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Modeling and Forecasting Exchange Rates Using Econometric Models and Neural Networks

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Abstract: Considering the importance of the exchange rate in economic policy, a variety of patterns are presented to explain how to determine the behavior of the exchange rate and how the modeling and forecasting is. In this context, the present study with a new approach to this problem has investigated the time-series' nature of exchange rate and performed a non-linear test for daily data of exchange rate in the period of 2003 to 2006 to explain the behavior of exchange rate using time-series regression pattern. So in this study, it was used an artificial neural network modeling in addition to daily modeling and forecasting the exchange rates and minimizing the forecasted error by this method and the results were compared with forecasted values by ARIMA model based on measuring criteria of forecast accuracy. It has been used 80% of date equivalent to 1160 days from March 25th of 2003 to June 5th of 2006 for training the models and in order to evaluate the sensitivity of the results of model in proportion to the exchange rate, the model was estimated with the same way for three categories of data as the exchange rate of the dollar, euro and pound. The results showed that the used neural network had the more forecasting power than ARIMA model and the exchange rates' price of the euro and pound were as a function of their previous days and the exchange rates' price of the dollar was as a function of the price in last 6 days. What distinguishes this study compared to other studies is the unique design of artificial neural network that can approximate any arbitrary function and obtain any amount of accuracy that is needed in addition to minimizing the forecasting error by concerning the activation function which is applied in it.

Keywords: Currency, Exchange Rates, Forecast, Artificial Neural Networks, Autoregressive Integrated Moving Average.

Introduction

Today's, forecasting has been arisen as one of the most important branches of science in economic-commercial topics and it is developing and progressing continuously. Mangers of various economic and business sectors prefer to have a mechanism that can help and advise them in their decision making because of many affecting variables (Azar & Rajabzadeh, 2003). So, all managers at all levels of organizations are dealing with such forecast and in all organizations, forecasts are motive engines of control systems in operating, financial and marketing sectors (Delurgio, 1998). It has been mostly used the forecasting models of econometric methods, analysis of variance/covariance and correlation in economic researches and for financial topics, methods of Box Jenkins and smoothing or multivariate regression for analysis on issues such as forecasting the corporate' profits, company's stock price, forecasting balance sheet and cash flow items and for business topics and issues, qualitative methods such as the Delphi method. Perhaps the most important reason for this usage has been precedent of using these methods in various sciences, but each pattern used for forecast has its own unique strengths and weaknesses (Azar & Rajabzadeh, 2003), but naturally, methods have viability and appropriate applicability that have the lowest possible error in the forecast. Because the forecasts are closer to reality, they will be the basis of the more accurate decisions (Tolouie-ashaghi & Haghdoost, 2007). Several forecasting models have been developed in recent decades. Recently, other models have been used as artificial neural networks in forecasting variables in line with previous conventional models and it usually offers a better result than the previous ones. Artificial neural networks have been used which to solve many financial problems including forecasts due to nonlinearity, non-parametric and adaptive training characteristics (Macian et al., 2010), and since studies in recent years represented the nonlinear behavior for the exchange rate, so, this study was an attempt to provide a model to forecast the exchange rate as well as to compare the efficiency of artificial neural network with autoregressive integrated moving average model in forecasting (the exchange rate).

Materials and Methods

In this study, it was discussed the forecast of exchange rate in the period of 25.3.2003 to 5.6.2006 using artificial neural networks and ARIMA model. It was used computational tools and MATLAB software for neural network and EViews 8 for ARIMA and economic data of Iran for this purpose.

Autoregressive integrated moving average (ARIMA) model

ARIMA model is one of the most widely used time-series models. The popularity of such models are because of their statistical properties as well as the Box Jenkins methodology in the process of modeling this kind of models (Box and Jenkins, 1970). In addition, numerous exponential smoothing models can be used by ARIMA models. These models are also quite flexible, because they can explain very different models of time series such as series of autoregressive (AR), moving average (MA) and combination of both of them (ARMA). The main limitation of these models is their default linearity that is assumed a linear correlation structure between the values of the time series in this type of models. Therefore, non-linear patterns cannot be calculated by the ARIMA model, and therefore, the estimation of linear models for complex real-world problems that are often non-linear models is not always satisfactory (Zhang and Michael, 1998).

