AN EXCHANGE RATE MODEL FOR TURKEY USING THE ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The success of decisions depends not only on the behaviors of decision makers (governments, producers, consumers, and so on) but also the ability of forecasting future correctly. Forecasting modeling has a great importance for many research areas as well as economics. In recent years artificial neural networks (ANNs) have increasingly been used for forecasting in economics. In this study both ANNs and vector auto regression method (VAR) are used to solve the exchange rate model developed for Turkey and the results obtained from the two methods are compared.

Key Words: Artificial Neural Networks, VAR Method, Exchange Rate, Turkey.

JEL Classification: C4,C45,C49,C51,C52,C53

ÖZET

Verilen kararların başarılı olması yalnızca karar vericilerin (hükümetler, üreticiler, tüketiciler, v.b.) davranışlarına bağlı olmayıp, aynı zamanda geleceği doğru biçimde tahmin edebilme yeteneğine de bağlıdır. Tahmin modellemesi birçok araştırma alanı ve ekonomi için büyük bir öneme sahiptir. Son yıllarda yapay sinir ağları (YSA) ekonomide tahmin amacıyla artan bir biçimde kullanılmaya başlanmıştır. Bu çalışmada hem YSA hem de vektör otoregresif metot

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(VAR) Türkiye için geliştirilen döviz kuru modelinin çözümünde kullanılmakta ve iki metodun sonuçları birbirleri ile karşılaştırılmaktadır.

Anahtar Kelimeler: Yapay Sinir Ağları, VAR Metodu, Döviz Kuru, Türkiye

JEL Sınıflandırılması: C4,C45,C49,C51,C52,C53

INTRODUCTION

In recent years, forecasting modeling has been extensively applied to many areas of economics. The behaviors of decision makers (governments, producers, consumers, and so on) differ according to the differences in forecasts of the future. Accuracy of forecasting is essential for the decision makers to employ an appropriate strategy. The importance of accuracy of forecasting has led to an increasing interest in forecasting models, and as a result, a variety of forecasting models have been developed.

Many different forecasting techniques from simple regression models to more complex statistical and econometric methods such as large-scale structural econometric models, vector auto regression (VAR) models, and Box-Jenkins models are used in forecasting modeling. As these widely known models are used, new methodologies have also been applied in forecasting. Artificial neural networks (ANNs) method is one of the important new techniques employed in forecasting modeling.

Because of its success in solving hard and complex problems in many fields, ANNs have become a widely used method. However, its use in economics has been relatively limited. Therefore, in this study we employ ANNs method in forecasting exchange rates in Turkey and compare its results with that of VAR.

I. ARTIFICIAL NEURAL NETWORKS METHODOLOGY

An artificial neural network is an artificial intelligence technology based on applying brain's physiological structure together with its abilities of thinking, remembering, and problem solving into computers. ANNs consist of artificial neural cells, which are connected with each other in various ways. ANNs are generally organized as layers.

Kohonen[1] defines ANNs as hierarchical organizations in which many simple elements are connected with each other in a parallel fashion and communicate with the elements of real world similar to biological neural system. On the other hand, Haykin[2] describes a neural network as a simple procedure that has a natural tendency to accumulate experimental knowledge and facilitates the usage of that knowledge.

Biological neural system is the inspirational basis of ANNs. As biological neural networks consist of neural cells, artificial neural networks are composed of artificial neural cells. However, Zurada[3] draws attention to the fact that there are also important differences between biological neural networks and artificial neural networks in terms of their architectures and abilities. According to Zhang, Patuwo, and Hu[4], artificial neural networks form a mathematical model and are known as a general functional approximation.

II. ELEMENTS OF ARTIFICIAL NEURAL NETORKS

According to Zhang, Patuwo, and Hu[5], the architecture of ANNs is important because it determines its modeling ability. In designing stage, among network structures, the one that is the most suitable for

[1] T. Kohonen (1982), "Self-organized Formation of Topologically Correct Feature Maps", *Biological Cybernetics*, 43, pp. 59-69.

[2] S. Haykin (1999), *Neural Networks: A Comprehensive Foundation*, Prentice-Hall.

[3] J. M. Zurada (1992), *Introduction of Artificial Neural Systems*, West Publishing Company.

[4] G. Zhang, B. E. Patuwo, and M.Y. Hu (1998), "Forecasting with Artificial Neural Networks: The State of the Art", *International Journal of Forecasting*, 14, pp. 35-62.

