THE EFFECT OF KERNEL VALUES IN SUPPORT VECTOR MACHINE TO FORECASTING PERFORMANCE OF FINANCIAL TIME SERIES AND COGNITIVE DECISION MAKING

A. Altan and S. Karasu

Abstract— Nowadays, one of the most important research topics in economic sciences is the estimation of different financial exchange rates. The reliable and accurate forecasting of the exchange rate in the financial markets is of great importance, particularly after the recent global economic crises. In addition, the high accuracy forecasting of the financial exchange rates causes that investors are less affected by financial bubbles and crashes. In this paper, a financial time series forecasting model is identified by support vector machine (SVM), which is one of the machine learning methods, for estimating the closing price of USD/TRY and EUR/TRY exchange rates. The closing price values and commodity channel index (CCI) indicator value are used as inputs in financial time series forecasting model. Various models are obtained with different kernel scale values in SVM and the model that estimates financial time series with the highest accuracy is proposed. The performance of the obtained models is measured by means of Pearson correlation and statistical indicators such as mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). It is seen that the forecasting performance of the proposed SVM model for the financial time series data set is higher than that the performance of the compared other models. The proposed model will provide a positive contribution to the cognitive decision-making process of investors.

Keywords— *Financial Time Series, Support Vector Machine, Kernel Scale, Exchange Rate Forecasting, Cognitive Process, Machine Learning.*

1. INTRODUCTION

IN the last decade, financial markets have often faced bubbles and crashes due to global economic crises. The forecasting of different financial indices based on time series allows investors to act more consciously against these bubbles and crashes in financial markets [1]. In the financial markets where there has been serious competition for many years, many different forecasting models have been developed by financial regulators, policy makers, risk and portfolio managers, financial institutions and investors to be one step ahead of the market or to explain the reason of price changes [2]. In this study, the exchange rate is estimated for different kernel scale values in support vector machine (SVM) which is one of the methods of machine learning by using time series consisting of closing prices of USD/TRY and EUR/TRY exchange rates.

In [3], the exchange rate estimation is performed by using the USD/TRY exchange rate data with Grey-Markov method. It is stated that the performance of the model is good for a short-term period but the performance of the model decreased as the estimation horizon is extended. It is expressed that the proposed model is highly dependent on the range distribution, and the number of cases in the Markov chain can be increased by increasing the forecasting accuracy of the model. Also, it is emphasized that the effect of volatility is reduced by the proposed model. In [4], a new hybrid artificial neural network (ANN) and autoregressive integrated moving average (ARIMA) model is proposed as an alternative forecasting technique to the traditional hybrid ARIMA/ANNs models for time series forecasting. It is highlighted that the proposed model captures different forms of relationship in time series data, especially in complex problems with both linear and nonlinear correlation structures. It is guaranteed that the performance of the proposed model is not be worse than the single ANN and ARIMA components used. In [5], a methodology is presented that using *k*-nearest neighbors (KNN) with dynamic time warping as distance function in a particular procedure to improve the directional status estimation results. It is pointed out that the study conducted with the USD/JPY exchange rate time series has improved the prediction regarding the direction of time series. In [6], exchange rates such as EUR/USD, GBP/USD and USD/JPY are estimated for daily, monthly and quarterly steps with ANN. It has been shown that the proposed short-term forecasting method has good predictive performance and can be used in practical systems to estimate the exchange rate for one step ahead. In [7], the relationship between the exchange rate of USD/TRY, gold prices and the Borsa Istanbul (BIST) 100 index has been estimated by using the ANN method and the method of Vector Autoregressive (VAR). The estimation results obtained by ANN and VAR are compared and it is indicated that ANN is more accurate than VAR. In [8], the performance of ARIMA, ANN and neuro fuzzy models have been investigated in the estimation of currencies traded in Indian currency markets. In [9], self-excited threshold autoregressive (SETAR) models have been used in order to be able to model the volatile changes in currency market. The linearity of the exchange rates, which are dealt with before the SETAR modelling approach is applied, have been examined with the help of various approaches such as Tsay, Keenan, Likelihood Ratio. In [10], the exchange rates of EUR/USD, GBP/USD and USD/JPY have been estimated by the multi-layer perceptron (MLP) neural network. The gold price has been used as an input to the MLP neural network. The fact that the use of gold as an external factor has been improved the exchange rate forecasting. In [11], the forex prediction model based on support vector regression (SVR) machine has been developed, taking the radial basis function as a kernel function.

