

Application of Singular Spectrum Analysis in Predicting Rupiah Exchange Yuan*

Muhammad Hendrawan¹, Zilrahmi^{1‡}, Yenni Kurniawati¹, and Dina Fitria¹

¹ Department of Statistics, Universitas Negeri Padang, Padang, 25132, Indonesia

[‡]corresponding author: zilrahmi@fmipa.unp.ac.id

Copyright © 2025 Muhammad Hendrawan, Zilrahmi, Yenni Kurniawati, and Dina Fitria. This is an open-access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Abstract

The exchange rate between two countries is the price of the currency used by residents of these countries to trade with each other, the relationship between the Rupiah exchange rate and the Yuan is one of the important aspects in the dynamics of international trade. Therefore, forecasting the exchange rate is important as an effort to predict the exchange rate of Rupiah against Yuan in the future. The method used for forecasting is Singular Spectrum Analysis, namely decomposition and reconstruction. The accuracy of the resulting forecast is measured using the Mean Absolute Percentage Error criterion. The exploration results obtained are forecasting accuracy based on the Mean Absolute Percentage Error value of 2.15% with a window length of 23 which identifies that the forecasting results are accurate and effective. Forecasting is said to be accurate if the Mean Absolute Percentage Error value is lower than 10% and close to 10%.

Keywords: Exchange rate, Forecasting, Singular Spectrum Analysis.

* Received: Jul 2024; Reviewed: Aug 2024; Published: Jun 2025

1. Introduction

A country's economy is strongly influenced by the dynamics between demand and supply in the market. High demand from consumers and investors drives economic growth by stimulating the production of goods and services. A country's economy is heavily influenced by the dynamics between demand and supply in the market. Since then the economy in Indonesia has continued to increase. Every year the high number of demand and supply from within the country for goods available abroad requires the country to conduct international trade with other countries, which is referred to as export and import activities. These activities are closely related to the rupiah exchange rate against foreign currencies, because in essence a lot of demand and supply can determine the rupiah exchange rate (Ichsan, S., Suhadak, & Sulassmiyati, S. 2016).

The exchange rate is a comparison of the price or value of one country's currency measured in another country's currency. Rates are also used in transaction activities involving two foreign currencies, rates are also used in transaction activities involving two foreign currencies. The exchange rate between two countries is the price of the currency used by residents of these countries to trade with each other (Golyandina and Zhigljavsky. 2013). The rupiah rate as a transaction tool can provide convenience for exporters, but the difficulty faced is the instability of the rupiah price against the yuan due to market fluctuations and the position of the rupiah value as a currency is not too strong compared to other countries' rates

Forecasting can be defined as a method used to get an idea of the value of an event for the next few periods. One of the forecasting methods is Singular Spectrum Analysis (SSA). The main idea of SSA is to decompose time series data into a number of mutually exclusive groups such as trend, seasonality and noise (Rocco 2013). SSA can be applied to data that has seasonal effects. One of the seasonal effects is the exchange rate. Therefore, SSA is used in forecasting the Rupiah currency exchange rate.

One of the time series data forecasting methods that is currently developing is Singular Spectrum Analysis (SSA). (Jatmiko et al., 2017), has conducted a comparison between SSA, SARIMA, ARAR, and Seasonal Holt-Winter in forecasting accidental death data in the USA in 1973. As a result, SSA is one of the best methods that can be used for forecasting, based on the Mean Absolute Error (MAE) and Mean Relative Absolute Error (MRAE) values. (Myung, N. K. 2009), showed that SSA is a good time series data analysis technique to decipher the time series data analysis technique that is good for decomposing trend patterns and other components with a simple structure. with a simple structure.

Singular Spectrum Analysis (SSA) is a new technique of time series analysis. It makes no statistical assumptions about the signal or noise when performing the analysis and investigates the properties of the algorithm (Hidayat et al., 2020).

This method can be used on multiple time series as it is a non-parametric method where the assumptions of classical time series analysis are no longer necessary. As a non-parametric and model-free method, Singular Spectrum Analysis can be used on multiple time series as it does not require stationary assumptions and does not

require logarithmic transformation. Time series forecasting is a very important particle area and Singular Spectrum Analysis can be very effective for forecasting. There are algorithms for forecasting using Singular Spectrum Analysis (SSA), namely the Recurrent Forecasting algorithm (Asrof, 2017).

