INFERENSI, Vol. 7(1), March. 2024. ISSN: 0216-308X (Print) 2721-3862 (Online)

Prediction of Rupiah Exchange Rate Against US Dollar Using Kernel-Based Time Series Approach

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Received: 5 March 2024
Revised: 15 March 2024
Accepted: 16 March 2024

ABSTRACT – Fluctuations in the rupiah exchange rate against the United States Dollar from 2020 to early 2024 have been analyzed using classical and modern time series approaches. In this study, the classical time series approach based on Gaussian Kernel successfully provides predictions with an RMSE value of 57.5722 and a MAPE of 0.29%. Meanwhile, the modern approach with RBF Kernel SVR shows an RMSE value of 74.9201 and a MAPE of 0.41%. The results of the model performance comparison show the superiority of the classical approach with the Gaussian Kernel in predicting the rupiah exchange rate against the US Dollar as an impact of the Federal Funds Rate (FFR) policy. Therefore, it is recommended to use the classical time series method based on the Gaussian Kernel in dealing with the impact of the FFR policy to improve the accuracy of predicting the Rupiah exchange rate against the United States Dollar. This research supports the achievement of the 8th Sustainable Development Goals (SDGs) related to economic and social matters while providing a better understanding of currency exchange rate fluctuations and providing recommendations that can help in managing economic risks related to global monetary policy.

Keywords– Kernel Function, Gaussian Kernel, Rupiah Exchange Rate, Radial Basis Function, Support Vector Regression.

I. INTRODUCTION

The threat of a global recession was caused by major events, such as the Russia-Ukraine War, the Evergrande Crisis, and the US Fed interest rate hike. This uncertainty puts pressure on the economies of various countries, including emerging market countries such as Indonesia [1]. The United States, through the Fed, has a major influence on global economic stability. The Fed's power in the world's capital markets is unrivaled. Currently, the Fed is the captain of US monetary policy, which means the world economy depends on the condition of the central bank and the US economy. The Fed's policies, particularly the Federal Fund Rate (FFR), have a significant influence on the global economy, including Indonesia.

The Fed's interest rate hike has a domino effect that impacts emerging economies such as Indonesia. In response, Bank Indonesia often feels the pressure to raise its own interest rates. However, this presents a difficult choice, higher interest rates make it more expensive for banks to borrow money, which in turn can lead to higher borrowing costs for businesses and individuals in Indonesia. This may discourage lending and slow economic growth, but keeping interest rates low may look attractive to encourage lending and growth, and may attract speculative investment and weaken the Rupiah. This could jeopardize financial stability and potentially make future rate hikes more important [2].

An increase in US interest rates by the Fed could hinder Indonesia's progress in achieving Sustainable Development Goals (SDGs) 8, which are related to decent work and economic growth in Indonesia. An escalation of 1% in the Federal Reserve's interest rate might cause a 0.5% decline in global economic growth [3]. This reduces job creation and economic opportunities in Indonesia. In addition, capital flight from Indonesia due to rising interest rates may weaken the Rupiah, further impacting the economy. Rupiah depreciation can increase companies' external debt burden and reduce export competitiveness. Rising interest rates may also narrow access to credit for MSMEs, the majority of which are owned by low-income groups. This could hamper MSME growth and exacerbate economic inequality [4].

One of the efforts to strengthen the stability of the Rupiah exchange rate is to project future exchange rate movements. This prediction is very important for market participants, companies, and the government in order to design appropriate economic policies based on the dynamics of foreign exchange rates. Several things, including local and international economic policies, trade activities, and political events, can cause the value of the Rupiah (Indonesia's currency) to change compared to other currencies, such as the US Dollar. As reported by Bank Indonesia, the value of the Rupiah against the US Dollar is unstable and often fluctuates. Therefore, a classical time series analysis is performed using the Kernel Estimator method which is one of the nonparametric methods [5]. On the other side, there is modern time series analysis using Support Vector Regression (SVR). The advantage of a time series approach using machine learning like SVR is its ability to handle complex and dynamic patterns in time series data, including non-linearities and complex interactions between variables [6]. It can effectively extract information from historical data to make accurate predictions related to future trends. In addition, machine learning approaches can also automatically adjust to changes in the data, increasing the adaptability of the model to changing market or environmental conditions. By using these techniques, time series analysis can become more flexible, more robust, and can provide deeper insights for decision makers in fields such as finance, economics, and social sciences.

Two nonparametric methods, Kernel Estimator and Support Vector Regression (SVR), are commonly used for data analysis. The Kernel Estimator is chosen for its flexibility in capturing various patterns of data without requiring any special assumptions about the relationship of the variables [7]. Similarly, SVR is a popular choice for time series analysis due to its ability to handle non-linear data and avoid the limitations of traditional regression methods. This makes SVR suitable for predicting future trends in time series data, even when the relationships are complex [8]. Notably, SVR is based on Support Vector Machines (SVM), a powerful machine learning technique. In addition, SVR offers advantages such as avoiding problems with local minima and being less sensitive to outliers in the training data.