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2. HUMAN BEHAVIOR AND COGNITION

The optimization of model parameters, including penalty factor and kernel function variance, has been performed by artificial fish swarm algorithm. The performance of the proposed model has been tested for nine exchange rate data with updated and rolling. In [12], Bitcoin (BTC) prediction is performed by linear regression and SVM by using time series consisting of daily BTC closing prices.

Decision making is one of the basic cognitive processes of human behavior based on specific criteria. These cognitive processes are defined as a preferred option or an action from among a set of alternatives [13]. In this study, the financial time series forecasting model which has high performance is proposed that will contribute positively to investors' cognitive decision making process.

The purpose of this study is to test the effect of the kernel values in SVM model on the forecasting performance of USD/TRY and EUR/TRY exchange rates so that investors can use them as technical analysis methods. The rest of the paper is organized as follows. The SVM models used for forecasting are described in Section 3. The experimental procedure and forecasting results are presented in Section 4. Finally, the conclusions are highlighted in Section 5.

3. FORECASTING MODEL

In this study, financial time series data sets, which include the closing prices of USD/TRY and EUR/TRY exchange rates, are used. The financial time series containing daily closing prices have been included data between 01 June 2010 and 11 May 2019 for the USD/TRY and between 21 September 2011 and 14 May 2019 for the EUR/TRY. The graphics of closing price for USD/TRY and EUR/TRY exchange rates are presented in Fig. 1. The minimum value, maximum value, mean value and standard deviation of the USD/TRY and EUR/TRY exchange rates for the data set used are given in Table 1 and 2, respectively. The number of samples used in this study is 2593 for USD/TRY data set and 2049 for EUR/TRY data set. Each data set is divided into three sets as training, validation and test. 10-fold cross validation method is used in the model training stage.

3.1. Filtering Process

For a filter with the length N and the filter coefficient w, the filtering is carried out with the aid of the

$$y_n^+ = \frac{\sum_{i=1}^{N} w_i y_i}{\sum_{i=1}^{N} w_i} \tag{1}$$

filtered value from the dependent variable y. The w coefficients for the weighted moving average (WMA) filter are determined as

$$w_i = i \quad \text{for} \quad i \le N \tag{2}$$

For the selected length on the signal in the WMA filter, linearly decreasing weight values that is from the nearest value of the filtered signal to the previous value are used [14].

3.2. Commodity Channel Index

The commodity channel index (CCI) is a momentum-based oscillator used to help determine when an investment vehicle is reaching a condition of being overbought or oversold. The CCI is an oscillator, which is unbounded in fluctuation. Its value is different without limits. The CCI measures the current price level relative to an average price level over a given period of time. It is also used to assess price trend direction and strength. This information allows traders to determine if they want to enter or exit a trade, refrain from taking a trade, or add to an existing position. In this way, the indicator can be used to provide trade signals when it acts in a certain way. The calculation of CCI is [15].

$$\text{CCI} = \frac{X_T - \overline{X}}{0.015 \times Mean\ Deviation} \tag{3}$$

where X_T is typical price, $\overline{X}$ is moving average, M is the number of days in data base and X_M is the oldest typical price in data base. X_T, $\overline{X}$, and mean deviation is defined as

$$X_T = (High + Low + Close)/3 \tag{4}$$

$$\overline{X} = \frac{1}{M}\sum_{j=1}^{M} X_j \tag{5}$$

$$Mean\ Deviation = \frac{1}{M}\sum_{j=1}^{M} \left| X_j - \overline{X} \right| \tag{6}$$

TABLE I
STATISTICAL VALUES OF USD/TRY

Years	*Min*	*Max*	*Mean*	*Std*
2010	1.3941	1.6012	1.5020	0.0529
2011	1.5092	1.9170	1.6846	0.1242
2012	1.7425	1.8902	1.7988	0.0267
2013	1.7473	2.1526	1.9040	0.1066
2014	2.0677	2.3693	2.1900	0.0673
2015	2.2809	3.0572	2.7242	0.1972
2016	2.7953	3.5352	3.0247	0.1895
2017	3.4003	3.9652	3.6440	0.1366
2018	3.7293	6.9724	4.8415	0.8720
2019	5.1784	6.1938	5.5197	0.2594

TABLE II
STATISTICAL VALUES OF EUR/TRY

Years	*Min*	*Max*	*Mean*	*Std*
2011	2.4205	2.5696	2.4765	0.0338
2012	2.1886	2.4493	2.3142	0.0511
2013	2.3115	2.9655	2.5317	0.1734
2014	2.7516	3.1947	2.9051	0.0894
2015	2.6326	3.4609	3.0220	0.2087
2016	3.1757	3.7883	3.3519	0.1495
2017	3.7053	4.7192	4.1256	0.2444
2018	4.4801	7.8344	5.6595	0.9058
2019	5.9220	6.9545	6.2569	0.2691