ARIMA process

In the autoregressive integrated moving average (ARIMA) model, future values of variables are assumed as a linear function of past observations and random errors, which means that the basic process that produces the time series is as follows:

$$y_t = \theta_0 + \emptyset_1 y_{t-1} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}$$

Where ε_t and y_t are random errors and real values in period t respectively, $\theta_j \ (j = 1,2,\dots,q)$ and $\emptyset_i \ (i = 1,2,\dots,p)$ are model's parameters and p and q are integers representing order of the model. Random error of ε_t is also assumed as independent by uniform distribution with zero mean and constant variance of σ^2. This equation contains multiple special cases of ARIMA models' family: if q = 0, equation is an autoregressive equation with the degree of p and when p = 0, the model turns to a moving average model of the q degree. One of the main steps of ARIMA modeling is to determine the correct order of the model (p, q). On the basis of previous work, a practical method has been created for making these models that has had a fundamental impact on analyzing time series and forecasting applications. Box-Jenkins methodology consists of three repeated stages of model identification, parameter estimation and diagnostic control. The main idea of identifying the model is also based on this principle that if a time series is produced by a ARIMA process, it must has some theoretical autocorrelation properties, therefore, it will be often possible to identify one or more potential models for time series by matching the empirical auto correlation patterns with theoretical auto correlation patterns. Box-Jenkins suggested using the autocorrelation function (ACF) and partial autocorrelation function (PACF) of sample data as a basis for identifying the order of ARIMA model. When the test model is detected, estimation of model's parameters has been a simple work and can be achieved through minimizing the error and linear optimization process can be used for this purpose. The last step of modeling is detection control of model to be proper and basically is used to test the fact that the model assumptions are true about errors or not. To test well fitting of accepted experimental model, it can be used several statistics and diagnostic graphs of residuals. If they chose model is not appropriate, a new test model should be recognized and the above cases must be repeated. This three-step modeling process is typically repeated several times until detecting a satisfactory model finally. The final chose model can be used to forecast (Khashei & Bijari, 2008).

Neural networks

Forecasting the behavior of complex systems is one of the most widespread applications of neural networks. It has been widely used particularly in applications such as forecasting weather, forecasting exchange rate, forecasting commercial bankruptcy, forecasting stock prices and other economic forecasts. Most approaches of neural network for a forecasting problem apply a feed forward multilayer network that has been taught using back-propagation algorithm or its improved and modified algorithms (Esfahanian and Amin-naseri, 2008). The reason of using multilayer Perception by back-propagation training method is to prove that a multilayer Perception neural network with mentioned training algorithm is an approximating public function. This means that any amount of accuracy that is required, there is a configuration of the mentioned network that is able to obtain such accuracy; it is why to consider the structure of this type of network (Zara-nejhad et al., 2008).

Multilayer Perceptron

Although modeling of the neuron is the basic component of key points in the neural network performance, but the connections and the layout of the network which is called topology is also very important and influential factor. Note that the topology of the human brain is so complex that cannot be used as a model for the neural network, because the model that is used is a simplified model, while the arrangement of the brain uses lots of elements. One of the simplest and yet the most efficient layout proposed for use in modeling actual nerves is the Multilayer Perceptron (MLP). This network is formed of an input layer, one or more hidden layers and an output layer. In this structure, all neurons in a layer are connected to all neurons of the next layer. This arrangement forms a network with complete connections literally. Figure 1 shows a schematic three-layer Perception network (input, hidden and output). It is easy to deduce that the number of neurons in each layer is independent of the number of neurons in other layers.

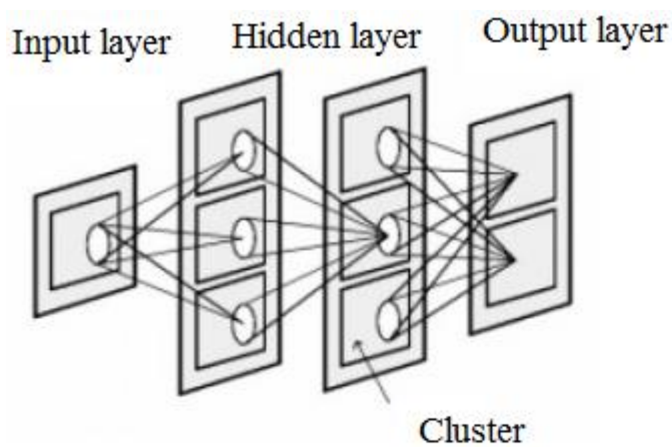

Figure 1. Perceptron neural network (Pazoki, 2010).

It is important to note that in Figure 1, each circle is accumulated of aggregation and thresholding (passing through non-linear function). In fact, each solid circle in this figure is a model of accumulator and thresholding block that are shown in this form for ease of displaying (Pazoki, 2010).