[5] Ibid.

application is chosen. The elements that regulate the functioning of ANNs can be summarized as follows:

Architecture: ANNs are first categorized according to their architectures. According to the direction of their connections, artificial neural network architectures comprise two structures, feed-forward and feedback networks.

As a general rule, a multilayer feed-forward artificial neural network consists of input layer, hidden layer, and output layer. Input layer takes the information from external world and transmits it to hidden layer. In the hidden layer, in turn, the information coming from input layer is processed and transmitted to output layer. According to Kaastra and Boyd[6], selection of the number of neurons in the hidden layer is very important in order to define the size of the network and to know its performance. Output layer processes the information coming from hidden layer and produces output for the input set provided by input layer.

Layers are made up of units called neurons. A complete determination of the architecture requires deciding the number of neurons in layers. In artificial neural networks neurons are connected to each other through weights. In feed-forward networks these connections are unidirectional and forward. There are no connections between the units of the same layer.

Learning Algorithm: Another classification criterion for ANNs is whether learning paradigm is supervised or unsupervised. One of extensively used learning algorithms is back-propagation algorithm.

Activation Function: Activation function is one of the important elements affecting the behavior of a neuron. It is called as the transfer function. The activation function processes the net input received from connection function and determines cell output. The choice of activation function depends on artificial neural network data

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[6] I. Kaastra, and M. Boyd (1996), "Designing A Neural Network For Forecasting Financial and Econometric Time Series", *Neurocomputing*, 10 (3), pp.215-236.

and what the network is expected to learn. According to Minsky and Papert[7], the chosen activation function should be a nonlinear function. However, other functional forms, such as linear, stepwise, sigmoid, and hyperbolic tangent function are also used. Gonzales[8] asserts that when the relation in the structure of the problem is not linear, choice of a nonlinear activation function for the artificial neural network allows for building a more efficient model.

III. VAR METHODOLOGY

According to Sims[9], if there is simultaneity among a group of variables, then each variable must be treated equally. That is, there should not be a priori distinction between variables as endogenous and exogenous.

The vector autoregressive (VAR) methodology was developed by Sims[10] on the basis of the causality test proposed by Granger[11]. VAR models are used in examining dynamic effects of stochastic shocks in a system of variables. According to Greene[12], unrestricted VAR provides better results in forecasting than classical structural models.

A two-variable model can be written as follows:

$$y_t = a_0 + \sum_{i=1}^{k} a_{1i} y_{t-i} + \sum_{i=1}^{k} a_{2i} x_{t-i} + u_{1t}$$

[7] M. Minsky, and S. Papert (1969), *Perceptrons,* MIT Press.

[8] S. Gonzalez (2000), "Neural Networks for Macroeconomic Forecasting: A Complementary Approach to Linear Regression Models", *Canada Department of Finance Working Papers,* 2000-07.

[9] C. Sims (1980), "Macroeconomics and Reality", *Econometrica*,48, pp. 1-49.

[10] Ibid.

[11] C. W. J. Granger (1969), "Investigating Casual Relations by Econometric Models and Cross-Spectral Methods", *Econometrica*, 37, pp. 424-438.

[12] W. H. Greene (1993), *Econometric Analysis*, Second Edition, Prentice-Hall.

(1)

$$x_t = b_0 + \sum_{i=1}^{k} b_{1i} x_{t-i} + \sum_{i=1}^{k} a_{2i} y_{t-i} + u_{2t}$$

where k denotes length of the lag, and u is a normally distributed random error term with zero mean, constant variance, and zero autocovariance. In the VAR methodology, the assumption that error term has zero autocovariance imposes no restriction on the model.

IV. EMPIRICAL APPLICATIONS

In this section we construct an artificial neural network model in order to estimate the parameters of the exchange rate model for the Turkish economy. To check the forecasting power of the artificial neural network model, we also use VAR approach in estimating the parameters of the exchange rate model, and compare the results obtained from the two approaches.

A) EXCHANGE RATE MODEL AND THE DATA SET

The exchange rate model constructed for the period from January 1987 to December 2004 by using monthly data can be written as follows[13]:

$$DK_t = f(\,TEFE_t, F_t, M2Y_t, GSYIH_t, u_t\,)$$

(2)

[13] The time series data for the variables of the model are obtained from the web sites of Turkish Central Bank (www.tcmb.gov.tr) and Turkish Statistical Institute (www.tuik.gov.tr).

where DK_t**:** Exchange Rate, $TEFE_t$**:** Wholesale Price Index (1987=100), F_t**:** Interest Rate (%), $M2Y_t$**:** Money Supply (Thousand YTL), and $GSYIH_t$**:** Gross Domestic Product (Thousand YTL).