There are two forecasting methods in SSA, namely recurrent (R-Forecasting) and vector (V-Forecasting) methods. The recurrent method is the basic method that is often used because it is relatively easier (Golyandina, N et al. 2001) . The vector method is a modified result of the recurrent method. The difference between the two forecasting methods is that the recurrent method performs continuation directly (with the help of LRF), while the vector method deals with L-continuation. This causes the approximate continuation to usually give different results. Forecasting is used in decision-making to obtain a certain goal by predicting future conditions (Kurnia et al., 2021). Many previous studies have used forecasting techniques to forecast various cases, such as forecasting inflation, product sales, weather, agricultural production or currency exchange rates.

Research using SSA has been conducted in forecasting rainfall in West Sumatra Province and obtained a MAPE of 17% (Fitri et al., 2020). Other research was also conducted, in forecasting Gross Domestic Product (GDP) using the SSA method and obtained a MAPE of 1.59%. In this study, rainfall forecasting will be carried out in Medan City using Singular Spectrum Analysis (SSA).

2. Methodology

The research conducted is applied research, by applying the Singular Spectrum Analysis (SSA) method in forecasting the Rupiah Exchange Rate. The rupiah exchange rate data obtained comes from the investing.com website based on the investing.com website for observations from January 2018 to December 2022.

2.1 Data Analysis Technique

The data analysis carried out is Singular Spectrum Analysis (SSA). The analysis steps according to (Fitri et al., 2020) using SSA are as follows.

1. Exploring the data by looking at the data plot of the Rupiah exchange rate against Yuan for observations from January 2018 to December 2022.
2. Divide the data into testing data and training data. The ratio of training data and test data used is 80% for testing data and 20% for training data. Testing data is used from January 2018 to December 2021, while the test data used is January 2022 to December 2022.
3. Perform embedding. Embedding is a stage of SSA to convert one-dimensional time series data into multidimensional. The result of embedding is a trajectory matrix of size $L \times K$. L is called the window length. The value of L is determined by trial and error whose value is between $2 \leq L \leq N/2$ (HIDAYAT et al., 2020). The L value with the smallest MAPE will be used for the next stage. Then the K value is obtained by equation 1.

The trajectory matrix formed is as follows

$$K = N - L + 1$$

(1)

The trajectory matrix formed is as follow

$$X = [X_1, X_2, \dots, X_K] = (x_{ij})_{i,j=1}^{L,K}$$

$$X_{L \times K} = \begin{bmatrix} x_1 & x_2 & x_3 & x_K \\ x_2 & x_3 & x_4 & x_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & \dots & x_N \end{bmatrix} \quad (2)$$

4. Perform *singular value decomposition* (SVD). SVD will produce an *eigentriple*. *Eigentriple* consists of *eigenvector* (U_1), *singular value* ($\sqrt{\lambda_1}$), and *principal component* (V_1), obtained from the decomposition of matrix $S = XX^T$. The *principal component* value is obtained from the following equation (2):

$$V_i = \frac{X^T U_i}{\sqrt{\lambda_1}} \quad (3)$$

The SVD of matrix X can be written as follows:

$$X_i = X_1 + X_2 + \dots + X_d$$

$$X = \sqrt{\lambda_1} U_1 V_1^T + \sqrt{\lambda_2} U_2 V_2^T + \dots + \sqrt{\lambda_d} U_d V_d^T$$

$$X = \sum_{i=1}^d \sqrt{\lambda_i} U_i V_i^T$$

5. Grouping. The results of the SVD are grouped into groups such as trend, seasonality and noise. Grouping is done based on trial and error. Expansion of the SVD result matrix leads to the following decomposition.

$$X_{ij} = X_{i1} + \dots + X_{i=Im}$$

6. Performing diagonal averanging. Diagonal averaging is a stage of SSA to convert each matrix X_{ij} grouped at the grouping stage into new data with the same length as the initial data (Isnawati, 2018). Suppose the matrix $Y = L \times K$, and the matrix element y_{ij} , Diagonal averaging (HIDAYAT et al., 2020) to convert matrix Y into time series $g_0, \dots, g_{N-1}$ is as follows:

$$g_k = \frac{\sum_{(l,k) \in A_s} y_{lk}}{|A_s|}$$

Where $|A_s|$ is the number of element in the matrix X_{ij} . g_k is the diagonal element of matrix $kk = 1$ is the average of the elements along the diagonal of the matrix $g_1 = y_{11}$, $k = 2$ we get $g_2 = \frac{(y_{12} + y_{21})}{2}$ and so on.