Back propagation algorithm (BP)

Various methods are used to estimate the optimal values of weight vectors that the most important and most widely used is the back propagation algorithm which is often used in Multilayer Perceptron networks. In this way, as the title implies, it is used for training multi-layer feed forward network. In other words, the topology of Multilayer Perceptron network is completed by the law of training error back propagation. The error back propagation law is formed of the two main paths. The first path is known as the forward path in which the input vector is applied to the MLP neural network and its effects is propagated through intermediate layers to the output layers. The output vector formed in the output layer forms the real response of the MLP network. Network parameters are considered fixed and unchanged in this path. The second path is called the backward path. In this path and to the opposite of the forward path, parameters of MLP network are changed and adjusted. This adjustment is done in accordance with the law of error correction. The error signal is formed at the output layer and the error value is distributed entire the network after calculation on the backward path from the output layer and through the network layers. Parameters of the network are adjusted so that the real response of network becomes as much as closer to the optimal response (Mansouri, 2008).

Back propagation algorithm for MLP networks is an extension of the Least Mean Square algorithm. The index of mean square is the error that is placed in the context of supervised training with below training data pairs:

$$\{(p^1,t^1),(p^2,t^2),\dots,(p^Q,t^Q)\}$$

Where p^i the input is vector and t^i is the desired output of the network for p^i input. After applying the input (KP(k)) th pattern to the network - that is one of p^is), the error signal at the j-th output of the neuron from the output layer (layer L) at the moment of K or K-th repeat is obtained from the following equation :

$$e_j(k) = t_j(k) - a_j(k)$$

And this minimization problem provides the greatest reduction in approximation algorithm (Mansouri, 2008)
In summary, the equations of forward path, backward path and adjustment of the network parameters are expressed as follows.

1. Forward path:

$$a = p(k)$$

$$a^{l+1}(k) = F^{l+1}\left(w^{l+1}(k)a^l + b^{l+1}(k)\right) \qquad l = 0,1,2,\dots,L-1$$

$$a(k) = a^l(k)$$

As can be seen in this path, network parameters do not change during execution of calculations and moving functions act on the individual neurons, namely:

$$F^{l+1}(n(k)) = [f^{l+1}\left(n_1(k)\dots f^{l+1}\left(n_{s+1}(k)\right)\right)]^T$$

Backward path

In this path, sensitivity vectors of (δ) are turned away from the last layer to the first layer. Following equations express the dynamicity of backward path:

$$\delta^L(K) = -2\dot{F}^L(n)e(k)$$

$$\delta^L(K) = \dot{F}^l(n^l)(w^{l+1})^T\delta^{l+1} \qquad , \quad l = L-1, L-2,\dots,1$$

$$e(k) = t(k) - a(k)$$

$$\dot{F}^L\left(n^L(k)\right) = \frac{\partial a^L(K)}{\partial n^L(K)}$$

Where there the error vector is available is the output layer (Mansouri, 2008). Then the error vector is distributed from right to left from the last layer to the first layer and local gradient is calculated neuron to neuron with a recursive algorithm. The network parameters won't be changed in this way also.

Adjusting parameters

The weight matrices and bias vectors of the network are divides by following relations ultimately:

$$W^l(k+1) = W^l(k) - \alpha\delta^l(k)(a^{l-1}(K))^T$$

$$b^l(k+1) = b^l(k) - \alpha\delta^l(k) \qquad , \quad l = 1,2,\dots,L$$

Here α is the training rate for convergence of the algorithm that is selected according to the following condition:

$$0 < \alpha < \frac{1}{Trace\,[R]} \qquad , \quad R = E(PP^T)$$

$Trace\,[R]$: Sum of the diagonal elements of the matrix R or sum of the eigenvalues of matrix R. It can be noted that after each pair of input and output as a model of training, input vectors do not change within the above three steps. That's why the number of repeats K is actually equal to the applying of pattern to the network. Figure 2 shows the behavior of the entire network (Mansouri, 2008)

Stop: the two following indices be used simultaneously to stop repeating of the BP algorithm.

(A) Mean square of error per cycle or EPOCH (the sum of squares error for all training patterns) is less than a predetermined value. It should be noted that each cycle is equal to the number of repeats and in the size of the samples of training. For example, if there are 100 training samples' data, the cycle is repeated in 100 steps.

(B) Normal gradient of error is very small: gradient's norm of error becomes smaller than a predetermined value (Mansouri, 2008).

