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An Application Of Exchange Rate Forecasting In Turkey

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ABSTRACT

In this study, exchange rate forecasting is studied which plays a key role in free market systems. Official daily data of Central Bank of The Republic of Turkey (CBRT) are used for USD/TL ($/TL), EURO/TL (€/TL) and POUND/TL (£/TL) pars. Moving averages (MA) method, single exponential smoothing method, Holt's method, Winter's method and ARIMA models are applied to the each pars, Performance of the models are assessed with the performance criteria of mean absolute percentage error (MAPE), root mean square errors (RMSE) and mean square error (MAE). As a result of study, successfully application of the methods based on trend analysis is exhibited for exchange rates in Turkey. According to MAPE, RMSE and MAE criteria, the best results are obtained by Winter's method which means that Winter's method is the most appropriate method to forecast exchange rates for the given time interval in Turkey.

Keywords: Exchange rate forecasting, Time series analysis, Box-Jenkins approach, ARIMA, time series analysis based techniques

1. INTRODUCTION

Forecasting financial time series such as stock prices or exchange rates is important to the investors and the government. A good forecasting of a financial time series requires strong domain knowledge and good analysis tools [1]. Economic vitality and inflation rate are highly affected by monetary policies. Financial players must be sure about the monetary policies in the country they act which is possible by understanding movements of exchange rates. The second reason why policy makers analyze foreign exchange rate market carefully is by the reason of that exchange rate is a financial asset and thus is potentially valuable source of timely information about economic and financial conditions. Therefore, by understanding the movement of exchange rate better, the policy makers will be able to extract the relevant information about the economic and financial conditions of the economy. This will enable them to design a better monetary policy for the future which will help them to achieve their desired objective of price stability and greater employment. Practically most of the countries have been managed by floating exchange rate system in which the central bank restricts the free movement of exchange rates. The interventions from central bank are needed to prevent undesirable or disruptive movements in the exchange rates which cause harm both internal and external sector of the economy. Similarly, firms or investors might wish to forecast exchange rates to make asset allocation decisions [2].

Exchange rate forecasting is an extensively discussed issue in the literature. Methods applied frequently in literature such as autoregressive (AR), autoregressive integrated moving averages (ARIMA), autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) [1]. ARIMA which is known as Box-Jenkins approach at the same time is enhanced by Box-Jenkins [4] and applied successfully in many areas such as tourism demand [5-10], energy [8,11] and many others. Economic time series are not generally linear and their mean and variance change in time. To overcome this difficulty, ARCH [12] and GARCH [13] methods are developed which are also applied extensively in literature [1,14]. Baillie et al. [15] and Bollerslev & Wright [16] present that AR models show results better than some GARCH-based models. Furthermore, vector autoregressive (VAR) and artificial neural network (ANN) methods are applied for exchange rate forecasting studies in the literature [2,4,14,18,19].

In this paper, linear models such as MA, single exponential smoothing method, Holt's method,

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Winter's method and ARIMA models are applied and forecasting performance of these methods are argued. This study is organized as introducing the used methods in second chapter, application of the methods to data in third chapter and in the last chapter arrived conclusions are discussed.

2. FORECASTING METHODS

It is possible to cluster extensively used forecasting methods in literature into four groups: 1) Causal Methods: regression analysis, causality analysis, vector autoregressive (VAR) methods, co-integration; 2) Non-Causal / Extrapolative Methods: decomposition methods, exponential smoothing methods, Box-Jenkins approach (ARIMA models); 3) Alternative Time Series Prediction Methods: artificial neural network (ANN), fuzzy time series approaches; 4) Qualitative methods: Delphi method, subjective probability approach, and administrator judgment method.

In this study, only non-casual methods, which can be said on the other hand as time series analysis based methods -also named as conventional methods- are applied to the data to exhibit that can be used successfully in exchange rate forecasting. In this section, forecasting methods used in the study are summarized.

a. Moving Averages Method

Prediction of future periods are obtained from mean of consecutive observations in moving averages method. Mathematical formulation of the method is;

$$\hat{Y}_{t+1} = \frac{1}{k} x \sum_{i=t-k+1}^{t} Y_i \quad (1)$$

where; $\hat{Y}_{t+1}$ is forecast value of the period (t+1), k is the degree of MA model. For application of MA method, firstly data must be collected and there mustn't be any missed observations in the series. Degree of MA model is determined in respect of the studying time series and to make forecasts of future periods by the estimated model. The most considerable point of this method is to determine the degree of the model. Furthermore, observations of at least k periods before the initial time must be recorded.

