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Contents

Application of ANFIS to exchange rate forecasting

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Abstract: The need of exchange rate forecasting in order to preventing its disruptive movements has engrossed many policy-makers and economists for many years. The determinants of exchange rate have grown manifold making its behavior complex, nonlinear and volatile so that nonlinear models have better performance for its forecasting. In this study the accuracy of ANFIS as the nonlinear model and ARIMA as the linear models for forecasting 2, 4 and 8 days ahead of daily Iran Rial/€ and Rial/US$ was compared. Using forecast evaluation criteria we found that nonlinear model outperforms linear model in all three horizons.

Key words: ANFIS; ARIMA; exchange rate; forecasting

1. Introduction

Assessing future changes in exchange rates has been of long interest to economists as well as policy-makers. Exchange rate plays a principal conduit through which monetary policy affects real activity and inflation. In order to keep inflation stable at an appropriate level and economic activity at a higher level, the monetary authority must have confidence, which will come through the better understanding of the movements of exchange rate, in conducting the monetary policy. Also, in order to intervene efficiently in the foreign exchange market, the policy-makers in the central bank must be very much aware of the movement of exchange rate and its consequences. Multinational corporations in order to gain a competitive advantage over their rivals are extending in the fast growing emerging markets. Although these corporations have enjoyed many benefits from economic growth in these regions, business operations in the developing economics, the recent financial turmoil in the developing economics highlights the instability of these growing economies and stresses the firms' need to closer scrutinize the foreign exchange rates. This notion has been echoed by many industrial leaders to call for greater transparency of the foreign exchange markets and enhancing the predictability of the currency exchange movements. Perhaps, these are few reasons why monetary authority, policy-makers and corporations might wish to forecast exchange rates (De Grauwe, et al., 1993).

Recently, it is well documented that many economic time series observations are non-linear while a linear correlation structure is assumed among the time series values. Therefore, the ARIMA model can not capture

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nonlinear patterns, and approximation of linear models to complex real-world problem is not always satisfactory. While nonparametric nonlinear models estimated by various methods such as Artificial Intelligence (AI) can fit a data base much better than linear models and it has been observed that linear models often forecast poorly, which limits their appeal in applied setting (Racine, 2001). Artificial Intelligence (AI) systems are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems (Kalogirou, 2003). They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with non-linear problems, and once trained can perform prediction and generalization at a high speed (Kalogirou, 2003). AI systems comprise areas like expert systems, ANNs, genetic algorithms, fuzzy logic and various hybrid systems, which combine two or more techniques (Kalogirou, 2003).

Concerning the application of neural nets to time series forecasting, there have been mixed reviews. For instance, WU (1995) conducts a comparative study between neural networks and ARIMA models in forecasting the Taiwan/US dollar exchange rate. His findings show that neural networks produce significantly better results than the best ARIMA models in both one-step-ahead and six-step-ahead forecasting. Similarly, Hann and Steurer (1996), ZHANG and HU (1998) find results in favor of neural network. Gencay (1999) compares the performance of neural network with those of random walk and GARCH[1] models in forecasting daily spot exchange rates for the British pound, Deutsche mark, French franc, Japanese yen, and the Swiss franc. He finds that forecasts generated by neural network are superior to those of random walk and GARCH models. Mark and Sul (2001) and Groen (2005) use panels of between 3 to 17 OECD countries to first test for cointegration between the exchange rate and monetary fundamentals, and secondly use this cointegrating relationship to successfully predict exchange rates at horizons of three to four years.

In this research, we compare the accuracy of ANFIS[2] as the nonlinear models and ARIMA as the linear models to forecasting 2, 4 and 8 days ahead of daily Iran Rial/US$ and Rial/€ using data collected from the Central Bank of Iran (CBI) website and forecast evaluation criteria include R^2, MAD and RMSE.