7. Perform forecasting. The model in R-Forecasting is built based on the Linear Recurrent Formula (LRF) coefficient. The LRF coefficient calculation uses the following equation (4).

$$R = (a_{L-1}, \dots, a_1)^T = \frac{1}{1-v^2} \sum_{i=1}^r \pi_i U_i^{\bar{v}} \quad (4)$$

Where $U = (u_1, u_2, \dots, u_{L-1}, u_L)^T$, $U^{\bar{v}} = (u_1, u_2, \dots, u_{L-1})^T$, π_1 is the last component of the vector U dan $v^2 = \sum_{i=1}^r \pi_i^2$

The RSSA forecasting model is obtained using the following equation.

$$g_i = \begin{cases} \tilde{y}_i & \text{untuk } i = 0, \dots, N \\ \sum_{j=1}^{L-1} a_j g_{i-j} & \text{untuk } i = N+1, \dots, N+h \end{cases}$$

8. Calculate the forecasting accuracy value, namely the Mean Absolute Percentage Error (MAPE) value and the reliability of forecasting, namely the tracking signal on the test data forecasting results. The MAPE equation can be written as follows.

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100 \%$$

9. Forecasting the exchange rate of the rupiah against the yuan for the next 12 periods.

3. Results and Discussion

3.1 Decomposition

3.1.1. Embedding

In this study using test data as much as $N = 48$ observations so that L is chosen in the range $2 < L < 24$. How to get the value of L can be done by trial and error by looking at the smallest MAPE value because there are no specific criteria in determining it. After doing trial and error, $L = 23$ was obtained with MAPE

The smallest compared to other L . Based on $L = 23$, $K = (48 - 23) + 1 = 26$. So that the trajectory matrix can be arranged as Equation (1) and the matrix result is obtained $X_{23 \times 26}$.

$$X_{23 \times 26} = \begin{bmatrix} 2.088,93 & 2.053,06 & \cdots & 2.050,53 \\ 2.053,06 & 2.178,40 & \cdots & 2.300,89 \\ \vdots & \vdots & \ddots & \vdots \\ 2.004,52 & 1.992,94 & \cdots & 2.240,53 \end{bmatrix}$$

3.1.2. Singular Value Decomposition (SVD)

In this step, we will find the eigentriple value of the cross matrix X by forming a symmetric matrix so that the matrix S is obtained and the matrix $S_{23 \times 23}$ is obtained.

$$S_{23 \times 23} = \begin{bmatrix} 113621573 & 114034934 & \cdots & 116922587 \\ 114034934 & 114552039 & \cdots & 117371702 \\ \vdots & \vdots & \ddots & \vdots \\ 116922587 & 117371702 & \cdots & 120875615 \end{bmatrix}$$

After obtaining the S matrix, then calculate the eigentriple eigenvalue (λ_1), eigentriple ($\sqrt{\lambda_1}$), and principal component (V_i^T) with $i = 1, \dots, d$. How to get the singular value then first look for the value of eigenvalue. After obtaining the eigenvalue, then the eigenvalue is square-rooted. The result of squaring the eigenvalue is the singular value. The results of eigenvalues and singular values are presented in Table 2.

Tabel 2: Eigenvalues and Singular values

No	λ_1	Singular Values
1	2,64E+15	513,96
2	1,69E+12	13,02
3	4,00E+11	632,28
$\vdots$	$\vdots$	$\vdots$

23 1,83E+10 135,10

Furthermore, calculating the eigenvector value, the eigenvector is useful in grouping data based on similar characteristics. From the calculation results, the eigenvector values are presented in Table 3.

Tabel 3: Eigen Vectors

No	U_1	U_2	...	U_{23}
1	-0,20717	-0,27520	...	0,46403
2	-0,20803	-0,27181	...	-0,43891
3	-0,20821	-0,27907	...	0,23026
⋮	⋮	⋮	⋮	⋮
23	-0,21374	0,22122	...	-0,27334

Next, calculate the main components based on the singular values and eigenvectors obtained previously using Equation (2). The calculation results are presented in Table 4.

Tabel 4: Principal Components

No	V_1	V_2	...	V_{23}
1	-10070,10	-29016,18	...	30,263780
2	-10050,07	-33748,20	...	-15,242131
3	-10031,99	-39477,69	...	40,094381
⋮	⋮	⋮	⋮	⋮
26	-10436,03	18157,40	...	-68,031639

The results of the SVD step will be useful in the reconstruction stage.