B) ARTIFICIAL NEURAL NETWORK MODELS

In this study we investigate how the artificial neural network model can be used in explaining exchange rates. According to Zhang[14] (1998), studies employing ANNs have shown that ANN models provide better results than traditional methods. The success of artificial neural network in time series applications is another reason for preferring it in forecasting.

1. Data Process

For artificial neural networks to process training and test data groups, they first need to be normalized and put into appropriate format. In this study we choose sigmoid function as the activation function for hidden layer and output layer. Therefore, by taking [0,1] boundary into account, data is normalized by using the formula:

$$x_n = \left(\frac{x_0}{x_{\max}}\right)$$

where x_n is the normalized data, x_0 is the original data, and $x_{\max}$ are the maximum values in rows and columns.

2. Network Architecture

In the model (2), wholesale price index, interest rate, money supply, and gross domestic product are taken as input variables, while exchange rate is used as the output variable.

In this study, feedforward network structure is used as the artificial neural network. Furthermore, error back-propagation

[14] Zhang, loc. cit.

algorithm is used in order to minimize the error. When the network is trained, supervised learning algorithm is chosen as the learning form.

We have used Matlab (7.0 version)'s nntool (Neural Network Toolbox) for the ANN model. Four input neurons are used to provide input variables into the network because we have four independent variables. In the output layer, on the other hand, there is one neuron to receive the network output for the dependent variable. After the trials with different numbers of hidden neurons and hidden layers, we have observed that the network architecture with two hidden layers provide better results than other options. The artificial neural network is constructed by using six neurons in the first hidden layer and eleven neurons in the second hidden layer. In addition, stochastic error terms are used for both hidden layers and output layer.

In the artificial neural network model, we choose linear summation as the summation function. Same activation function and sigmoid function are used for the neurons in hidden and output layers.

One of the factors affecting the performance of artificial neural networks is the training algorithm. Our trials have shown that the network structure using Levenberg-Marquart (trainlm) training algorithm provides better results than the alternatives. Therefore, we have chosen *trainlm* as the training algorithm. On the basis of trials, 0.2 is taken as the learning ratio.

3. Training and Test Stages of the Network

In this section we train a network architecture and use it in applications. The data at hand are grouped into training data and test data. However, there is no general rule for grouping the data. On the other hand, many researchers use 90% of their data as the training data, and the rest as the test data. Zhang[15] notes that %80-%20 or %70-%30 division ratios are also used in the literature.

We use the first 200 observations of our data set as the training data. These observations cover January 1987-August 2003 period.

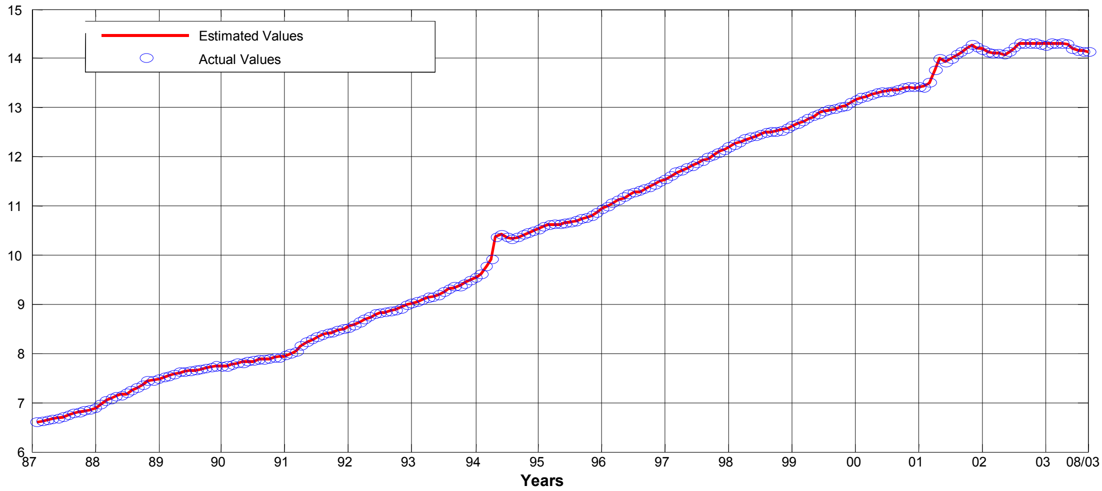
In order to determine whether the constructed artificial neural network is a good estimator, accuracy of the estimated values of the variable have to be tested. There are many tests that can be used

[15] Ibid.

for this purpose. In this study we use Mean Squared Errors (MSEs), Sum Squared Errors (SSE), and Root Mean Squared Errors (RMSE) as the objective function.

