# EXCHANGE-RATES FORECASTING: EXPONENTIAL SMOOTHING TECHNIQUES AND ARIMA MODELS

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*Exchange rates forecasting is, and has been a challenging task in finance. Statistical and econometrical models are widely used in analysis and forecasting of foreign exchange rates. This paper investigates the behavior of daily exchange rates of the Romanian Leu against the Euro, United States Dollar, British Pound, Japanese Yen, Chinese Renminbi and the Russian Ruble. Smoothing techniques are generated and compared with each other. These models include the Simple Exponential Smoothing technique, as the Double Exponential Smoothing technique, the Simple Holt-Winters, the Additive Holt-Winters, namely the Autoregressive Integrated Moving Average model.*

*Keywords: Forecasting, Simple Exponential Smoothing, Double Exponential Smoothing, Holt-Winters Additive, Holt-Winters Multiplicative.*

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## I. Introduction

The exchange rate reflects the ratio at which one currency can be exchanged with another currency, namely the ratio of currency prices. The relevant literature implies, by the purchasing power parity theory, that in the long-run exchange rates converge to an equilibrium level. The question that arises is related to the behavior in the short-term of the exchange rates, and how these fluctuations might affect the financial market players, the investors as well as those directly influenced by changes in the exchange rate. To forecast exchange rates there are numerous models, which are more or less complicated for modeling the relationship between currencies, but those interested do not always have the resources needed to fully benefit from them, or as suggested by the literature, most of exchange rate models based on macro economic data are considered outperformed. So prediction methods based on the random walk models and exponential smoothing techniques can be used in capturing the fluctuations the short-run. The main goal of this study is to present the performance of methods for the task of exchange rate forecasting, using the exchange rates of Romanian Leu versus the most important currencies in terms of international trade, namely the Euro, United States Dollar, British Pound, Japanese Yen, Chinese Renminbi and the Russian Ruble.

## II. Literature Review

The efficiency of exchange rate predictability by models based on past information in time series is the main question raised. The relevant literature on currency forecasting issues includes a wide range of methods. (Meese and Rogof: 1983) have shown that models that are based on the random walk hypothesis in forecasting exchange rates outperform those based on macroeconomic indicators. But when the time horizon is extended past 12 months, the same authors, together with (Chinn and Meese: 1995), respectively (Mark: 1995) argue that this efficiency is lost. (Mark: 1995) investigates the movements of the U.S Dollar against four major currencies in a time period of 18 years, his findings indicating that exchange-rate models based on macroeconomic fundamentals have a higher forecast ability than those based on random walk. (Chinn and Meese: 1995) using non-parametric and parametric models examine the predictive performance of both types of models, using the exchange rate of U.S Dollar against four currencies, over a time horizon of 17 years. They reach to the conclusion that random walk models outperform the models based on fundamentals, but only in the short-term, when it comes to larger periods of time, more than 36 months, this superiority is lost. (Marsh and Power: 1996) use 22 forecasters to predict movements in three major currencies against the U.S. Dollar, including the random walk estimators. (Andreou, Georgpoulus and Likothanassis: 2002) employ neural networks to predict four currency movements against the Greek Drachma, using information about macroeconomic factors from the point of view of the market participants, concluding that the greatest impact have those information which correspond to the trend of the time series. (Goldberg and Frydman: 1996), testing a time period over 15-years the exchange rate of the U.S. Dollar against German Mark, found that all structural exchange rate models are outperformed by the random walk model. They consider that the failure of empirical exchange rate models is largely due to periodic shifts in the long-run relationship governing the exchange rate and macroeconomic fundamentals, due to an instable monetary-policy, which in turn produces shifts in the cointegrating vector. However (Hwang: 2001) finds long-term cointegrating relationships between exchange rate and macroeconomic factors in some of the analyzed series, but in the short-term two random walk models are found to exceed the traditional models. (Kilian and Taylor: 2001) try to combine the models based on macroeconomic indicators with those on random walk, considering that in the long-run these models are optimal. It is apparent that in the related literature both types of models are used, but the ones using macroeconomic indicators are efficient in the long-run, while predictability in the short-term is ensured by models based on random walk.

