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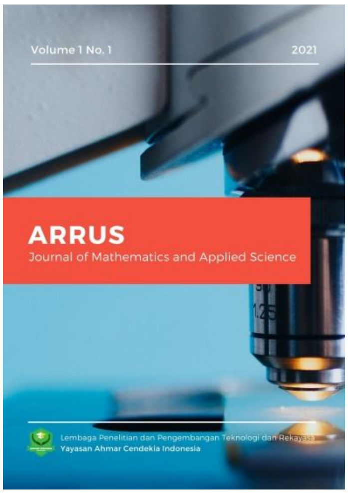

RESEARCH ARTICLE

Comparison of R-Forecasting and V-Forecasting Singular Spectrum Analysis in Forecasting Farmers' Exchange Rates in Indonesia

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Abstract: Indonesia is an agricultural country where one of the main sources of income comes from the agricultural sector. One of the indicators often used to assess farmer welfare is the Farmer Exchange Rate (FER) index. Research on FER forecasting using the Singular Spectrum Analysis (SSA) method has been widely conducted, however, to date, there has been no research comparing the recurrent forecasting and vector forecasting methods in Indonesia. The purpose of this study is to obtain FER forecasting results using r-forecasting and v-forecasting, then compare the forecasting results based on MAPE values to obtain the best forecasting results. The results of the study show that v-forecasting produces better forecasting results with a MAPE value of 0.57%. The forecast results for the next 12 months show an increase and decrease of FER in Indonesia. The highest FER value occurred in May 2022 at 103.79, while the lowest value was in September 2021 at 101.80.

Keywords: SSA, R-forecasting, V-forecasting

1. Introduction

Time series analysis is a series of observational data built sequentially in time (Aswi & Sukarna, 2006). From this analysis, a time series pattern will be obtained, using previous observations to forecast a value in the future. Forecasting is one of the methods in statistics to estimate data in the future with respect to past and present data. Data is collected periodically based on time sequence, either in hours, days, weeks, months or years (Basari & Achmad, 2021).

Forecasting time series data can be done if the time series pattern is known, so that the appropriate forecasting method can be applied (Ukhra, 2014). If a data is disturbed by noise or data that fluctuates to the extreme and then analyzed using a method with a linear data approach, it will show unsatisfactory results. The existence of extreme data in a time series data results in the analysis carried out often being biased, or not reflecting the actual phenomenon (Made et al., 2017). The Singular Spectrum Analysis method is a time series method that can be applied to data that has both linear and nonlinear relationships (Hasanah & Lestari, 2022). SSA is a time series analysis method introduced by Broomhead and King in 1986 (Golyandina et al., 2001). Basically, the SSA method can decompose time series data into time series components namely trend, seasonality, and noise. SSA is a more flexible forecasting method than other forecasting methods because it uses a nonparametric approach so there is no need for assumption tests such as independence and normality of residuals and is suitable for stationary and non-stationary data. There are two forecasting methods in SSA, namely the recurrent method (R-Forecasting) and the vector method (V-Forecasting).

As an agricultural country, the largest proportion of Indonesia's population is in the agricultural sector. According to data from the 2013 Agricultural Census conducted by BPS, the number of agricultural households reached 26.14 million households or 42.7 percent of total national households (BPS, 2013). One of the indicators used to assess the level of farmers' welfare is the Farmers Terms Of Trade (FER) index. FER is the ratio between the index received by farmers (lt) and the price index paid by farmers (lb) (Rachmat, 2013).

Previous research using the SSA method has been conducted by (Lubis et al., 2017) which Farmers Terms Of Trade (FER) index data by comparing the SSA and SARIMA methods. From this research, the SSA method shows a fairly high increase in FER value or high inflation. Research conducted by (Sitohang & Darmawan, 2018) regarding the comparison of the accuracy of recurrent forecasting and vector forecasting on the SSA method in forecasting the number of foreign tourists to Bali. The results in the study found that the vector forecasting method has better forecasting accuracy than the recurrent forecasting method.