3.2 Reconstruction

3.2.1. Grouping

In this step, the eigentriple values obtained in the diagonal averaging step at the SVD stage will be grouped based on the similarity of the properties of each component. The grouping is obtained by trial and error by displaying the graph of the eigenvector.

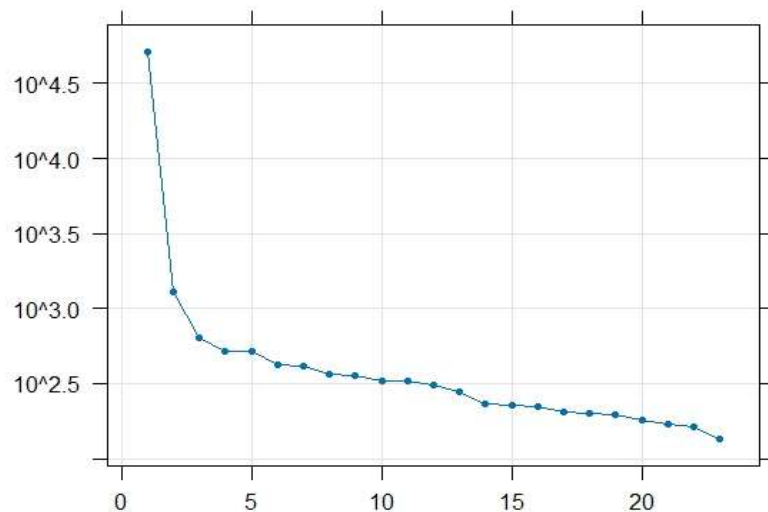


Figure 2: Singular Value Graph

Figure 2 shows that the singular value slowly decreases from singular 2 to 5. If the singular value decreases slowly, it can be said to be a noise element. However, to classify specifically can be seen from graphing the eigenvector values. Eigenvalues that have similar characteristics can be grouped into one group.

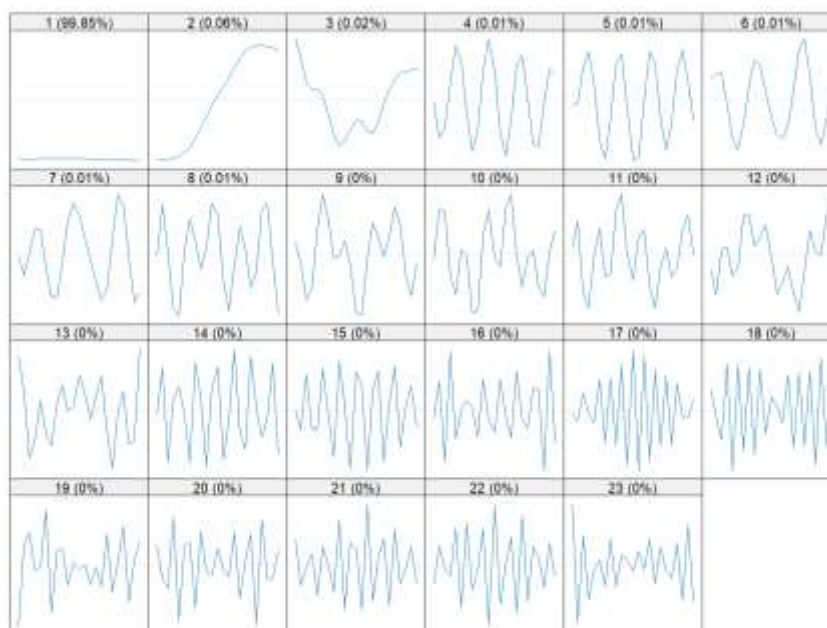


Figure 3: eigenvector graph

Based on Figure 3 by using a window length of 23, the optimal grouping parameter is obtained at $m = 3$. This means that the eigentriple value is grouped into 3 groups. Group 1 is a trend with group members consisting of eigenvalue vector 1, group 2 is seasonal 1.