b. Single Exponential Smoothing Method

Single exponential smoothing method [20], is based on smoothing past observations with forecast values of that time. In other words, this method is based on multiplying each with particular weights. Here, mathematical formulation of single exponential smoothing method is given by Equation (2);

$$\hat{Y}_{t+1} = \alpha Y_t + (1-\alpha)\hat{Y}_t \ , \ 0 \leq \alpha \leq 1 \quad (2)$$

where $\hat{Y}_{t+1}$ is forecast value of the period (t+1), α is exponential smoothing constant, Y_t is observation value in period t, $\hat{Y}_t$ is forecast value in period t. The most considerable point of this method is to determine exponential smoothing constant correctly. The single exponential smoothing method with α is expected to give the least residuals when applied to the data. The closer α is to 1, the closer $\hat{Y}_{t+1}$ is to Y_t and the closer α is to 0, the closer $\hat{Y}_{t+1}$ is to $\hat{Y}_t$. Single exponential smoothing method is a method to be extensively used for time series not exhibiting trend and not distributing normally, and gives reliable results. $\hat{Y}_t$ has to be known to start the algorithm.

c. Holt's Method

Holt's linear exponential smoothing method [21] is designed to handle data with a well-defined trend and is also named as double exponential smoothing method. Holt's method has two steps. First, level of the time series is estimated exponentially; second, trend of the time series is smoothed exponentially. In other words, whilst applying Holt's method to time series, various exponential smoothing constants can be used for both level and trend. Thus a great flexibility is brought in and this is the main advantage of the model. Mathematical formulation of this method is given below:

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1}) \ , \ 0 \leq \alpha \leq 1 \quad (3)$$

$$T_t = \beta (L_t - L_{t-1}) + (1-\beta) T_{t-1} \ , \ 0 \leq \beta \leq 1 \quad (4)$$

$$\hat{Y}_{t+k} = L_t + k T_t \quad (5)$$

where L_t is level operator in period t, α is exponential smoothing constant for level of the series, Y_t is observation value in period t, T_t is trend operator in period t, β is exponential smoothing constant for trend of the series, k is the number of forecasts, and $\hat{Y}_{t+k}$ is forecast value of k^{th} period after period t. Equation (3) and Equation (4) indicate *Level* and *Trend* exponential smoothing of Holt's method, respectively. The final mathematical formulation is presented in Equation (5). The larger α and β values, produce fast changes; the smaller α and β values, produce lower changes in the model. To start the Holt's method, L_t and T_t must be known.

d. Winter's Method

Winter's method is the extended form of Holt's method. Model becomes sensitive to seasonal effects by adding seasonality operator, and seasonal component to Holt's method. Equations of Winter's method are given by Equations (6) through (9);

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1}) \ , \ 0 \leq \alpha \leq 1 \quad (6)$$

$$T_t = \beta (L_t - L_{t-1}) + (1-\beta) T_{t-1} \ , \ 0 \leq \beta \leq 1 \quad (7)$$

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)\, S_{t-s}\ ,\ 0 \leq \gamma \leq 1 \quad (8)$$

$$\hat{Y}_{t+k} = (L_t + k\,T_t)\, S_{t-s+p} \quad (9)$$

where L_t is level operator in period t, α is exponential smoothing constant for level of the series, Y_t is observation value in period t, T_t is trend operator in period t, β is exponential smoothing constant for trend of the series, S_t is seasonality operator, γ is seasonal exponential smoothing component, k is the number of forecasts and $\hat{Y}_{t+k}$ is forecast value of k[th] period after period t. Equations (6), (7), and (8) indicate *Level*, *Trend* and *Seasonality* equations of the series, respectively. The final mathematical formulation of Winter's method is presented in Equation (9). More reliable and correct forecasts can be done by Winter's method for series which exhibit seasonality. The most considerable advantage of Winter's method is the capability to catch seasonality of series.

e. Box-Jenkins Approach

ARIMA models which is also known as Box-Jenkins approach [4] is based on AR and MA models [11,23-29]. Whilst AR model is being used to note that present observation is depended on past observations, MA model is being used to note that present and past residuals compose a linear function [7]. General statement of these models is composed as ARIMA(p,d,q) where p indicates the degree of AR model, d indicates the degree of difference order and q indicates the degree of MA model. Mathematical formulations of AR(p), MA(q) and ARMA(p,q) models are presented in Equations (10), (11) and (12) respectively.

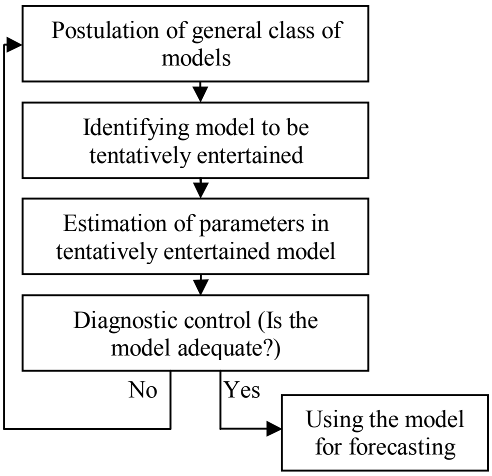

Figure 1. Steps of Box-Jenkins approach [4]