The artificial neural network is trained using 3000 epochs. The estimated values obtained after this training process are compared with the actual values of the exchange rate. As can be seen in Figure 1, estimated and actual values match each other. This result shows that training process has been completed with minimum error.

Figure 1: Estimated and Actual Values of Exchange Rate



after the Training Stage

Figure 2: Training Errors

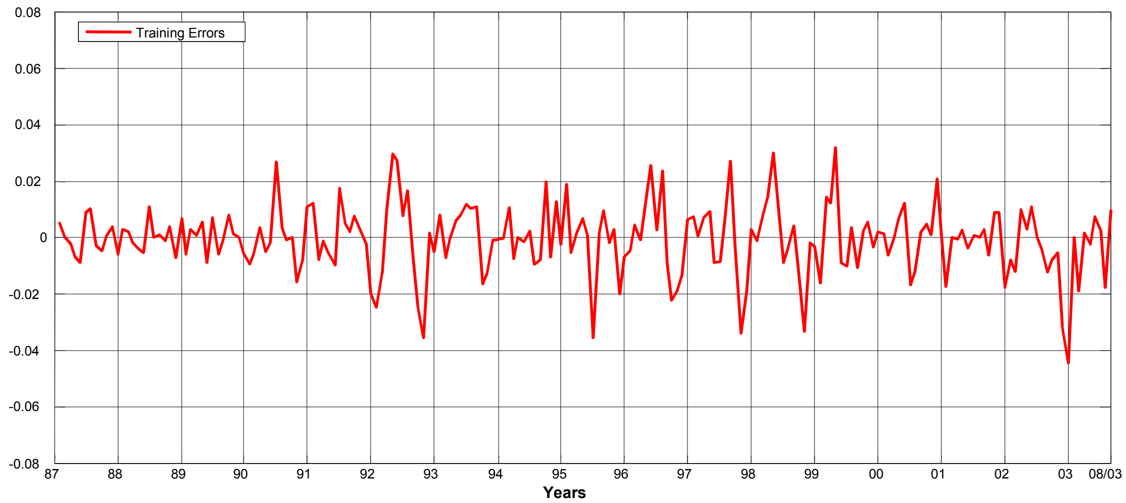


Figure 2 shows the training errors. Examination of Figure 2 reveals that training process has been completed effectively. Even though during the training period considered Turkey experienced two deep economic crises (in 1994 and 2001), we can take the training process as very successful.

By using the weights obtained in training process and the data set aside as the test data, we can test the constructed artificial neural network.

Figure 3: Actual and Estimates Values after the Test Stage

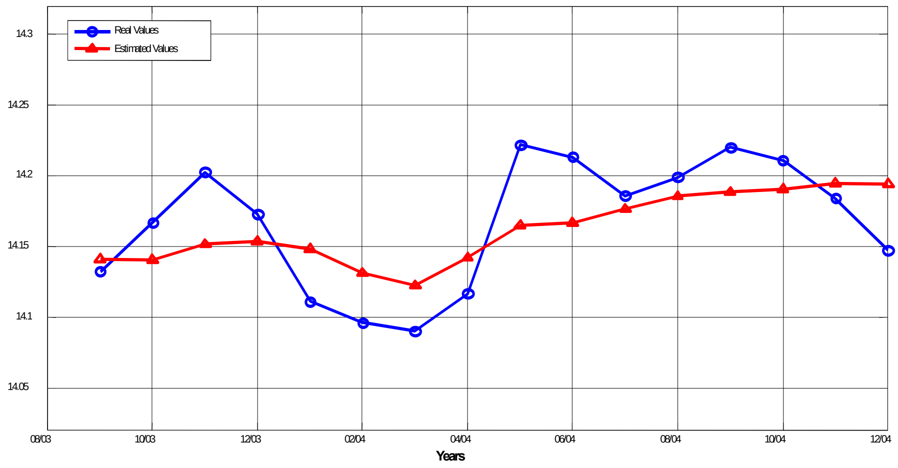


Table 1 shows mean squared error (MSE), sum squared error (SSE), and root mean squared error (RMSE) we obtained after training and test stages.