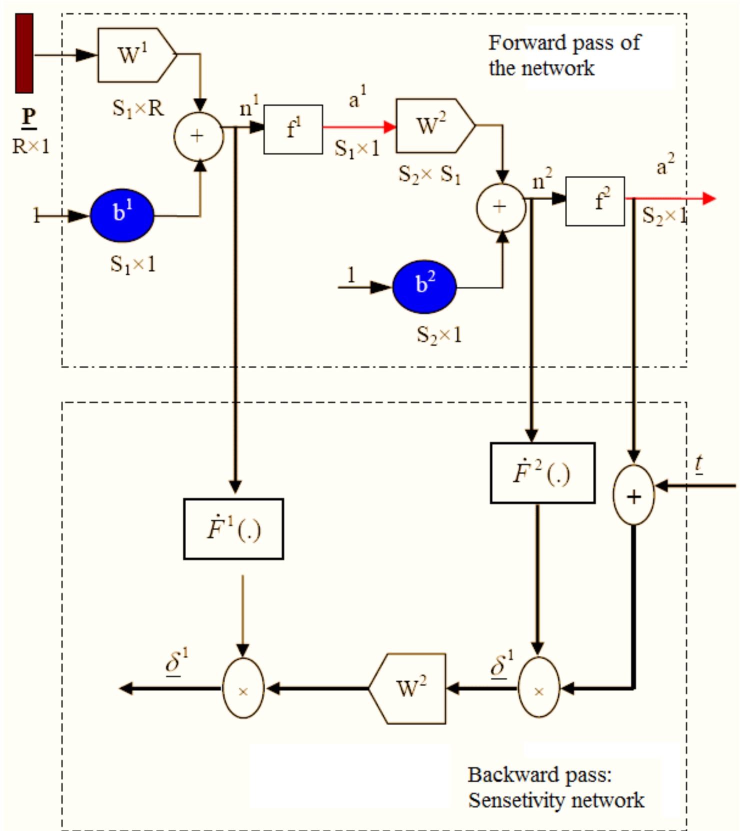

Figure 2. MLP with one hidden layer with back warding sensitivities (Mansouri, 2008).

Results

In this study on the neural network and to determine the number of effective past days, it was used the average criterion of MSE performances of each experiment as a result of one test (each test was repeated 10 times in order to avoid exposing the network to the local minimums) and by adding every day for entry in the network, it has been calculated the values of this criterion on the basis of output and the number of days (that were given to the network based on various inputs) had low average of MSE performance criterion were selected as optimal model. The test results are shown in Tables 1 to 3.

Table 1. Choosing the best structure for neural network for data of pound/Rial exchange rate using MSE performance criterion.

MSE-TEST	N = Training rate, N_1 = The number of neurons of input layer, N_2 = The number of neurons of hidden layer, N_3 = The number of neurons of output layer, N_1 = n, N_2 = 5, N_3 = 1, n = 0, 1, size (train) = 80%, size (train) = 20%										
N1=n , N2=5 , N3=1 , n=0. 1 , size(train)=505 , size(test)=50 %	MSE1	MSE2	MSE3	MSE4	MSE5	MSE6	MSE7	MSE8	MSE9	MSE10	AVE
											0.00015
	1	1.7031e-004	1.2541e-004	1.3094e-004	1.2692e-004	1.6457e-004	1.3363e-004	1.4157e-004	2.2963e-004	1.3689e-004	1.3597e-004
2	2.8107e-004	2.0967e-004	1.9148e-004	2.0207e-004	2.4445e-004	2.4254e-004	1.9330e-004	2.1462e-004	2.2858e-004	2.1557e-004	0.000222
3	2.6130e-004	3.5536e-004	3.6507e-004	4.5995e-004	3.3126e-004	2.5221e-004	3.3501e-004	3.2969e-004	2.6357e-004	3.6248e-004	0.000332
4	5.1513e-004	5.0270e-004	5.4088e-004	9.1067e-004	3.0982e-004	5.8389e-004	5.4227e-004	5.3353e-004	3.7565e-004	6.0102e-004	0.000542
5	6.1419e-004	3.8877e-004	3.8134e-004	7.0030e-004	2.6511e-004	5.16667e-004	3.7969e-004	4.7521e-004	4.6006e-004	4.4595e-004	0.000463
6	5.1337e-004	6.0836e-004	7.7904e-004	5.6895e-004	6.3533e-004	7.2505e-004	0.0011	4.8799e-004	3.1409e-004	0.0012	0.000693
7	6.3194e-004	2.4658e-004	4.6987e-004	7.5751e-004	4.6458e-004	9.2500e-004	7.4771e-004	8.6575e-004	0.0013	7.7511e-004	0.000718
8	7.5735e-004	8.3107e-004	5.3101e-004	6.0511e-004	5.0122e-004	0.0011	7.7304e-004	7.0415e-004	8.0673e-004	5.1863e-004	0.000713
9	4.3664e-004	8.1373e-004	7.1708e-004	7.6433e-004	0.0013	0.0031	9.7579e-004	0.0016	0.0014	7.2305e-004	0.001183
10	8.2875e-004	0.0014	4.8643e-004	8.6412e-004	8.3083e-004	8.4778e-004	0.0012	2.3101e-004	4.8605e-004	8.5742e-004	0.000803

Source: research findings

Table 2. Choosing the best structure for neural network for data of dollar/Rial exchange rate using MSE performance criterion.