$$A_t = \sum_{i=1}^{p} \phi_i A_{t-i} + \varepsilon_t \quad (10)$$

$$A_t = \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \quad (11)$$

$$\left(1-\phi_1 L - \cdots - \phi_p L_p\right) A_t = C + \left(1+\theta_1 L - \cdots - \theta q L q \varepsilon t,\ \ t=1,\ldots,n,\ C=(1-\phi 1-\ldots-\phi p)\mu\right. \quad (12)$$

where A_t is observation value of point t, μ is mean of observations, ϕ_i are AR model parameters (i=1, … , p), θ_j are MA model parameters (j=1, … , q), L is lag operator, ε_t is residual of point t. Autoregressive moving average (ARMA) model is able to be used in stationary series. In a stationary time series, mean and variance is constant in time and auto-covariance between two lagged values in series is depended on degree of lag, while is not depended on time. In condition of existing of non-stationary time series, ARIMA(p,d,q) model is used which is generalized form of ARMA(p,d,q). As d is the difference operator, the formulation of ARIMA(p,d,q) for $\left(1-\phi_1 L - \cdots - \phi p L p A t = C + 1 + \theta 1 L - \ldots - \theta q L q \varepsilon t,\ \ t=1, \ldots, n\right.$ is given below;

$$A_t = C + \varphi_1 A_{t-1} + \cdots + \varphi_{t-p} A_{t-p-d} + \varepsilon_t + \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \theta_q \varepsilon_{t-q} \quad (13)$$

In Box-Jenkins approach, three main steps to construct the model are shown in Figure 1.

The advantages of the Box-Jenkins method involve extracting a great deal of information from the time series, and using a minimum number of parameters [7,30]. Furthermore, this approach is popular because it can handle stationary and non-stationary time series, both with and without seasonal elements [7,31,32]. The most considerable disadvantage of this approach is being assumed that residuals are normally distributed.

3. AN APPLICATION FOR EXCHANGE RATES IN TURKEY

Official daily data of Central Bank of Republic of Turkey (CBRT) between January 1, 2005 and August 8, 2010 are used for USD/TL ($/TL), EURO/TL (€/TL) and POUND/TL (£/TL) pars in this study. MA, single exponential smoothing method, Holt's method, Winter's method and Box-Jenkins approach are applied to the each pars and performance of these methods are evaluated by mean absolute percentage error (MAPE), root mean square error (RMSE) and mean absolute percentage error (MAE) performance criteria.

a. Implementation of Time Series Methods

Daily observations of $/TL, €/TL and £/TL pars between January 1, 2005 and August 8, 2010 are shown in Figure 2.

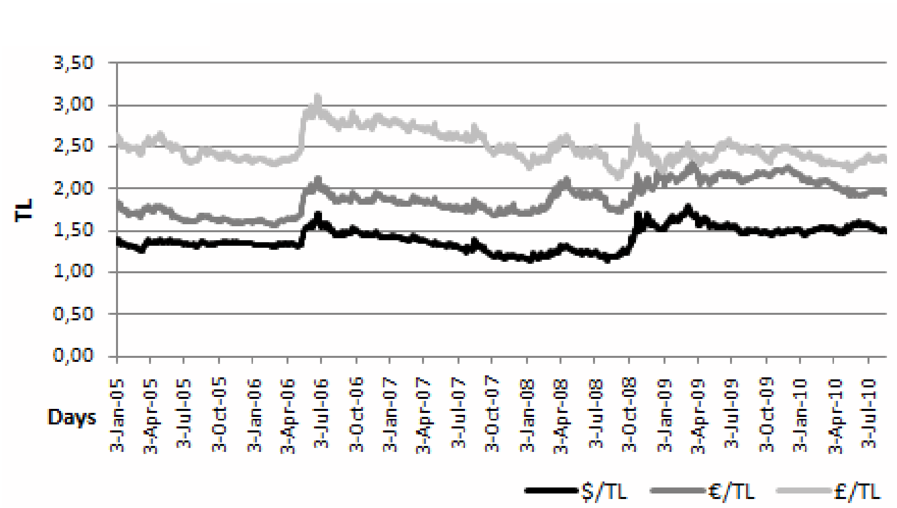

Figure 2. Real observations of $/TL, €/TL and £/TL pars

Various degrees of MA models and single exponential smoothing method; Holt's method with various trend operators -γ- and the best level operator -α- calculated in single exponential smoothing method; Winter's method with various seasonal operator -δ- and seasonal length -SL-, α and γ coefficients calculated in Holt's method; and finally various ARIMA models are applied to time series of three pars. Minitab software is used in application of models. In Minitab software, β and γ coefficients in Equations (4), (7), and (8) are symbolized as γ, and δ, respectively.