3.3. Support Vector Machines

The support vector machines used to maximize the width between dependent support points in decision making are the supervised learning algorithms developed by Vladimir Vapnik and Alexey Chervonenkis. It is successfully used in applications such as pattern recognition, time series analysis and classification. The SVM can be applied to both linear and nonlinear data. The SVM uses a kernel function that maps the inseparable input data to a higher dimensional hyperspace. The purpose of SVM is to find an optimal separating hyperplane by maximizing the margin between the separating hyperplane and the data set [16]. The function that is carried the nonlinear x data sequence to the higher dimension is defined as the mapping function and is indicated by $\Phi(x)$. In this case, the regression process is carried to the high-dimensional area with the kernel function

$$K(x_i, x_j) = (\Phi(x_i, x_j)^T \Phi(x_i, x_j) + 1)^p \tag{7}$$

where p is the degree of polynomial.

3.4. Statistical Error Criteria

The statistical error criteria given in Table 3 are used to calculate the error in the exchange rate forecasting. In the model evaluation stage, the performance of the financial time series forecasting model is measured by taking into account the mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) [17]. Pearson correlation coefficient, which is an indicator of the relationship between input and output, is calculated as in Table 3 [18]. The performance of the model has been tested on the USD/TRY and EUR/TRY exchange rates data set. For each exchange rate, the kernel scale value of model minimizing error are determined.

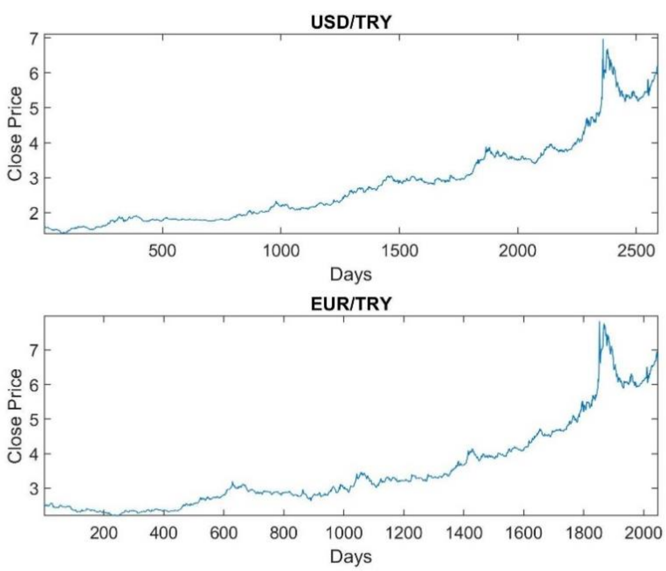

Fig.1. Closing price change for USD/TRY and EUR/TRY exchange rates.

4. RESULTS AND DISCUSSIONS

In this study, we estimate the closing prices of USD/TRY and EUR/TRY exchange rates for the next step with SVM. The financial time series data set consisting of 2593 samples between 2010 and 2019 years have been used for USD/TRY exchange rate. Similarly, the financial time series data set consisting of 2049 samples between 2011 and 2019 years have been used for EUR/TRY exchange rate. These data sets consist of daily closing price, minimum price, maximum price and trading volume parameters.

For SVM model, kernel scale values are changed between 0.5 and 10 with 0.5 step size and the model that has the minimum error has been obtained. 10-fold cross validation method has been used in the model training stage. The delay step for the WMA filter is set to 3. In addition, the CCI oscillator value has been used with the previous step value in the model input. The MSE changes of the models identified by different model parameters for both exchange rates are given in Figure 2 and 3, respectively. When the kernel scale value is 4, it is seen that the MSE value is the minimum for both exchange rates.

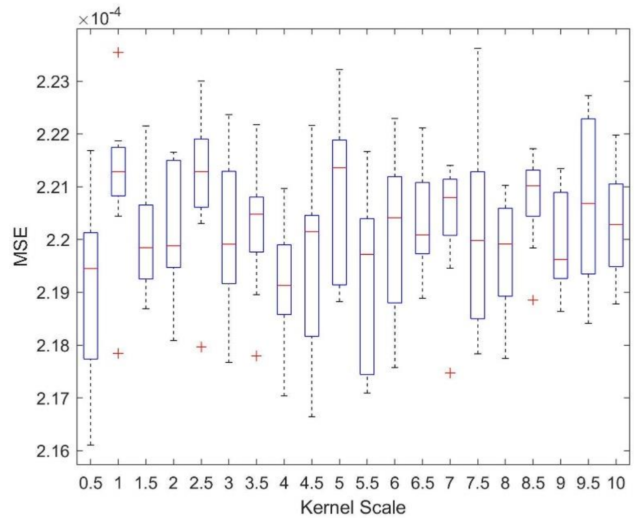

Fig.2. MSE changes for kernel scale values of USD/TRY exchange rates.

