Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 4 Issue 10, October - 2017

Exchange Rate Forecasting using ARIMA, NAR and ARIMA-ANN Hybrid Model

Roneda Mucaj
Department of Computer Science
University of Vlora "Ismail Qemali"
Vlora, Albania
mucaj.roneda@gmail.com

Valentina Sinaj
Department of Applied Mathematics
University of Tirana
Tirana, Albania
sinajv@yahoo.com

***Abstract*—In this paper we have studied the time serie of USD/ALL exchange rate. Based on the data of USD/ALL for the years 2000-2015, with monthly frequency, obtained by the Bank of Albania, we have done its modeling and forecasting using three types of methods: the autoregressive integrated moving average ARIMA, nonlinear autoregresive neural network (NAR) and the proposed hybrid method of ARIMA-ANN. As exchange rates are influenced by many political, economic and psychological factors, it is difficult to identify a unique economic model which can yield stable forecasts. However, we have used the univariate time series model, where is considered only the records of a single variable, exchange rate. We make the technical analysis, using the historical data to build the model to forecast future rate.**

The empirical analysis has shown very good results, mainly in the proposed hybrid model. The performance of the three methods was compared based on standard statistical measures. The ARIMA-ANN model generated the best model, with the lowest RMSE, MAE, MPE, MAPE, U of Theil statistics.

Keywords—forecasting; exchange rate; times series; ARIMA, NAR, ARIMA-ANN

I. INTRODUCTION

In the new era of globalization and financial liberalization, the exchange rate plays a key role not only in the international trade, but also in the financial system of a developing country like Albania. The role of exchange rate is very important, because every change on it has impacts on every part of the financial system. A stable exchange rate helps companies and entrepreneurs to evaluate their investment performance, liquidity, solvency, obligations and to be able to predict their economic situation for the next few years. Changes in exchange rates can have important effects mainly in the volatility of macroeconomic factors. Among these factors are: interest rates, commodity prices and services, inflation, trade balances, etc. Therefore, the exchange rate behavior is one of the objectives of the governments of each country.

The exchange rates link a country's economy to the world economy. It reflects all transactions between economic agents, both domestically and internationally. Fluctuations in foreign exchange rates are probably the most important factors affecting sales, profit forecasting, capital budgeting plans, and the value of foreign investment. From this point of view, changes in foreign exchange rates play an important role in the economic and political stability of the world in general as well as the well-being of the nations taken in particular. On the other hand, this is also a matter of particular importance for the very conditions of Albania, where there is a great dependence on foreign trade and the remittances from abroad, an issue which concerns other banks and other interest groups. Foreign trade and investments are realized in the framework of an international monetary system consisting of the currency system and their links through the foreign exchange markets.

We have to analyze the discrete series of USD/ALL exchange rate. The data are for each month of the years 2000 – 2015.

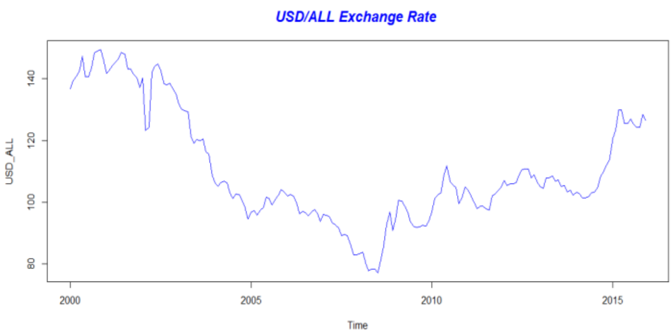

Fig. 1 *The performance graph of exchange rate in the years 2000-2015.*

As we can see, the USD/ALL rate shows different phases of evolution, a decreasing part from 2000 to 2005, and second one globally slightly increasing from 2005 to 2015. Globally, the trend seems not really important, however the seasonal component and the random one appears to be preponderant.

