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# *THE ACCURACY OF EXCHANGE RATE FORECASTS IN ROMANIA*[*]

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**Abstract**

*The main aim of this research is to predict the average exchange rate RON/USD in Romania using various quantitative methods. Recent researches have confirmed the prediction power of neural networks, but in this article econometric models and exponential smoothing techniques have been employed. For predicting the average RON/USD exchange rate using neural networks the following variables have been used: the real growth of monetary supply M2, the real interest rate, index of production prices and real exchange rate. For predictions based on multiplicative Holt-Winters model on 2011-2013, we obtained a recognised superiority in terms of accuracy, outperforming other predictions based on neural networks (perceptron multilayer and radial basis function) and econometric models (autoregressive model and vector-autoregressive model).*

**Keywords**: exchange rate, forecasts, neural network, econometric model, accuracy
**JEL Classification**: C51, C53

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## 1. Introduction

For financial data sets, the elaboration of predictions suppose the use of relevant explanatory variables (input variable), the prediction model capturing the characteristics of independent variables and of the used time series. The recent economic theory classified in 2 categories the prediction models used for financial variables:

- Linear or structural models (state space models, ARCH and GARCH models), that suppose that a behaviour model can explain well the decision makers actions by using an explicit function;
- Non-linear models or black-box ones (fuzzy models, expert system, genetic algorithms, neural networks), that predict the non-linear and non-random dynamics without the use of a logical function or of identified relationship.

Recent studies in literature highlighted that the neural networks has a huge prediction power, aproximating any continuous function. Unlike ARIMA models that work with linear relationships between variables, the neurla networks approximate the non-linear functions. Numerous researches used this forecasting method for predicting the financial variables. Beside the nonlinear component extraction, Kamruzzaman and Sarker (2003) have shown that another advantage of articifial neural networks is the identification of interactive effects.

## 2. Literature review

More researchers have proved that the neural network improves the exchange rate forecasts accuracy in many cases, but the random walk tends to perform better on higher horizons. It seems that the non-linear relationship and the market fundamentals are not the cause for the improvement in exchange rate forecasts.

In using the artificial neural network (ANN), we do not have to mention a specific type of model, because it adapts in accordance with the data. It is recommened the use of ANN for certain types of data that do not follow a theoretical background.

The most used ANN has 3 layers of units: an input layer, a hidden layer to which input layer is connected and an output layer to which hidden layer is linked. If there is not feedback between output and input and there is only one direction of communication, from input layer to output layer, the ANN is known as feedforward network. If a certain target is followed, we have a supervised training, the outputs being compared to targets. To diminish the distance between targets and output layers, the biases and weights are adjusted. The weights are determined as to minimize the error between targeted value and calculated ones. For feedforward networks with supervised rules of learning the backpropagation algorithm is used. In this case it is followed the minimization of sum of squared errors.

The efficiency of a neural network is related to many factors. The combination of input, the parameters used in the training algorithm, the number of used hidden layers in the specific neural network depend on the error method and trial technique. These factors are changed in order to generate the most appropiate model. The combination of inputs seems to be the most important element in improving the forecasts accuracy. The convergence is hardly achieved while the number of hidden layers grows, as Chandrasekara and Tilakaratne (2009) suggested.

If there is a large number of hidden nodes, the overfitting problem appears and the forecasts performance is afected. However, if there are too few hidden nodes the power of the model decreases. A number of hidden neurons from 2 to 6 is usually prefered. The convergence process speed grows if there is a large momentum or a low learning rate.

The non-stationary character and the chaotic behaviour of deterministic type for recent time series of the exchange rate generated the intensive study of exchange rate forecasting, as Chandrasekara and Tilakaratne (2009) stated. The past behaviour of the financial markets does not provide enough information for showing the relationships between the past values and the future values of the variables. The historical data include all the behaviour characteristics of the time series and it is, from this perspective, the essential element in forecasting.

Wong, Xia, et al. (2010) made chronological series predictions using an adaptive neural network with new way of mixing the outputs and with adaptive measures for the inputs. This new structure performed better in terms of predictions than artificial neural network, k-nearest neighbors in the adaptive form and random walk model for real data.

Yu and Huang (2009) used the neural network to develop a fuzzy model to increase the degree of predictions accuracy. This mechanism outperforms the predictions of stock index in Taiwan compared to other modified neural network implementations.

Oancea and Ciucu (2014) realised a comparative analysis between the USD/RON and EURO/RON exchange rate using daily data over the period from 2005 to 2013, the following forecasting methods being used: training algorithms, recurrent neural networks and feed forward ones.