Table 1: Errors after Training and Test Stages

After Training Stage		After Test Stage	
MSE	0.0001446	MSE	0.0011
SSE	0.0289	SSE	0.0174
RMSE	0.01202	RMSE	0.03316

The values of mean squared error (MSE), sum squared error (SSE), and root mean squared error (RMSE) provided in Table 1 demonstrate that the artificial neural network we constructed provides good results. Besides, error during the training period is especially small. Artificial neural network used also completes its training by learning the breaking points in the exchange rates. We have obtained good results for both sample period and out of sample period. Our model captures 1994 and 2001 crises correctly.

Figure 4: Results of Artificial Neural Network Model

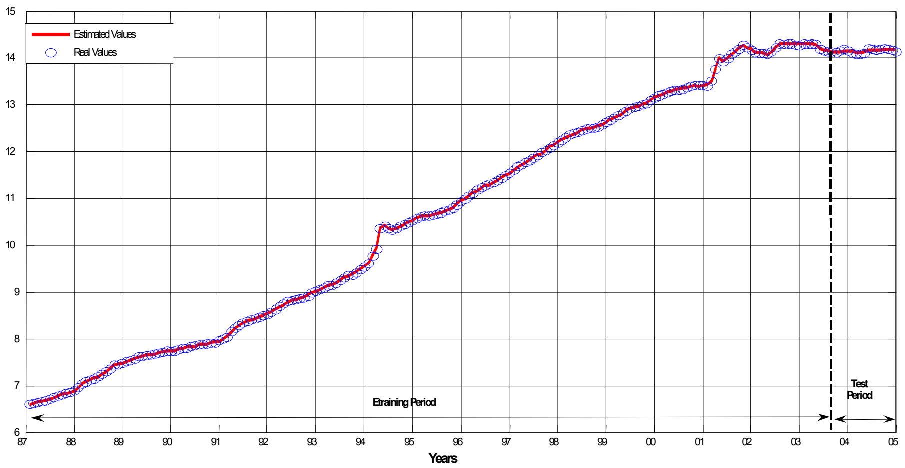
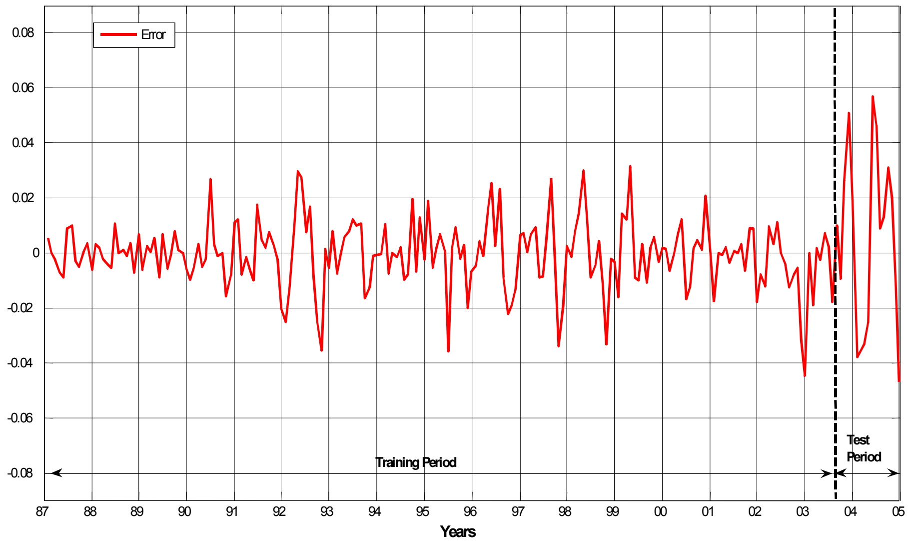


Figure 5: Artificial Neural Network Errors



We normalized parameters in [0,1] range because we used sigmoid function during the training stage. Thus, results that the artificial neural network produce are in [0,1] range. We therefore reverse the normalization after obtaining network results in order to produce values suitable for comparison.

C) VAR SOLUTION OF EXCHANGE RATE MODEL

Economic models are constructed on the assumptions of equilibrium relations defined by economic theory. However, time series need to be stationary in order to obtain econometrically meaningful relations. In order to test for stationarity we use Augmented Dickey-Fuller (ADF) unit root test.