Previously, a study was conducted to examine the impact of the Federal Funds Rate (FFR) on monthly stock returns in the US [9]. The study used the Ordinary Least Square Regression Method and found that FFR has no significant effect on monthly stock returns, but changes in FFR affect monthly stock returns significantly. The study did not consider other financial risk factors such as inflation rates, currency exchange rates, and other factors, so its findings may be limited to the interest rate and policy aspects of the Federal Reserve. Similar research has also been conducted using the Kernel-based Time Series Method on fuel usage data at the Gas and Steam Power Plant (PLTGU). The Polynomial Kernel estimator was used in the study, which produced excellent predictions with an epsilon smoothing parameter value of 0.0266, a weighting parameter value of 0.0285, and a Mean Absolute Percentage Error of 7.7513% [10].

This research focuses on the application of Support Vector Regression (SVR) with different Kernel functions, particularly nonlinear Kernels, to predict the impact of the Federal Funds Rate (FFR) on the Rupiah exchange rate against the US Dollar. One of the innovative aspects of this research is the comparison of the performance of various Kernel functions in SVR for prediction purposes. Evaluation of model accuracy is done using two common metrics, namely Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). The main objective of this research is to provide valuable input to the Indonesian government in managing the risks and opportunities associated with currency exchange rate fluctuations.

II. LITERATURE REVIEW

A. Nonlinearity Test

Analyzing data for nonlinearity is essential, as it helps determine the most appropriate method for further analysis. Among the various tests available, the Terasvirta Test stands out for its effectiveness in detecting nonlinear patterns. This test, classified as the Lagrange Multiplier (LM) Test, comes from the field of neural network models and is considered a powerful tool for identifying nonlinearities in data. According to Mahdiloo et al. (2018), although the Terasvirta Test and the White Test originate from the neural network world and aim to identify nonlinearities in data, they differ in their approach [11]. The Terasvirta Test uses Taylor Series to analyze certain neural network parameters, whereas the White Test relies on random selection of these parameters [12]. The procedure in the Terasvirta Test was described by Terasvirta et al. in 1993 as follows [13]:

1. Regressing Y_t in $1, Y_{i-1}, \dots, Y_{i-p}$ so that the following linear model is obtained:
$$Y_t = f_i + \widehat{e_i} \tag{1}$$
with
$$f_i = \emptyset_1 X_{i-1} + \emptyset_2 X_{i-2} + \cdots + \emptyset_p X_{i-p} \tag{2}$$
Then, calculate the sum of squared residual values with the following formula:
$$SSR_0 = \sum \widehat{e_i}^2 \tag{3}$$
2. Regressing $\widehat{e_t}$ in $1, X_{t-1}, \dots, X_{t-p}$ and m additional predictors by utilizing the coefficient values obtained from the quadratic terms and cubic terms obtained through the Taylor Series expansion method. Then, calculate the sum of squares of the residuals by using the provided formula:
$$SSR_1 = \sum \widehat{v_i}^2 \tag{4}$$
3. Calculate the test statistic value using the following formula:
$$F_{hit} = \frac{\frac{SSR_0 - SSR_1}{m}}{\frac{SSR_1}{(n-p-1-m)}} \tag{5}$$
where n is the number of observations. The Terasvirta Test hypothesis consists of two parts:
H_0: $f(x)$ is a linear function in x (linear model)
H_1: $f(x)$ is a nonlinear function in x (nonlinear model)
Decision to reject H_0 if $F_{hit} > F_{(n-p-1-m)}$ or if the p-value is smaller than the alpha significance level of 0.05.

B. Kernel Function Estimator in Classical Nonparametric Time Series Approach

In the classical nonparametric time series approach, kernel estimators are often used in obtaining prediction results. The concept of kernel estimator in nonparametric time series approach is similar to the concept of nonparametric regression approach [14]. Kernel estimators offer flexibility, represent simple mathematics, and have a relatively stable convergence rate. Unlike other linear estimators, kernel estimators have special expertise in optimizing bandwidth usage.

In this study, the selection of optimal bandwidth is also an important consideration in obtaining a good estimate, which is balanced between bias and variance [15].

In classical nonparametric time series modeling, there are five types of commonly used Kernel functions: Gaussian (G), Quartic (Q), Cosine (C), Triweight (T), and Epanechnikov (E). The formula for each kernel function is shown in Table 1 as follows.