## III. Methodology

### *A. Single Exponential Smoothing Technique (MNES)*

To forecast the exhange rates in the first step the single exponential smoothing procedure is applied, this model assuming that the series is stationary, without a trend. Simple exponential smoothing is used for short-range forecasting, usually just one month into the future. The relationship which characterizes the the single exponential smoothing procedure is:

$$Y_n = a + \varepsilon_n \qquad (1)$$

Where *a* represents the constant, while $\varepsilon_n$ stands for the residuals. To forecast the *n+1* moment in the moment *n*, the following series is computed recursively :

$$\hat{Y}_{n+1} = \alpha \cdot Y_n + (1-\alpha) \cdot \hat{Y}_n \text{, where } n = \overline{1, t+k}; \qquad (2)$$

The number of available observations is shown by *t*, where *k* stands for the time horizon for which forecasts is made. $\alpha$ is the smoothing factor, which can take values between 0 and 1, a close value to 0 means that the expected values for *n+1* are equal to the prior forecast, and a value close to 1 suggests that the forecasts are equal to the previous observation. The value of $\alpha$ is usually determined by minimizing the sum of squares of the forecast errors:

$$\frac{1}{n}\sum_{i=0}^{n-1}\left(Y_{n+1} - \hat{Y}_{n+1}\right)^2 = \frac{1}{n}\sum_{i=0}^{n-1} e_{n+1}^2 \qquad (3)$$

The (2) relationship is applied recursively for each observation from the series, each new smoothed value $\hat{Y}_{n+1}$ is computed as the weighted average of the current observation, $Y_n$ and the previous smoothed observation, $\hat{Y}_n$. Thus each smoothed value $\hat{Y}_{n+1}$ is the weighted average of the previous a n observations, the weights of these decrease exponentially in the past, so $Y_1$ has a weight of $\alpha \cdot (1-\alpha)^{n-1}$, $Y_2$ a weight of $\alpha \cdot (1-\alpha)^{n-2}$, $Y_{n-1}$ being weighted with $\alpha \cdot (1-\alpha)$. So ecuation (2)can be written as:

$$\hat{Y}_{n+1} = \alpha \cdot \sum_{i=1}^{n} (1-\alpha)^i \cdot \hat{Y}_{n+1-s} \quad (4)$$

The initial value of $\hat{Y}_1$ is usually equal to $Y_1$, or with the average of the initial values of the series.

**B. Double Exponential Smoothing Technique (MNED)**

This method applies two ecuations recursively for the $Y_n$, namely:

$$S_n = \alpha \cdot Y_n + (1-\alpha) \cdot S_{n-1} \quad (5)$$

$$D_n = \alpha \cdot S_n + (1-\alpha) \cdot D_{n-1} \quad (6)$$

where $S_n$ is the single smoothed series and $D_n$ is the double smoothed series. $\alpha$ stands for the smoothing parameter, between $0 < \alpha \leq 1$. This method is appropriate for series with a linear trend, the forecasts from double smoothing are computed as:

$$\hat{Y}_{n+h} = \left(2 + \frac{\alpha \cdot k}{1-\alpha}\right) \cdot S_n - \left(1 + \frac{\alpha \cdot k}{1-\alpha}\right) \cdot D_n = \left(2S_n - D_n + \frac{\alpha}{1-\alpha} \cdot (S_n - D_n) \cdot k\right) \quad (7)$$

Expression (7) can be interpreted as an equation with intercept $2S_n - D_n$ and slope $\frac{\alpha}{1-\alpha} \cdot (S_n - D_n)$. The initial values for $S_1$, respectively $D_1$ are usually set to be equal with $Y_1$, or with the average of the initial values of the series.

