JURNAL MATEMATIKA, STATISTIKA DAN KOMPUTASI e–ISSN: 2614–8811
Published by Departement of Mathematics, Hasanuddin University, Indonesia
https://journal.unhas.ac.id/index.php/jmsk/index
Vol. 22, No. 3, May 2026, pp. 717-729
DOI: 10.20956/j.v22i3.50120

Rupiah Exchange Rate Forecast Against the United States Dollar Using the Singular Spectrum Analysis Method

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Received: 1 March 2026, revised: 30 April 2026, accepted: 4 May 2026

Abstract

Singular Spectrum Analysis (SSA) is a nonparametric time series forecasting method that decomposes a time series into signal and noise components without relying on predetermined model assumptions. This study aims to forecast the rupiah exchange rate against the United States Dollar (USD) using the Singular Spectrum Analysis (SSA) method based on data from the period August 2023 to August 2024. The in-sample data consists of 191 points from August 1, 2023, to May 21, 2024, while the out-of-sample data consists of 48 points from May 22, 2024, to August 1, 2024. The results showed that the SSA method achieved Mean Absolute Percentage Error (MAPE) values of 0.44% on in-sample data and 0.64% on out-of-sample data, indicating that the method is quite effective in predicting the rupiah exchange rate against the USD.
Keywords: Exchange Rate; Forecast; SSA.

1. INTRODUCTION

Global economic developments has led to an increase in dependence between countries and strengthened bilateral and multilateral economic relations, both through trade in goods and services, as well as capital and investment flows [2]. In this context, the exchange rate is an important variable because it affects the export-import competitiveness and external balance of a country, including Indonesia [9]. Dynamic exchange rate fluctuations can significantly impact economic stability and external sector performance. Various international trade activities involving currency transactions further emphasize the importance of the role of exchange rates in the economy [18].

An exchange rate can be expressed as the number of units of domestic currency that can be used to buy one unit of another country's currency [12]. The exchange rate plays a vital role in a country's monetary stability and economic measurement [5]. Exchange rate fluctuations play a crucial role in the functioning of the modern economy as they affect various economic activities, such as investment and trade [11]. The strength of the rupiah exchange rate in the foreign exchange market, often measured by appreciation and depreciation, is determined by the rupiah's value relative to foreign currencies such as the USD.

Exchange rate appreciation is an increase in a currency, while depreciation refers to a decrease in that currency [1]. The rupiah exchange rate tends to be appreciated when the rupiah exchange rate against the USD shows a very small difference, while the USD indicates depreciation of the rupiah exchange rate. On the other hand, if the rupiah exchange rate against the USD shows a significant difference, the rupiah tends to depreciate against the USD, while the USD appreciates the rupiah.

Rupiah exchange rate forecasting is essential for various purposes because the exchange rate is not just a prediction of numbers, but a navigation tool to maintain trade competitiveness, domestic price stability, and sustainable economic growth in the midst of increasingly unpredictable global dynamics. Along with the development of technology and science, various approaches have been taken to forecast future values to obtain more accurate forecasting results. In the analysis of time-lapse data, economic and business data are generally separated into several main component groups [15]. The Singular Spectrum Analysis (SSA) method is one of the methods that can be applied to rupiah exchange rate data forecasting because it is able to separate and identify the main components of the data without the need for testing certain assumptions.

Several studies have used the SSA method for forecasting. Forecasting data on accidental deaths in the United States has been carried out by comparing the SSA method with several other methods, such as Seasonal Autoregressive Integrated Moving Average (SARIMA), Autoregressive – Autoregressive (ARAR), and Seasonal Holt-Winters, which shows the advantages of the SSA method [7]. The accuracy of the SSA method is also proven to be higher than the SARIMA method in predicting rainfall in Padang Panjang City [17]. In addition, the implementation of SSA has been used to forecast rainfall in Gorontalo Province [16] as well as the amount of rice production in Gowa Regency [8]. Economic data such as the Indonesia Composite Index (ICI) have also been predicted using this approach [20]. In other agricultural sectors, rice production forecasting for the first, second, and third quarters in Pinrang Regency was successfully carried out by applying a similar method [10]. Overall, these studies confirm that the SSA method is able to produce data forecasts with a low error rate.