Table 1 Kernel Functions

Kernel Type	Formula K(x)	Limitations
Epanechnikov	$\frac{3}{4}(1-x^2)$	$I(\|x\|) \leq 1$
Quartic	$\frac{15}{16}(1-x^2)^2$	$I(\|x\| \leq 1)$
Triangular	$(1-\|x\|)$	$I(\|x\| \leq 1)$
Gaussian	$\frac{1}{\sqrt{2\pi}} exp\left(-\frac{1}{2}(x^2)\right)$	$-\infty < x < \infty$
Uniform	$\frac{1}{2}$	$I(\|x\| \leq 1)$
Triweight	$\frac{35}{32}(1-x^2)^3$	$I(\|x\| \leq 1)$
Cosinus	$\frac{\pi}{4} cos\left(\frac{\pi}{2}x\right)$	$I(\|x\| \leq 1)$

After reviewing Table 1 which contains the formulas for these Kernel functions, it can be concluded that the Gaussian Kernel is adaptive for all intervals. Unlike the other kernels, the maximum value of the data used is 1 or the data used is proportional data so it is clear that the Gaussian Kernel is the most suitable interval for the study data. The Gaussian Kernel function equation is formulated in equation (6) as follows:

$$\hat{y}_i = \hat{m}(x_i) = \frac{\sum_{i=1}^{n} K_x(x_1 - X_i)y_i}{\sum_{i=1}^{n} K_x(x_1 - X_i)} \tag{6}$$

With X_{iq} is the input value, h as *bandwidth*, and K_h denotes the kernel function, specifically the Gaussian function described in equation (6) for each response variable. A commonly used bandwidth selection method is to use the Generalized Cross Validation (GCV) criterion. The general formula for GCV is as follows:

$$GCV(h) = \frac{MSE}{\left(\frac{1}{n} trace(\boldsymbol{I} - \boldsymbol{H}(h))\right)^2} \tag{7}$$

where $\boldsymbol{H}(h)$ is hat matrix that shown in equation (8), $\boldsymbol{I}$ is the identity matrix, and the Mean Square Error (MSE) value is shown in equation (9) as follows:

$$\boldsymbol{H}(h) = \boldsymbol{K}(h)(\boldsymbol{K}(h)^{\boldsymbol{T}}\boldsymbol{W}\boldsymbol{K}(h))^{-1}\boldsymbol{K}(h)^{\boldsymbol{T}}\boldsymbol{W} \tag{8}$$

with

$\boldsymbol{K}(h)$: Kernel matrix

$\boldsymbol{W}$: Weight matrix

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y - f_h(x_i))^2 = \frac{1}{n}\sum_{i=1}^{n}(y - \hat{y}_i)^2 \tag{9}$$

More about matrix hats can be seen in Harvey & Oryshchenko [16].

C. Support Vector Regression (SVR) in Modern Nonparametric Time Series Approach

In contemporary nonparametric time series methodologies, SVR is often used to achieve precise prediction results. SVR is an extension of SVM that is customized for regression scenarios. This approach is adept at reducing overfitting, thus allowing it to operate efficiently and produce optimal performance [17]. By having training data, the concept of SVR becomes $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ where $\boldsymbol{x_i} \in R^n$, $\boldsymbol{x_i}$ is the vector to be inserted. While y_i is the output value, and n is the amount of training data. SVR can be formulated as follows:

$$f(\boldsymbol{x}) = \boldsymbol{w}^T\varphi(\boldsymbol{x}) + b \tag{10}$$

In this context, $\boldsymbol{w}$ represents the weight vector, φ(x) denotes the function that maps $\boldsymbol{x}$ into a higher-dimensional space, and b is a constant term.

To ensure robust generalization of the regression function *f(x)*, the next step is to minimize the criterion value w. This optimization problem seeks the following solution:

$$min_w \frac{1}{2}\|\boldsymbol{w}\|^2 \text{ dengan } \begin{cases} y_i - \boldsymbol{w}^T\boldsymbol{x}_i - b \leq \varepsilon \\ \boldsymbol{w}^T\boldsymbol{x}_i + b - y_i \leq \varepsilon \end{cases} \tag{11}$$

In the regression function *f*, it is stated that all points within the range *f(x)* ± *ε* are considered feasible, while points outside this range are considered infeasible. To overcome the shortcomings of the optimization problem constraints, it is important to include slack variables. ξ dan ξ^*. In addition, equation (3) can be reformulated into the following form:

$$min_w \frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{12}$$

with the following constraints:

$$\begin{gathered} y_i \leq \boldsymbol{w}^T\varphi(\boldsymbol{x}_i) + \varepsilon + \xi_i \\ y_i \geq \boldsymbol{w}^T\varphi(\boldsymbol{x}_i) - \varepsilon - \xi_i^* \\ \xi_i, \xi_i^* > 0 \end{gathered} \tag{13}$$

