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Long term currency forecast with multiple trend corrected exponential smoothing with shifting lags

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ABSTRACT

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In the current global economy, exchange rate forecasting is critical for investors and businesses seeking to make informed investment decisions and manage risk. While many short-term exchange rate forecasting methods exist, long-term forecasting methods are limited and often fail to account for the complex macroeconomic factors that influence exchange rate trends. However, investors need to have an analytically examined basis for deciding to invest, which requires knowing more about the future values of the related market currency. This paper proposes a new Multiple Trend Corrected Exponential Smoothing with Shifting Lags model to forecast long-term exchange rates, which incorporates multiple trend corrections and shifting lags to provide more accurate predictions of future currency values. We apply the proposed method to six currency pairs (USD/EUR, USD/NOK, USD/TRY, USD/CNY, USD/XOF, and USD/MGF) from 2006 to 2018 and compare its performance to existing methods, such as moving average, weighted moving average, and exponential smoothing. Our results show that the proposed model provides more accurate long-term exchange rate forecasts for developed countries than existing methods. Our findings have important implications for investors and businesses seeking to manage currency risk and make informed investment decisions in the global economy.

INTRODUCTION

Volatility in the currency can be significant for firms working internationally because it affects long-term business decisions while moving into new markets. Therefore, firms need to plan and foresee the future for their investment in other countries. In this regard, several models are used to find the future currency rate. However, most of them are appropriate for short-term forecasting, and none can claim to be highly effective, meaning that a single forecast model cannot predict every currency rate with the same efficiency.

In this paper, a new long-term forecasting model is introduced. The model combines multiple trends and exponential smoothing methods by shifting lags, which is explained in the methodology. Six currencies against Dollar (USD) are selected to be predicted according to their development level. As developed, Norwegian Krone (NOK) and Euro (EUR), as developing Turkish Lira (TRY) and Chinese Yuan (CNY) and as undeveloped Malagasy Franc (MGF) and Senegal Franc (XOF) are determined to use the data throughout 2006-2018. After applying new method to selected currencies, desired results are obtained by doing the required analyses. The model for each currency minimizes the error which is calculated by taking the difference between forecast value and real value. In this way, it will be seen that in which type of currency the model predicts long-term currency rate well.

Foreign Exchange (FX) is the biggest financial market in the world. To catch trends in this market, people invest money that cannot be negligible to learn the future of FX. It causes people to work on forecasting for FX forecasting topics. Foreign exchange rate forecasting is an essential issue because it impacts a country's financial development. For estimating the currency exchange, there are numerous problematic things such as unpredictable currency rate behavior, unsteady currency exchange prices, and so on. These complicated issues are derived from economic, political, and social factors. Due to these reasons, forecasting currency rates has become a complex topic. To handle this complexity, deep knowledge, and analysis are needed.

Generally, currency rates have different characteristics, so a single forecast model cannot represent every currency rate because it is hard to include the same parameters to apply to currencies with other characteristics. Therefore, it is necessary to work on different currencies to cover most areas. To cope with this, countries are separated into several classes, and samples from currency rates are taken for analysis and forecasting.

An investor needs to consider parameters to understand the current situation in the market. Based on historical data, which is analyzed technically, the investor should check that currency's future. However, checking currencies' futures for an investment is not effortless. It is formidable situation to fit an appropriate forecast model to a currency. To make investor's process easier and more confident, it is planned to generate a forecast model with sub models for every individual class of countries. This model will be providing currency exchange forecasts based on technically analyzed historical data of the currency.

Faust et al. [1] examine the errors made in several exchange rate forecast models. A dataset containing the main economic indicators published by OECD (The Organisation for Economic Co-Operation and Development) from 1988 to 2000 is examined in the study. Under the study, "Mark' s Forecasting.

Regression" is the most notable model that was analyzed, where the regression is made based on the log of the exchange rate, foreign and domestic money stocks and outputs. The model is mainly used for long-horizon exchange rate predictability. Within the dataset, RMSE (Root Mean Square Error) was between 10 and 16 percent for years, indicating that the relationship with the fundamental elements in the model and exchange rates are difficult to establish occasionally. In general, the study reveals the parameters of the econometric models for long-term exchange rate forecasts.