II. LITERATURE REVIEW

The exchange rate forecast is useful in Banks, financial system, international trade and policymakers. According to Greenspan (1994), "implicit in any monetary policy action or inaction is an expectation of how the future will unfold, that is, a forecast". Many researchers have attempted to forecast exchange rates, but their empirical results are often contradictory. Meese and Rogoff (1983) examine the Frenkel-Bilson, Dornbusch-Frankel, and Hooper-Morton structural exchange rate models and find that the random walk performs better. The authors conclude that the out-of-sample failure is due to the volatile nature of exchange rates, the poor inflation measurements and their money demand misspecifications. On the other hand, Tenti (1996) presents promising results in predicting the exchange rate of the Deutsche Mark with three different RNN architectures. Probably the best cited exchange rate model ever is Dornbusch's model (1976). It implies that exchange rate changes are predictable.

Many studies have shown that neural networks are effective in modeling financial data, regardless of the non-linearity they contain. This is why, in recent years, applications with ANN in the field of modeling and forecasting have been increased, [Widrow. 1994, Chan and Foo. 1995, Zhang. 2004, Kamruzzaman. 2004]

Many other studies have compared ARIMA with ANN (Jhee and Lee, Wang and Leu, Tang and Fishwich, Hill) and have concluded that ANNs perform better than ARIMA models. Bissoondeeal (2008) use linear and nonlinear methods in forecasting AUD/USD and GBP/USD exchange rates and conclude that ANNs outperform the ARMA and GARCH models.

Recent years, many hybrid approaches, combining two or more techniques (linear and non-linear) have been proposed in order to yield more accurate modeling and forecasting results. Saeed Matroushi (2011) from Lincold University, in his research proposed two hybrid systems composed by ARIMA and ANN models. The modeling results revealed that ARIMA-MLP hybrid model provided a better alternative. Khashei (2008) based on the basic concepts of artificial neural networks and fuzzy regression proposed a new hybrid model in order to obtain more accurate forecasting results. Zeng (2008) proposed a hybrid ARIMA-ANN model to forecast traffic flow. Aladage (2009) proposed a hybrid model using ARIMA and Elman's recurrent neural networks. Areekul (2010) used the combination of ARIMA and MLP for short-term price forecasting. Fam and Yang (2010) proposed a hybrid model by using ARIMA and GARCH to model and forecast machine health condition. Kristjanpoller & Minutolo (2015) constructed a hybrid model by ANN and GARCH to forecast gold price. A hybrid model based on ARIMA and the radial basis function neural network (RBFNs) was proposed by Shafie-khah (2011) and was used to forecast electricity price. Almost, the results of all these and other studies have shown that the hybrid approaches produce a better prediction in time series.

III. Empirical Analyses

A. Stationarity

We first analyze the stationarity of the series. The USD/ALL series is not stationary due to the variations that are very significant, and by consequent we have to differentiate the variable in order to better assimilate its seasonality.

In order to better analyze our time series, we decompose it. As we can see from the graph, the trend component seems not important regarding at the bar at the left of the graph that stills small. The USD/ALL rate varies around a constant mean and the trend variations are globally not important.

The two remaining components are important in our time series. The graph shows a seasonal behavior and also random component that appears to be significant in some observations. The stationarity of the time series is graphically rejected, but to be statistically confident we perform the Augmented Dickey fuller test on the original time series first and then on the differentiated one.

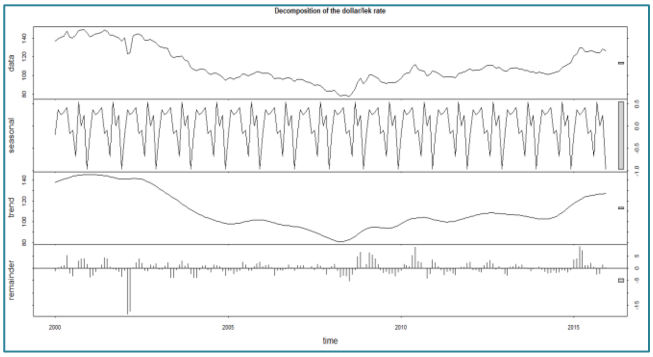

Fig. 2 *The decomposition of USD/ALL*

B. Identification of the model

Two alternatives are used to identify the appropriate models; the H-K identification algorithm, the TRAMO identification procedure and then we will use a temporary selection test for non-seasonal parameters.