In accordance with Smola and Schölkopf (2004), solving equation (5) involves the use of Lagrange coefficients for each constraint [18]. The Lagrangian method produces the optimal solution of the parameter w in the form of Lagrange coefficients α_i and α_i^* as follows:

$$\boldsymbol{w} = \sum_{i=1}^{n} (\alpha_i + \alpha_i^*)\varphi(\boldsymbol{x}_i) \tag{14}$$

While the final estimation result of the b value is $b = y_i - \boldsymbol{w}\varphi(\boldsymbol{x}_i) - \varepsilon$ for $0 \leq \alpha_i \leq C$ and $b = y_i - \boldsymbol{w}\varphi(\boldsymbol{x}_i) + \varepsilon$ for $0 \leq \alpha_i^* \leq C$ so that the SVR function can be formulated as in the following equation (15):

$$f(\boldsymbol{x}) = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i)K(\boldsymbol{x}_i, \boldsymbol{x}_j) + b \tag{15}$$

Where α_i and α_i^* is the lagrange multiplier and $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is the kernel function. While there are various options for kernel functions, the Radial Basis Function (RBF) is one that is highly preferred. This preference stems from the fact that the RBF function requires minimal parameter specification and has the ability to nonlinearly map training data into an infinite dimensional space [19]. The formulation of the RBF kernel function is as follows:

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(-\gamma\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2\right) \tag{16}$$

Therefore, RBF is used in this study as the kernel function, where γ represents the RBF bandwidth.

Grid search involves finding the best parameters for SVR within a predefined range of minimum and maximum values for the hyperparameters [20]. This process divides the parameter range into grids and systematically explores all points to identify the optimal parameters. Using Cross Validation (CV) the grid search algorithm attempts to determine the most effective combination of hyperparameters to accurately predict the test data. Therefore, it is recommended to assess several variations of parameter pairs on the SVR hyperplane [21].

Finding the optimal hyperparameters through grid search can be time-consuming. Therefore, it is recommended to adopt a two-step strategy of loose grids and finer grids [22]. In the loose grid phase, the optimal parameters are selected from a set of integer powers. Furthermore, in the finer grid phase, a finer search for the optimal parameters is performed based on the values around the parameters generated in the loose grid step. This research utilizes the optimal hyperparameter search methodology using a two-stage grid search approach. The optimal parameter is defined as the parameter that produces the most accurate prediction with the smallest error value.

D. Best Model Selection

The selection of the best model is based on the model goodness test derived from the residual value. Model goodness is assessed using the MAPE metric. MAPE offers several advantages, including ease of interpretation, clarity in presentation, unit-free measurement, and support from statistical evaluation, which is formulated as follows [23]:

$$MAPE = \frac{\sum_{i=1}^{T} \frac{|y_i - \hat{y}_i|}{y_i}}{T} \times 100\% \tag{17}$$

with

y_i : Actual data at time *i*

$\hat{y}_i$: Predicted data at time *i*

T : Number of observation periods

Besides MAPE, another commonly used measure to assess the goodness of a model and determine prediction accuracy is RMSE. RMSE is a metric that measures the spread of prediction error within the model. It is widely used in fields such as climatology, prediction, and regression analysis to evaluate the accuracy of experimental results [24]. RMSE is calculated by taking the square root of the mean square of the residual values, as described in equation (18).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(\hat{y}_t - y_t)^2}{T}} \tag{18}$$

with

y_i : Actual data at time *i*

$\hat{y}_i$: Predicted data at time *i*

T : Number of observation periods

III. METHODOLOGY

A. Data Sources and Research Variables

The data used in this study are weekly secondary data obtained from Bank Indonesia through the bi.go.id website, covering the period from July 2020 to February 2024. Based on the approach adopted by Woschnagg & Cipan, the dataset division is done by taking into account that 80% of the total data will be used as training data and the remaining 20% will be used as testing data [25]. Therefore, from July 2020 to May 2023, 146 data will be used as training data, while from May 2023 to February 2024, 36 data will be used as testing data. Next, Table 2 displays the variables that will be used in this study.

Table 2 Research Variables

Research Variables	Unit
Rupiah to dollar exchange rate (y_t)	Rupiah
Time period (x)	Weekly period

B. Research Steps

The analysis steps in this study can be described in detail as follows:

a. Obtain weekly data on the Rupiah exchange rate against the Dollar from the Bank Indonesia website (bi.go.id).
b. Create a A visual description of the weekly Rupiah to Dollar exchange rate data can be provided through a time series plot. This plot will show the changes in the Rupiah to Dollar exchange rate over time during the selected period. With this plot, we can visually see the movement pattern of the Rupiah to Dollar exchange rate.
c. Selecting training and testing data in proportions of 80% and 20% respectively.
d. Using the Terasvirta test to test the linearity of the training data.
e. Model the training data and make predictions on the test data using the Kernel function approach.
f. Model the training data and make predictions on the test data using the SVR approach.
g. Selecting the best model by comparing the prediction results of the kernel function estimator model and SVR based on the lowest MAPE and RMSE values.

