mathbf{u-t}}{\lambda}$) . The trained network is tested with the overall 110 data. The results of the testing(the prediction) are given in Figure (5) and Figure (6) for the two cases respectively.

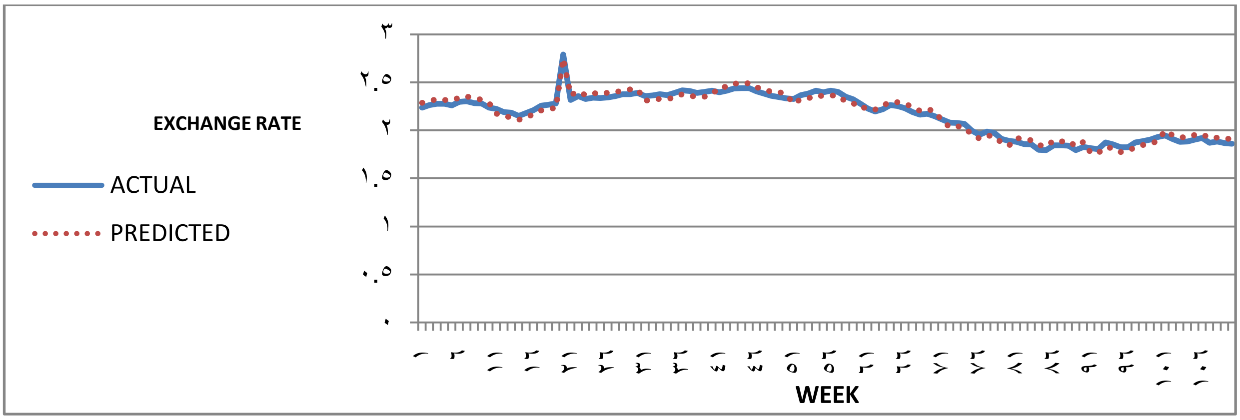
To compare the performance with that of using neural network the multilayer perceptron network is also used for prediction .The neural network is used in two different cases . In the first case three input network is used while in the second case four input network is used. The neural network in both cases are trained for 500 epochs with 0.4 learning rate .The activation function is a sigmoid function. The results of testing(the prediction) for the cases of three input and four input are shown in Figure (7). and Figure (8) respectively. The mean square errors in testing for the four cases is shown in table(1).

Table(1)Mean square error in testing.

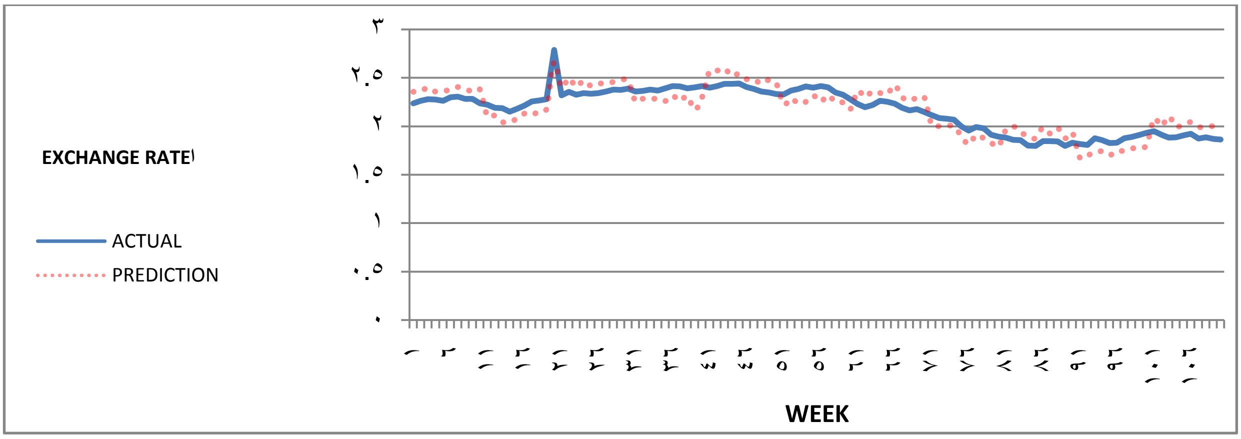
Wavelet Network (3-Input)	Wavelet Network (4-Input)	Neural Network (3-Input)	Neural Network (4-Input)
o.0054	0.0012	0.0145	0.0043