Eva and Maria [2] evaluated their study's performance of exponential smoothing techniques. Six forecasting methods were employed: single exponential smoothing, double exponential smoothing, Holt–Winters simple, multiplicative and additive exponential smoothings, and Box- Jenkins method. All the examined models except the ARIMA give good results in the series with linear trends, whereas ARIMA is a generally used model for any stationary time series. There are three parameters in ARIMA, and by changing their values, ARIMA models can be converted to other forecasting methods. In the study, several error measures are used for evaluating the performance: sum of squared errors, root mean squared error, mean absolute error, bias proportion, variance proportion and covariance proportion. Methods are used on the exchange rates of EUR/RON, USD/RON, GBP/RON, JPY/RON, CNY/RON, and RUB/RON. According to the results, it has been seen that simpler models outperform ARIMA models in most of cases, as ARIMA models are shown to be better at adapting to changes in the trend under given market conditions. However, the validation of ARIMA models was more complicated in the study. It is also important to note that the forecast horizon for the study is six weeks, between January 2011 and April 2011. Another thing to notice is the base currency was RON (Romanian Leu), as different parties such as JPY/USD or CNY/RON could give different results within the mentioned models. With these considerations, it can be assumed that although some models may not perform as well as others, the trend-catching ability is another thing to consider for exchange rate forecasting.

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The research of Ghalayini [3] focuses on forecasting USD/EUR parity by using ARIMA method and mentions the purchasing power parity theory Gustav Cassel presented. The theory aims to equate the market levels in the countries of parity. It considers exchange rates and market prices for calculating nominal exchange rates of the parities. Also interest rate parity is calculated to explain the variation in the exchange rates, however, they only achieve it partially. An ARIMA model with parameters (2,1,0) was built, but it also fails to explain the causal structure behind the evolution of the time series. Fundamentals that affect the exchange rates are explained in the rest of the study, namely “money aggregates” and “business cycles”, then implemented into an econometric model. In the end of study, it is found that models are partially effective in forecasting the exchange rate levels. It is also discovered that the most affecting factor for exchange rates is the inflation rate between the countries.

The study of Apergis [4] focuses on forecasting the AUD by gold prices. For the study, gold prices between 2000 and 2012 are considered along with the AUD/USD rates. Gold interest rates are also included in the model, in addition to applying stationary tests within a 5% significance level. Means in the shifts are calculated, and the primary method for the study is ECM (Error Correction Model), with a lag length of 8. The result of the study showed that gold prices affect the parity of AUD/USD within both daily and monthly data and within both nominal and real exchange rates, as behavior is classified as vis-à-vis random walk behavior.

Today, exchange rates play a crucial role in controlling the foreign exchange market dynamics. Economists and investors generally tend to predict future exchange rates, so they can use estimates to derive monetary values. For ten years, the forecasting exchange rate has been a subject that is widely and continuously studied in the field of finance. Several calculation methods are used for estimation. These methods can be separated into single (or base) and combination (or aggregate) methods. Several basic methods are presented for forecasting exchange rate, including traditional techniques like ARIMA, logistic regression, multiple regression, and some non-linear models such as Artificial Neural Networks, Support Vector Machine, etc. However, it has been noted that the individual prediction methods still have limited capacity, since each classifier has unstable results in many data sets. An aggregate method is expected to decrease variance of estimated errors and increase the stability of overall forecasting performance.

For aggregate methods, the diversity and performance of members are key factors in providing a successful model. If the basic methods are the same or give the same results, the aggregate method will not bring improvement apart from increasing complexity. Moreover, if an aggregate member performs poorly, even if the combination is completely different, it cannot achieve a good result [5].

To understand the accuracy of the model academicians, economists, investors and so on, generally compare the results of proposed models with the well-known or other methods they applied. While comparing the proposed model, they checked several error types’ results, such as SSE, MAPE [6]. After observation, they indicate their error results to understand how the proposed model works. To conclude that the proposed model works better than the compared ones, it is necessary to have lower error values, which means the new model demonstrates the current situation more precisely.

In the most recent decade, Taylor (2003) [7] has built up a double seasonal exponential smoothing method, which permits the consideration of one cycle settled inside another. Taylor’s double seasonal (DS) exponential smoothing method (Taylor, 2003) was developed to forecast time series with two seasonal cycles: a short one that repeats itself many times within a longer one. Taylor's method speaks to a significant change; however, accept the same intraday cycle for all days of the week. Also, refreshes in light of late data (the intra- day cycle) are the same for every day of the week.