Variables used in exchange rate forecasting model are Turkish Lira-U.S. Dollar exchange rate (DK), whole sale price index (TEFE), gross domestic product (GSYIH), money supply (M2Y), and interest rate (F). All variables but exchange rate are in logarithmic forms and seasonally adjusted. General structure of the estimated VAR model is given in equation (3) below:

$$LnDK = f(\sum_{i=1}^{k} LnDK, \sum_{i=1}^{k} LnTEFE, \sum_{i=1}^{k} LnGSYIH, \sum_{i=1}^{k} LnM2Y, \sum_{i=1}^{k} LnF) \quad (3)$$

Unit root test results for the variables included in the model are provided in Table 4.2 below:

Table 2: Unit-root Test Results

		ADF Statistics	
Variable	Lag (k)	Level I(0)	First Difference I(1)
LnTEFE	1	-1.2032	-6.6073
LnM2Y	3	-1.2744	-4.2304
LnDK	1	-0.8973	-8.0707
F	1	-1.1108	-10.0336
LnGSYIH	6	-1.6299	-2.6123

MacKinnon critical values for 1%, 5%, and 10% significance levels are –3.4633, -2.8755, and –2.5742 respectively.

As it can be seen from Table 2, all variables except gross domestic product are I(1) at 1% significance level, and gross domestic product is I(1) at 10% significance level.

Since VAR model is extremely sensitive to lag length, we need to determine the lag length correctly. We use Akaike Information Criterion (AIC) to determine the lag length. We started our trials with 12 lags and reduced lags by one on each trial and determined optimal lag length as 2.

We use Granger causality test to determine if the variables included in the model affect each other. Granger causality test results are provided in Table 3.

Table 3: Granger Causality Test Results

Null Hypothesis	Number of Observations	F Statistics	P Probabilities
H_0 : M2Y does not Granger cause F. H_0 : F does not Granger cause M2Y.	198	2.08943 21.5957	0.12655 3.4E-09
H_0 :TEFE does not Granger cause F. H_0 :F does not Granger cause TEFE.	198	2.33758 8.57309	0.09929 0.00027
H_0 :GSYIH does not Granger cause F. H_0 : F does not Granger cause GSYIH.	198	4.02428 9.04988	0.01940 0.00018
H_0 :DK does not Granger cause F. H_0 :F does not Granger cause DK.	198	2.30888 8.33840	0.10211 0.00034
H_0 :TEFE does not Granger cause M2Y. H_0 :M2Y does not	198	2.93730 4.94672	0.05538 0.00803

Granger cause TEFE.			
H_0 :GSYIH does not Granger cause M2Y. H_0 :M2Y does not Granger cause GSYIH.	198	7.30043 3.26556	0.00088 0.04030
H_0 :DK does not Granger cause M2Y. H_0 :M2Y does not Granger cause DK.	198	0.34247 3.94228	0.71044 0.02099
H_0 :GSYIH does not Granger cause TEFE. H_0 :TEFE does not Granger cause GSYIH.	198	3.22338 5.87386	0.04197 0.00334
H_0 :DK does not Granger cause TEFE. H_0 :TEFE does not Granger cause DK.	198	7.95125 4.72676	0.00048 0.00991
H_0 :DK does not Granger cause GSYIH. H_0 :GSYIH does not Granger cause DK.	198	3.98102 3.84809	0.02022 0.02298

By using the information obtained from causality test we get the forecasts and forecast errors shown in Figure 6 and Figure 7. As it can be seen from these figures, VAR method fails to capture 1994 economic crisis occurring during the training period. Furthermore, there is a significant forecast error in estimating 2001 crisis occurring during the training period.