Many well-established methods, such as AR, ARMA and GARCH, have been successfully applied for financial forecasting [1,14]. When autocorrelation and partial autocorrelation functions of $/TL, €/TL and £/TL are investigated, it can be seen that each series theoretically represents as AR(1). However various ARIMA models are applied to the data. Figure.3-4 show autocorrelation function and partial autocorrelation function of $/TL. Autocorrelation and partial autocorrelation functions of €/TL, and £/TL series are very similar to $/TL. Each series becomes non-stationary by taking first order differences. Stationary is tested with ADF test for each series. Accordingly, difference degree of each series is d=1. The most appropriate ARIMA model for $/TL, €/TL and £/TL are determined as ARIMA(2,1,2), ARIMA(2,1,2) and ARIMA(1,1,1), respectively.

In recent years, non-statistical methods such as MAPE, RMSE and MAE are being used to evaluate forecast performance [33]. There is no universally preferred measure of estimation accuracy and forecasting experts often disagree on which measure should be used. Most commonly known measures of accuracy include mean error (ME), mean percentage error (MPE), mean absolute percentage error (MAPE) and root mean square error (RMSE). The ME and MPE measures are not very useful, because positive errors are canceled by negative errors, and the mean is always close to zero. The MAPE which is the basic measure generally is widely used [5]. Absolute error methods are more adequate than squared error methods according to Witt & Witt [34] and many other researchers.