Based on the existing literature, most studies have demonstrated the effectiveness of SSA in a variety of forecasting applications. However, most of the research still focuses on the environmental or agricultural sectors, and there is still limited research in evaluating specifically the reliability of the SSA method in predicting the daily fluctuations of the Rupiah exchange rate against the USD amid the current global economic uncertainty. Therefore, this study aims to forecast the exchange rate of the Rupiah against the USD using the SSA method and evaluate its accuracy through a low error rate.

2. MATERIAL AND METHODS

2.1 Preliminaries

Currency exchange rates are the relative prices between one currency and another. Continuous and quite sharp changes in the rupiah exchange rate are indicators of national economic instability [14]. Fluctuations in currency exchange rates affect domestic inflation and the competitiveness of exports and imports.

Singular Spectrum Analysis (SSA) is a non-parametric forecasting method that decomposes the original time series into several independent components, such as signals and noise [7]. Basically, the SSA method consists of two main stages, namely decomposition and reconstruction [4]. The first phase of the SSA method is decomposition, which begins with an *embedding* process to transform the time series into a trajectory matrix. Next, the *Singular Value Decomposition* (SVD) phase is carried out, in which the trajectory matrix is decomposed into a set of eigentriples.

The reconstruction phase, performed after decomposition, consists of grouping and diagonal averaging [13]. In the grouping phase, the selected eigentriples are grouped to form components that represent the basic structure of the time series, such as signals and noise. Subsequently, a diagonal averaging process is carried out to change the matrix of the resulting grouping back into a time series by equalizing the elements on each diagonal of the matrix.

Embedding is the phase of mapping the transfer results from the original series to a trajectory matrix, measured by $L \times K$, where L or window length is an integer satisfying $2 \leq L \leq {}^{n}/_{2}$ with n denoting the length of the time series, K can be calculated through the formula $K = n - L + 1$ and lagged vector $X_i = (y_i, y_{i+1}, \ldots, y_{i+L-1})^{\mathrm{T}}$ is formed for each i in the range $1 \leq i \leq K$ [19]. The selection of a large size for parameter L is suggested, but [6] no larger than $n/2$. The trajectory matrix can be illustrated as in Equation (1).

$$\mathbf{X} = [X_1 : \ldots : X_k] = (x_{ij})_{i,j=1}^{L,K} = \begin{bmatrix} y_1 & y_2 & \cdots & y_K \\ y_2 & y_3 & & y_{K+1} \\ \vdots & & \ddots & \vdots \\ y_L & y_{L+1} & \cdots & y_n \end{bmatrix} \quad (1)$$

The trajectory matrix $\mathbf{X}$ is then decomposed at the Singular Value Decomposition (SVD) eigenvalue ($\lambda_1 \geq \ldots \geq \lambda_L \geq 0$) and the eigenvector ($U_1 \geq \ldots \geq U_L \geq 0$) of the $L \times L$ matrix $\mathbf{S} = \mathbf{X}\mathbf{X}^{\mathrm{T}}$. The SVD values of the trajectory matrix $\mathbf{X}$ can be written in the form of Equation (2).

$$\mathbf{X} = \sum_{i=1}^{d} \mathbf{X}_i \quad (2)$$

where with $\mathbf{X}_i = \sqrt{\lambda_i} U_i V_i^{\mathrm{T}} i = 1, \ldots, d$ and $V_i = \frac{\mathbf{X}_i^{\mathrm{T}} U_i}{\sqrt{\lambda_i}}$. The rank of the matrix $\mathbf{X}$ is $d = \max\{i\}$ so $\lambda_i > 0$. Thus, the i-th eigentriple of SVD is $\left(\sqrt{\lambda_i}, U_i, V_i\right)$ with $\sqrt{\lambda_i}$ is a singular value, U_i is an eigenvector, and V_i is the principal component.