For predicting the exchange rate, Philip, Taofiki, et al. (2011) used Hidden Markov technique and neural networks, for the second method the forecasts accuracy being higher (81.2% compared to 69.9% for the first forecasting method). Khashei, Bijari, et al. (2012) proposed a hybrid model called ARIMA-PNN for improving the accuracy of forecasts based on ARIMA process. For improving the predictions accuracy, some transformations in data like Box-Cox power change are employed by Proietti and Lütkepohl (2013).

## 3. Predicting average exchange rate in Romania

The data series for average exchange rate covers the period from 1986 to 2013 and it is provided by the National Bank of Romania. The variable is determined as arithmetic average of the values corresponding to each month. The data series is deflated using the values of index of consumer prices. In the econometric model the real exchange rate is used. For having a stationary data set, it is applied the logarithm and the double differentiation. The new variable is denoted by log_d2_er. This stationary data set is modelled using an autoregressive moving average (ARMA) process. An autoregressive model of order 1 was valid. According to correlogram, the errors are not correlated up to a lag of 12. The errors are homoscedastic, according to ARCH test.

A differentiation of order one was applied to the inflation rate in order to ensure the stationary character. The inflation rate is determined using the harmonized index of prices in comparable prices (2005=100), being provided by Eurostat. The Granger causality has been checked using the stationary data for exchange rate and inflation rate. For a level of significance of 10%, we can assume that the inflation is a Granger cause for exchange rate. Moreover, a vector-autoregressive model of order 1 was built (VAR(1)), for which the errors are not auto-correlated:

D_I = - 0.4266899614*D_I(-1) - 0.01519786457*LOG_D2_IR(-1) + 0.005542972781

LOG_D2_IR= 3.133252922*D_I(-1) + 0.733926991*LOG_D2_IR(-1) + 0.07858493114

**Table 1: Variance decomposition of the transformed real exchange rate.**

| Period | D_I | LOG_D2_CS |
|---|---|---|
| 1 | 0.100783 | 0.239440 |
| | (0.04899) | (0.03320) |
| 2 | 0.193904 | 0.175732 |
| | (0.06670) | (0.03878) |
| 3 | 0.086336 | 0.117572 |
| | (0.05423) | (0.05393) |
| 4 | 0.078015 | 0.082786 |
| | (0.04803) | (0.05460) |
| 5 | 0.046895 | 0.056655 |
| | (0.04331) | (0.05112) |
| 6 | 0.035124 | 0.039390 |
| | (0.03723) | (0.04427) |
| 7 | 0.023244 | 0.027146 |
| | (0.03077) | (0.03692) |
| 8 | 0.016468 | 0.018800 |
| | (0.02503) | (0.02987) |
| 9 | 0.011232 | 0.012984 |
| | (0.01979) | (0.02366) |
| 10 | 0.007824 | 0.008981 |
| | (0.01549) | (0.01844) |

In the first period, the changes in differenced inflation rate explains 10.07% of the variation in exchange rate, the highest percent being explained in the second period (19.39%), the influence decreasing in time.

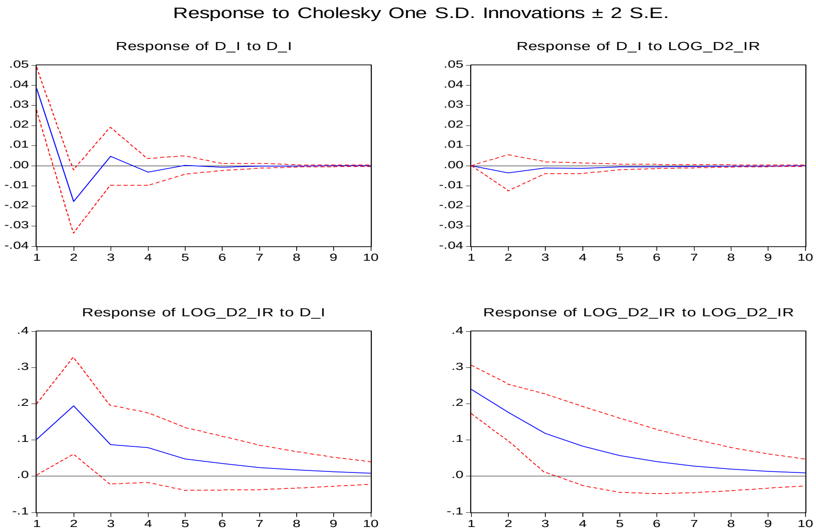


**Figure 1: Impulse-response function corresponding to VAR(1) model.**

The predictions for average exchange rate were built on short-run, the horizon being 2011-2014.