We identify the best SARIMA models that could fit our time series, the function identifies all the models that minimize the criteria information AIC, AICc and also the sigma² estimated of the fits.

```
ARIMA(2,1,2)(1,1,1)[12]                    : 866.2205
ARIMA(0,1,0)(0,1,0)[12]                    : 991.2743
ARIMA(1,1,0)(1,1,0)[12]                    : 909.9454
ARIMA(0,1,1)(0,1,1)[12]                    : 919.5581
ARIMA(2,1,2)(0,1,1)[12]                    : 900.6686
ARIMA(2,1,2)(2,1,1)[12]                    : 833.628
ARIMA(2,1,2)(2,1,0)[12]                    : 831.4459
ARIMA(1,1,2)(2,1,0)[12]                    : 830.9384
ARIMA(1,1,1)(2,1,0)[12]                    : 828.9836
ARIMA(0,1,0)(2,1,0)[12]                    : 853.9893
ARIMA(1,1,1)(1,1,0)[12]                    : 907.1086
ARIMA(1,1,1)(2,1,1)[12]                    : 831.1234
ARIMA(0,1,1)(2,1,0)[12]                    : 830.8651
ARIMA(2,1,1)(2,1,0)[12]                    : 831.8985
ARIMA(1,1,0)(2,1,0)[12]                    : 841.045
```

Fig. 3 *The identified models*

The results shows the identified SARIMA-s and their AICc criteria.

Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 4 Issue 10, October - 2017

C. *Estimation of the model*

After testing several models, the best seasonal ARIMA chosen is the SARIMA(2,1,1)(2,1,1).

The second step is the estimation of the model parameters by the maximum likelihood method. For an efficient estimate, there must be at least 50 observations and preferably 100 observations.

```
> fit_dollar
Series: dollar_lek
ARIMA(2,1,1)(2,1,1)[12]

Coefficients:
          ar1      ar2     ma1     sar1     sar2     sma1
      -0.3118  -0.1584  0.5239  -0.3697  -0.2687  -0.5134
s.e.   0.1928   0.0905  0.1849   0.2219   0.1735   0.2347

sigma^2 estimated as 9.808:  log likelihood=-461.42
AIC=936.84   AICc=937.49   BIC=959.15
```

Fig. 4 *Estimation of the model*

The figure above provides the estimates of autoregressive and non-seasonal and seasonal moving average, as well as the value of the significance test of each and its p-value. It is therefore concluded that almost all the parameters are significantly different from 0. The model appears to be adequate in terms of the order of the identified parameters.

```
> (1-pnorm(abs(fit_arima_coef)/sqrt(diag(fit_arima_varcoef))))*2
        ar1         ar2         ma1        sar1        sar2        sma1
0.105898483 0.079893615 0.004599607 0.095660100 0.121361389 0.028698637
```

The second autoregressive coefficients and the first seasonal one are significant at 10% significance level, the mean average coefficients are significant at 5% significance level. And the other parameters are almost significant.

D. *Validation of the model*

The SARIMA model adopted so far seems plausible; the non-seasonal autoregressive coefficients are significantly different from 0 as well as the non-seasonal and seasonal moving average coefficients. The model minimizes the AIC, BIC and AICc information criteria.

The next step is to analyze the residues from the Ljung-Box test and validate the model definitively or to start looking for a more suitable one. The ljung box test results are:

```
> Box.test(res_dollar, lag=16, fitdf=12, type="Ljung")

        Box-Ljung test

data:  res_dollar
X-squared = 8.8586, df = 4, p-value = 0.06473
```

Residual analysis can be used to determine whether residues are naturally white or not. The chi-square statistics for the different delay intervals obtained, accept the hypothesis of no autocorrelation of the residuals.

We check the stability of our model by the inverse of the roots of the characteristic polynomials AR and MA. If all the inverses of the roots belong to the complex unit disk, we conclude that the model is stable and well stationary.

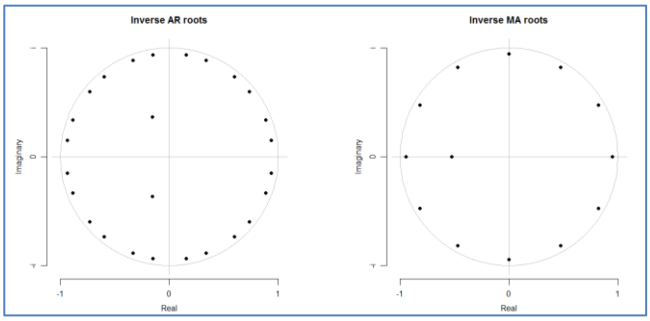

Fig. 5 *The inverse of the roots*

The inverse of the roots associated with the AR and MA part indeed belongs to the complex unit disk. We therefore conclude that our model is stationary.