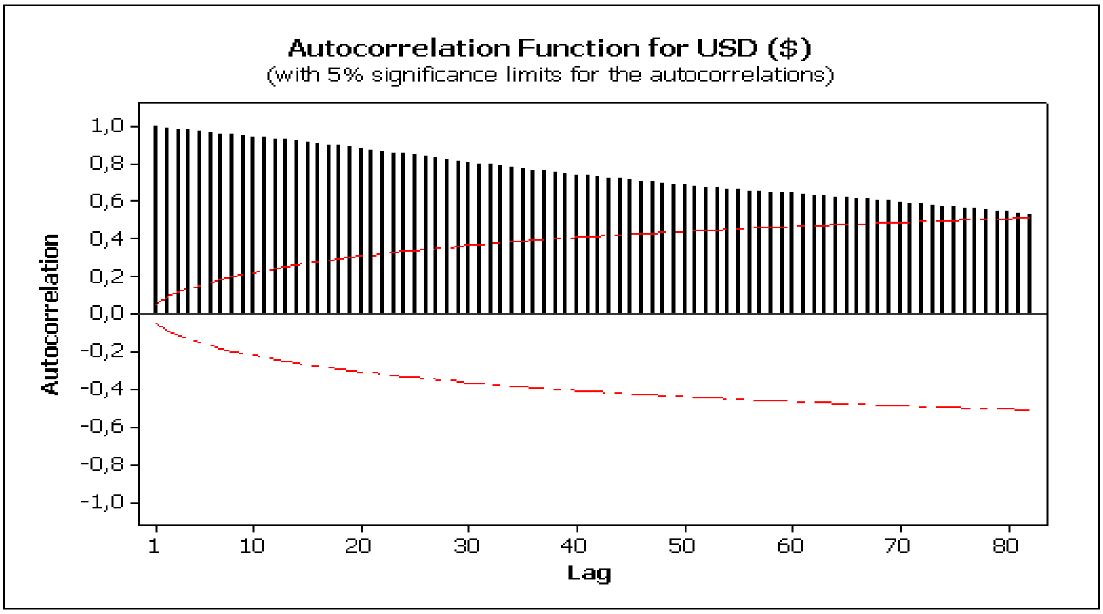

Figure 3. Autocorrelation function of $/TL series

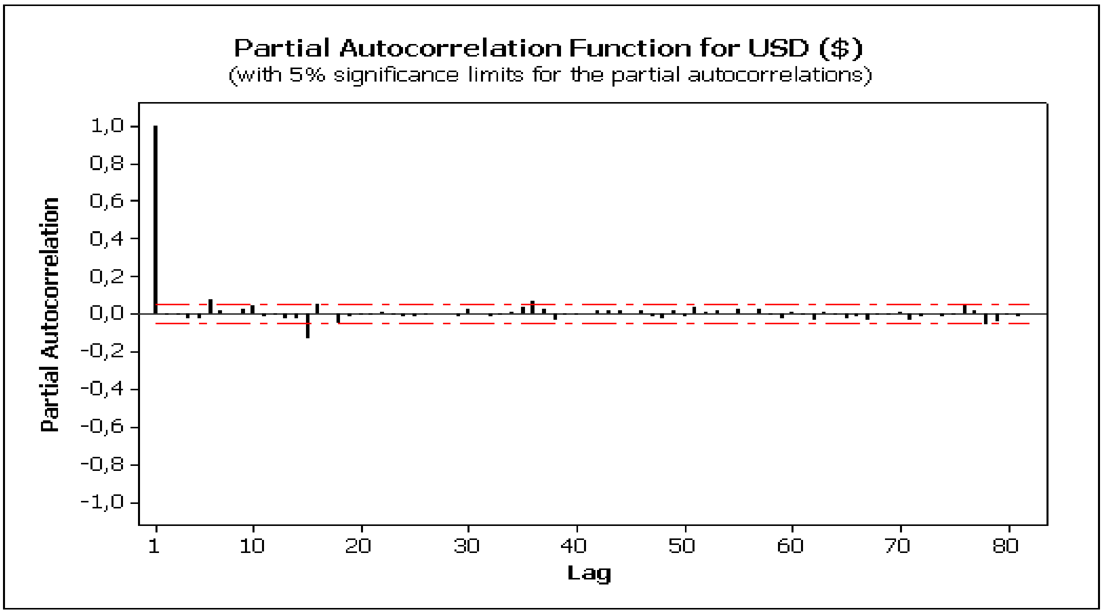

Figure 4. Partial autocorrelation function of $/TL series

In this paper, MAPE, RMSE and MAE performance criteria are used to evaluate the accuracy of models. The most considerable advantages of these methods extensively used in the literature can be noted as ease-of-use, not spending much time to apply, found in most statistical softwares and wasting little memory in computers while running.

To evaluate the accuracy of each model class, MAPE, RMSE and MAE criteria are used for each $/TL, €/TL and £/TL series. And then, the most appropriate model is chosen for each pars. The results of application of MAPE, RMSE and MAE criteria for $/TL, €/TL, and £/TL are tabulated in Table1-3, respectively.

Table 1. The performance criteria of models for $/TL

		MAPE	RMSE	MAE
Moving averages				
	MA(14) Model :	1.504090	0.032863	0.021600
	MA(7) Model :	1.165850	0.025298	0.016680
	MA(5) Model :	1.022830	0.022361	0.014620
	MA(4) Model :	0.935302	0.020445	0.013361
	MA(3) Model :	0.848101	0.018547	0.012105
	MA(2) Model :	0.756452	0.016583	0.010776
*	MA(1) Model :	**0.672630**	**0.014765**	**0.009572**
Single exponential smoothing method				
	α=0.2	1.124360	0.024495	0.016110
	α=0.5	0.782759	0.017205	0.011166
	α=0.7	0.708118	0.015556	0.010083
*	α=0.999	**0.673778**	**0.014799**	**0.009587**
Holt's (double exponential smoothing) method				
	α=0.2 ; γ=0.2	1.136920	0.024698	0.016260
	α=0.6 ; γ=0.1	0.749876	0.016492	0.010681
	α=0.9 ; γ=0.2	0.715784	0.015524	0.010183
	α=0.9 ; γ=0.1	0.697554	0.015199	0.009928
*	α=1.0 ; γ=0.005	**0.675892**	**0.014832**	**0.009619**
Winter's method				
	α=1.0 ; γ=0.005 ; δ=0.5 ; SL=5	0.718404	0.015133	0.010186
	α=1.0 ; γ=0.005 ; δ=0.2 ; SL=5	0.718404	0.015133	0.010186
	α=1.0 ; γ=0.005 ; δ=0.9 ; SL=5	0.718404	0.015133	0.010186
	α=1.0 ; γ=0.005 ; δ=0.001 ; SL=25	0.672125	0.014731	0.009559
	α=1.0 ; γ=0.005 ; δ=0.001 ; SL=100	0.670922	0.014318	0.009520
*	α=1.0 ; γ=0.005 ; δ=0.001 ; SL=300	**0.629090**	**0.013153**	**0.008910**
Box-Jenkins approach				
	ARIMA(1,1,0)	0.673299	0.014765	**0.009581**
	ARIMA(0,1,1)	0.673299	0.014765	**0.009581**
	ARIMA(1,1,1)	0.676424	0.014764	0.009583
	ARIMA(2,1,1)	0.673783	0.014763	0.009588
	ARIMA(1,1,2)	0.673835	0.014763	0.009589
	ARIMA(2,1,0)	0.673574	0.014764	0.009585
	ARIMA(0,1,2)	0.673556	0.014765	0.009584
*	ARIMA(2,1,2)	**0.673158**	**0.014717**	0.009585