**Table 2: Forecasts based on econometric models for average exchange rate (RON/USD) (horizon: 2011-2014).**

| Year | AR(1) | VAR(1) | Actual values |
|---|---|---|---|
| 2011 | 3.5104 | 3.71 | 3.0486 |
| 2012 | 3.7811 | 3.4901 | 3.4682 |
| 2013 | 3.6390 | 3.7862 | 3.3279 |
| 2014 | 4.1629 | 3.2208 | |

The predictions for 2011 and 2013 based on the AR model are closer to actual values than the ones based on VAR model. For 2012, the VAR model performed better than AN model.

For forecasting the average RON/USD exchange rate, another method liker exponential smoothingg has being employed in 5 variants: simple method, doulble method, Holt-winters model in three versions (simple, additive and multiplicative approach).

**Table 3: Forecasts based on exponential smoothing techniques for average exchange rate (RON/USD) ( horizon: 2011-2014).**

| Year | Simple method | Double method | Simple Holt-Winters model | Additive Holt-Winters model | Multiplicative Holt-Winters model |
|---|---|---|---|---|---|
| 2011 | 3.1588 | 3.3741 | 3.3802 | 3.3458 | 3.0935 |
| 2012 | 3.0396 | 3.0311 | 3.0195 | 2.9530 | 3.5790 |
| 2013 | 3.4539 | 3.7099 | 3.7165 | 3.6959 | 3.5609 |
| 2014 | 3.5045 | 3.8893 | 3.9231 | 3.7745 | 3.6023 |

For predicting the average RON/USD exchange rate using neural networks the following variables have been used, available from 1994 to 2013: the real growth of monetary supply M2, the real interest rate, index of production prices and real exchange rate. The data for real growth of M2, real interest rate and index of consumer prices were provided by the World Bank. The data processing was done under the following variants: perceptron multi-strat-PM and radial basis function-FBR, the representations being presented in Appendix 1. For various forecasts, the following accuracy measures had been employed: relative error, root mean square error and sum of square error. The values of these indicators were compared to those for the predictions based on the other methods.

**Table 4: Accuracy measures for predictions based on neural networks.**

| Accuracy measure | PM1 | PM2 | PM3 | FBR1 | FBR2 | FBR3 |
|---|---|---|---|---|---|---|
| Relative error | 0.345 | 0.087 | 0.158 | 0.199 | 0.25 | 0.303 |
| Mean squared error (MSE) | 1.128 | 0.119 | 0.314 | 1.132 | 0.524 | 0.234 |
| Root mean squared error (RMSE) | 1.062 | 0.345 | 0.560 | 1.064 | 0.724 | 0.484 |

The comparison of RMSE values for the forecasts based on all the proposed models has been made. In the next table the RMSE values are presented for the forecasts based on econometric models and exponential smoothing techniques. According to Yan, Leu and Lee (2014), root mean squared error and mean absolute error are the most frecquently used accuracy measures.

**Table 5: RMSE for predictions based on econometric models and exponential smoothing techniques (horizon: 2011-2013).**

| Forecasting method | RMSE |
|---|---|
| AR(1) model | 0.368759 |
| VAR(1) model | 0.464747 |
| Simple exponential smoothing | 0.265655 |
| Double exponential smoothing | 0.384244 |
| Simple Holt-Winters model | 0.392556 |
| Additive Holt-Winters model | 0.403808 |
| Multiplicative Holt-Winters model | **0.151197** |

The multiplicative Holt-Winters model has provided the predictions with the highest degree of precision, outperforming the neural networks and the econometric models. The PM2 multy-layer perceptron generated slowly superior forecasts compared to econometric processes and double exponential smoothing technique and simple and additive Holt-Winters model on the horizon 2011-2013.

## 4. Conclusions

In this empirical study we used various forecasting methods to predict the annual average exchange rate in Romania. Recent studies in literature has been validated the superiority of neural networks and autoregressive models. However, we added to these methods another quantitative technique like exponential smoothing. For empirical data of Romanian economy the multiplicative Holt-Winters model provided more accurate forecasts during 2011-2013.

A future direction of research would be the consideration of other forecasting models for predicting real exchange rate in Romania. However, the data are annual and the usual econometric models like ARCH and GARCH is not always possible.