The eigentriple is then grouped at the grouping phase by partitioning the index $\{1, 2, \ldots, d\}$ into m group $I_1, \ldots, I_m$ that is separated from each group. For each group $I = \{i_1, \ldots, i_p\}$, the resultant matrix $\mathbf{X}_I = \mathbf{X}_{i_1} + \cdots + \mathbf{X}_{i_p}$ is calculated for each $I_1, \ldots, I_m$. Therefore, the matrix $\mathbf{X}$ can be written as Equation (3).

$$\mathbf{X} = \mathbf{X}_{I_1} + \mathbf{X}_{I_2} + \cdots + \mathbf{X}_{I_m} \quad (3)$$

Any matrix $\mathbf{X}_{I_k}$ with $k = 1, 2, \ldots, m$ in Equation (3), the set can consist of one or more eigentriple groups $\left(\sqrt{\lambda_i}, U_i, V_i\right)$.

The formation of a new time series with length n is carried out after the formation of the matrix as a result of grouping. Let $\mathbf{X}$ be a matrix $L \times K$ with x_{ij} where $1 \leq i \leq L$ and $1 \leq j \leq K$ and $L^* = min(L, K), K^* = max(L, K)$, then $x_{ij}^* = x_{ij}$ if $L < K$ and $x_{ij}^* = x_{ji}$ if $L \geq K$. The matrix $\mathbf{X}$ is then reconstructed to a time series using the formula in Equation (4).

$$\tilde{y}_t = \begin{cases} \dfrac{1}{t}\sum_{m=1}^{t} x^*_{m,t-m+1} & ; 1 \le t < L^* \\ \dfrac{1}{L^*}\sum_{m=1}^{L^*} x^*_{m,t-m+1} & ; L^* \le t < K^* \\ \dfrac{1}{n-t+1}\sum_{m=t-K^*+1}^{n-K^*+1} x^*_{m,t-m+1} & ; K^* \le t < n \end{cases} \tag{4}$$

Equation (4) shows how to calculate the average of the values in a matrix located along the diagonal, with the relationship $i + j = s + 1$. The meaning of the diagonal applied to the matrix $\mathbf{X}_{I_k}$ Equation (3) results in a reconstructed series $\widetilde{Y}^{(k)} = \left(\tilde{y}_1^{(k)}, \dots, \tilde{y}_n^{(k)}\right)$. Therefore, the initial series can be reconstructed by summing $y_t = \sum_{k=1}^{m} \tilde{y}_t^{(k)},\ t = 1,2,\dots,n$.

The SSA forecasting phase applies to the recurrent method (R-forecasting) based on a reconstruction matrix, using diagonal averaging. The recurrent method relies on the Linear Recurrent Formula (LRF), which is a linear recurrent formula that states that a single value in a time series can be predicted as a linear combination of the previous values. The recurrent method uses the eigenvector of the SVD result to estimate the LRF coefficient, namely $a_1, a_2, \dots, a_d$. Let $U = (u_1, u_2, \dots, u_{L-1}, u_L)^{\mathrm{T}}$, $U^{\nabla} = (u_1, u_2, \dots, u_{L-1})^{\mathrm{T}}$, and π_q is the last component of the *eigenvector* U then the formula for obtaining the LRF coefficient is written in Equation (5) with $v^2 = \sum_{q=1}^{r} {\pi_q}^2$.

$$\boldsymbol{\mathcal{R}} = (a_{L-1}, a_{L-2}, \dots, a_1)^{\mathrm{T}} = \frac{1}{1-v^2}\sum_{q=1}^{r} \pi_q U^{\nabla} \tag{5}$$