2. Methodology

2.1 Auto-Regressive Integrated Moving Average (ARIMA) model

Introduced by Box and Jenkins (1970), in the last few decades the ARIMA model has been one of the most popular approaches of linear time series forecasting methods. An ARIMA process is a mathematical model used for forecasting. One of the attractive features of the Box-Jenkins approach to forecasting is that ARIMA processes are a very rich class of possible models and it is usually possible to find a process which provides an adequate description of the data. The original Box-Jenkins modeling procedure involved an iterative three-stage process of model selection, parameter estimation and model checking. Recent explanations of the process (Makridakis, Wheelwright & Hyndman, 1998) often add a preliminary stage of data preparation and a final stage of model application (or forecasting). The ARIMA (p, d, q) model is as follows:

$$y_t = f(t) + \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + e_t + \theta_1 e_{t-1} + \dots + \theta e_{t-q} \tag{1}$$

Where y_t and e_t are the target value and random error at time t, respectively, $\phi_i\left(i = 1,2,\dots, p\right)$ and $\theta_j\left(j = 1,2,\dots, q\right)$ are model parameters, p and q are integers and often referred to as orders of autoregressive and moving average polynomials.

[1] Generalized Auto-Regressive Conditional Hetroskedasticity.
[2] Adaptive Neuro-Fuzzy Inference System.

2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS) model

ANFIS is a neuro-fuzzy system developed by Jang (1995). It has a feed-forward neural network structure where each layer is a neuro-fuzzy system component (Fig. 1).

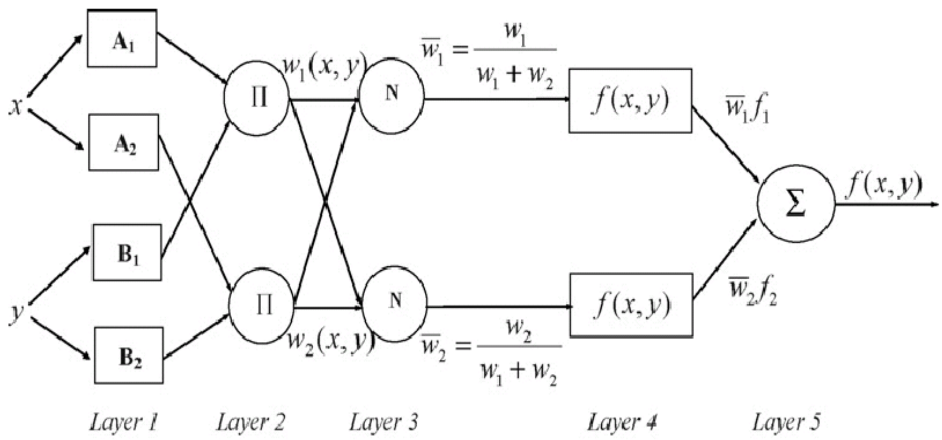


Fig. 1 The scheme of adaptive neural fuzzy inference system

It simulates TSK (Takagi–Sugeno–Kang) fuzzy rule of type-3 where the consequent part of the rule is a linear combination of input variables and a constant. The final output of the system is the weighted average of each rule's output (Sugeno & Kang, 1998). The form of the type-3 rule simulated in the system is as follows:

IF x_1 is A_1 AND x_2 is A_2 AND. . . AND x_p is A_p

THEN $y=c_0+ c_1 x_1+ c_2x_{2+\ldots+}\, c_p x_p$

Where x_1 and x_2 are the input variables, A_1 and A_2 are the membership functions, y is the output variable, and c_0, c_1, and c_2 are the consequent parameters. The neural network structure contains six layers.

• Layer 0 is the input layer. It has n nodes where n is the number of inputs to the system.