IV. FORECASTING METHODS

A. *ARIMA Forecasting*

Using the ARIMA method, we plot the predicted values and their confidence interval for the 20 observations.

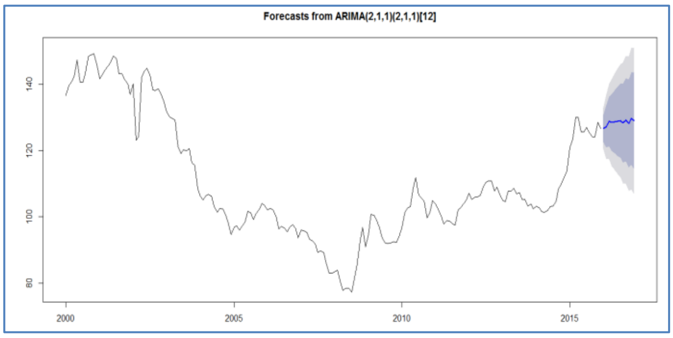

Fig. 6 *Forecasting with ARIMA*

As we see, the predicted values follow the trend and the seasonality of USD/ALL exchange rate series.

Next we will see the quality of the identified SARIMA model, the fitted values of the model, plotting the two series in one figure, the one of obtained SARIMA model and the data of the original USD/ALL serie.

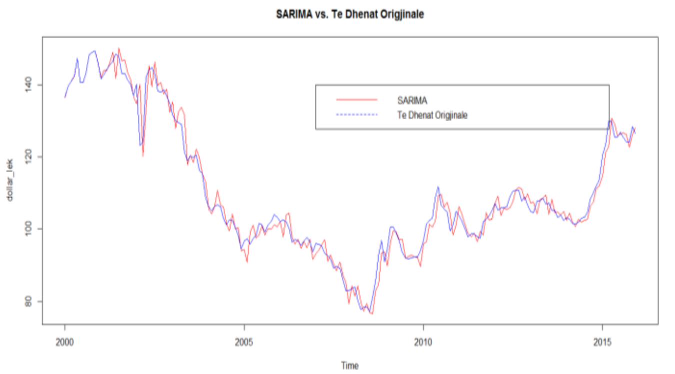

Fig. 7 *The graphical comparison of SARIMA model and original data*

The graph shows the fitted values of the model did follow perfectly all the components of the original data, indeed the ARIMA model the random variables is perfectly specified via the mean average components and also the seasonal component.

B. NAR Forecasting

The SARIMA model (2,1,1) (2,1,1) was the one that minimizes the information criteria. This model is characterized by the presence of a moving average seasonal component that cannot be taken into account by the NAR model (p, k). We will use in NAR modeling this SARIMA model and also the autoregressive parameters to be able to take into account the seasonal component which could not be represented by the 1st identification. Thus one retains the order p = 2 and P = 2.

For a non-seasonal series, the optimal delay number selected is that which minimizes the AIC criterion for an AR (p) model. For a seasonal series, the value P = 1 is used by default, as the parameter p is chosen after the seasonal adjustment of the series.

The chosen model by using the neural network pacage is:

```
> fit_nar_dollar
Series: dollar_lek
Model:  NNAR(2,2,2)[12]
Call:   nnetar(y = dollar_lek, p = 2, P = 2)

Average of 20 networks, each of which is
a 4-2-1 network with 13 weights
options were - linear output units

sigma^2 estimated as 8.414
```

We have defined fours outputs for the NAR model and then adequate number of nodes in the hidden layer is 2.

NAR has minimized the sigma² estimated, which is inferior to the one estimated for the seasonal ARIMA model.

Let's see how the NAR model has predicted the 20 next values of our data series.