Table 2. The performance criteria of models for €/TL

		MAPE	RMSE	MAE
Moving averages				
	MA(14) Model :	1.410860	0.038987	0.026940
	MA(7) Model :	1.063640	0.029833	0.020330
	MA(5) Model :	0.946437	0.026833	0.018102
	MA(4) Model :	0.879027	0.024515	0.016806
	MA(3) Model :	0.801476	0.022494	0.015305
	MA(2) Model :	0.722300	0.020273	0.013764
*	MA(1) Model :	**0.639410**	**0.018028**	**0.012169**
Single exponential smoothing method				
	α=0.2	1.044220	0.009055	0.019920
	α=0.5	0.736415	0.020712	0.014049
	α=0.7	0.671896	0.018894	0.012800
*	α=0.999	**0.639248**	**0.018028**	**0.012166**
Holt's (double exponential smoothing) method				
	α=0.1 ; γ=0.9	1.656220	0.047117	0.031830
	α=1.0 ; γ=1.0	0.910315	0.026268	0.017293
	α=1.0 ; γ=0.9	0.868708	0.025100	0.016502
	α=1.0 ; γ=0.5	0.749206	0.021587	0.014245
	α=1.0 ; γ=0.2	0.686773	0.019748	0.013060
*	α=1.0 ; γ=0.005	**0.649431**	**0.018708**	**0.012354**
Winter's method				
	α=1.0 ; γ=0.005 ; δ=0.2 ; SL=5	0.649541	0.018111	0.012349
	α=1.0 ; γ=0.005 ; δ=0.5 ; SL=5	0.649541	0.018111	0.012349
	α=1.0 ; γ=0.005 ; δ=0.001 ; SL=50	0.635872	0.017748	0.012101
*	α=1.0 ; γ=0.005 ; δ=0.001 ; SL=300	**0.604349**	**0.016248**	**0.011482**
	α=1.0 ; γ=0.005 ; δ=1.0 ; SL=300	**0.604349**	**0.016248**	**0.011482**
Box-Jenkins approach				
	ARIMA(1,1,0)	0.639033	0.018018	0.012162
	ARIMA(0,1,1)	0.638989	0.180180	0.012161
	ARIMA(1,1,1)	0.638590	0.018015	0.012154
	ARIMA(2,1,1)	0.638278	0.018000	0.012148
	ARIMA(1,1,2)	0.638292	**0.017999**	0.012147
	ARIMA(2,1,0)	0.638292	0.018003	0.012149
	ARIMA(0,1,2)	0.638294	0.018004	0.012149
*	ARIMA(2,1,2)	**0.638182**	**0.017999**	**0.012146**

Table 3. The performance criteria of models for £/TL

		MAPE	RMSE	MAE
Moving averages				
	MA(7) Model :	1.129240	0.039497	0.028260
	MA(5) Model :	0.992537	0.034943	0.024487
	MA(4) Model :	0.919791	0.032373	0.023052
	MA(3) Model :	0.839430	0.029682	0.021044
	MA(2) Model :	0.752639	0.026758	0.018867
*	MA(1) Model :	**0.658949**	**0.023643**	**0.016540**
Single exponential smoothing method				
	α=0.2	1.098750	0.038859	0.027490
	α=0.5	0.770431	0.027331	0.019324
	α=0.7	0.699234	0.024880	0.017536
*	α=0.999	**0.659179**	**0.023643**	**0.016546**
Holt's (double exponential smoothing) method				
	α=1.0 ; γ=0.7	0.810872	0.029189	0.020367
	α=1.0 ; γ=0.5	0.757843	0.027295	0.019031
	α=1.0 ; γ=0.2	0.696607	0.024980	0.017489
*	α=1.0 ; γ=0.005	**0.660710**	**0.023707**	**0.016588**
Winter's method				
	α=1.0 ; γ=0.005 ; δ=0.2 ; SL=5	0.673927	0.023896	0.016911
	α=1.0 ; γ=0.005 ; δ=0.7 ; SL=5	0.673927	0.023896	0.016911
	α=1.0 ; γ=0.005 ; δ=0.1 ; SL=50	0.653738	0.023259	0.016930
	α=1.0 ; γ=0.005 ; δ=0.001 ; SL=150	0.634086	0.022159	0.015874
*	α=1.0 ; γ=0.005 ; δ=0.001 ; SL=300	**0.604068**	**0.021000**	**0.015110**
Box-Jenkins approach				
	ARIMA(1,1,0)	0.657555	0.023625	0.016507
	ARIMA(0,1,1)	0.657506	0.023624	0.016507
*	ARIMA(1,1,1)	**0.657444**	0.023611	**0.016505**
	ARIMA(2,1,1)	0.657671	**0.023594**	0.016512
	ARIMA(1,1,2)	0.657465	**0.023594**	0.016507
	ARIMA(2,1,0)	0.657765	**0.023594**	0.016514
	ARIMA(0,1,2)	0.657785	**0.023594**	0.016514
	ARIMA(2,1,2)	0.657462	**0.023594**	0.016507

The most important advantage of MAPE criteria through others is to be meaningful by only itself because of expressing residuals with absolute values [35]. However, at least two of MAPE, RMSE, MAE or MSE criteria are generally used together by the reason of being non-statistical methods. These methods lack of statistical test capability, so cannot neither construct nor test hypothesis. Therefore MAPE, RMSE, MAE or MSE criteria do not have the capability of deciding about accuracy of models certainly and so they can only be used for comparing models. The most appropriate model of each model class is signed with '*' on the left top corner and the best MAPE, RMSE and MAE values are indicated in **bold** as it can be seen in Table.1-3. The best model for each par is Winter's method with α=1.0, γ=0.005, δ=0.001 and SL=300 coefficients.

Figure.5-7, real observation values, and fitted values of the most appropriate model for $/TL, €/TL and £/TL, respectively.