• The fuzzy part of ANFIS is mathematically incorporated in the form of membership functions (MFs). A $\mu_{A^i}(x)$ membership function can be any continuous and piecewise differentiable function that transforms the input value x into a membership degree, that is to say a value between 0 and 1. The most widely applied membership function is the generalized bell (gbell MF), which is described by the three parameters, a, b, and c (Eq.2). Therefore, Layer 1 is the fuzzification layer in which each node represents a membership value to a linguistic term as a Gaussian function with the mean.

$$\mu_{A^i}(x) = \frac{1}{1+[(\frac{x-c_i}{a_i})^2]^{b_i}} \tag{2}$$

Where a_i, b_i, and c_i are parameters of the function. These are adaptive parameters. Their values are adapted by means of the back-propagation algorithm during the learning stage. As the values of the parameters change, the membership function of the linguistic term A_i changes. These parameters are called premise parameters. In that layer there exist n*p nodes where n is the number of input variables and p is the number of membership functions. For example, if size is an input variable and there exist two linguistic values for size which are SMALL and LARGE, then two nodes are kept Layer 1 and they denote the membership values of input variable size to the linguistic values SMALL and LARGE.

• Each node in Layer 2 provides the strength of the rule by means of multiplication operator. It performs AND operation.

$$w_i = \mu_{A^i}(x_0) * \mu_{B^i}(x_1) \tag{3}$$

Every node in this layer computes the multiplication of the input values and gives the product as the output as in the above equation. The membership values represented by $\mu_{A^i}(x_0)$ and $\mu_{A^i}(x_0)$ are multiplied in order to find the firing strength of a rule where the variable x_0 has linguistic value A_i and x_1 has linguistic value B_i in the antecedent part of Rule l.

There are p^n nodes denoting the number of rules in Layer 2. Each node represents the antecedent part of the rule. If there are two variables in the system namely x_1 and x_2 that can take two fuzzy linguistic values, SMALL and LARGE, there exist four rules in the system, whose antecedent parts are as follows:

IF x_1 is SMALL AND x_2 is SMALL.

IF x_1 is SMALL AND x_2 is LARGE.

IF x_1 is LARGE AND x_2 is SMALL.

IF x_1 is LARGE AND x_2 is LARGE.

• Layer 3 is the normalization layer which normalizes the strength of all rules according to the equation:

$$\overline{w}_i = \frac{w_i}{\sum_{j=1}^{R} w_j} \tag{4}$$

Where w_i is the firing strength of the ith rule which is computed in Layer 2. Node i computes the ratio of the ith rule's firing strength to the sum of all rules' firing strengths. There are p^n nodes in this layer.

• Layer 4 is a layer of adaptive nodes. Every node in this layer computes a linear function where the function coefficients are adapted by using the error function of the multi-layer feed-forward neural network.

$$\overline{w}_i f_i = \overline{w}_i (p_0 x_0 + p_1 x_1 + p_2) \tag{5}$$

p^i are the parameters where i = n + 1 and n is the number of inputs to the system (i.e., number of nodes in Layer 0). In this example, since there exist two variables (x_1 and x_2), there are three parameters p_0, p_1 and p_2 in Layer 4 and $\overline{w_i}$ is the output of Layer 3. The parameters are updated by a learning step. Kalman filtering based on least-squares approximation and back-propagation algorithm is used as the learning step.

• Layer 5 is the output layer whose function is the summation of the net outputs of the nodes in Layer 4. The output is computed as:

$$\sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6}$$

Where $\overline{w_i} f_i$ is the output of node i in Layer 4. It denotes the consequent part of rule i. The overall output of the neuro-fuzzy system is the summation of the rule consequences. ANFIS uses a hybrid learning algorithm in order to train the network. For the parameters in the Layer 1, back-propagation algorithm is used. For training the parameters in the Layer 4, a variation of least-squares approximation or back-propagation algorithm is used.