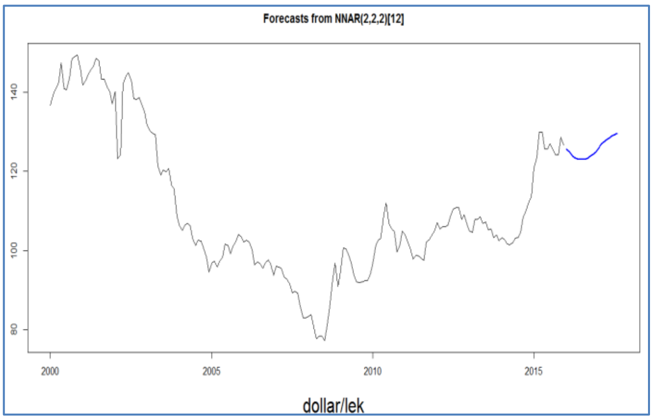

Fig. 8 *The NAR forecasting*

Finally the comparison between the fitted values of the NAR model and original data:

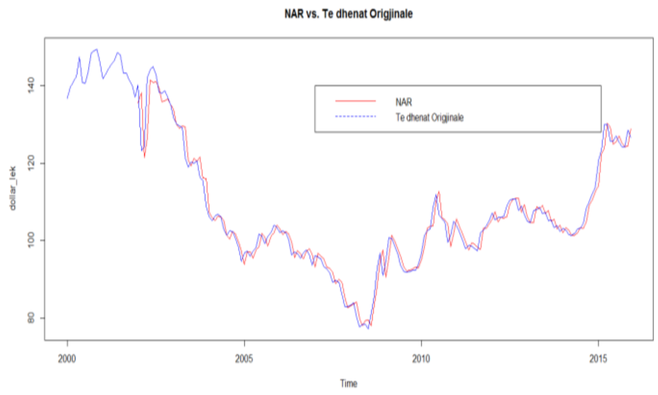

Fig. 9 *The graphical comparison of NAR model and original data*

The graph shows visually the quality of the identified NAR model. The fitted values of the model follow perfectly all the components of the original data, The learning process of the NAR model allows better understanding of the times series characteristics. All the components are well presented. This is the power of the non linear method and the machine learning algorithms.

C. Hybrid ARIMA-ANN Forecasting

Firstly, we have to create the architecture of model. process passes in two stages. In the first stage, the AF model is used to capture the linear component. Let de the residual of the ARIMA model at time *t*, then:

$$e_t = y_t - L_t$$

where, the L_t is the forecasting value at time *t* which is obtained by ARIMA model.

Then in the second stage, nonlinear relationships can be discovered by modeling residuals using ANN,. With *n* input nodes, the ANN model for the residuals will be:

$$e_t = f(e_{t-1}, e_{t-2}, \ldots, e_{t-n}) + \varepsilon_t \rightarrow N_t = f(e_{t-1}, e_{t-2}, \ldots, e_{t-n})$$

where, f is a nonlinear function determined by the ANN model, N_t is the forecasting value at time *t* which is obtained by ANN model and ε_t is the random error.
The combined forecast will be:

$$y_t = L_t + N_t$$

We use a neural network with two computational layers regarding the elevate number of variables and observations, to allow the ANN assimilate the relation between the inputs and the hidden layer also between the hidden and the output layer.

We have 19 co-variables, which are the explicative variables retained in the logistic regression. The activation function is the sigmoid (Tangent hyperbolic) and the error function is the Sum Squared Error that we want to minimize.

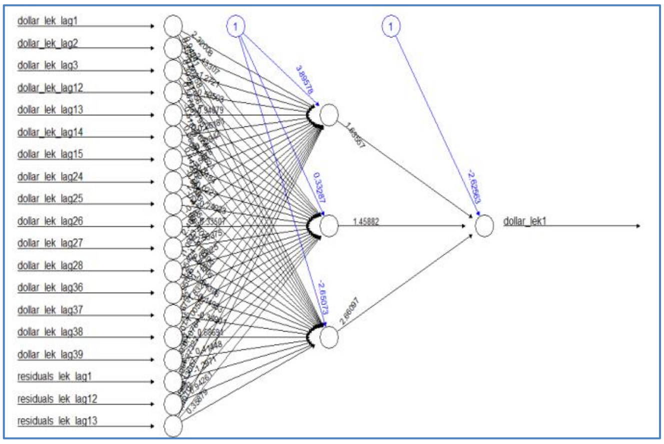

Fig. 10 *The architecture of hybrid ARIMA-ANN model*

The architecture above shows a higher number of links between the co-variables and the hidden layer that contains three neurons. The hidden layer is also linked to the output via 3 links plus the bias unit that represents the constant of the model.