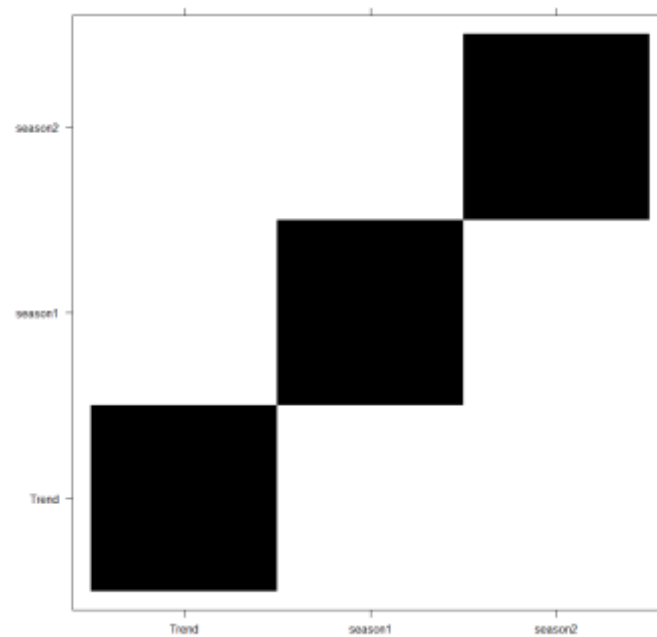
Figure 4: *W-correlation*

Figure 4 is a w-correlation graph used to see the separation between the groups formed. A good grouping is if there is no strong correlation between groups. This can be seen from the color gradations that exist between groups. Based on Figure 4, it can be concluded that the grouping between trend and seasonal has no correlation, as well as the seasonal 1 group with seasonal 2 has no correlation.

3.2.2. Diagonal Averaging

At the beginning of this step, reconstruction is performed on each group obtained in the grouping step. Diagonal averaging is done using equation (4) by summing the average reconstruction results in each group. The reconstruction results are presented in Table 5.

Tabel 5: Reconstruction Results

No	Data	Reconstruction Result			diagonal averaging
		<i>Trend</i>	<i>Seasonal 1</i>	<i>Seasonal 2</i>	
1	2088,93	2086,29	-34,8147	7,7466	2059,23
2	2053,06	2088,52	-8,27068	1,06921	2081,31
3	2178,4	2088,63	39,3334	6,55667	2134,52
⋮	⋮	⋮	⋮	⋮	⋮
48	2240,53	2230,69	13,1256	-4,93997	2238,88

Next perform forecasting from the results of diagonal averaging. The result of diagonal averaging is a new time series with length $N = 48$.

After obtaining the LRF coefficient, then perform forecasting using the forecasting model in Equation (5) as follows:

$$f_i = \begin{cases} \tilde{f}_i & \text{untuk } i = 0, \dots, N - 1 \\ \sum_{j=1}^{L-1} a_j \tilde{f}_{i-j} & \text{untuk } i = N, \dots, N + M - 1 \end{cases}$$

The results of forecasting the exchange rate of Rupiah against Yuan for the next 12 periods in 2023 are presented in Table 7.

Table 7: Forecasting Result in 2023

Month	Result Data Forecasting
Jan-23	2216,46
Feb-23	2221,64
Mar-23	2224,15
Apr-23	2238,23
May-23	2264,47
Jun-23	2289,12
Jul-23	2300,75
Aug-23	2304,09
Sep-23	2314,3
Oct-23	2339,01
Nov-23	2368,66
Dec-23	2385,78
MAPE	2,15%

Table 7 shows that the exchange rate of Rupiah against Yuan in 2023 tends to increase compared to 2022. The total exchange rate in 2023 is Rp27,446.71, while in 2022 the total exchange rate is Rp26,502.23. Visually, the comparison of forecasting data and actual data on the exchange rate of Rupiah against Yuan is shown in Figure 5.