Furthermore, M, which is a new data point to be predicted, can be determined using the formula in Equation (6) with $\hat{y}_{n+1}, \dots, \hat{y}_{n+M}$ is the result of forecasting on the SSA method.

$$\hat{y}_t = \begin{cases} \tilde{y}_t & \text{untuk } t = 1,2,\dots,n \\ \sum_{j=1}^{L-1} a_j \hat{y}_{t-j} & \text{untuk } t = n+1,\dots,n+M \end{cases} \tag{6}$$

The accuracy of the forecast results is evaluated using the Mean Absolute Percentage Error (MAPE), which is calculated using the formula in Equation (7), because this metric is able to measure errors in the form of percentages, so that it is easier to interpret and compare. In addition, MAPE is widely used in time series forecasting research because it provides an overview of errors relative to actual values. The classification of forecasting capabilities based on the magnitude of the MAPE value is divided into several categories, as shown in Table 2.1 [3].

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100\% \tag{7}$$

Table 2.1 MAPE Value Categories

MAPE Values	Interpretation
$MAPE < 10\%$	Highly accurate
$10\% \leq MAPE < 20\%$	Good
$20\% \leq MAPE < 50\%$	Reasonable
$MAPE \geq 50\%$	Inaccurate

2.2 Research Procedure

Data on the rupiah exchange rate against the USD for the period August 1, 2023, to August 1, 2024, was used in this study. The data was taken from Bank Indonesia's official website, namely https://www.bi.go.id/. In-sample *data* consists of 191 points from August 1, 2023, to May 21, 2024, and out-of-sample data consists of 48 points from May 22, 2024, to August 1, 2024. The methodological framework for SSA forecasting is illustrated in Figure 2.1.

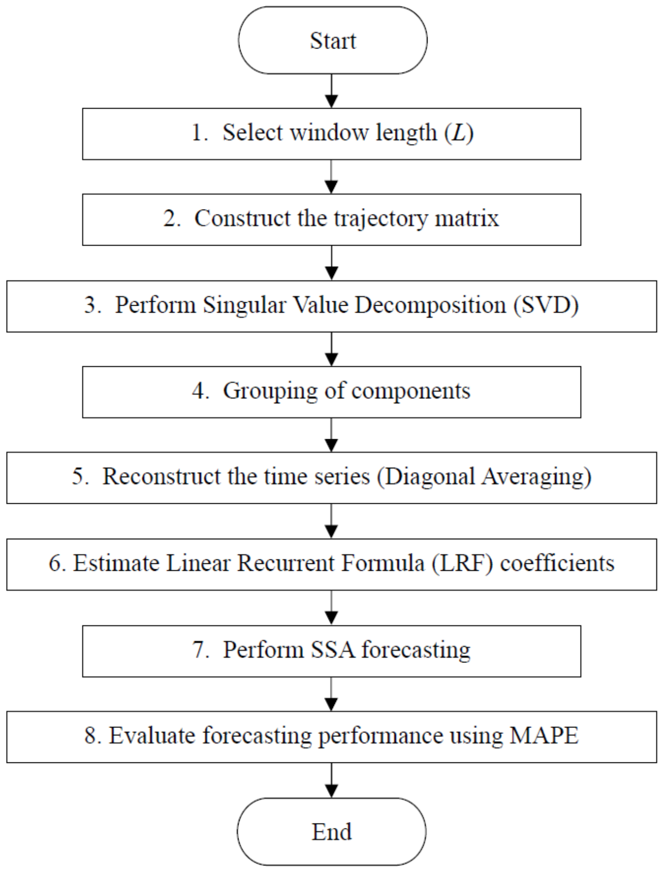

Figure 2.1 Methodological framework for SSA forecasting

3. MAIN RESULTS

The rupiah exchange rate data against the USD for the period from August 1, 2023, to August 1, 2024, is displayed as a time series plot in Figure 3.1.