In the hidden layer is calculated the linear combination between vector of input and weights, this combination will be transformed using the tangent hyperbolic .

The following table represents the synaptic weights of the artificial neural network. These weights have no interpretations. The ultimate objective of these weights is to minimize the Mean Square Error, which is still among the limitations of the artificial neural network.

		First neuron	Second neuron	Thrid neuron	Dollar_lek
Input Layer	Bias	3.8957750948	0.33286575286	-2.65073479152	
	dollar_lek_lag1	2.3200786106	0.94841333639	0.45716720895	
	dollar_lek_lag2	-2.4330732503	0.50458255568	0.30381335062	
	dollar_lek_lag3	-1.2721035323	2.79563927786	0.56788074546	
	dollar_lek_lag12	0.5950271026	-1.17950531568	-0.51549029695	
	dollar_lek_lag13	0.9487904791	-0.76247706369	0.06662750513	
	dollar_lek_lag14	-0.2618062201	-0.86620723513	0.44196485216	
	dollar_lek_lag15	-0.2294172227	-0.24840057209	-0.58592922636	
	dollar_lek_lag24	0.4507767345	0.02269935861	-0.41353894828	
	dollar_lek_lag25	1.3268438162	-0.24022839713	0.67407283776	
	dollar_lek_lag26	-0.8257005532	-0.33507242766	-0.01038764885	
	dollar_lek_lag27	2.4886037539	2.55375360847	0.66005113883	
	dollar_lek_lag28	-1.0922994944	1.65024767496	-0.64305647856	
	dollar_lek_lag36	0.2542445924	-0.11205285006	-0.14933034422	
	dollar_lek_lag37	-0.9550644536	-1.83209906820	-0.34900832284	
	dollar_lek_lag38	1.1675161560	-1.00585493873	0.58691339949	
	dollar_lek_lag39	-0.2073487176	0.10783884379	0.41448399197	
	residuals_lek_lag1	-1.0936167277	-1.27326559081	-1.29710037742	
	residuals_lek_lag12	0.7496557871	-0.13667435223	0.94260918995	
	residuals_lek_lag13	0.3556949315	1.40701690610	0.35878909368	
Hidden Layer	bias				-2.625630772
	First neuron				1.635565554
	Second neuron				1.458821550
	Third neuron				2.660973050

Fig. 11 *The synaptic weights of the hybrid model*

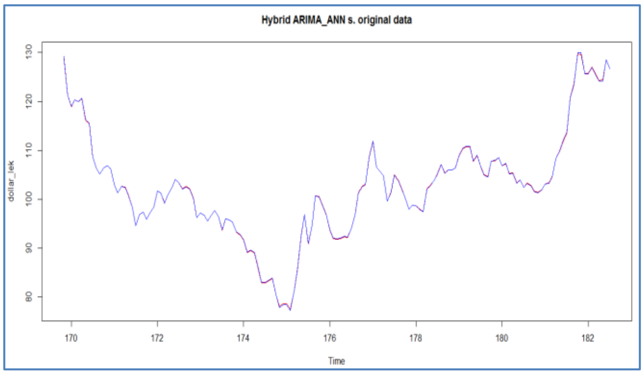

Fig. 12 *The comparison of hybrid ARIMA-ANN model and original data*

The hybrid ARIMA-ANN fit perfectly the time series. All the component are well-presented and the error between the fits and real data tend to be null.

V. Measures of Accuracy

In this section we will use the predictive capabilities of three models, comparing with each other. The performance indicators are: RMSE, MAE, MPE, MAPE, and U of Theil statistics.

Method	RMSE	MAE	MPE	MAPE
ARIMA	0.09135064079	2.972844547	2.114502481	0.109338395
NAR	0.001327147932	2.863767926	1.902304608	-0.06556912
Hybrid	0.00002940905893	0.1065297893	0.08000589717	-0.000335740

Fig. 13 *The performance of three models*

The hybrid method shows better results for all indicators and with significant difference.