The analysis steps described above can be presented in the form of a research flow chart as shown in Figure 1 below.

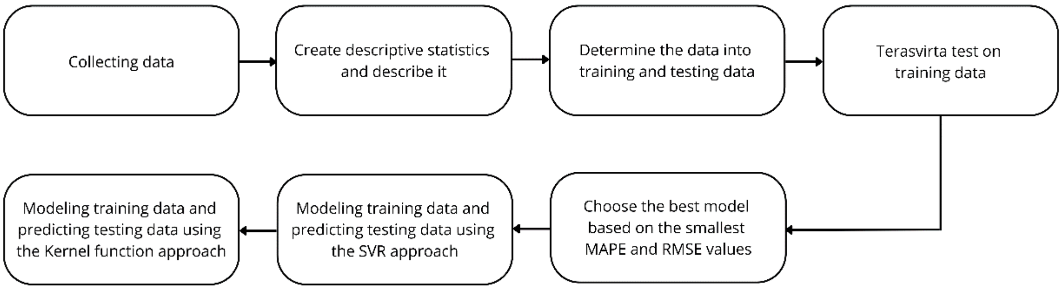

Figure 1 Research Flow Chart

IV. RESULTS AND DISCUSSIONS

A. Data Characteristics

Before starting data analysis, the first step that needs to be done is to describe the characteristics of the data using descriptive statistics. Overall, it can be seen that the Rupiah to Dollar exchange rate from July 2020 to February 2024 tends to increase every year, with the peak exchange rate occurring in October 2023 reaching Rp15,943. From 182 weekly data on the Rupiah to Dollar exchange rate, the average obtained is IDR14,7920 with a standard deviation of IDR511. The low standard deviation indicates that the Rupiah to Dollar exchange rate is relatively stable, or does not experience significant fluctuations over time.

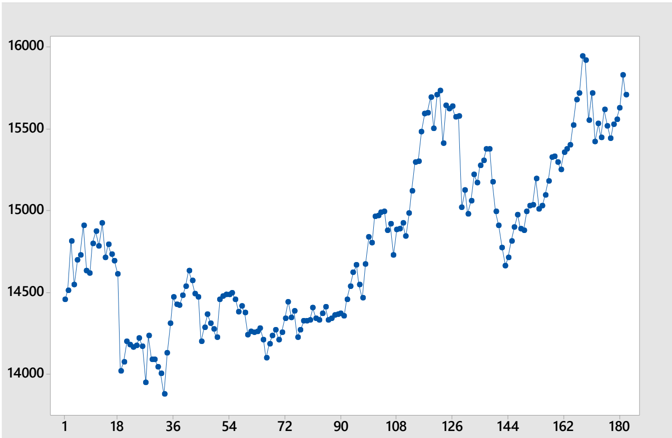

Figure 2 Plot of Rupiah against Dollar Exchange Rate Data from July 2020 to February 2024

B. Nonlinearity Test

Linearity testing using the Terasvirta test is required as a basis for applying nonlinear time series methods. The Terasvirta test results are presented in Table 3 as follows.

Table 3 Terasvirta Test on Rupiah to Dollar Exchange Rate Data

Variabel	P-value
y_t	0.03421

From Table 3, it is found that the p-value of the Terasvirta test result is 0.03421, which is smaller than the alpha significance level (0.05). This indicates that the null hypothesis is rejected. Therefore, it can be concluded that the weekly Rupiah exchange rate data has a nonlinear pattern. Thus, data analysis needs to be carried out using a nonlinear model to obtain optimal model predictions.

C. Kernel Model

As mentioned earlier, the Gaussian Kernel is highly flexible and can capture complex non-linear relationships between variables than another Kernel function on literature review. It is characterized by a smooth, bell-shaped curve centered around each data point as it shown in figure 2. The Gaussian Kernel is often a suitable choice when the underlying data does not exhibit strong discontinuities or abrupt changes. The next step is to test the data using kernel estimator with Gaussian Kernel. From the test results, the comparison is presented in Table 4 as follows.