In another recent study by Taylor (2010), the three methods shown to be competitive in recent empirical studies are double seasonal ARMA, the adaptation of Holt-Winters exponential smoothing for double seasonality, and the recently exponential smoothing method. In addition to the day-to-day and week-to-week cycles, the intuitive seasonal cycle is appeared in the years of load data. To be able to meet the yearly seasonal cycle, Taylor expanded the three-double seasonal method. After that, to provide accuracy improvement, two triple seasonal methods are combined [8]. This research considered public holidays, industrial holidays, and clock-change periods to smooth the data and improve accuracy. To have precise model, Taylor (2010) compared Holt- Winter-Taylor (HWT) method with ARMA and Intraday Cycle (IC) exponential smoothing. The results show that the IC method was not better than the HWT method and also, depending on the number of parameters, the ARMA method has the disadvantage of requiring significant specification and more demanding optimization [8].

The material of forecasting methods is data, which generally has fluctuations, seasonality, trend, etc. The study carried out by Japanese and Indonesian academicians (2016), discusses the ARIMA (Autoregressive Integrated Moving Average) method to identify seasonal variation on data of their specific topic [9]. At the beginning of data analysis, they first checked whether the data had stationary or nonstationary trends. After deciding that the data has stationary trend, they estimated the ARIMA parameters as a second step. With the smallest value of BIC (Bayesian Information Criterion), and MSD (Mean Square Deviation) they concluded that the ARIMA (0,1,1) is the best fitting model for given data. After selecting the model with its equation, the last step was measuring accuracy and in this step, they used MAD and MSD methods to see error values. Getting low values for MAD and MSD ensures that the model works well [9].

Statistical modeling is a big field in science, and forecasting is one part of this area. In forecast studies, having complete and appropriate data has significant importance. The study by Arumugam and Saranya [10] investigates how to predict missing data for monthly rainfall. To deal with this issue, SARIMA (Seasonal Autoregressive Integrated Moving Average) is preferred to apply. Since in the observed data, it realized that there exists seasonality. They will start forecasting future values of a time series with this model when the model has been identified and all the parameters have been estimated. Parameters are estimated by using the MLE (Maximum Likelihood Estimation) and minimizing SSR (Sum Squared Residuals). After applying the model, they replaced outliers of the taken data with the observed mean value. As a result, the fitted SARIMA model was performing well and providing a simplistic instrument.

Table 1. Comparison of RMSE on different horizons

Forecast	**RMSE, *h***			
	1	**5**	**10**	**20**
1	0.744	0.815	0.886	0.959
2	0.793	0.833	0.889	0.957
3	0.756	0.836	0.927	1.054
4	0.880	0.928	1.013	1.150
5	0.735	0.802	0.870	0.947
6	0.738	0.808	0.895	1.023
7	0.900	0.961	1.050	1.072
8	0.802	0.871	0.963	1.043
9	0.919	0.875	1.072	1.161
10	0.781	0.874	0.955	1.112

In the study of MacDonald and Taylor [11], the monetary approach to the exchange rate is examined using the monthly data of the US dollar and the Deutsch mark over the period 1976 and 1990. Firstly, it is shown that the long-run exchange rate has some validity on the forward-looking monetary approach. Then, cointegration is tested using the multivariate cointegration technique, which uses ordinary least squares to estimate the cointegration relationship. As a result, it is shown that there exists a cointegration, then it is said that dynamic error correction also exists. After applying the forecast method based on dynamic error-correction for long-rung estimation, root means squared error (RMSE) are compared to the random walk model, and it is proven that the dynamic error-correction model gave better results considering RMSE, which is shown in Table 2.

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Table 2. Comparison of error correction and random walk model based on RMSE

Horizon (Months)	RMSE from Error-Correction Model	RMSE from Random Walk Model
12	0.131	0.148
9	0.103	0.112
6	0.081	0.088
3	0.043	0.053
2	0.032	0.040
1	0.028	0.030

In the study of Pong et al. [12], forecasts of the volatility of GBP/USD, D-Mark/USD, and JPY/USD are compared using four forecast techniques. ARMA for the short-run, ARFIMA for the long-run, GARCH model, and implied volatilities (FIV) model are calculated from intraday rates with high-frequency returns, 5-minute and 30-minute changes throughout 1987 to 1998. The ARFIMA (p, d, q) model estimates parameters using maximum likelihood estimation. After forecasting volatilities using four methods, the accuracy for each model is measured using mean squared error (MSE) and regression analysis. Results of MSE that is presented in Table 3 show that ARFIMA and ARMA models are more accurate than FIV and GARCH models.