***C. Holt –Winters Simple Exponential Smoothing Technique (MHWES)***

This method is appropiate for series with a linear trend and no seasonal variations. This technique is using two recursions, the forecasted series being:

$$Y_{n+k} = a + b \cdot k \quad (8)$$

Where a is the intercept, while b, stands for the slope, which are computed recursively:

$$a_n = \alpha \cdot Y_n + (1-\alpha) \cdot (a_{n-1} + b_{n-1}) \quad (9)$$

$$b_n = \beta \cdot (a_n - a_{n-1}) + (1-\beta) \cdot b_{n-1} \quad (10)$$

$\alpha$ and $\beta$ are smoothing factors, where these can be found within the interval $\alpha, \beta \in [0,1]$, being determined by minimizing the sum of squares of the forecast errors. Each predictio is computed based on the previous one, so the slope $b_n$ of the series is multiplied by the forecast horizont, *k*, and this will be added with the intercept of the series, $a_n$ the estimated values of the series will be determined by the relationship:

$$\hat{Y}_{n+k} = \hat{a}_n + \hat{b}_n \cdot k \qquad (11)$$

The initial value of $a_1$, is usually $Y_1$, while $b_1$ is general set to be equal with 0, or with the average of the initial values of the series, or with the difference of the initial observations.

***D. Holt –Winters Multiplicative Exponential Smoothing Technique (MHWEM)***

This method is appropiate for series with a linear trend and multiplicative seasonal variation, the smoothed series is given by:

$$\hat{Y}_{n+k} = (a \;\; + b \;\; \cdot k) \cdot c_{n+k} \qquad (12)$$

Where $a_n$ *a* is the intercept, while $b_n$ is the trend of the series and $c_n$ the multiplicative seasonal factor,each of these three coefficients are defined by the following recursions:

$$a_n = \alpha \cdot \frac{Y_n}{c_{n-s}} + (1-\alpha) \cdot (a_{n-1} + b_{n-1}) \qquad (13)$$

$$b_n = \beta \cdot (a_n - a_{n-1}) + (1-\beta) \cdot b_{n-1} \qquad (14)$$

$$c_n = \gamma \cdot \frac{Y_n}{a_n} + (1-\gamma) c_{n-s} \qquad (15)$$

Where $\alpha, \beta$ and $\gamma$ are smoothing factors, where these can be found within the interval $\alpha, \beta, \gamma \in [0,1]$, and are determined by minimizing the sum of squares of the forecast errors while *s* is the seasonal frequency component. The forecasts are computed as:

$$\hat{Y}_{n+k} = (\hat{a}_n + \hat{b}_n \cdot k) \cdot \hat{c}_{n-s+k} \qquad (16)$$

The initial value of $a_s$ are equal with the average of the initial values of the series from the first seasonal cycle, $a_s = \frac{1}{s} \cdot \sum_{i=1}^{s} Y_i$ , while $b_s$ is given by $b_s = \frac{1}{s} \cdot \left( \frac{Y_{s+1} - Y_1}{s} + \frac{Y_{s+2} - Y_1}{s} + \ldots + \frac{Y_{2s} - Y_s}{s} \right)$, and the the multiplicative seasonal component is estimated by $c_1 = \frac{Y_1}{a_s}; c_2 = \frac{Y_2}{a_s}$, ..., $c_s = \frac{Y_s}{a_s}$.

***E. Holt –Winters Additive Exponential Smoothing Technique (MHWEA)***

This method is appropiate for series with a linear trend and additive seasonal variation, the smoothed series is given by:

$$\hat{Y}_{n+k} = a + b \cdot k + c_{n+k} \qquad (17)$$

Where $a_n$, $b_n$ and $c_n$ are defined as in the prevoius model, only this time $c_n$ is the additive seasonal factor, each of these three coefficients are defined by the following recursions:

$$a_n = \alpha \cdot (Y_n - c_{n-s}) + (1-\alpha) \cdot (a_{n-1} + b_{n-1}) \qquad (18)$$

$$b_n = \beta \cdot (a_n - a_{n-1}) + (1-\beta) \cdot b_{n-1} \qquad (19)$$

$$c_n = \gamma \cdot (Y_n - a_n) + (1-\gamma) c_{n-s} \qquad (20)$$

Where $\alpha, \beta$ and are smoothing factors, within the interval $\alpha, \beta, \gamma \in [0,1]$, and are determined by minimizing the sum of squares of the forecast errors, while *s* is the seasonal frequency component. The forecasts are computed as:

$$\hat{Y}_{n+k} = \hat{a}_n + \hat{b}_n \cdot k + \hat{c}_{n-s+k} \quad (21)$$

The initial values of the additive seasonal factor are estimated by: $c_1 = Y_1 - a_s$ ; $c_2 = Y_2 - a_s$, ..., $c_s = Y_s - a_s$ .