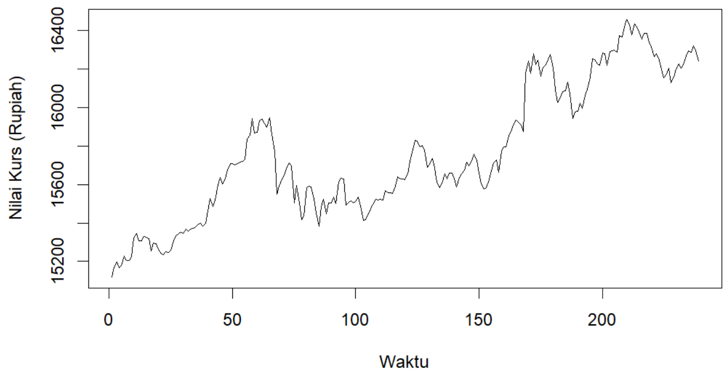

Figure 3.1 Plot of Rupiah Exchange Rate Data Against USD

Figure 3.1 shows that the rupiah exchange rate against the USD generally exhibits an increasing trend over time. However, the series also displays noticeable fluctuations, indicating the presence of short-term volatility in the exchange rate movements.

The first phase of the decomposition process is embedding. During the embedding phase, a trajectory matrix is constructed. However, the formation of this trajectory matrix requires a parameter L, which has a condition $2 \leq L \leq {}^{n}/_{2}$. The determination of this parameter, L, is done through a trial-and-error process by looking at the smallest MAPE value. This range was chosen because theoretically the value of L must be large enough to capture seasonal patterns but not exceed half of the total observations in order for decomposition to remain stable. The trial-and-error process is carried out by testing each integer value in that range in stages. From the process, the parameter value with the smallest MAPE value is 25, which optimally separates the main signal from the noise in this rate data. From these values, the value can be calculated with $K = n - L + 1 = 191 - 25 + 1 = 167$. Thus, the *embedding* process has produced trajectory matrices $\mathbf{X}_{25\times 167}$ as follows.

$$\mathbf{X} = \begin{bmatrix} 15117 & 15171 & 15198 & \cdots & 15907 \\ 15171 & 15198 & 15178 & \cdots & 15873 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 15260 & 15307 & 15334 & \cdots & 16024 \end{bmatrix}$$

With the trajectory matrix **X** the Singular Value Decomposition (SVD) value is calculated by decomposing into 25 eigentriples as shown in Table 3.1.

Table 3.1 Eigentriple Components

Singular Values $(\sqrt{\lambda_i})$	Eigenvectors (U_i)			Principal Components (V_i)		
1010197,92	$-0{,}1991$	$\cdots$	0,0971	$-0{,}0755$	$\cdots$	$-0{,}0807$
5452,47751	$-0{,}1992$	$\cdots$	$-0{,}2332$	$-0{,}0755$	$\cdots$	$-0{,}0773$
$\vdots$	$\vdots$		$\vdots$	$\vdots$		$\vdots$
204,308132	$-0{,}2008$	$\cdots$	0,0857	$-0{,}0798$	$\cdots$	0,0480

The next phase is grouping, which is carried out to group the eigentriple components that have been obtained from the SVD phase into signal and noise with the grouping effect parameter (r). The determination of the value of the r parameter is seen from the sum of eigentriples that do not describe the noise in the scree plot of the singular values. The determination of noise is seen from the slow decline in the singular values plot.