Table 3. Results of the mean squared error for forecast methods

Forecast/horizon	5-minute series				30-minute series			
	1 day	1 week	1 month	3 months	1 day	1 week	1 month	3 months
A. USD/GBP								
FIV	4.16	3.14	1.95	2.14	7.03	4.34	2.53	2.84
ARFIMA(1,d, 1)	3.81	2.48	1.96	2.15	6.32	3.90	2.89	2.79
ARMA(2, 1)	3.80	2.48	1.91	2.21	6.30	3.88	2.84	2.81
GARCH(1, 1)	4.75	4.19	3.57	3.92	9.29	7.77	4.17	9.29
B. USD/DEM								
FIV	7.09	4.89	4.34	4.45	10.79	7.05	5.02	5.26
ARFIMA(1,d, 1)	6.55	5.17	4.42	4.23	10.32	7.24	4.95	4.61
ARMA(2, 1)	6.55	5.14	4.45	4.21	10.38	7.31	5.14	4.87
GARCH(1, 1)	7.47	6.25	6.23	5.10	12.78	9.81	9.38	7.26
C. USD/JPY								
FIV	19.37	12.72	9.01	8.39	24.00	15.14	10.48	9.19
ARFIMA(0, d, 0)	15.11	12.96	11.09	11.39	20.00	16.34	12.64	13.67
ARMA(2, 1)	15.24	13.14	11.43	11.50	20.44	16.55	12.81	13.91
GARCH(1, 1)	17.51	12.91	16.47	12.36	21.51	13.57	18.42	15.04

In regression analysis, the method is shown to have more information, FIV is the worst, and ARFIMA is the best method based on calculated R squared.

In the article of Taylor [13], daily low and high prices from 1977 to 1983 are used to forecast the volatility of currency exchange rates. Prices from 1977 to 1981 are used to estimate parameters, and then prices for 1982 to 1983 (post sample for two years and forecast horizons h=1, 5, 10 and 20 trading days) are used to assess various forecasts. The prices of Deutsche Mark futures at the International Monetary Market in Chicago from 1977 to 1983 were employed. It also says that using daily low and high prices is better than daily closing prices. The root mean squared error (RMSE) is calculated. The table shows the RMSE for horizons h=1, 5, 10 and 20 trading days. (N=10 which is the data range). There is no comparison with any other method to forecast exchange rates, but there is a comparison for horizons shown in Table 1.

Researchers are also studying the digital currencies market because the price forecasting of digital currencies has become increasingly important in recent years, particularly following the global economic crises. However, due to the nonlinear dynamics of digital currencies, a single model may not be sufficient for accurate forecasting. Researchers have suggested that a hybrid forecasting framework can improve forecast accuracy by combining the strengths of multiple models while minimizing their weaknesses [14].

Another study investigates integrating an asymmetric GJR model into an ANN consisting of an NARX augmented by an NAR network to predict the exchange rate volatility [15]. The proposed hybrid ANN-GJR model significantly improves forecast accuracy compared to benchmark models, such as GARCH and APGARCH, by capturing asymmetric volatility and volatility clusters. The study also found that incorporating commodity prices as input variables can improve model performance over different forecast horizons.

In the literature, there exist many studies that discuss the relationship between exchange rates and various factors. Some analyze the relationship between interest rates, forecast errors, exchange rates, etc.; another part of the literature researcher examines the performance of experts and novices in making forecasts based on various trends, noise levels, and forecast horizons; several of those investigate the transmission of exchange rate shocks to the national banks [16], [17], [18], [19].

Researchers are interested in estimating the future in different ways. They use other techniques, instruments, and approaches to predict uncertainty in the future. This situation becomes more exciting when the topic is monetary value. Numerous studies are about the ensemble learning approach that combines individual methods using multi-objective evolutionary algorithms and modified algorithms to achieve higher forecasting performance. Some researchers try to use hybridized system that combines neural networks and genetic training to forecast exchange rates accurately and correctly forecast the direction of change in exchange rate movement. Some others use machine learning algorithms to achieve the minimum rate of error [20], [21], [22], [23]. Different studies discuss the basic approaches to hybrids to optimize the estimation steps. Also, they compare the models for volatility and exchange rates for the accuracy level check of each [24], [25], [26], [27].