3. Data description and forecast evaluation criteria

The exchange rate data used in this study are daily Iran Rial/U$ and Rial/€, covering the period from 20-Mar-2002 to 21-Nov-2008 with a total of 2436 observations, as illustrated in Fig. 2. Although there is no consensus on how to split the data for neural network applications, the general practice is to allocate more data for model building and selection. Most studies in literatures use convenient ratio of splitting for in-and out-samples such as 70%:30%, 80%:20% or 90%:10%. This investigation selects the 70%:30% one. We take the daily data from March 20, 2002 to October 20, 2006 as in-sample data set with 1706 observations for training and the remainder as out-sample data set with 730 observations for testing purposes. For space reasons, the original data are not listed here, and detailed data can be obtained from the website www.CBI.ir.

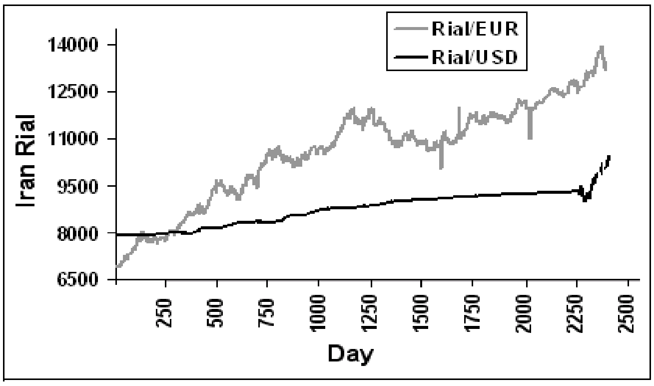


Fig. 2 Daily Iran Rial/US$ and Rial/€ changes from March 20, 2002 to November 21, 2008

In order to evaluate and compare the forecasting performance, it is necessary to introduce forecasting evaluation criteria. In this research, three criteria include; R-squared, Mean Absolute Deviations (MAD) and Root Mean Square Error (RMSE). Table 1 shows the R^2, MAD and RMSE formulation:

Table 1 Forecasting evaluation criteria

Criteria	Formulation
R-squared (R^2)	$R^2 = 1 - \frac{\sum(\hat{y}_t - y_t)^2}{\sum \hat{y}_t^2}$
Mean Absolute Deviation (MAD)	$MAD = \frac{\sum \lvert \hat{y}_t - y_t \rvert}{n}$
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{\sum(\hat{y}_t - y_t)^2}{n}}$

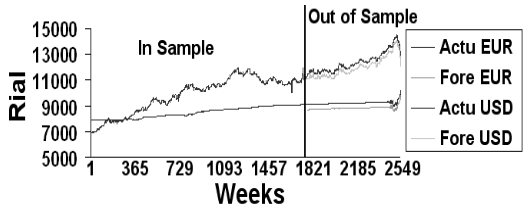
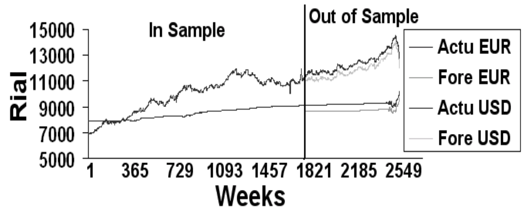
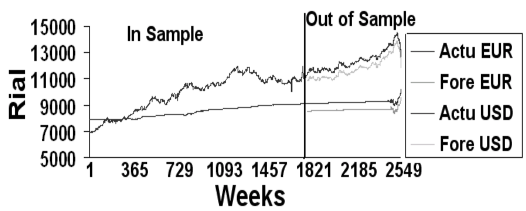
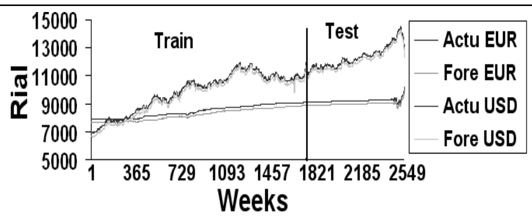
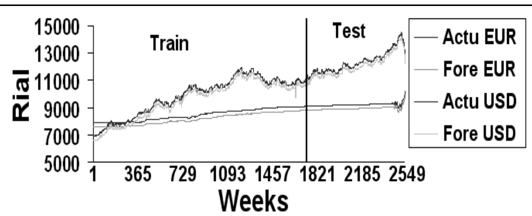
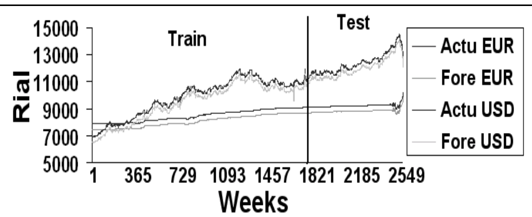
Note: Where y_t, $\hat{y}_t$ and n are the actual value, output value and the number of observations, respectively.