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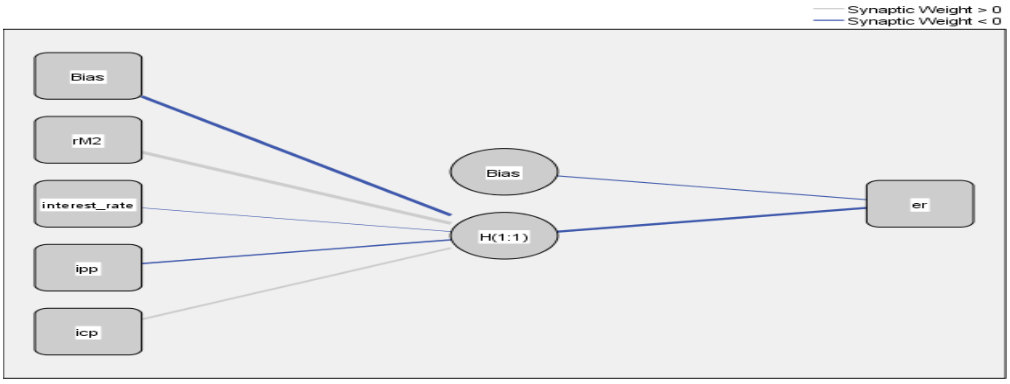
## *APPENDIX – Neural Networks*

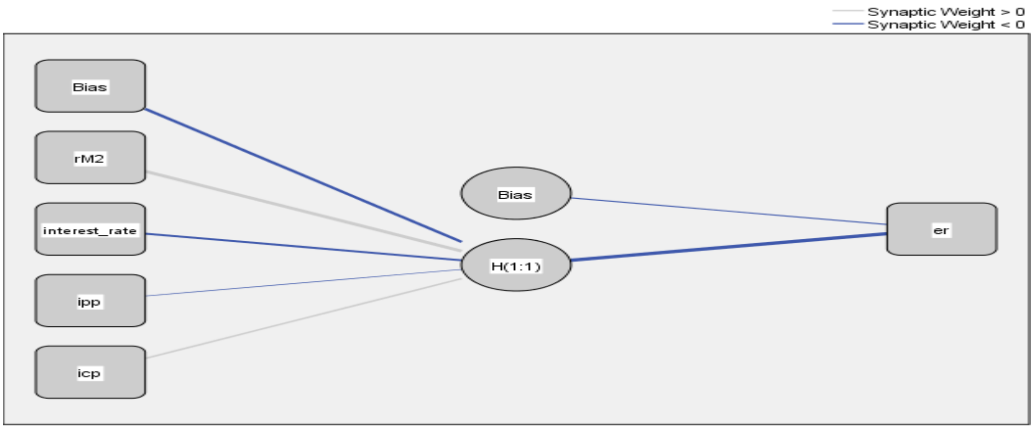
### Multilayer perceptron

### MP1



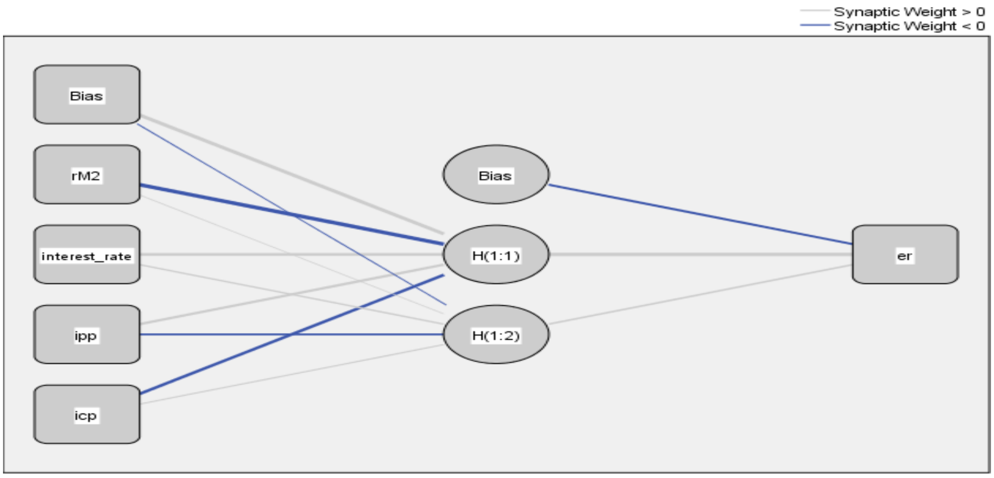

Hidden layer activation function: Hyperbolic tangent
Output layer activation function: Identity