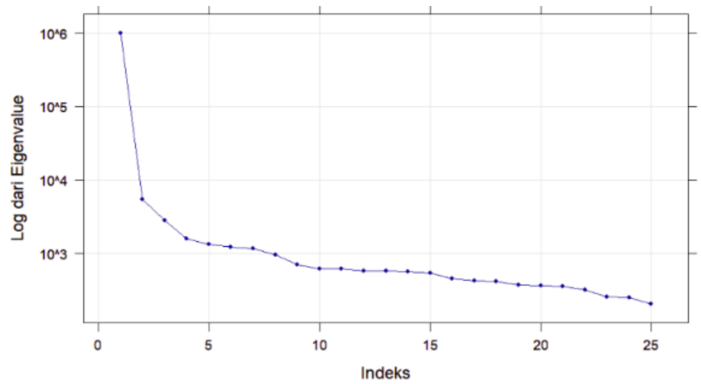

Figure 3.2 Scree Plot Singular Values

Based on Figure 3.2, the 4th to 25th singular values show a decline that begin to slow down so that the singular values tend to be of little value and can be considered as noise because they are less significant in describing the main components. In this case, the parameter r can be estimated at 3. However, further analysis is needed for the parameter r using the eigenvector plot, which provides information on the eigenvector's percentage contribution, as seen in Figure 3.3.

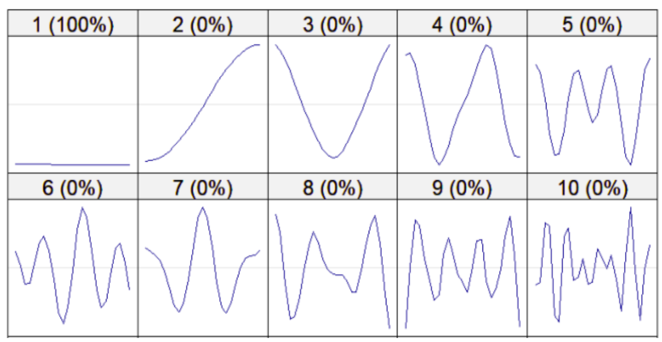

Figure 3.3 Plot of Eigenvectors

Figure 3.3 shows the plot of eigenvectors, which gives an idea of the percentage of eigenvector contribution to the main component. The first eigenvector appears to have a contribution of 100%, so that this eigenvector has the dominant pattern, which means that all data has been depicted by the first eigenvector only. The first eigenvector depicts a powerful trend pattern because it visually contains no variation. Since there is only one eigenvector that makes the dominant contribution, the parameter r is valued at 1.

The results of the previous scree plot suggest the use of the value r = 3 as the sum of the main components. However, further analysis through eigenvector plots shows that the contributions of the second and third components are very insignificant and tend to represent only noise or interference in the data. The determination of the value r = 1 was ultimately chosen to maintain the simplicity of the model and avoid the risk of overfitting. This decision is based on the fact that the first component is already able to predominantly represent the main trend patterns of the data, so the addition of other components no longer provides meaningful information for forecasting accuracy.

The next step is to identify eigentriple using a W-correlation matrix. The plot of the W-correlation matrix shows the magnitude of the correlation for each eigentriple. The more intense the color, the stronger the correlation between eigentriples. However, the correlation between eigentriples is weaker if there is a gray color.

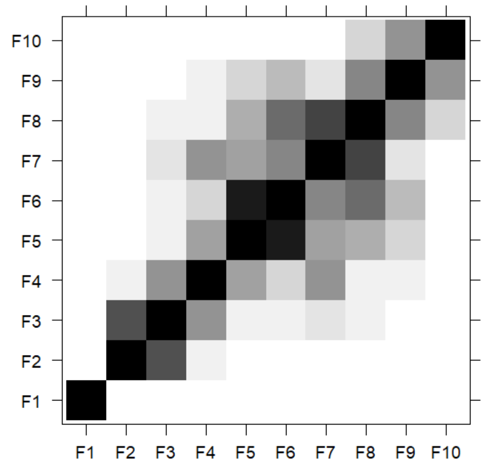

Figure 3.4 W-Correlation Matrix Plot

Figure 3.4 shows that F1 is uncorrelated with F2, so eigentriple 1 and eigentriple 2 represent completely separate components. The dark gray color F2 and F3 indicates a low correlation between eigentriple 2 and eigentriple 3, thus indicating that the pattern on eigentriple 2 is not entirely related to eigentriple 3. This condition illustrates heterogeneity in the data, where not all eigentriples show a clear correlation. After analyzing the correlations among eigentriple, the eigentriple groups are separated into signal and noise.