4. Experiments

4.1 Linear and non-linear models performance to exchange rate forecasting

In ARIMA model we identified the degree of integration (d) by augmented Dickey-Fuller and Schwarz criteria, and the degree of autoregessive (p) and moving average (q) by Log-likelihood function and Akaike Information Criterion. In ANFIS the hybrid learning algorithm is used to identify the membership function parameters of single-output, Sugeno type fuzzy inference systems (FIS). A combination of least-squares and backpropagation gradient descent methods are used for training FIS membership function parameters to model a given set of input/output data. In Genfis1 which generates an initial Sugeno-type FIS for ANFIS training using a grid partition the “gauss” and “gauss 2” types of membership function are used for each input and “linear” membership function is used for output. Also, 3 and 4 numbers of membership functions are used for each input. The forecasting performance of Rial/USD and Rial/EUR exchange rates obtained by the ARIMA and ANFIS models is shown in Table 2:

Table 2 ARIMA and ANFIS performance to exchange rate forecasting

Fitness	ARIMA					
	2 days ahead					
	Structure (2,1,2)					
	RMSE		MAD		R^2	
	$	€	$	€	$	€
	0.0101	0.0105	0.0117	0.0128	0.9228	0.9135
	4 days ahead					
	Structure (4,1,1)					
	RMSE		MAD		R^2	
	$	€	$	€	$	€
	0.0101	0.0112	0.0117	0.0130	0.9219	0.9126
	8 days ahead					
	Structure (8,1,1)					
	RMSE		MAD		R^2	
	$	€	$	€	$	€
	0.0101	0.0114	0.0118	0.0131	0.9210	0.9120
Fitness	ANFIS					
	2 days ahead					
	Structure (gauss-4-100)					
	RMSE		MAD		R^2	
	$	€	$	€	$	€
	0.0090	0.0090	0.0082	0.0110	0.9840	0.9698
	4 days ahead					
	Structure (gauss-3-100)					
	RMSE		MAD		R^2	
	$	€	$	€	$	€
	0.0092	0.0097	0.0084	0.0115	0.9791	0.9690
	8 days ahead					
	Structure (gauss2-4-100)					
	RMSE		MAD		R^2	
	$	€	$	€	$	€
	0.0093	0.0100	0.0085	0.0116	0.9662	0.9658

The left side of Table 2 demonstrates the out-sample fitness of ARIMA and ANFIS models for forecasting 2, 4 and 8 days ahead of Rial/USD and Rial/EUR exchange rates in comparison with the actual observations. And its right side presents the quantity of evaluation criteria to forecast the considered horizons of Rial/USD and Rial/EUR exchange rates. In ANFIS structure, for example structure (gauss-4-100) for forecasting 2 days ahead of Rial/USD or Rial/EUR the terms gauss, 4 and 100 represent the type of membership function, the number of membership function and the number of training epochs respectively. Table 2 states that ARIMA and ANFIS models provide better forecasting results for Rial/USD in contrast with Rial/EUR by all three performance measures. Also, this table indicates that the forecasting accuracy of these models will be reduced through the horizon increscent.

4.3 Comparison of linear and nonlinear models performance to exchange rate forecasting

In order to comparison the performance of considered linear and nonlinear models to Rial/USD and Rial/EUR exchange rates forecasting, we divided the quantity of forecast evaluation criteria of ANFIS to ARIMA model, per each horizon. Table 3 demonstrates the results of these comparisons.