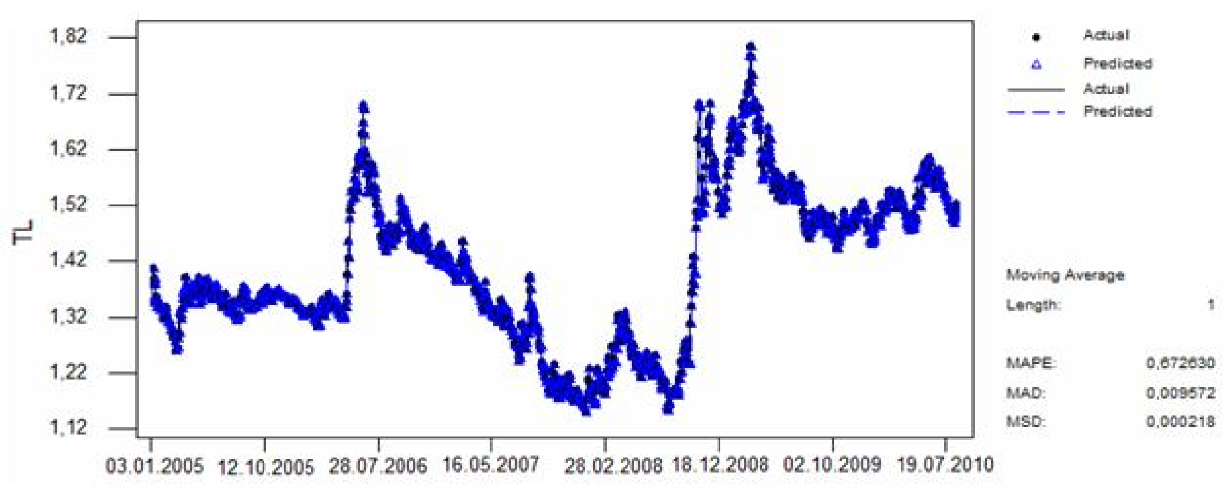

Figure 5. The real observation values and fitted values of Winter's method for $/TL.

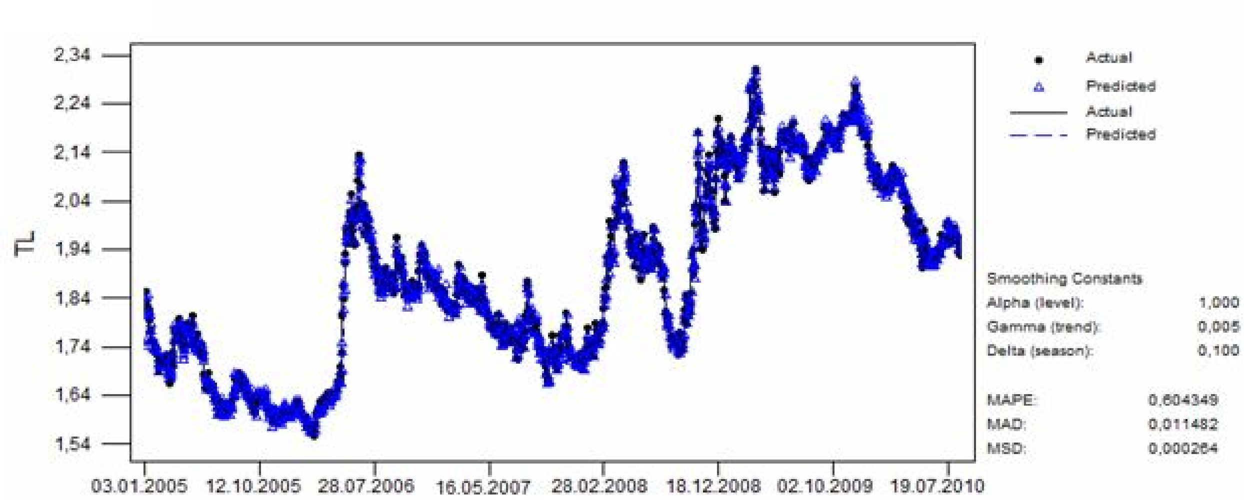

Figure 6. The real observation values and fitted values of Winter's method for €/TL