In summary, currency forecasting is the practice of predicting future movements in currency exchange rates, and it is a challenging task because a variety of factors influences currency values, including economic indicators, geopolitical events, and market sentiment, among others [28], [29], [30], [31]. All in all, it is observed that as the forecasting horizon increases, it appears best to let the forecasts regress toward a mean value. It is shown that, when the horizon increases, the error rate increases. However, with the proposed approach of this study, it's seen that the results are converging to a logical error rate. On the other hand, when those results are compared to the domestic central bank's estimations, better results are obtained thanks to the proposed novel hybrid algorithm.

On the other hand, popular methods are general-purpose algorithms for estimation aims, but the proposed novel algorithm is dedicated to currency forecasting. The research gap is the lack of an algorithm focusing mainly on forecasting the exchange rate. The proposed algorithm aims to correct trends multiple times for different horizons and make the estimation process more precise. Thus, the objective of the study, which is to present a better forecasting method for currency estimation, was achieved.

METHOD

For this study, weekly data starting from 2006 is taken. As the data, including plots, are examined in terms of trend, it can be observed that the trend differs when the horizon changes, as the trend in the recent 5 years may be more than the trend in the last 6 months. For that, a

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trend-corrected exponential smoothing model is built. The main aim is to convert a short-term forecast into a long-term one and to achieve that, lag numbers for exponential smoothing changes in specific periods. For instance, if the data containing six years is taken every six weeks, the lag number increases by one. In the beginning, exponential smoothing is made according to the previous data. Within lag two, smoothing is done according to the data which belonged to two periods ago, and it goes until the last data, which has a lag of 52. Trend and smoothing constants are arranged through the Microsoft Excel solver tool. MAD (Mean Absolute Deviation) is used as a performance metric, and while doing so, the data exceeding the horizon are not considered. Two different objective functions are used to determine the parity's end-year value. One of these functions aims to minimize the total error up to that point, while the other aims to minimize the maximum of the MAD values among the made forecasts.

The same process is repeated for every forecast horizon, but the period of shifting lag numbers changes in the horizon. For instance, a 6-year data containing a forecast for 2012 changes the lag numbers in every 6-data, whereas a 4-year data containing a forecast for 2012 changes the lag numbers in every 4-data. The only exception is the 1- year data containing forecast, as in the same manner, all the forecasts should be done according to the first data. To avoid that, daily data is used instead of weekly data. Some equations below show how the forecast is made with different lags. Equation 1 shows the operation with lag number 1, Equation 2 shows the operation with lag number 6, and Equation 3 shows the operation with lag number 45. The same is applied for trend correction, and they are summed to obtain a forecast value for n periods ahead, where n is equal to the lag number for the operation.

$$F_i = \lambda F_{i-1} + (1-\lambda)(D_{i-1} - F_{i-1}) \tag{1}$$
$$F_i = \lambda F_{i-1} + (1-\lambda)(D_{i-6} - F_{i-6}) \tag{2}$$
$$F_i = \lambda F_{i-1} + (1-\lambda)(D_{i-45} - F_{i-45}) \tag{3}$$

After all the forecasts in a parity is completed, they are collected in another Excel sheet as seen in Table 4. Then, with the coefficients found by the optimization model, values are calculated and compared. MAD is taken as a measure, and the objective is to minimize total deviation from the real values. Values in 2012, 2013, 2014, and 2015 are taken as training set, while 2016 and 2017 are taken as the test set. Within these methods, the performance is calculated for 2016 and 2017 while we obtain a value for 2018.

Table 4. Sample Excel Sheet for finding the value in the end of 2018

	6 Years	**5 Years**	**4 Years**	**3 Years**	**2 Years**	**1 Year**	**Forecast**	**Real**	**Error**
2012	2.072	1.860	1.825	1.514	1.905	1.61	1.97	1.75	0.22
2013	2.267	1.960	2.036	1.926	2.110	1.8944	2.26	2.26	0.000
2014	2.320	2.080	2.220	2.352	2.320	2.2	2.551	2.44	0.111
2015	2.520	2.420	2.540	2.650	2	4.12	2.84	2.95	0.11
2016	3.550	3.290	4.210	3.920	3.2	2.95	3.918	3.77	0.148
2017	4.020	4.140	2.440	2.900	3.36	2.8	3.798	3.75	0.048
2018	4.510	3.780	4.510	4.110	3.86	3.7875	4.442		
	0.062	0.24	0	0.41	0.408	0			0.441

For a better understanding of the procedure followed in this study, a figure is prepared and given as in the following Figure 1.