Table 3 Comparison of ARIMA and ANFIS performance

ANFIS criteria to ARIMA criteria										
Days ahead	Structure		RMSE		MSE		MAD		R^2	
	ANFIS	ARIMA	\$	€	\$	€	\$	€	\$	€
2	gauss-3-100	(2,1,2)	0.892	0.859	0.796	0.738	0.702	0.860	1.064	1.061
	gauss-4-100	(2,1,2)	0.891	0.857	0.794	0.735	0.701	0.859	1.066	1.062
	Gauss2-3-100	(2,1,2)	0.895	0.861	0.801	0.741	0.705	0.863	1.060	1.058
	Gauss2-4-100	(2,1,2)	0.894	0.860	0.799	0.740	0.704	0.892	1.063	1.059
4	gauss-3-100	(4,1,1)	0.911	0.866	0.830	0.750	0.718	0.885	1.062	1.062
	gauss-4-100	(4,1,1)	0.913	0.868	0.834	0.753	0.719	0.886	1.061	1.060
	Gauss2-3-100	(4,1,1)	0.914	0.869	0.835	0.755	0.721	0.888	1.059	1.059
	Gauss2-4-100	(4,1,1)	0.916	0.871	0.839	0.759	0.722	0.891	1.058	1.057
8	gauss-3-100	(8,1,1)	0.925	0.881	0.856	0.776	0.724	0.891	1.044	1.056
	gauss-4-100	(8,1,1)	0.923	0.880	0.852	0.774	0.723	0.888	1.046	1.057
	Gauss2-3-100	(8,1,1)	0.922	0.879	0.850	0.773	0.721	0.887	1.047	1.058
	Gauss2-4-100	(8,1,1)	0.921	0.877	0.848	0.769	0.720	0.885	1.049	1.059

As can be seen in Table 3, the ANFIS nonlinear model forecasting performance is better in contrast with the ARIMA linear model because (1) the RMSE, MSE and MAD divided are less than 1, and (2) the R^2 divided is more than 1.

5. Conclusions

This study compares the accuracy of ANFIS as the nonlinear model and ARIMA as the linear model for forecasting 2, 4 and 8 days ahead of daily Iran Rial/€ and Rial/US$ exchange rates. Results indicated that ANFIS nonlinear model forecasts are considerably more accurate than the linear traditional ARIMA model which are used as benchmarks in terms of error measures, such as RMSE, MSE and MAD. Besides, as the R^2 criterion is concerned, ANFIS nonlinear model is absolutely better than ARIMA linear model.

Briefly using forecast evaluation criteria, we found that ANFIS nonlinear model outperforms ARIMA linear model. And we cannot deny that the ANFIS model is an effective way to improve the Iran Rial/€ and Rial/US$ exchange rates forecasting accuracy.

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(continued from Page 21)

explicitly includes the capital charge to cover such losses. At the same time, the Committee proposes the LDA model for measuring the regulatory capital. This approach should be adapted to the specific characteristics of the financial entity since the model variables, that is, frequency and severity, are estimated from the internal data. With this paper, we emphasize how relevant the model inputs are when determining a realistic internal approach for covering external fraud. Thus, as long as the Weibull distribution tends to underestimate the resulting CaR in comparison to the lognormal, which provides the best statistical fit, the exponential function make CaR overestimated.

In absolute values, the CaR estimate should be interpreted assuming the reduced dimension of the reference entity. Moreover, even the historical IOLD could be insufficient to reflect the risk exposure the financial entity is really facing; in particular, those operational losses that have not occurred yet but to which the financial entity is exposed too. To some extent, the financial entities should include the Scenario Analysis in conjunction with the external data to supplement the missing points of the IOLD and to reinforce the statistical robustness of the internal model.

Finally, despite of the LDA wide acceptance, its future development will be conditioned to the quality and depth of the operational loss database.

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