Table 4 Comparison of Best Kernel Estimator Models

Fungsi Kernel	h	GCV	MSE	RMSE	R^2	MAPE
Gaussian	0.96	9701.1	3331.86	57.722	98.29%	0.28909

From the data presented in the table, the kernel estimator model chosen based on the minimum GCV criteria is the Gaussian Kernel model with an h parameter value of 0.96 and a MAPE value of 0.28909%. Furthermore, in the kernel regression modeling process, the search for the optimal h bandwidth value is carried out by trial and error method at a certain interval so that the smallest GCV value can be found.

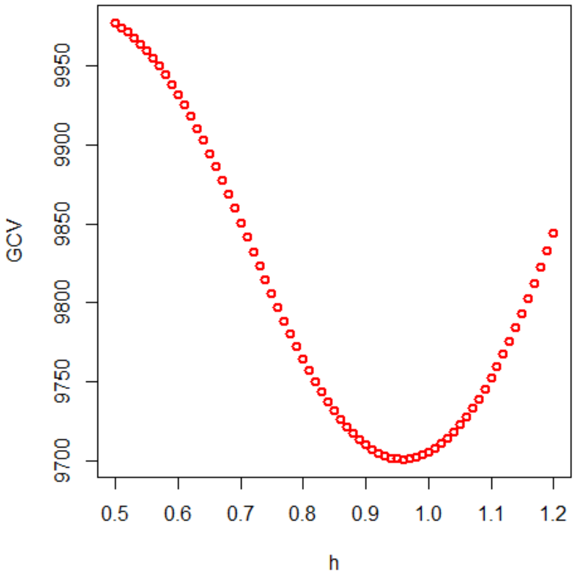

Figure 3 Plot Graph of Optimal GCV Value

The optimal GCV value results are shown in Figure 3 with a value of 0.96. The best model is then applied to make predictions on out sample data, the results of which are shown in Figure 4. The prediction results show an out sample MAPE value of 0.28909%, indicating that the performance of the kernel model is very good because the MAPE value is below 10%.

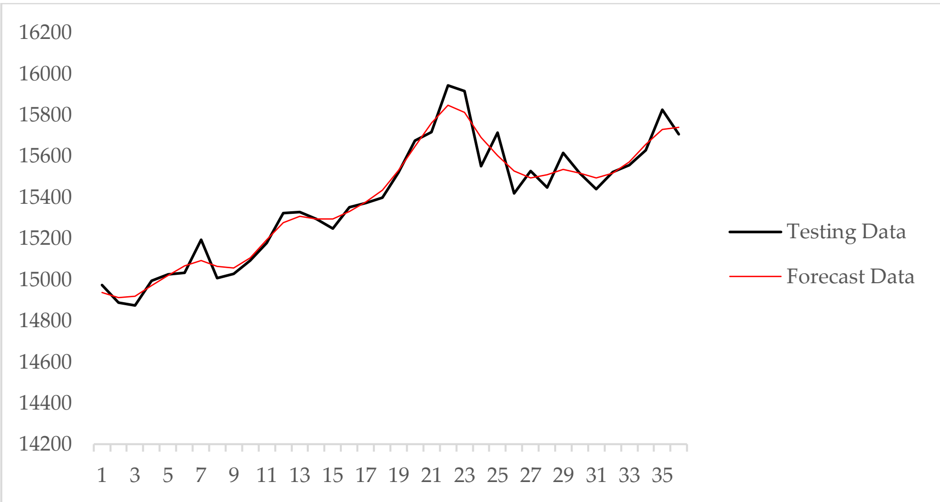

Figure 4 Plot of Testing Data and Prediction of Rupiah Value Against Dollar Using Gaussian Kernel Estimator

From the visualization above, it can be seen that the actual and predicted data are very similar. The best model shows an R-squared value of 0.9829, which indicates that the predictor variables can explain about 98.289% of the variation in the response variable. With this R-squared value, the kernel model can be considered a strong model. Using the best model, we can make predictions for the next few days as long as we have data for the previous two periods. For example, to predict the exchange rate of Rupiah against US Dollar in the first week of February 2024 (February 4 - 8, 2024), we must have closing price data on January 21 - 26, 2024. Furthermore, the prediction results of the weekly Rupiah to Dollar exchange rate from May 2023 to February 2024 using the Gaussian Kernel estimator are presented in Table 5 below.