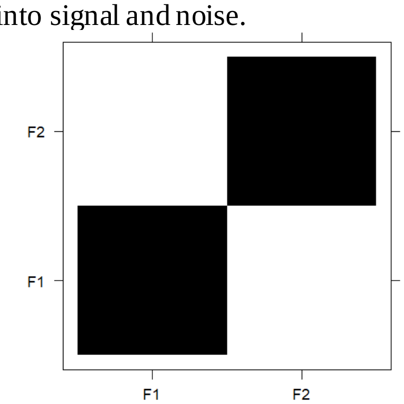

Figure 3.5 W-Correlation Matrix Plots of Signal and Noise Groups

Figure 3.5 shows that F1 corresponds to eigentriple 1, which shows a clear separation from F2, corresponding to eigentriple 2 to eigentriple 25. The group of eigentriple components, as detailed, can be seen in Table 3.2.

Table 3.2 Eigentriple Component Groups

Component	***Eigentriple***
Signal	1
Noise	2, 3, 4, …, 25

The diagonal averaging is performed after grouping components into signals and noise. In this process, the components separated into signals and noise are reconstructed using the appropriate eigentriple for each component. The next step is to reconstruct each group of eigentriple components, as shown in Figure 3.6.

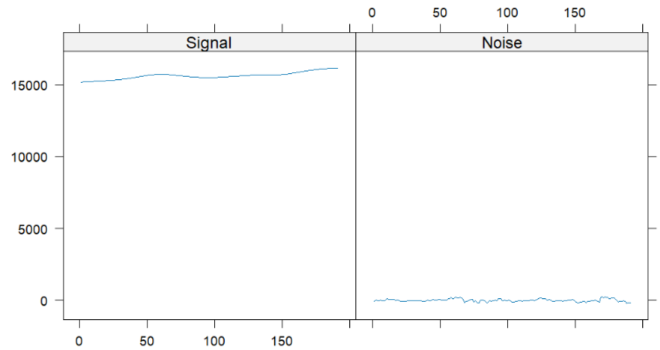

Figure 3.6 Plot of Reconstruction Results Component Group

Figure 3.6 shows the plot of the reconstruction of the component group, namely the signal and noise, where the signal is the result of the reconstruction of the trend component. Furthermore, the comparison plot of forecasting data derived from signals and in-sample data is shown in Figure 3.7, along with the forecasting results in Table 3.3.

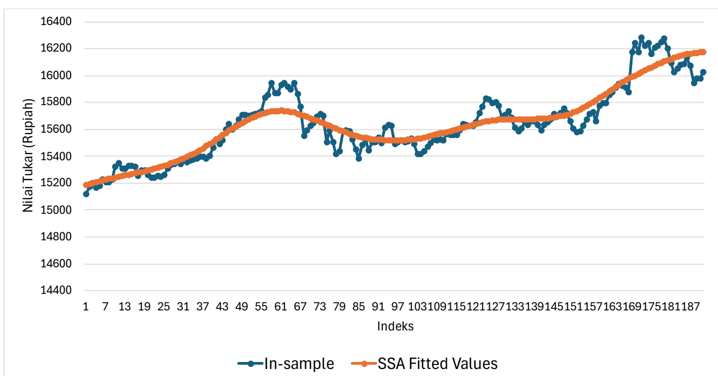

Figure 3.7 Comparison of In-Sample Data and SSA Fitted Values

Figure 3.7 shows the plot of in-sample data and fitted values using SSA. The blue line is in-sample data that shows fluctuations in the index value but still shows an increasing pattern. The orange line represents the SSA fitted values, which also shows a growing pattern.