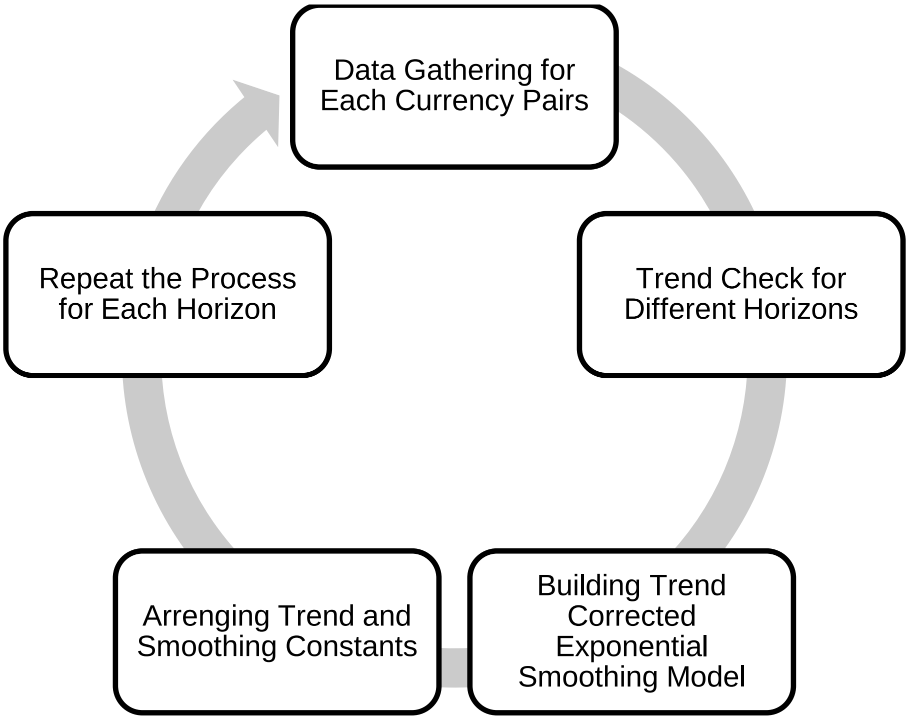

Figure 1. Steps followed for the proposed novel methodology

RESULTS AND DISCUSSION

Using data from 2006 to 2018 (May), the results obtained are shown in Table 5. Results are compared with other forecast results predicted by the Central Bank of Turkey, the Deutsch Bank, and the Economic Forecast Agency.

Table 5. Forecast Results for 2018

Parity	Coefficient					Forecast
	5-year	4-year	3-year	2-year	1-year	
USD/EUR	0.254	0	0.004	0	0.707	0.910
USD/NOK	0.331	0	0.613	0.150	0	8.665
USD/TRY	0.062	0.240	0	0.410	0.408	4.4420
USD/CNY	0.056	0.130	0.665	0.050	0.130	7.710
USD/XOF	0.063	0.260	0.001	0.402	0.381	556.130
USD/MGF	0	0.190	0.090	0.773	0.003	3126.311

In our model, USD/TRY is predicted to be 4.442, which is compared with the forecast value of 4.44 calculated by the Central Bank of Turkey. Based on comparison, our model predicts USD/TRY better. USD/EUR is predicted to be 0.912 at the end of the 2018 by the Economy of Forecast Agency and our model is predicted as 0.91. Additionally, this institution has a prediction for USD/CNY as 6.49; in our model, it is 7.71. Finally, the forecast value of USD/NOK for 2018 is 8,665 in this model and it is predicted as 7.46 by Deutsch Bank. Other forecast methods are not compared because no forecast predicts USD/XOF and USD/MGF.

The forecast value from 2012 to 2017 for USD/TRY is also given in Table 6. It shows that the currency rate is 3.75 in 2017 and the forecast value is 3.798, which is close to the real value.

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Table 6. Forecasts from 2012 to 2018 for USD/TRY

Year	Forecast	Real	Error
2012	1.970	1.750	0.220
2013	2.260	2.260	0
2014	2.551	2.440	0.111
2015	2.840	2.950	0.110
2016	3.918	3.770	0.148
2017	3.798	3.750	0.048
2018	4.442		

This result shows that USD/TRY and USD/EUR, a developing and developed currency, are predicted as expected for the long term. However, the error, the mean absolute deviation for other currencies, is higher than expected. Therefore, it can be said that the new model is appropriate for the Turkish Lira and Euro, the second most used currency worldwide.