Table 5 Comparison of Actual and Predicted Data of Gaussian Kernel Rupiah to Dollar Exchange Rate for the Period of May 2023 - February 2024

Index	Actual Data	Predicted Data	Index	Actual Data	Predicted Data
1	14973	14937,1	20	15675,01	15646,56
2	14888	14912,12	21	15716	15759,42
3	14874	14919,45	22	15943	15846,81
4	14994	14970,09	23	15916	15811,66
5	15026	15020,34	24	15550	15691,24
6	15034	15066,39	25	15713	15603,22
7	15192	15091,83	26	15419	15526,37
8	15007	15062,98	27	15527	15494,78
9	15028	15054,87	28	15446	15509,22
10	15092	15105,66	29	15614	15535,85
11	15178	15192,13	30	15516	15518,11
12	15323	15275,33	31	15439	15492,67
13	15329	15306,89	32	15522	15516,14
14	15294	15295,23	33	15555	15572,38
15	15247	15294,76	34	15627	15655,58
16	15352	15331,67	35	15825,01	15728,74
17	15373	15375,98	36	15705	15739,93
18	15399	15433,57			
19	15519	15531,1			

D. SVR Model

Before applying SVR for modeling, the first step that needs to be done is to convert the initial data into a time lag form that will be input to the SVR model. Determination of the time lag can be seen based on the Partial Autocorrelation (PACF) plot shown in Figure 5 as follows.

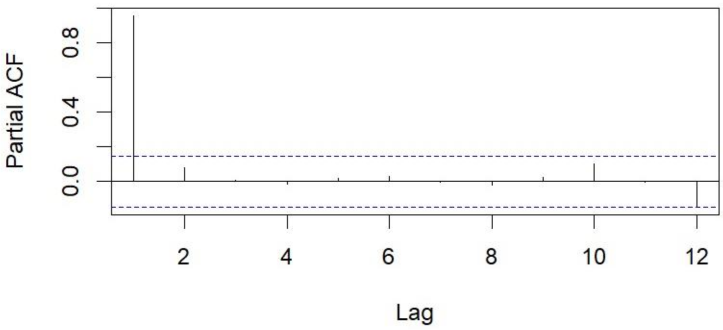

Figure 5 PACF Plot of Rupiah to Dollar Exchange Rate Data

Based on Figure 4, it is found that lags 1 and 12 are significant lags, so the number of time lags for SVR input data is 2 lags. In developing the SVR model, it is important to determine the optimal parameters to ensure the most accurate prediction. The determination of the optimal parameters is carried out using a grid search algorithm with the parameters sought, namely C, γ, and ε. The process of determining the optimal parameters goes through two stages, namely loose grid and finer grid. In the grid search stage, the first step is to determine the range of values of each parameter. In the loose grid stage, the parameter values of C and γ use a range of integer values, while the value of ε has a range of values from 0 to 1 that varies. The range of parameter values used in the search for optimal parameters at the loose grid stage can be seen in Table 6 below.

Table 6 Parameter Value Range of Loose Grid Stages Grid Search Method

Parameter	Value Range
C	$2^{-3}, 2^{-2}, 2^{-2}, \ldots, 2^{4}, 2^{5}, 2^{6}$
γ	$2^{1}, 2^{2}, 2^{3}, \ldots, 2^{8}, 2^{9}, 2^{10}$
ε	$0.1, 0.2, 0.3, \ldots, 0.8, 0.9, 1$

Based on Table 5, the optimal parameter values obtained from the loose grid stage for each parameter are $C = 1$, $\gamma = 2$, and $\varepsilon = 0.2$. The next process is to determine the final optimal parameter values through the finer grid stage by considering the neighborhood values of C and γ obtained from the loose grid stage. The range of parameter values used in the finer grid stage can be seen in Table 7.

Table 7 Parameter Value Range of Finer Grid Stages Grid Search Method

Parameter	Value Range
C	$2, 2^{0.25}, 2^{0.5}, \ldots, 2^{2.5}, 2^{2.75}, 2^{3}$
γ	$2^{-1}, 2^{-0.75}, 2^{-0.5}, \ldots, 2^{2.5}, 2^{2.75}, 2^{3}$
ε	0.2

Based on Table 6, the optimal parameter values obtained from the finer grid stage are $C = 2.5$, $\gamma = 1$, and $\varepsilon = 0.2$, respectively. After obtaining the best SVR model, the next step is to evaluate the accuracy of the model in forecasting the rupiah exchange rate data against the dollar using the MAPE and RMSE values listed in Table 8 and the time series plot between the training data and the prediction results shown in Figure 6.

Table 8 Training Data Model Evaluation Measures

RMSE	MAPE
103.2291	0.56%

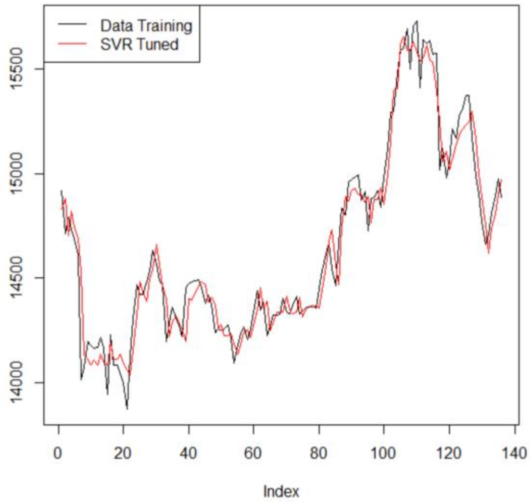

Figure 6 Comparison of Training Data with Prediction Results of RBF Kernel SVR Model on Training Data

Based on the MAPE value in Table 8, the built SVR model shows a very high prediction accuracy rate of 0.56%. Therefore, the training model is applied to predict the testing data. Furthermore, the prediction results of the rupiah exchange rate against the dollar weekly from May 2023 to February 2024 are presented in Table 9 as follows.