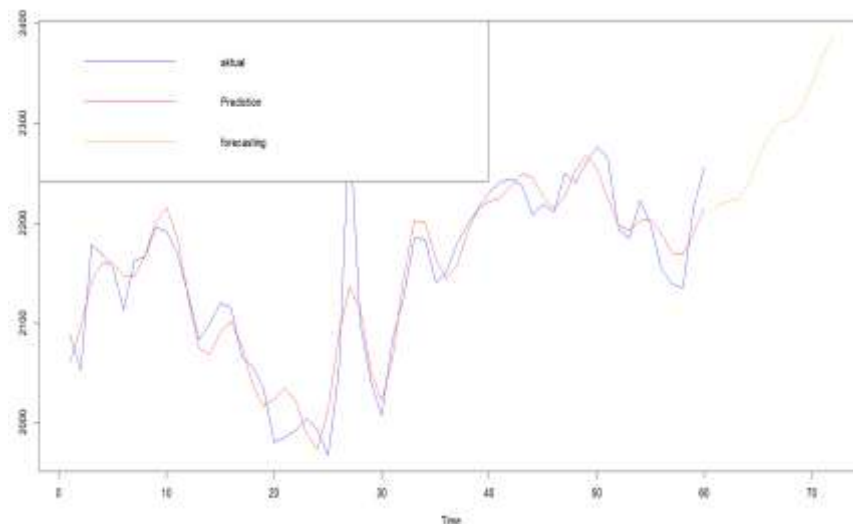


Figure 5. Comparison of Forecasting Result with Actual Data

It can be seen that the plot of forecasting results has similarities with the actual data plot or in other words, the pattern of forecasting results follows the actual data pattern.

3.3 Forecasting Accuracy

Forecasting accuracy can be calculated using Equation (6) and the interpretation of the MAPE value can be seen in Table 1. Based on Table 7, the MAPE value of the results of forecasting the Rupiah exchange rate against Yuan using $L = 23$ is 2.15%, meaning that the SSA method used in forecasting is accurate so that it can be used in forecasting the exchange rate in the next period.

4. Conclusions

The exchange rate of Rupiah against Yuan for 12 periods in 2023 tends to increase compared to the exchange rate of Rupiah against Yuan in 2022. Therefore, it is expected that by using the results of this forecasting the government can take early policies regarding the exchange rate of the Rupiah against the Yuan in the future to maintain stability in future exchange rates. Forecasting the exchange rate using the SSA method with $L = 23$ is accurate with the MAPE obtained of 2.15%. Suggestions that can be given for future research are by adding more data and also being able to apply other SSA methods such as SSA V- forecasting to the Rupiah exchange rate data against Yuan.

References

- Asrof, A. (2017). Peramalan Produksi Cabai Merah di Jawa Barat Menggunakan Metode Singular Spectrum Analysis (SSA). *Statistika: Journal of Theoretical Statistics and Its Applications*, 17(2), 77–87. <https://doi.org/10.29313/jstat.v17i2.2839>
- Kurnia, M. D., Anitasari, M., Pembangunan, J. E., Ekonomi, F., & Bisnis, D. (2021). Pengaruh Neraca Perdagangan Barang dan Jasa pada Nilai Tukar Rupiah

- Terhadap Yuan. *Convergence : The Journal of Economic Development*, 3(2), 159–178.
- Fitri, F., Rahmat, R., & Pengestuti, A. D. (2020). Forecasting of Rainfall in Sumatera Barat: Singular Spectrum Analysis (SSA) Application. *Journal of Physics: Conference Series*, 1554(1). <https://doi.org/10.1088/1742-6596/1554/1/012047>
- Hidayat, K. W., Wahyuningsih, S., & Nasution, Y. N. (2020). Pemodelan Jumlah Titik Panas di Provinsi Kalimantan Timur Dengan Metode Singular Spectrum Analysis. *Jambura Journal of Probability and Statistics*, 1(2), 78–88. <https://doi.org/10.34312/jjps.v1i2.7287>
- Isnawati, S. (2018). Model Hibrida Singular Spectrum Analysis dan Automaticarima Untuk Peramalan Air Terjual Di Pdam Giri Tirta Sari Kabupaten Wonogiri Jawa Tengah. In *Tugas Akhir - Ss141501*.
- Jatmiko, Y. A., Rahayu, R. L., & Darmawan, G. (2017). Perbandingan Keakuratan Hasil Peramalan Produksi Bawang Merah Metode Holt-Winters Dengan Singular Spectrum Analysis (SSA). *Jurnal Matematika "MANTIK,"* 3(1), 13. <https://doi.org/10.15642/mantik.2017.3.1.13-24>
- Negeri, U. I., & Makassar, A. (n.d.). Peramalan Indeks Harga Konsumen (IHK) di Sulawesi Selatan dengan Menggunakan Metode Singular Spectrum Analysis (SSA) Satriani. In *Jurnal Matematika dan Statistika serta Aplikasinya* (Vol. 8, Issue 1).
- Purnama, E. (2022). Aplikasi Metode Singular Spectrum Analysis (Ssa) Pada Peramalan Curah Hujan Di Provinsi Gorontalo. *Jambura Journal Of Probability And Statistics*, 3(2). <https://doi.org/10.34312/jjps.v3i2.16537>