CONCLUSION

Predicting exchange rates in today's globalizing environment throws much weight on the future economic plans of globally active businesses and governments. Although numerous models for predicting short-term exchange rates exist, many studies have not been on predicting long-term exchange rates. This study proposes a novel method for long-term currency forecasting based on multiple trend-corrected exponential smoothing with shifting. The novel method is applied to the exchange rates for the currencies USD/EUR, USD/NOK, USD/TRY, USD/CNY, USD/XOF, and USD/MGF from 2006 to 2018. It uses various long-term forecasting techniques, such as moving averages, weighted moving average, and exponential smoothing. When compared to the well-known models, it has been found that the results from the suggested model are more accurate for developed countries.

The next step of our study will include a new forecast model for the currencies of given countries. Currently, the tested forecast method is 'weighted multiple trend-corrected exponential smoothing', which makes multiple exponential smoothing forecasts on the same data with different lags, sums them according to their weights, and applies the same trend process. The most significant difference in this forecast method from the other methods is including multiple trend types in the same data. As mentioned in the literature review part, some forecast models use different types of seasonality to make an accurate forecast; however, none of the existing forecast methods include multiple trend types. Our study showed that trend behavior differs in different historical data lengths; thus, it is potentially more accurate than having a single trend. Although it is currently under development, it gives better results in several forecasts. After the forecast method is fully developed, the performance of the method will be determined by comparing the estimates that are done in the previous parts. And finally, the currencies that are the most suitable for the investment will be defined in this way.

In addition to the mentioned new forecast method, another method will also be developed, which uses the forecasts of factors affecting long-term currency levels. The correlation between possible affecting factors and currency levels will be determined, and forecasts will be made for relevant factors. A new forecast will be done for the currency within the obtained forecast values. The model is still in development.

REFERENCES

[1] J. Faust, J. H. Rogers, and J. H. Wright, "Exchange rate forecasting: the errors we've really made," Journal of International Economics, vol. 60, no. 1, pp. 35-59, May 2003.
[2] F. C. Maria and D. Eva, "ExchangeRates Forecasting: Exponential smoothing techniques and ARIMA models," Annals of Faculty of Economics, vol. 1, no. 1, pp. 499-508, 2011.
[3] L. Ghalayini, "Modeling and forecasting the US dollar/euro exchange rate," International Journal of Economics and Finance, vol. 6, no. 1, p. 194, January 2013.
[4] N. Apergis, "Can gold prices forecast the Australian dollar movements?" International Review of Economics & Finance, vol. 29, pp. 75-82, September 2014.
[5] J. Sun and H. Li, "Listed companies' financial distress prediction based on weighted majority voting combination of multiple classifiers," Expert System with Applications, vol. 35, pp. 818-827, September 2008.
[6] J. Song, J. Wang, and H. Lu, "A novel combined model based on advanced optimization algorithm for short-term wind speed forecasting," Applied Energy, vol. 215, pp. 643-658, March 2018.
[7] J. Taylor, "Short-term electricity demand forecasting using double seasonal," Tech. Rep., Center for Research in Econometric Analysis of Time Series (CREATES), Department of Economics and Business Economics, Aarhus University, Denmark, 2003.
[8] J. Taylor, "Triple Seasonal Methods for Short-Term Electricity Demand Forecasting," European Journal of Operational Research, vol. 204, pp. 139-152, January 2010.
[9] S. Widowati, S. Putro, V. Koshio, and V. Oktaferdian, "Implementation of ARIMA Model to Assess Seasonal Variability Macrobenthic Assemblages," Aquatic Procedia, vol. 7, pp. 277-284, August 2016.
[10] P. Arumugam and R. Saranya, "Outlier Detection and Missing Value in Seasonal ARIMA Model Using Rainfall Data," Materials Today: Proceedings, vol. 5, pp. 1791-1799, January 2017.
[11] R. MacDonald and M. Taylor, "The monetary approach to the exchange rate: rational expectations, long-run equilibrium, and forecasting," Palgrave Macmillan Journals, vol. 40, no. 1, pp. 23-38, March 1993.
[12] S. Pong, M. Shackleton, S. Taylor, and X. Xu, "Forecasting currency volatility: A comparison of implied volatilities and AR(FI)MA models," Journal of Banking & Finance, vol. 28, pp. 2541-2563, November 2004.
[13] S. Taylor, "Forecasting the volatility of currency exchange rates," International Journal of Forecasting, vol. 3, no. 1, pp. 159-170, March 1987.
[14] A. Altan, S. Karasu, and S. Bekiros, "Digital currency forecasting with chaotic meta-heuristic bio-inspired signal processing techniques," Chaos, Solitons & Fractals, vol. 126, pp. 325-336, 2019.
[15] A. A. Baffour, J. Feng, and E. K. Taylor, "A hybrid artificial neural network-GJR modeling approach to forecasting currency exchange rate volatility," Neurocomputing, vol. 365, pp. 285-301, 2019.
[16] R. MacDonald and J. Nagayasu, "Currency forecast errors and carry trades at times of low interest rates: Evidence from survey data on the yen/dollar exchange rate," Journal of International Money and Finance, vol. 53, pp. 1-19, 2015.
[17] M. E. Wilkie-Thomson, D. Önkal-Atay, and A. C. Pollock, "Currency forecasting: an investigation of extrapolative judgement," International Journal of Forecasting, vol. 13, no. 4, pp. 509-526, 1997.
[18] P. Abbassi and F. Bräuning, "Exchange rate risk, banks' currency mismatches, and credit supply," Journal of International Economics, vol. 141, art. no. 103725, 2023.
[19] M. E. Wilkie and A. C. Pollock, "An application of probability judgement accuracy measures to currency forecasting," International Journal of Forecasting, vol. 12, no. 1, pp. 25-40, 1996.
[20] L. T. Bui, V. T. Vu, and T. T. H. Dinh, "A novel evolutionary multi-objective ensemble learning approach for forecasting currency exchange rates," Data & Knowledge Engineering, vol. 114, pp. 40-66, 2018.