MSE-TEST	N = Training rate, N_1 = The number of neurons of input layer, N_2 = The number of neurons of hidden layer, N_3 = The number of neurons of output layer, N_1 = n, N_2 = 5, N_3 = 1, n = 0, 1, size (train) = 80%, size (train) = 20%										
N1=n , N2=5 , N3=1 , n=0. 1 , size(train)=505 , size(test)=50 %	MSE1	MSE2	MSE3	MSE4	MSE5	MSE6	MSE7	MSE8	MSE9	MSE10	AVE
											0.000298
	1	3.1034e-004	2.5122e-004	2.9548e-004	3.0509e-004	3.0331e-004	2.7974e-004	3.1124e-004	3.0772e-004	2.5936e-004	3.5873e-004
2	3.0105e-004	3.1290e-004	3.4911e-004	5.0651e-004	4.4186e-004	2.8475e-004	5.2527e-004	3.3403e-004	3.9101e-004	2.8832e-004	0.000373
3	4.0090e-004	5.0490e-004	4.9109e-004	3.4367e-004	4.8424e-004	4.2793e-004	2.9948e-004	4.8075e-004	5.5729e-004	3.8725e-004	0.000438
4	3.6125e-004	4.0625e-004	9.1205e-004	5.1436e-004	5.3194e-004	9.8932e-004	0.001	5.8252e-004	4.1212e-004	9.7803e-004	0.000679
5	5.5268e-004	8.4836e-004	5.2567e-004	6.3186e-004	8.4430e-004	4.0780e-004	8.0498e-004	3.9055e-004	4.2756e-004	5.8122e-004	0.000601
6	9.3194e-004	6.3554e-004	0.0014	6.3272e-004	6.5546e-004	4.2858e-004	9.0105e-004	7.1635e-004	0.0013	8.4445e-004	0.000845
7	0.0014	6.4858e-004	0.0015	8.3762e-004	0.0015	0.0010	5.8593e-004	0.0011	8.2927e-004	6.3682e-004	0.001004
8	0.0012	0.0024	0.0010	7.7281e-004	7.9509e-004	0.0011	8.0744e-004	0.0011	0.0011	9.3585e-004	0.0001121
9	7.0648e-004	0.0015	58087e-004	0.0014	7.1274e-004	8.5839e-004	7.9559e-004	8.3743e-004	7.8388e-004	0.0011	0.000928
10	7.1769e-004	8.8037e-004	0.0014	0.0010	0.0010	9.9049e-004	7.2707e-004	9.7075e-004	8.5729e-004	9.6375e-004	0.000951

Source: research findings

Table 3. Choosing the best structure for neural network for data of euro/Rial exchange rate using MSE performance criterion.

MSE-TEST	N = Training rate, N_1 = The number of neurons of input layer, N_2 = The number of neurons of hidden layer, N_3 = The number of neurons of output layer, N_1 = n, N_2 = 5, N_3 = 1, n = 0, 1, size (train) = 80%, size (train) = 20%										
N1=n , N2=5 , N3=1 , n=0. 1 , size(train)=505 , size(test)=50 %	MSE1	MSE2	MSE3	MSE4	MSE5	MSE6	MSE7	MSE8	MSE9	MSE10	AVE
											0.000212
	1	2.1541e-004	1.9735e-004	2.1789e-004	2.1663e-004	1.8224e-004	2.4882e-004	2.0570e-004	1.8548e-004	2.5667e-004	1.8912e-004
2	2.5056e-004	1.7931e-004	2.0120e-004	2.0619e-004	2.4669e-004	2.9059e-004	2.0967e-004	1.9236e-004	2.2288e-004	2.5668e-004	0.000226
3	2.9286e-004	2.0647e-004	2.8958e-004	2.5716e-004	1.8124e-004	2.9993e-004	3.2859e-004	2.3082e-004	2.9254e-004	2.5556e-004	0.000263
4	3.4981e-004	3.4977e-004	2.6807e-004	2.3238e-004	2.7511e-004	4.5219e-004	2.9392e-004	2.4434e-004	2.5216e-004	4.2852e-004	0.000315
5	3.6899e-004	3.4307e-004	3.1160ee-004	3.2440e-004	3.0019e-004	2.4071e-004	4.0090e-004	2.7271e-004	2.8204e-004	2.9970e-004	0.000314
6	4.4186e-004	4.6109e-004	3.1110e-004	3.3971e-004	2.4069e-004	4.6741e-004	5.7372e-004	3.000e-004	2.5081e-004	4.1068e-004	0.00038
7	2.6182e-004	6.1568e-004	3.1745e-004	6.4310e-004	4.4583e-004	2.0918e-004	4.9053e-004	3.6276e-004	2.5806e-004	5.1667e-004	0.00412
8	4.6619e-004	4.2734e-004	3.3210e-004	3.5165.e-004	4.2101e-004	3.9227e-004	3.2158e-004	3.4574e-004	2.0039e-004	2.3031e-004	0.000349
9	1.4146e-004	7.4265e-004	3.4258e-004	2.2035e-004	1.6311e-004	2.7731e-004	3.4163e-004	3.4673e-004	4.5171e-004	4.30006e-004	0.000346
10	0.0011	7.1999e-004	4.3935e-004	1.8889e-004	3.1717e-004	4.0131e-004	1.8613e-004	1.8635e-004	3.4268e-004	3.3859e-004	0.000422