Figure 6: VAR Results

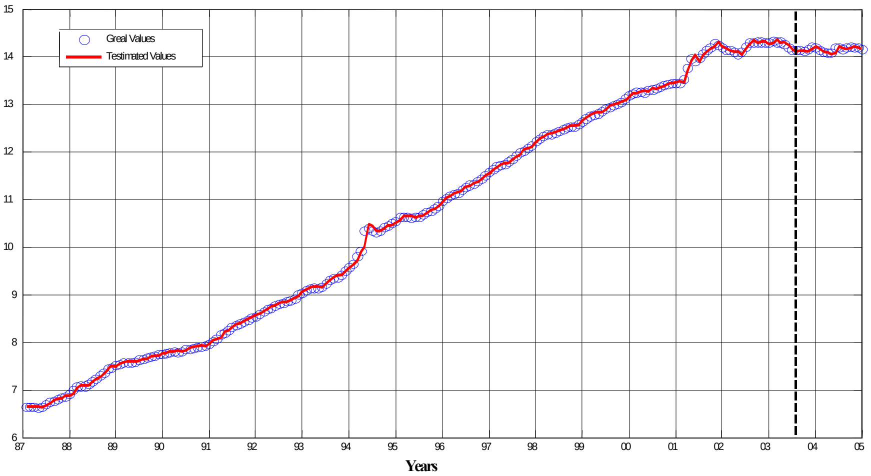
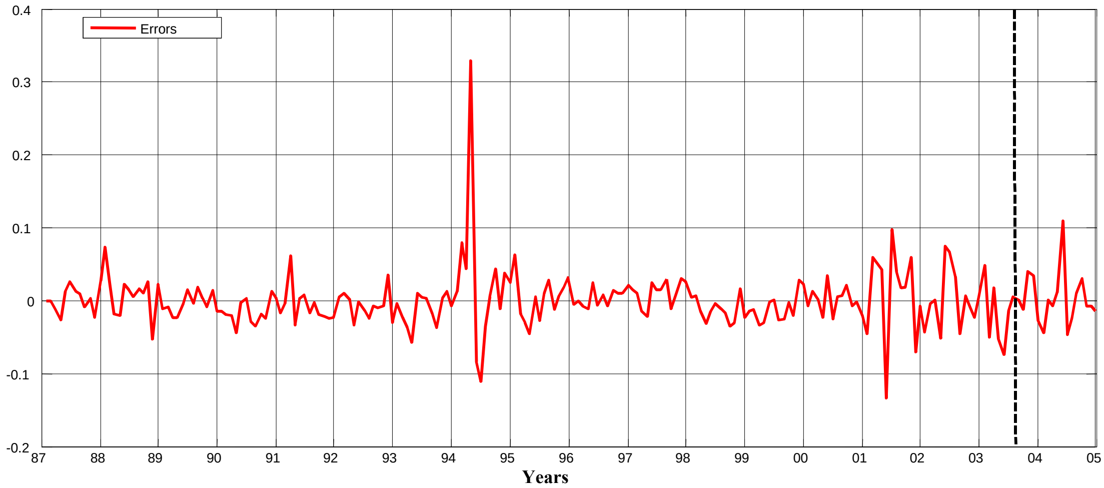


Figure 7: VAR Errors



D) COMPARISIONS OF FORECASTS

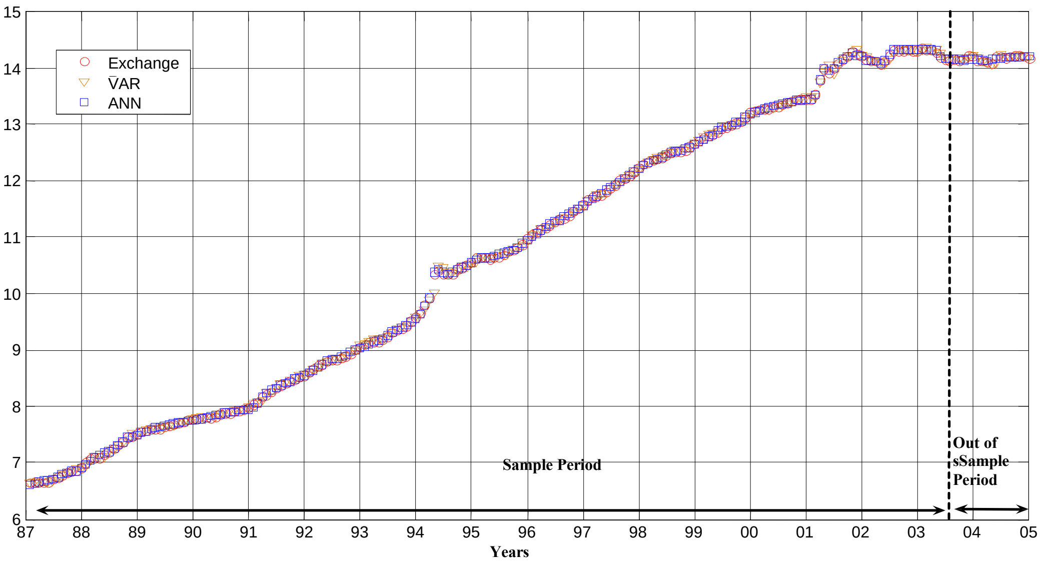
Results obtained from artificial neural network method and VAR method for both sample and out of sample periods are provided in Table 4.