***F. ARIMA Models***

Autoregressive moving average models -ARMA(p,q)- are recomented to be based on stationary series, with the form:

$$Y_n = a_1 Y_{n-1} + a_2 Y_{n-2} + \cdots + a_p Y_{n-p} - b_1 \varepsilon_{n-1} - b_2 \varepsilon_{n-2} - \cdots - b_q \varepsilon_{n-q} + \varepsilon_n \quad (22)$$

$$\rightarrow Y_n -_1 Y_{n-1} + a_2 Y_{n-2} + \cdots + a_p Y_{n-p} = \varepsilon_n - b_1 \varepsilon_{n-1} - b_2 \varepsilon_{n-2} - \cdots - b_q \varepsilon_{n-q} \quad (23)$$

$$\rightarrow \left(1 - a_1 L - a_2 L^2 - \cdots - a_p L^p\right) Y_n = \left(1 - b_1 L - \cdots - b_q L^q\right) \varepsilon_n \quad (24)$$

$$\rightarrow \phi(L) Y_n = \theta(L) \varepsilon_n \quad (25)$$

Where $p$ is the order of the autoregressive part, while q is the order of the moving average part, and $\varepsilon_n$ represents the white noise. Validation of *ARMA (p,q)* models is based on minimizing the AIC and BIC criterias, also by verifying the correlation of the error terms of the model, finally measuring the departure from normality of theese. The ARMA models, as stated, can only be used on stationary series. A series is stationary if its values oscillate around a reference level. In the terminology of time series analysis, if a time series is stationary it is said to be integrated of order zero, or I(0) for short. If a time series needs one differential operation to achieve stationarity, it is an I(1) series, and a time series is I(n) if it is to be differenced for n times to achieve stationarity. So for nonstationary series the *ARIMA (p,d,q),* models will be used, namely the autoregressive integrated moving average models, where *d* is the order of differentiation for the series to become stationary. So an *ARIMA (p,d,q)*model can be rewritten as:

$$\phi(L)(1-L)^d Y_n = \theta(L) \varepsilon_n \quad (26)$$

Where L is the lag operator, and the order of differentiation is equal to: $\Delta^d Y_n = (1-L)^d Y_n$ (27)

***E. Forecasting results:***

The forecasting results are measured by the following indicators:

Sum of squared errors: *SPE*= $\sum_{1}^{n+k} e_{n+1}^2 = \sum_{1}^{n+k} \left(\hat{Y}_n - Y_n\right)^2$ (28)

Root mean squared error: *RME*= $\sqrt{\sum_{1}^{n+k} \left(\hat{Y}_n - Y_n\right)^2 /(n+k)}$ (29)

Mean absolute error: *MAE*= $\sum_{1}^{n+k} \left|\hat{Y}_n - Y_n\right|^2 /(n+k)$ (30)

Bias Proportion: *DM*= $\left(\left(\sum_{1}^{n+k} \hat{Y}_n \Big/ n+k\right) - \bar{Y}\right)^2 \Big/ \sum_{1}^{n+k} \left(\hat{Y}_n - Y_n\right)^2 \Big/ n+k$ (31)

Shows how far the mean of the forecast is from the mean of the actual series.

Variance Proportion: *DV*= $\left(\sigma_{\bar{Y}} - \sigma_Y\right)^2 \Big/ \sum_{1}^{n+k} \left(\hat{Y}_n - Y_n\right)^2 \Big/ n+k$ (32)

Where $\sigma_{\bar{Y}}$ , $\sigma_Y$ represent the standard deviation of the series $\hat{Y}_n$ respectively $Y_n$, indicating how far the variation of the forecast is from the variation of the actual series $Y_n$.

Covariance Proportion: $DCOV = 2\left(1 - \mathrm{cov}(\hat{Y}_n, Y_n)\right) \cdot \sigma_{\bar{Y}} \cdot \sigma_Y \Big/ \sum_1^{n+k} \left(\hat{Y}_n - Y_n\right)^2 \Big/ n + k$ (33)

Where $\mathrm{cov}(\hat{Y}_n, Y_n)$ represents the relationship between the forecasted series $\hat{Y}_n$, and the actual series $Y_n$; the proportion measuring the remaining unsystematic forecasting errors.