Source: research findings

After performing this step based on designed optimal model, the price of next day for pound and euro exchange rates was a function of the prices for the past day and price of the next day for the dollar exchange rate was a function of its price in past 6 days. In this regard, the model was chosen and to forecast the next day, it was given one input neuron to the forecaster network of pound and euro exchange rates and 6 input neurons to the forecaster network of dollar exchange rate. After determining the number of input neurons and to select hidden layer neurons of the network, it has been designed and trained different networks with different number of hidden neurons and the optimal network among these networks was selected according to the MSE criterion that is the network with the least MSE with 5 hidden neurons has been employed. Therefore, net optimal forecaster network for pound and euro exchange rates had the number of optimal neurons of the first layer, the number of optimal neurons of the second layer, training rate and the proportion of training data to test as equal to 1, 5, 0.1 and 80 to 20%, so, the optimal network (with the lowest MSE) is like as (N^{1-5-1}). As for the dollar and based on the results observed, optimal network is achieved based on the prices of exchange rate for past 6 days, so, the optimal network (with the lowest MSE) had the number of optimal neurons of the first layer, the number of optimal neurons of the second layer, training rate and the proportion of training data to test as 6, 5, 0.1 and 80 to 20% (N^{6-5-1}) (Table 4).

Table 4. Designing and modeling exchange rates of pounds, Euros and dollars in neural network.

Type of neural network	Multilayer feed forward	Training algorithm of neural network	Back propagation of error
Activation function (hidden layer-output layer)	Hyperbolic tangent- Linear	Stop condition of training process	$eav \leq 1e^{-4}$
Number of input neurons (pound, euro and dollar)	6-1-1	Training period time	25.3.2003 to 5.6.2006
Number of output neurons	1	Experiment period time	6.6.2003 to 20.3.2007
Determining criterion of hidden neurons	MSE	the proportion of training data to test	80% to 20%
Number of hidden layers	1	Training rate	0.1
Number of hidden neurons	5	-	-

Source: research findings

Comparison of actual and forecasted values of exchange rates: Date on actual and forecasted values by the network are shown in Figures 3, 4 and 5.

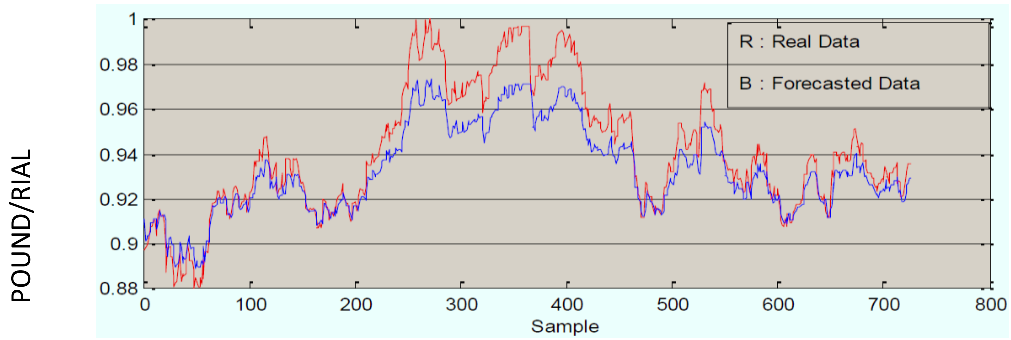

Figure 3. The actual and forecasted values of pound / Rial, Source: research findings.

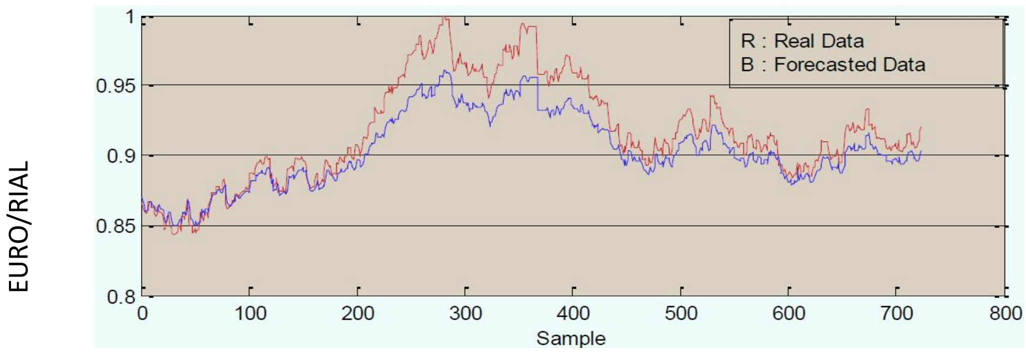

Figure 4. The actual and forecasted values of euro / Rial, Source: research findings.