The value of the Statistics U of Theil is:

$$U = \sqrt{\frac{\sum_{i=1}^{n-1}\left(\frac{pr_{i+1} - prevpr_{i+1}}{pr_i}\right)^2}{\sum_{i=1}^{n-1}\left(\frac{pr_{i+1} - pr}{pr_i}\right)^2}}$$

Method	U of Theil
ARIMA	0.9979888301
NAR	0.890525013
Hyrbid	0.045323929

Fig. 14 *The value of Statistics U of Theil for three models*

The value of the Statistics U is inferior to 1, which means an excellent precision of the forecasts obtained by our hybrid model. Consequently and basically, the hybrid model is superior to a naive method not requiring advanced statistical knowledge.

VI. Conclusions

Based on the data by the respective years, obtained by the official website of the Bank of Albania, we conclude the USD/ALL exchange rate has a decreasing part from 2000 to 2005, and second one globally slightly increasing from 2005 to 2015. We concluded that this time series is not stationary, but a difference is enough to transform it in a stationary series, called the first order integral I(1).

We presented three models of our series, ARIMA, NAR and ARIMA-ANN. The hybrid model was proposed in order to improve forecasting accuracy. According to the fitting and prediction accuracy, the empirical analysis shows that hybrid model has the best results. It produced outstanding results than its components, ARIMA and ANN.

Thus, combining a linear and non-linear model is an effective way to obtain more accurate results for exchange rate series forecasting.

REFERENCES

[1] C. Hamzacebi, "Improving artificial neural networks performance in seasonal time series forecasting", Information Sciences 178 pages: 4550-4559. 2008

[2] G.E.P. Box, G. Jenkins, "Time Series Analysis, Forecasting and Control", Holden-Day, San Francisco, CA, 1970.

[3] www.bankofalbania.org

[4] G.P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model", Neurocomputing 50, pages: 159–175. 2003

[5] H. Park, "Forecasting Three-Month Treasury Bills Using ARIMA and GARCH Models", Econ 930, Department of Economics, Kansas State University, 1999.

[6] H. Tong, "Threshold Models in Non-Linear Time Series Analysis", Springer-Verlag, New York, 1983.

[7] J. Lee, "Univariate time series modeling and forecasting (Box-Jenkins Method)", Econ 413, lecture 4. Stochastic and Genetic Neural Network Combinations in Trading and Hybrid Time-Varying Leverage Effects. Georgios Sermpinis

[8] L. Sarno, Mark P. Taylor "Purchasing power parity and the real exchange rate." IMF Staff Papers Vol. 49, No. 1 © 2002 International Monetary Fund.

[9] K.W. Hipel, A.I. McLeod, "Time Series Modelling of Water Resources and Environmental Systems", Amsterdam, Elsevier 1994.

[10] Z. Hajirahimi, M. Khashei, "Improving the performance of financial forecasting using different combination architectures of ARIMA and ANN models". JIEMS Journal of Industrial Engineering and Management Studies Vol. 3, No. 2, pp. 17-32. 2016

[11] Franz Hamilton , Alun L. Lloyd, Kevin B. Flores, "Hybrid modeling and prediction of dynamical systems". 2017

[12] A. Samia, N. Kaouther, T. Abdelwahed, "A Hybrid ARIMA and Artificial Neural Networks model to forecast air quality in urban areas: case of Tunisia", 2012.

[13] Charles Engel University of Wisconsin and NBER Nelson C. Mark University of Notre Dame and NBER Kenneth D. West University of Wisconsin and NBER Exchange Rate Models Are Not as Bad as You Think March 21, 2007

[14] Wongsathan, R., Seedadan, I., 2016, "A hybrid ARIMA and Neural Networks model for PM-10 pollution estimation: The case of Chiang Mai city moat area", *Procedia Computer Science*, No, PP. 86 273 – 276.

[15] Xiong,T., Li,Ch and Bao., Y., 2017, "Interval-valuedtimeseriesforecastingusinganovelhybrid Holtl and MSVR model", *Economic Modelling*, Vol. 60, PP. 11–23.

[16] Yuan, X., Tan, Q., Lei, X., Yuan, Y., and Wu , X.,2017, "Wind power prediction using hybrid autoregressive fractionally integrated moving average and least square support vector machine", *Energy*, NO.129, PP. 122-137.

[17] Zeng, D., Xu, J., Gu, J., Liu, L and Xu, G., 2008, "Short term traffic flow prediction using hybrid ARIMA and ANN models", *in Power Electronics and Intelligent Transportation System,* , PP.621-625.