Table 9 Comparison of Actual and Predicted Data of Rupiah Exchange Rate against Dollar Model SVR Kernel RBF Period May 2023 - February 2024

Index	Actual Data	Predicted Data	Index	Actual Data	Predicted Data
1	14874	14935.11	18	15675	15619.29
2	14994	14938.43	19	15716	15771.78
3	15026	14981.50	20	15943	15771.14
4	15034	15112.36	21	15916	15792.57
5	15192	15136.28	22	15550	15605.79
6	15007	15124.86	23	15713	15530.41
7	15028	15083.55	24	15419	15512.47
8	15092	15082.21	25	15527	15582.12
9	15178	15122.25	26	15446	15531.25
10	15323	15200.87	27	15614	15558.34
11	15329	15359.16	28	15516	15465.50
12	15294	15305.55	29	15439	15494.72
13	15247	15263.33	30	15522	15493.15
14	15352	15297.12	31	15555	15579.14
15	15373	15424.84	32	15627	15682.66
16	15399	15454.64	33	15825	15769.40
17	15519	15559.56	34	15705	15649.24

The evaluation amount of the SVR model in predicting the testing data of the rupiah exchange rate against the dollar is shown in Table 10 as follows.

Table 10 Training Data Model Evaluation Measures

RMSE	MAPE
74.92009	0.41%

E. Best Model Selection

Estimation using Kernel and SVR approaches are compared to select the best method based on the smallest MAPE and RMSE values. A comparison of the results of the MAPE and RMSE values of the two methods is presented in Table 11 as follows.

Table 11 Performance Comparison of Kernel Function Method and SVR

Methods	RMSE	MAPE
Gaussian Function Kernel	57.5722	0.29%
Kernel RBF Kernel	74.9201	0.41%

Based on Table 11, it can be seen that the Gaussian function Kernel estimator is the best method in this study with an RMSE value of 57.5722 and a MAPE value of 0.29%. The Kernel regression model with the Gaussian function to model the fluctuation of the rupiah exchange rate against the US dollar is presented in equation (17) below:

$$\hat{m}(x) = \frac{\sum_{i=1}^{182} \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{1}{2}\left(\frac{x-x_i}{0.96}\right)^2 y_i\right)}}{\sum_{i=1}^{182} \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{1}{2}\left(\frac{x-x_i}{0.96}\right)^2\right)}} \quad (17)$$

V. CONCLUSIONS AND SUGGESTIONS

The exchange rate of the rupiah against the US dollar in 2020 until the beginning of 2024 has fluctuated. First, the classic Kernel-based time series analysis uses the best function, namely the Gaussian Kernel, which is used to predict the rupiah exchange rate against the US dollar as a result of the FFR policy. It is concluded that the Kernel-based time series model with the Gaussian function has an RMSE value of 57.5722 and a MAPE value of 0.29%. Furthermore, a modern time series analysis using RBF Kernel SVR will be carried out with the results of an RMSE value of 74.9201 and a MAPE value of 0.41%. Based on the comparison of the performance of the two models, it can be concluded that the classic time series model with Gaussian Kernel is more effective in predicting the rupiah exchange rate against the US dollar as a result of the FFR policy implemented by the Fed. Therefore, to overcome the impact of the FFR policy, it is recommended to use the classic Kernel-based time series method with the Gaussian function to predict the rupiah exchange rate against the US dollar.

To improve the accuracy of predictions, it is recommended to continue expanding the data coverage by considering external factors that can affect exchange rates, such as global economic conditions and monetary policies from other countries. In addition, it is necessary to periodically evaluate the prediction model used to adjust to the changing market dynamics. Finally, collaboration with economic experts and market analysts can provide additional valuable insights in interpreting the prediction results and making more informed decisions in managing market risks.

ACKNOWLEDGEMET

The authors would like to thank the Ministry of Education, Culture, Research, and Technology of Higher Education for providing the MBKM policy so that students can take part in the Research Internship course at the Statistics Study Program, Faculty of Science and Technology, Universitas Airlangga. Appreciation is also given to Bank Indonesia for providing research data, as well as all those who have provided support in the research process and this publication.

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