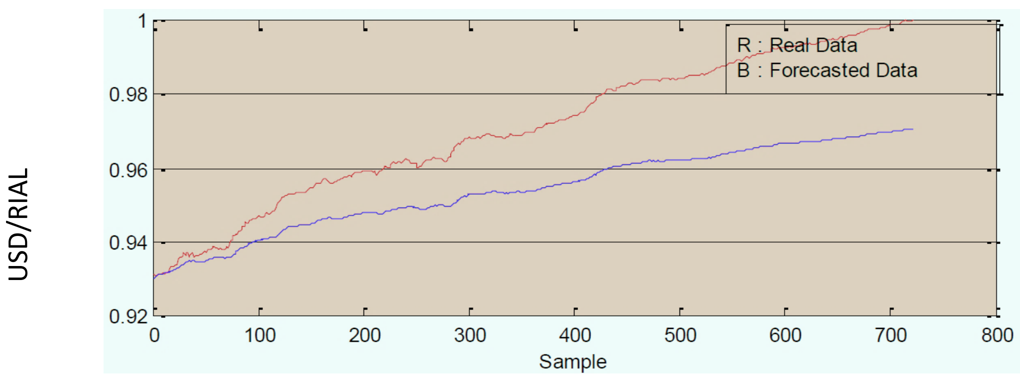

Figure 5. The actual and forecasted values of dollar / Rial, Source: research findings.

Now, in order to obtain the maximum and minimum error between the actual and forecasted values by the network in respect to each of the exchange rates, these errors could be calculated using the following tables and then compared with each of the actual values and forecasted values corresponding to these errors (Table 5-10):

$D = ytf - yfh$

d = The actual values – The forecasted values

Table 5. The maximum and minimum error in forecasting exchange rates of pound/Rial.

Maximum error (MAX_d)	Minimum error (MIN_d)
533	0

Source: research findings

Table 6. Comparison of the actual and forecasted values corresponding to the maximum - minimum error of Network.

Actual value	Forecasted value	Actual value	Forecasted value
17063	16530	15670	15670

Source: research findings

Table 7. The maximum and minimum error in forecasting exchange rates of euro/Rial.

Maximum error (MAX_d)	Minimum error (MIN_d)
558	1

Source: research findings

Table 8. Comparison of the actual and forecasted values corresponding to the maximum - minimum error of network.

Actual value	Forecasted value	Actual value	Forecasted value
11846	11288	10556	10555

Source: research findings

Table 9. The maximum and minimum error in forecasting exchange rates of dollar/Rial.

Maximum error (MAX_d)	Minimum error (MIN_d)
330	1

Source: research findings

Table 10. Comparison of the actual and forecasted values corresponding to the maximum - minimum error of network.

Actual value	Forecasted value	Actual value	Forecasted value
9140	8810	8512	8511

Source: research findings

Comparison of the criteria for evaluating the performance of the neural network in forecasting exchange rates: In order to demonstrate the ability of the network to forecast exchange rates (dollars, Euros and pounds), it was compared the criteria for evaluating the performance of the model in forecasting exchange rates:

Table 11. Comparison of evaluation criteria of the performance for neural network in forecasting dollar / euro / pound.

Exchange rate/measure	MAE	MSE	RMSE	U. Theil
Pound	0.0097	0.00014	0.0124	0.0064
Euro	0.0136	0.00030	0.0175	0.0097
dollar	0.0165	0.00034	0.0185	0.12

Source: research findings

As can be seen in Table 11, the neural network had better performance in forecasting the pound exchange rate towards both dollar and euro exchange rates. It seems that lack of superiority in neural network forecasting for dollars and euro was due to the control of these currencies by the government, because most of the trade in Iran was done based on dollars and euro and repairs of the rate of theses currencies can have a significant effect on the economic structure of the country and domestic markets, therefore, these controls caused to reduce a range of fluctuation of the currencies, and if the amplitude of fluctuation for dollar and euro would be like as the pound, the network had had much better performance in forecasting them.

Comparison of the performance of ANN and ARIMA models in forecasting exchange rates: Since the main purpose of this research was to observe the performance of ANN in enhancing predictability, so, its results were compared with linear AMRIA model at this stage in order to better assess the performance of the model. The measures of mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and U. Theil statistic were used to compare the predictability of AMRIA and ANN process (Table 12).