Theil Inequality Coefficient:

$$CT = \sqrt{\sum_1^{n+k} \left(\hat{Y}_n - Y_n\right)^2 /(n+k)} \Big/ \sqrt{\sum_1^{n+k} \hat{Y}_n^{\,2} /(n+k)} + \sqrt{\sum_1^{n+k} Y_n^{\,2} /(n+k)} \quad (34)$$

This coeficient lies between [0;1], where a value close to 0 indicates a perfect fit of the forecasted series, $\hat{Y}_n$ to the actual one $Y_n$.

## IV. Empirical findings

The statistical data used in this study consist of daily exchange rate between 6 currencies, which were extracted from http://bnr.ro/. The sample period is from 03 January, 2011 to 22 April, 2011; totalling 80 daily observations for each series, on 16 weeks. The exchange rates are: EUR/RON, USD/RON, GBP/RON, JPY/RON, CNY/RON, RUB/RON.

These exchange rates were selected because of theire role in international transactions of Romania. The results of the first five models are compressed in (Table 1), namely in (Table 2), together with the forecast evaluation coefficients.

To identify the adequate *ARIMA(p, d, q)* model, the stationarity of the series was tested, by applying the testele *ADF-Augmented Dickey-Fuller* and *PP-Phillips-Perron* unit root tests. At these tests the results regarding the stationarity of the indices are the same, namely the series EUR/RON, USD/RON, JPY/RON, CNY/RON are stationary, in the case in which the observed series has no intercept and no trend, $\Delta y_t = \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-1} + \varepsilon_t$, with o probability of 95%, so d=0.

The other series, GBP/RON și RUB/RON, are nonstationary, at first differentiation they become stationary, so they are I(1), and d=1.

**Table 1. Forecast results obtained by applying the Single, Double and Holt –Winters Simple Exponential Smoothing Techniques**

| | *A. MNES* | | | *B. MNED* | | | *C. MHWES* | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\alpha$ | *SPE* | *RME* | $\alpha$ | *SPE* | *RME* | $\alpha$ | $\beta$ | *SPE* | *RME* |
| **EUR/RON** | 0,999 | 0,009 | 0,010 | 0,412 | 0,010 | 0,011 | 0,930 | 0,000 | 0,008 | 0,010 |
| **USD/ RON** | 0,999 | 0,037 | 0,021 | 0,554 | 0,041 | 0,023 | 1,000 | 0,000 | 0,032 | 0,020 |
| **GBP/RON** | 0,999 | 0,065 | 0,028 | 0,508 | 0,079 | 0,031 | 1,000 | 0,020 | 0,060 | 0,027 |
| **JPY/ RON** | 0,772 | 0,000 | 0,000 | 0,382 | 0,000 | 0,000 | 0,720 | 0,000 | 0,000 | 0,000 |
| **CNY/RON** | 0,983 | 0,001 | 0,003 | 0,528 | 0,001 | 0,003 | 0,960 | 0,000 | 0,001 | 0,003 |
| **RUB/RON** | 0,999 | 0,000 | 0,001 | 0,522 | 0,000 | 0,001 | 1,000 | 0,020 | 0,000 | 0,001 |

(Source: Author`s calculations)

**Table 2. Forecast results obtained by applying Holt –Winters Multiplicative and Additive Exponential Smoothing Techniques**

| | | | | *D. MHWEM* | | *E. MHWEA* | |
|---|---|---|---|---|---|---|---|
| | $\alpha$ | $\beta$ | $\gamma$ | *SPE* | *RME* | *SPE* | *RME* |
| **EUR/RON** | 0,920 | 0,000 | 0,000 | 0,008 | 0,010 | 0,001 | 0,010 |
| **USD/ RON** | 1,000 | 0,000 | 0,000 | 0,033 | 0,020 | 0,033 | 0,020 |
| **GBP/RON** | 1,000 | 0,000 | 0,000 | 0,061 | 0,028 | 0,061 | 0,028 |
| **JPY/ RON** | 0,740 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 |
| **CNY/RON** | 0,980 | 0,000 | 0,000 | 0,001 | 0,003 | 0,001 | 0,003 |
| **RUB/RON** | 1,000 | 0,000 | 0,000 | 0,000 | 0,001 | 0,000 | 0,001 |