Table 4: Measures of Forecast Accuracy

	Sample Period		Out of Sample Period	
	VAR	ANN	VAR	ANN
MSE	0.0015	0.0001446	0.0014	0.0011
SSE	0.29456	0.0289	0.0220	0.0174
RMSE	0.03857	0.01202	0.03741	0.03316

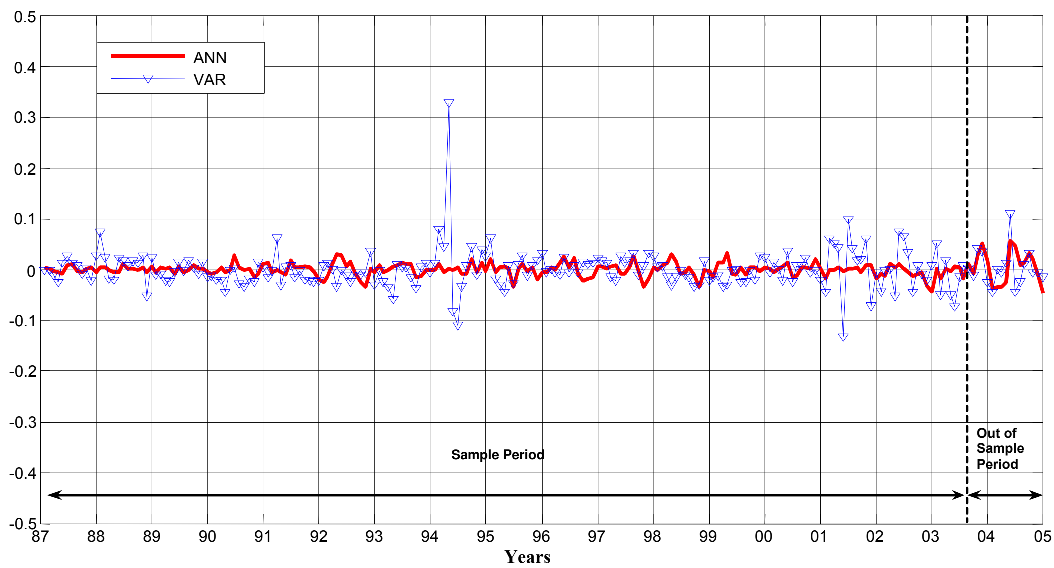
We observe from Table 4 that artificial neural network method performs better than VAR method in estimating exchange rates in Turkey. Actual exchange rate values and forecasted values obtained from both methods for both sample and out of sample periods are also shown in Figure 8. Figure 9 depicts forecast errors of both approaches.

Figure 8: Forecast Comparisons for Sample and out of Sample Periods



As it can be seen from Figure 8, forecast values of exchange rate obtained using ANN method and VAR method are close to each other. Forecasts from both methods can be judged successful for both sample and out of sample periods. On the other hand, following the crisis in 1994, there have been sudden fluctuations in exchange rates in Turkey. As it can be seen from Figure 9, when we look at the forecast errors, we observe that VAR approach is not as successful as artificial neural network approach after 1994. After 2001 economic crisis, Turkey changed its exchange rate regime. In terms of forecast errors, artificial neural network approach performs better than VAR approach after 2001 period as well.

Figure 9: Forecast Errors for Sample and out of Sample Periods



In comparison of the performances of forecast models, out of sample period is more important than the sample period. As it can be seen from Figures 8 and 9, ANN provides better forecast than VAR for not only sample period but also out of sample period.

CONCLUSION

Artificial neural network approach is widely used in forecasting. It is because of the fact that this approach has the potential to reveal relations among variables that are hard to be captured by other approaches used in forecasting. Furthermore, ANN approach requires less observations than other approaches such as VAR. ANN approach performs especially good when the architecture of network is appropriate for the problem at hand. Therefore, one should look for the correct network architecture for the problem. This study compares the performances of ANN and VAR approaches in forecasting exchange rates in Turkey. In estimating exchange rate model, we chose back-propagation network architecture among many artificial neural network architectures.

ANN approach produced better results than VAR approach for both sample and out of sample periods. In addition, ANN forecasts 1994 and 2001 economic crises better than VAR approach. When we consider our analysis as a comparison of linear and nonlinear modeling techniques, we can conclude that nonlinear modeling works better in modeling exchange rate for 1987-2003 period in Turkey.

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