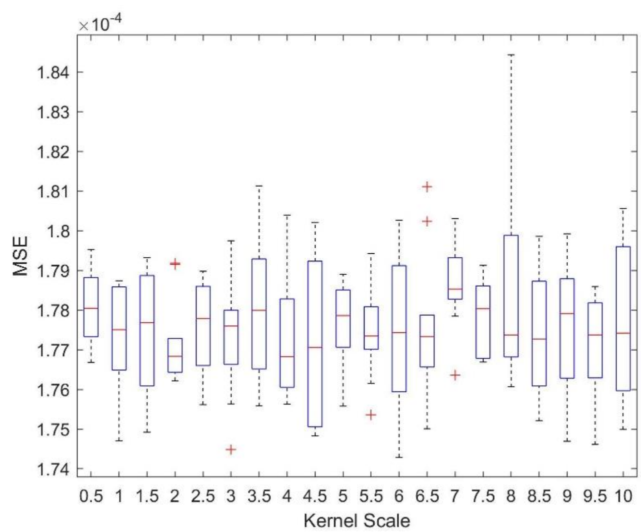

Fig.3. MSE changes for kernel scale values of EUR/TRY exchange rates

TABLE III
ERROR METRICS FOR EVALUATION OF MODEL

$$\boldsymbol{MAE} = \frac{\mathbf{1}}{\boldsymbol{M}}\sum_{k=1}^{M}\left|p_{estimated}^{k} - p_{real}^{k}\right|$$

$$\boldsymbol{MSE} = \frac{\mathbf{1}}{\boldsymbol{M}}\sum_{k=1}^{M}\left(p_{estimated}^{k} - p_{real}^{k}\right)^2$$

$$\boldsymbol{RMSE} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{M}}\sum_{k=1}^{M}\left(p_{estimated}^{k} - p_{real}^{k}\right)^2}$$

$$\boldsymbol{R} = \frac{\sum_{k=1}^{M}(p_{real}^{k} - \overline{p}_{real})(p_{estimated}^{k} - \overline{p}_{estimated})}{\sqrt{\sum_{k=1}^{M}(p_{real}^{k} - \overline{p}_{real})^2}\sqrt{\sum_{k=1}^{M}(p_{estimated}^{k} - \overline{p}_{estimated})^2}}$$

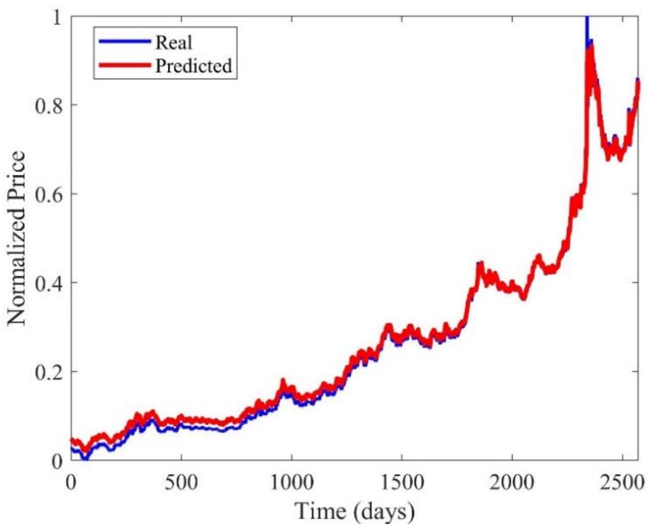

Fig.4. Forecasting results for USD/TRY exchange rates with kernel scale=4 in SVM model.

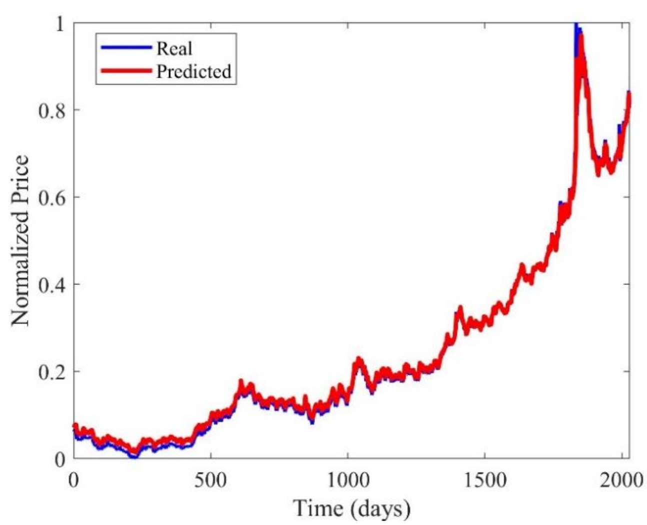

Fig.5. Forecasting results for EUR/TRY exchange rates with kernel scale=4 in SVM model.