(Source: Author`s calculations)

To determine the autoregressive order, namely the moving average order the PAC- partial autocorrelation coefficients and the AC- autocorrelation coefficients were evaluated. To validate the obtained models the significance of the coefficients was tested, all the parameters of the model are significant with a probability of 95%. The second set of tests was applied to the residuals, to establish if they follow a white noise process. So the autocorrelation of the residuals was tested by the Q Statistics, at Q(10), Q(15) and Q(30), all indicating that the first 30 correlations between the residual are insignificant. To investigate the normality of the residuals the Jarque-Bera test was applied, which indicates that they are normally distributed. The final results of ARIMA models (p, d, q) can be found in (Table 3) while the forecast coefficients indicators are in (Table 4.).

***Table 3. Forecast results obtained by applying the ARIMA(p, d, q) model***

| | ARIMA(p,d,q) | AIC | BIC | $R^2$ | Q(10) Statistics | Q(15) Statistics | Q(30) Statistics) | Jarque-Bera |
|---|---|---|---|---|---|---|---|---|
| **EUR/ RON** | ARIMA(1,0,0) | -6,331 | -6,300 | 0,976 | 11,331 (0,254) | 14,162 (0,438) | 25,108 (0,673) | 0,649 (0,723) |
| **USD/ RON** | ARIMA(1,0,0) | -4,942 | -4,911 | 0,977 | 5,404 (0,798) | 9,546 (0,795) | 17,898 (0,946) | 0,094 (0,954) |
| **GBP/ RON** | ARMA(1,1,1) | -4,377 | -4,287 | 0,082 | 0,686 (0,877) | 10,204 (0,667) | 17,962 (0,927) | 2,269 (0,322) |
| **JPY/ RON** | ARMA(4,0,6) | - 13,056 | - 12,933 | 0,959 | 4,265 (0,641) | 5,040 (0,929) | 9,631 (0,999) | 3,729 (0,155) |
| **CNY/ RON** | ARMA(1,0,0) | -8,852 | -8,822 | 0,977 | 4,885 (0,844) | 8,481 (0,863) | 15,821 (0,977) | 1,749 (0,417) |
| **RUB/ RON** | ARMA(1,1,3) | - 12,137 | - 12,046 | 0,052 | 8,288 (0,308) | 10,640 (0,560) | 28,774 (0,372) | 2,022 (0,364) |

(Source: Author`s calculations)

***Table 4. Forecast evaluation coefficients for the ARIMA(p, d, q) model***

| | RME | MAE | DM | DV | DCOV | CT |
|---|---|---|---|---|---|---|
| **EUR/RON** | 0,034 | 0,027 | 0,500 | 0,119 | 0,380 | 0,004 |
| **USD/RON** | 0,054 | 0,042 | 0,526 | 0,117 | 0,358 | 0,009 |
| **GBP/RON** | 0,103 | 0,088 | 0,677 | 0,024 | 0,298 | 0,011 |
| **JPY/RON** | 0,001 | 0,001 | 0,265 | 0,036 | 0,699 | 0,009 |
| **CNY/RON** | 0,007 | 0,006 | 0,441 | 0,151 | 0,408 | 0,008 |
| **RUB/RON** | 0,002 | 0,002 | 0,021 | 0,978 | 0,000 | 0,011 |

(Source: Author`s calculations)

## V. Conclusions

All the results indicate the apreciation of the Romanian Leu against the other currencies. In the case of the first five forecast techniques the results are similar, from the point of view of the forecast coefficients, which points out that the optimal models were found. The exponential smoothing techniques in some cases outperform the ARIMA models, because of the speed eith which they addapt to the smallest changes to the market conditions. In addition, the ARIMA models present some difficulties in estimating and validating the model, are more effective in rendering the medium-term trend, in our case 4 months. So these models show the changes in trend, while the forecasting models based on exponential smoothing techniques are an effective tool for those interested in the evolution of the exchange rate.

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