2. Literature Review

2.1. *Time Series Analysis*

Time series analysis was introduced by George E. P. Box and Gwilym M. Jenkins in 1970 through his book entitled Time Series Analysis: Forecasting and Control (Aswi & Sukarna, 2006). A time series is a series of observational data that occurs based on a time index in sequence with a fixed time interval. Time series analysis is one of the statistical procedures applied to forecast the probabilistic structure of the situation that will occur in the future in order to make decisions. According to (Aswi & Sukarna, 2006) that a sequence of observations has a time series model if it meets the following two things:

(a). The time interval between time indices t can be expressed in the same (identical) units of time.
(b). There is a dependency between observations Zt and Zt+k which is separated by a time distance in the form of multiples of Δt as many as k times (expressed as lag k).

In determining the forecasting method on time series data, it is necessary to know the pattern of the data so that data forecasting can be done with the appropriate method. Data patterns can be divided into four types, namely seasonal, cyclical, trend, and constant (irregular) patterns (Ukhra, 2014).

2.2. *Singular Spectrum Analysis (SSA)*

Singular Spectrum Analysis has the advantage of excellent forecasting accuracy and can be applied to data that has both linear and nonlinear relationships. In general, Singular Spectrum Analysis consists of two stages, namely: Decomposition and Reconstruction. The basic algorithm of Singular Spectrum Analysis divides the initial time series data into new time series data consisting of trends, seasonal components, and noise. The decomposition stage consists of Embedding and Singular Value Decomposition (SVD) stages, while the reconstruction stage consists of Grouping and Diagonal Averaging stages.

In the embedding stage, the time series data is converted into a trajectory matrix, which transforms one-dimensional data (vector) into multidimensional data (matrix). Suppose the time series data of length N, without missing data is expressed by $X = \{x1,x2,\ldots,xN\}$,, the data is transformed into a matrix of size L×K. L is the window length where $2 < L < N / 2$ (Golyandina & Korobeynikov, 2014), while $K = N - L + 1$. In matrix form it can be written as follows:

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$$\boldsymbol{X} = [X_1, X_2, \dots, X_K] = \begin{bmatrix} x_1 & x_2 & \cdots & x_K \\ x_2 & x_3 & \cdots & x_{K+1} \\ \vdots & \cdots & \ddots & \vdots \\ x_L & x_{L+1} & \cdots & x_N \end{bmatrix}.$$

The second step in decomposition is to make a Singular Value Decomposition (SVD) of the trajectory matrix. Suppose $\lambda_1, \cdots, \lambda_L$ are the eigenvalues of the matrix S where $\mathbf{S} = \mathbf{XX}^{\mathrm{T}}$ with the order according to $\lambda_1 \geq \cdots \geq \lambda_L \geq 0$ and $U_1, \cdots, U_L$ are the eigenvectors of each eigenvalue. The rank of matrix X can be represented by $d = \max\{i, \lambda_1 \geq 0\}$. If denoted $V_1 = \frac{X^T U_i}{\sqrt{\lambda_i}}$ for i=1,⋯,d, then the SVD of the trajectory matrix is as follows:

$$\boldsymbol{X} = X_1 + X_2 + \cdots + X_d$$

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

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

The basic concept at this stage is to obtain a matrix row from matrix S, where each matrix in the row contains an eigentriple consisting of eigenvector U_i, singular value $\sqrt{\lambda_i}$ and principal component V_i^T.

In the reconstruction stage, uses the grouping effect parameter (r). Grouping effect is the second parameter in Singular Spectrum Analysis that plays an important role in determining the pattern on the data plot. After using the L parameter in decomposition, the SVD results will present a series of initial series that have been well separated (Sakinah, 2012). In the reconstruction stage there are two steps that must be taken, namely the Grouping step then continued with the formation of the reconstruction series based on the results obtained in the Diagonal Averaging step.

The next step is grouping. In this step, the grouping of the $L \times K$ trajectory matrix decomposition results will be carried out with the aim of separating the Singular Value Decomposition (SVD) additive components into several subgroups, namely trends, seasonality, and noise (Darmawan, 2016).

After grouping, the next stage will be the transformation of the grouping results into a new series with length N. The purpose of this stage is to get the singular value of the components that have been separated, which will then be used in forecasting (Darmawan, 2016). diagonal average is formulated as follows:

$$g_k = \begin{cases} \frac{1}{k}\sum_{m=1}^{k} f^*_{m,k-m-1} \; for\; 1 \leq k \leq L^* \\ \frac{1}{L^*-1}\sum_{m=1}^{L^*-1} f^*_{m,k-m-1} \; for\; L^* < k \leq K^*+1 \\ \frac{1}{N-k+1}\sum_{m=k-K+1}^{N-K^*+1} f^*_{m,k-m-1} \; for\; K^*+1 < k \leq N \end{cases}$$