The forecasting values for the model with the minimum error value for both exchange rates are presented in Figure 4 and 5, respectively. The regression curves of the best forecasting models for both exchange rates are shown in Figure 6 and 7, respectively, together with the Pearson correlation coefficient. The MSE, RMSE and MAE values of the proposed financial time series forecasting model for USD/TRY exchange rate have been determined as 2.1912×10^{-4}, 0.0148, 0.0122, respectively. The MSE, RMSE and MAE values of the proposed financial time series forecasting model for EUR/TRY exchange rate have been determined as 1.7666×10^{-4}, 0.0133, 0.0099, respectively.

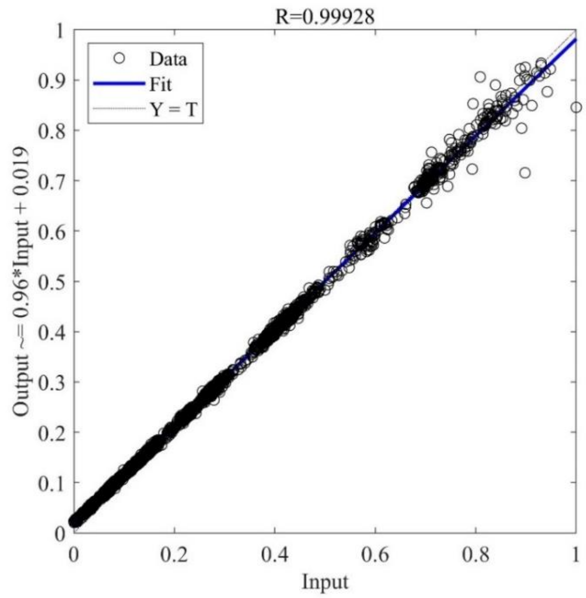

Fig.6. Regression curve in the case of kernel scale = 4 in the SVM model for USD/TRY exchange rate.

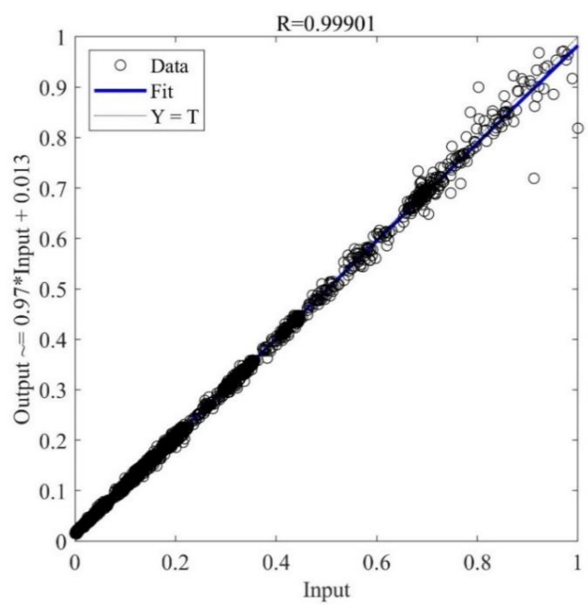

Fig.7. Regression curve in the case of kernel scale = 4 in the SVM model for EUR/TRY exchange rate.

5. CONCLUSION

In this study, the closing prices of USD/TRY and EUR/TRY exchange rates have been estimated for the next step with SVM, one of the machine learning methods. Financial time series consisting of daily closing price, minimum price, maximum price and trading volume parameters have been used in the study. The effect of different kernel scale values on the financial time series forecasting performance of SVM model has been investigated. The kernel scale value, which has the minimum error, has been determined. The USD/TRY and EUR/TRY exchange rate have been estimated by the SVM model with the determined kernel scale value. It is shown experimentally that the proposed forecasting model has high performance in forecasting the USD/TRY and EUR/TRY exchange rate consisting of financial time series. It is thought that this study will significantly contribute to the estimation of the volatility of different exchange rates with high performance. The proposed model will contribute positively to investors' cognitive decision making process.

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