Table 3.3 Comparison of In-Sample Data and SSA Fitted Values

t	*In-Sample* Data (y_t)	SSA Fitted Values ($\hat{y}_t$)
1	15117	15186,516
2	15171	15192,523
3	15198	15198,680
4	15168	15204,732
5	15178	15211,026
⋮	⋮	⋮
191	16024	16176,800

After forecasting the in-sample data, the forecasting on the out-of-sample data was carried out using the LRF coefficients. The value of the LRF coefficient with $L = 25$ can be seen in Table 3.4.

Table 3.4 The LRF Coefficients

No	a_j
1	0,04166
2	0,04167
3	0,04169
⋮	⋮
24	0,04198

With the LRF coefficients in Table 3.4, the SSA forecasting model can be seen in Equation (8). The forecasting results are presented in Table 3.5, while the comparison plot of forecast results and out-of-sample data is shown in Figure 3.8.

$$\hat{y}_t = \sum_{j=1}^{25-1} a_j y_{t-j} = 0{,}04166 y_{i-1} + \cdots + 0{,}04198 y_{i-24} \quad (8)$$

Table 3.5 SSA Forecast Results

t	Forecast Results ($\hat{y}_t$)
192	16159,665
193	16167,370
194	16174,871
195	16182,160
196	16189,234
⋮	⋮
239	16414,735

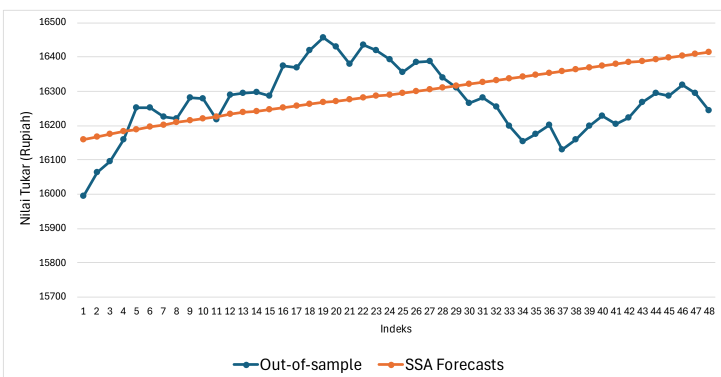

Figure 3.8 Comparison of Plot Out-Sample Data and SSA Forecasts

Figure 3.8 shows the plot of two data sets, namely out-of-sample data and forecasting results using SSA. The blue line is out-of-sample data, while the orange line is the result of forecasting using SSA. The forecast results show an increasing trend pattern. This increasing trend pattern indicates that the rupiah exchange rate is predicted to experience a sustained depreciation against the USD in the coming period. Economically, this trend reflects external and domestic pressures that affect the demand for dollars in the market.

The evaluation of the forecast results can be seen from the Mean Absolute Percentage Error (MAPE) value. The error rate of the SSA method forecast results can be seen in Table 3.6.

Table 3.6 Evaluation of Forecast Results

Data	MAPE Values
In-sample	0.44%
Out-of-sample	0.64%

Table 3.6 shows that the SSA method has very small MAPE values in both in-sample and out-of-sample data. The results of the forecasting prove that indicates good forecasting performance.

4. CONCLUTION

The forecast results show that the SSA method is able to capture the dynamic pattern of the Rupiah exchange rate against the USD well. This is evidenced by the acquisition of a MAPE value of 0.44% in the in-sample data and 0.64% in the out-of-sample data. The consistency of the error rate that remains low, even when applied to data outside of the in-sample data, demonstrates the model's excellent stability and reliability in generalizing patterns. The low difference between in-sample and out-of-sample performance also indicates that the model is not overfitting, so it is able to adapt well to the volatility characteristics of currency markets.

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