Table 12. Comparison of the predictability of neural networks and ARIMA models to forecast exchange rate of pound.

Model/measure	RMSE	MAE	U. Theil	MSE
ANN	0.0124	0.0097	0.0064	0.00014
ARIMA	81.640	57.154	0.742	6665.08

Source: research findings

Table 13. Comparison of the predictability of neural networks and ARIMA models to forecast exchange rate of euro.

Model/measure	RMSE	MAE	U. Theil	MSE
ANN	0.0175	0.0136	0.0097	0.00030
ARIMA	51.48	33.08	0.923	2650.19

Source: research findings

Table 14. Comparison of the predictability of neural networks and ARIMA models to forecast exchange rate of dollar.

Model/measure	RMSE	MAE	U. Theil	MSE
ANN	0.0185	0.0165	0.011	0.00034
ARIMA	2.4280	1.7812	0.661	5.8564

Source: research findings

Comparison of the results of neural network model with the results of the ARIMA model indicated that the forecasting the price of exchange rate for the next day with neural network model had less error resulting in better performance than ARIMA model from the standpoint of all criteria of evaluating the performance of the forecast in tables 12-14. In other words, the forecast of exchange rate price by ANN reduced the estimation error than the ARIMA model. The results supported the theory of nonlinear time series of currency.

Discussion and Conclusion

The aim of this study was to provide a model to forecast the exchange rate and to compare the performance of artificial neural network model with autoregressive integrated moving average model in forecasting (the exchange rate). The results showed that the offered neural network has had the ability of more accurate forecast and can forecast the level of price fluctuations more accurately than ARIMA method; as a result, it can be used as an appropriate tool to forecast economic variables in conjunction with other methods. This model was able to forecast fluctuations in the exchange rates due to the appropriate structure significantly. Other results showed that a single network cannot be provided to forecast three currencies' exchange rates and evidences represented inappropriate forecast of network about the dollar exchange rate. It is worth noting that the lack of forecast was due to many restrictions that the central bank imposed on the dollar, because fluctuations of exchange rate can have a negative impact on the economy and as a result, it must be controlled. So, the present designed neural network model can be better to forecast the exchange rate according to the data used. Some common patterns are using in forecasting nowadays in many economic research centers and study centers of organizations in the country that are required to forecast. However, perhaps very accurate forecasts are not very important in some cases but, certainly short-term forecasts for many variables have great importance to policy makers. Therefore in this study, it was attempted to consider the ARIMA models as leading classical time series models for forecasting financial markets and neural network model as a representation of the artificial intelligence models and then to compare them with various criteria and in addition to the comparison, it was tried to design and propose a model to forecast changes in the exchange rate variable using artificial neural network and to minimize the forecasting error with this method. To evaluate the sensitivity of the results of medals to the exchange rates, estimation of model has been conducted in the same way for three categories of data as exchange rate of the dollar, euro and pound. The comparison of results of neural network model with the results of the ARIMA model indicated that from the standpoint of the criteria for evaluating the forecasts performance, forecasting exchange rates of the next day was more accurate by neural network model than the ARIMA model representing confirmation of research hypothesis. In other words, forecasting the price of exchange rate using neural network reduces error of estimating the exchange rate price rather than ARIMA technique. So the research findings represented that the neural network can forecast properly that this model can be used as an accurate tool to forecast exchange rate along with other methods, but the evidences suggested that a single network is not capable of forecasting all exchange rates. As it was seen, the optimal network has been provided just by using the price of the past day in forecasting both pound and euro exchange rates, while in forecasting the dollar exchange rate, optimized network was introduced using the price of past 6 days for exchange rate and the result may be because of placing the network of forecasting the dollar in various minimums, but forecasting network of pound and euro was able to forecast properly in addition to using lass data providing fewer errors. It is necessary to prove the validity of claims by examining this network with other independent data. Perhaps the lack accuracy in forecasting was due to many restrictions that the central bank imposed on the dollar, because most of the trade in Iran is done on the basis of this currency, so, fluctuations of exchange rate can have a negative impact on the economy. This exchange rate is controlled by the government to avoid fluctuations. This control reduces the amplitude of fluctuations. If the amplitude of fluctuations of dollar would be extensive as well as other currencies, it is likely to provide a single network for forecasting all exchange rates. Finally, it should be noted that the provided models are not comprehensive and does not have the ability of practical use in the industry necessarily, because this network has been trained using economic data of Iran, but the model can popularized in order to forecast similar variables and foreign markets. Overall, according to the results, it can be said that changes in exchange rates may alter the revenue, costs and profits of active firms in international trade and investment. So, the exchange rate forecasting affects decision-making of firms in order to gain more profit. It is recommended to use artificial neural networks model for this firms because of the ability of them to forecast financial markets.

Conflict of interest

The authors declare no conflict of interest

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