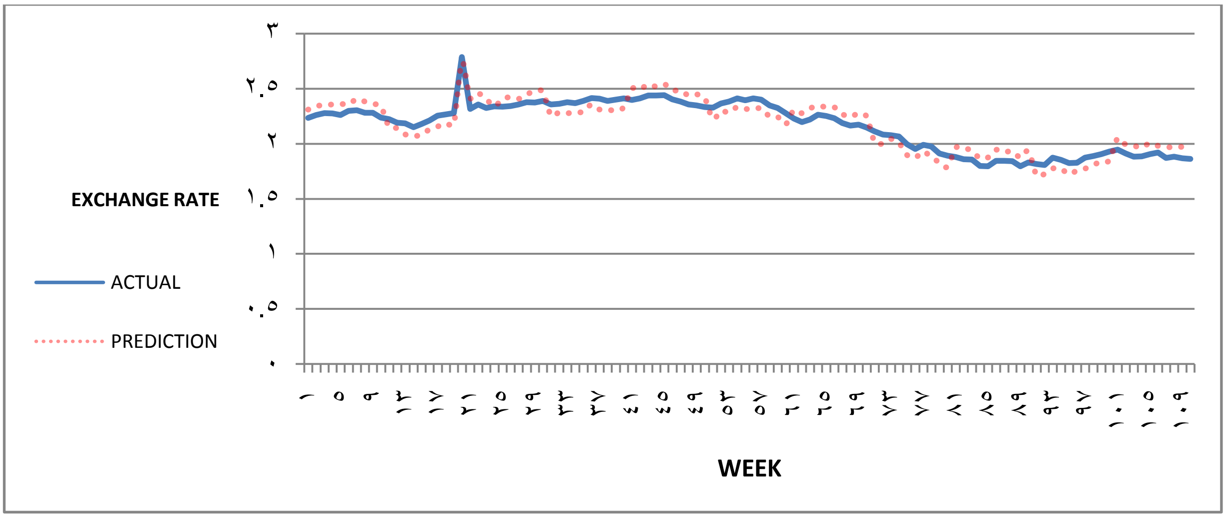
Figure(5): Exchange rate prediction using wavelet network [Three Input]



Figure(6): Exchange rate prediction using wavelet network [Four Input]



Figure(7): Exchange rate prediction using Neural network [Three Input]



Figure(8): Exchange rate prediction using Neural network [Four Input]

6- Conclusion

Wavelet network prediction scheme is presented and used for currency exchange rate prediction. The method is applied for data set contains weekly averaged exchange rates between two currencies - the British pound and US dollar .Simulation results show good performance for the proposed wavelet network scheme. Results of using wave let network is better than that of using neural network.

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التنبؤ بأسعار صرف العملات باستخدام شبكة تحويلة المويجة

عدالة مهدي جياد

قسم علوم الحاسبات - كلية العلوم - جامعة البصرة

الملخص:

يعتبر التنبؤ بأسعار صرف العملات من التطبيقات المهمة لموضوع التنبؤ بالسلاسل الزمنية الحديثة. ان الاسعار في جوهرها غير واضحة وعشوائية. ولا توجد معلومات كاملة يمكن الحصول عليها من السنوات السابقة لأسعار الصرف في اسواق تبادل العملات لوضع علاقة بين أسعار الصرف المستقبلية والسابقة لها. تم في هذا البحث دراسة مسالة التنبؤ بأسعار صرف العملات واقتراح اسلوب للتنبؤ باسعار صرف العملات باستخدام شبكة تحويلة المويجة. تم اختبار الطريقة المقترحة ومقارنة النتائج مع الطرق الاخرى.