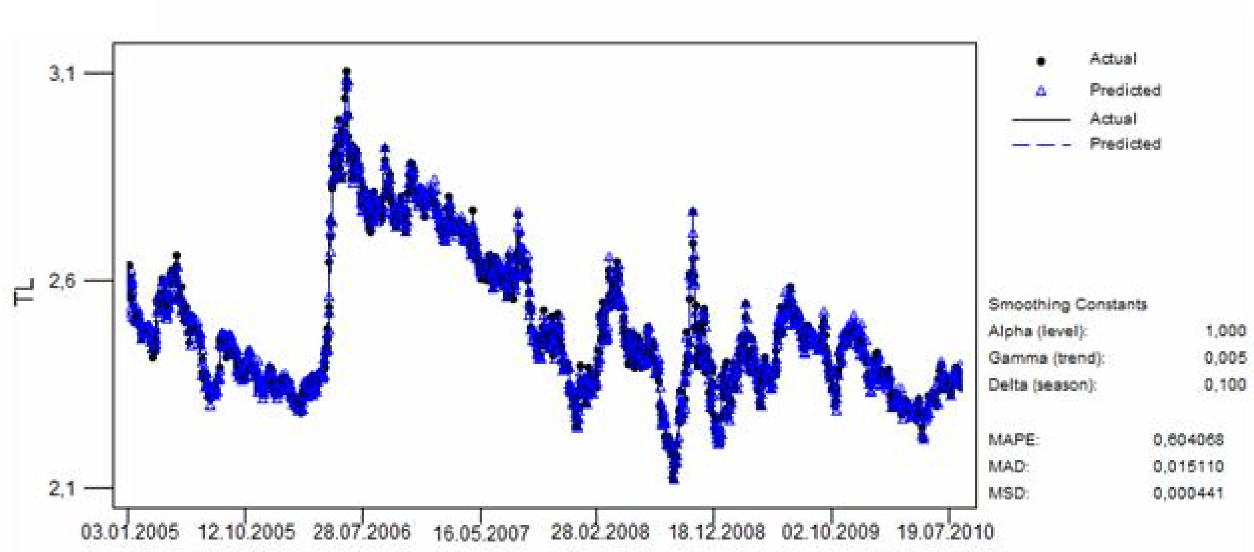

Figure7. The real observation values and fitted values of Winter's method for £/TL

For $/TL par, the most appropriate MA model is MA(1), single exponential smoothing with the best α value of 0.999 is the most adequate in single exponential model cluster, Holt's method with the values of α=1.0, and γ=0.005 gives the nearest results to real values, in Winter's method the best α, γ and δ values are 1.0, 0.005 and 0.001 respectively. The most appropriate model for each $/TL, €/TL and £/TL par is Winter's method with α, γ and δ values of 1.0, 0.005 and 0.001 respectively.

4. CONCLUSION

In this study, official daily data of CBRT of $/TL, €/TL and £/TL pars between January 1, 2005 and August 8, 2010 are investigated. The best model in MA model class is MA(1) which proves that the next future observation is not very far from the initial observation. Similarly, the best value of α coefficient in single exponential smoothing method is 0.999 for all pars which means that future observation is more similar to real value of last observation than forecast value of last observation. In Holt's method, the best α value obtained from single exponential smoothing method is rounded to 1.0 and γ is investigated. In Winter's method, α and γ values obtained from Holt's method are constant and δ and SL are investigated. Changes of δ in Winter's method does not cause any changes in performance criteria. Although this is an expected result because exchange rates do not include seasonal effects theoretically, increasing of SL gives better results in performance criteria. The best values of α, γ and δ are 1.0, 0.005 and 0.001 respectively in Winter's method which is the most appropriate model for each pars according to MAPE, RMSE and MAE performance criteria. Finally, ARIMA(1,1,0), ARIMA(0,1,1), ARIMA(1,1,1), ARIMA(2,1,1), ARIMA(1,1,2), ARIMA(2,1,0), ARIMA(0,1,2) and ARIMA(2,1,2) are applied to each series and ARIMA(2,1,2), ARIMA(2,1,2), and ARIMA(1,1,1) models are the most appropriate ARIMA models for $/TL, €/TL, and £/TL pars respectively. Winter's method with the values of 1.0, 0.005 and 0.001 for the coefficients α, γ and δ respectively overcomes all the other models and becomes the most appropriate model for each par.

Lewis [36] labels the MAPE values under %10 as high accuracy and this classification is still valid. Whole the best models in their classification are even under MAPE value of %1 for each par and this result is highly noteworthy. These conclusions exhibit that models constructed with non-casual forecasting methods represents the series. High accuracy is obtained for each par although Preminger and Franck [37] exhibits that exchange rates are mostly unpredictable. This accuracy is obtained by the 5 years long daily observations, so it provides high reliability for future forecasts. For instance, great decrease of value of TL in the middle of 2006 can be predicted by the applied models.

Single exponential smoothing method is hard to use to forecast mid and long terms. Because this method involves real value of initial observation to forecast the next observation; so forecast horizon of this method is 1 term. On the other hand, mid and long term forecasts can be done more accurately, and reliably by MA, Holt's method, Winter's method and ARIMA models. Forecast method is greatly related to forecast horizon, such that forecast method should be chosen by considering forecast horizon.

Winter's method overcomes the whole other methods and fitted values of Winter's method for each par gives MAPE values under %1. So, maybe the most considerable result of this study is that Winter's method is as useful as extensively used models like VAR, ARCH and GARCH for economic series.

For future studies, seasonal ARIMA models and extensively being used non-parametric methods in literature like ANN and support vector regression (SVR) can be used for the data. Even, hybrid approaches which combine parametric and non-parametric methods can be applied for utilizing the advantages of both parametric and non-parametric approaches. Moreover, besides analyzing time series quantitatively, qualitative criteria such as preferences and tendencies of decision makers, environmentally conditions and speculations can be incorporated to the decision problem.

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