### MP2




Hidden layer activation function: Hyperbolic tangent
Output layer activation function: Identity

### MP3

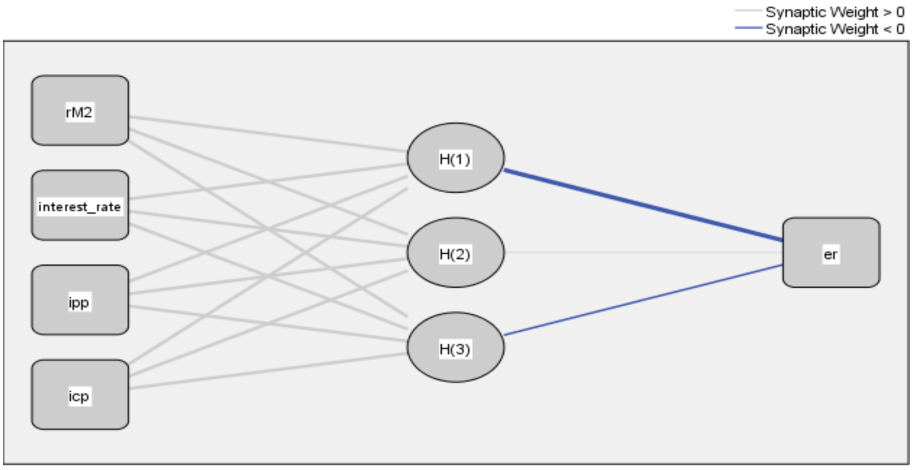



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

## RADIAL BASIS FUNCTION

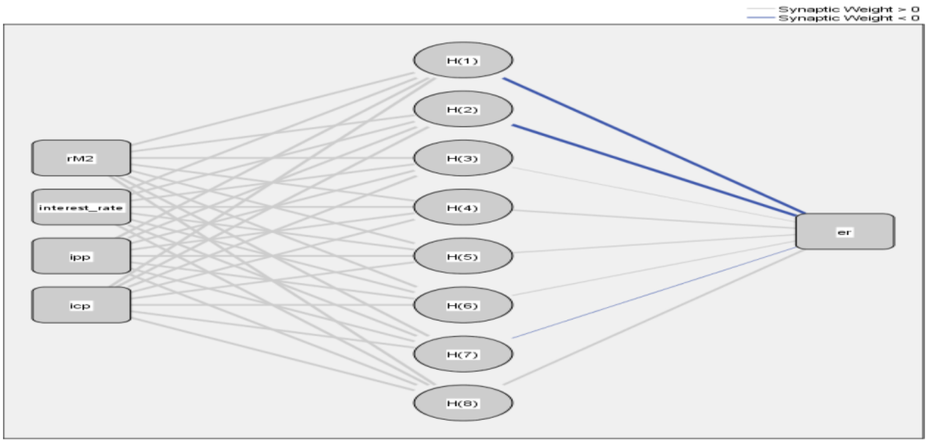
### RBF1




Hidden layer activation function: Softmax

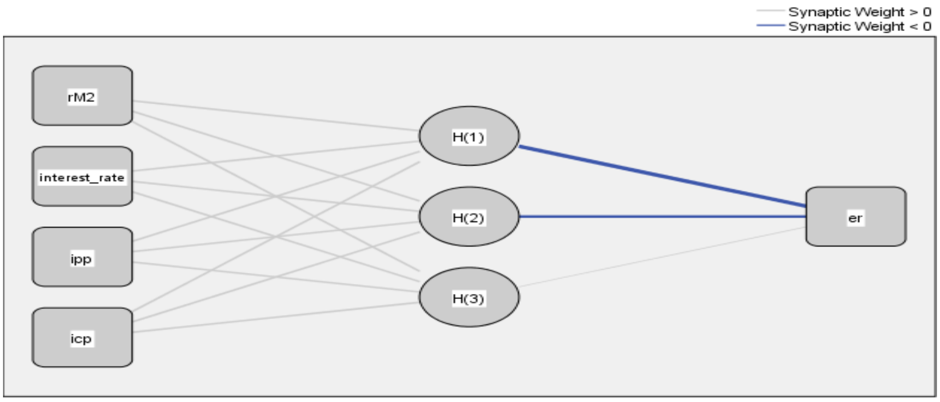
Output layer activation function: Identity

### RBF2




Hidden layer activation function: Softmax
Output layer activation function: Identity

## RBF3




Hidden layer activation function: Softmax
Output layer activation function: Identity