 10.12928/ijio.v4i1.6972

[21] M. R. El Shazly and H. E. El Shazly, "Forecasting currency prices using a genetically evolved neural network architecture," International Review of Financial Analysis, vol. 8, no. 1, pp. 67-82, 1999.
[22] T. T. L. Chong and I. K. Yan, "Forecasting currency crises with threshold models," International Economics, vol. 156, pp. 156-174, 2018.
[23] S. R. Das, K. Kuhoo, D. Mishra, and M. Rout, "An optimized feature reduction-based currency forecasting model exploring the online sequential extreme learning machine and krill herd strategies," Physica A: Statistical Mechanics and its Applications, vol. 513, pp. 339-370, 2019.
[24] M. Rout, B. Majhi, R. Majhi, and G. Panda, "Forecasting of currency exchange rates using an adaptive ARMA model with differential evolution based training," Journal of King Saud University - Computer and Information Sciences, vol. 26, no. 1, pp. 7-18, 2014.
[25] S. Pong, M. B. Shackleton, S. J. Taylor, and X. Xu, "Forecasting currency volatility: A comparison of implied volatilities and AR(FI)MA models," Journal of Banking & Finance, vol. 28, no. 10, pp. 2541-2563, 2004.
[26] J. Mehran and M. Shahrokhi, "An application of four foreign currency forecasting models to the U.S. dollar and Mexican peso," Global Finance Journal, vol. 8, no. 2, pp. 211-220, 1997.
[27] M. D. Chinn and R. A. Meese, "Banking on currency forecasts: How predictable is change in money?," Journal of International Economics, vol. 38, no. 1-2, pp. 161-178, 1995.
[28] G. Bekaert and R. Hodrick, International Financial Management, 3rd ed. Cambridge: Cambridge University Press, 2017, ch. 10, pp. 394-442.
[29] J. Crespo Cuaresma, I. Fortin, and J. Hlouskova, "Exchange rate forecasting and the performance of currency portfolios," Journal of Forecasting, vol. 37, pp. 519-540, 2018.
[30] A. Suharsono, Suhartono, A. Masyitha, and A. Anuravega, "Time series regression and ARIMAX for forecasting currency flow at Bank Indonesia in Sulawesi region," in AIP Conference Proceedings, vol. 1691, 050025, 2015.
[31] A. Inoue and B. Rossi, "Monitoring and forecasting currency crises," Journal of Money, Credit and Banking, vol. 40, pp. 523-534, 2008.