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where $L^* = \min(L, K)$ and $K^* = \max(L, K)$. From the above equation if applied to the resultant matrix X_{im}, it will form a new sequence $\tilde{Y}^{(K)} = (\tilde{y}_1^{(k)}, \tilde{y}_2^{(k)}, \cdots, \tilde{y}_N^{(k)})$.. Therefore, the original will be decomposed into a sum of m sequences.

$$y_n = \sum_{k=1}^{m} \tilde{y}_n^{(k)} \quad (n = 1, 2, \cdots, N).$$

2.3. *Forecasting Methods*

There are two forecasting methods in Singular Spectrum Analysis, namely the recurrent method (R-forecasting) and the vector method (V-forecasting). In Singular Spectrum Analysis forecasting, the model is built with the help of Linear Recurrent Formula (LRF). The polynomial form is as follows:

$$x_{i+d} = \sum_{k=1}^{d} r_k \, x_{i+d-k} \; for, 1 \le i \le N - d$$

The first method is R-forecasting. A key property of SSA decomposition is that the original series can satisfy the Linear Recurrent Formula (LRF) equation. The following is the LRF equation:

$$f_n = a_1 f_{n-1} + \cdots + a_d f_{n-d}$$

where a_i is the LRF coefficient with $i = 1,2, \cdots, d$

If the original series f_n satisfies equation 2.7 then the series f_n is the sum of the exponential, polynomial and harmonic components in a short period of time. This causes future forecasting to be done using the same LRF value because the continuation effect is appropriate for a short period of time.

The recurrent forecasting algorithm is as follows (Golyandina & Korobeynikov, 2014):

(1). Time series $Y_{N+M} = (y_1, \cdots, y_{N+M})$ is defined by

$$y_i = \begin{cases} \bar{x}_i \; for \; i = 1, \cdots, N \\ \sum_{J=1}^{L-1} a_j y_{i-j} \; for \; i = N+1, \cdots, N+M \end{cases}$$

(2). The numbers $y_{N+1}, \cdots, y_{N+M}$ will make the term M of the recurrent forecasting.

Recurrent forecasting is performed with Linear Recurrence Relation (LRR) using coefficients $\{a_j, j = 1, \cdots, L-1\}$.

Here is the formula that defines the linear operator $P_{Rec} : R^L R^L$

$$P_{Rec} = \begin{pmatrix} \bar{Z} \\ R^T \bar{Z} \end{pmatrix}$$

where, $\bar{Z}$ consists of the last $L-1$ coordinates of Z, then

$$Y_i = \begin{cases} \tilde{X}_i for\ i = 1, \cdots, K \\ P_{Rec}Y_{i-1} \quad for\ i = K+1, \cdots, K+M \end{cases}$$

matrix $\boldsymbol{Y} = [Y_1 \colon \cdots \colon Y_{K+M}]$ is the trajectory matrix of Y_{N+M}. Therefore, equation (2.9) is considered the vector form of equation (2.7).

The second method is V-forecasting. The vector forecasting method is usually slightly more stable than recurrent forecasting but requires a larger computational process. The vector forecasting algorithm is as follows (Golyandina & Korobeynikov, 2014):

(1). Define the vector Y_i as follows:

$$Y_i = \begin{cases} \hat{X}_i\ for\ i = 1, \cdots, K \\ P_{Vec}Z_{i-1} \quad for\ i = K+1, \cdots, K+M+L-1 \end{cases}$$

(2). By constructing the matrix$\boldsymbol{Y} = [Y_1 \colon \cdots \colon Y_{K+M+L-1}]$ d and making a diagonal average, we get $y_1, \cdots, y_{N+M+L-1}$.

(3). The numbers $y_{N+1}, \cdots, y_{N+M}$ form the M terms of the forecasting vector.

2.4. *Forecasting Accuracy Measurement*

To measure the level of forecasting accuracy, the mean absolute percentage error (MAPE) value is used. MAPE is an error measurement that calculates the percentage deviation between actual data and forecasting data (Krisma et al., 2019).

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

where $\hat{y}_t$ = estimated value, y_t = actual values, and n = number of data.

According to Zhang (2015), a MAPE value of less than 10 percent indicates that forecasting is very accurate (Andhika et al., 2020). The following is given the level of accuracy based on MAPE in Table 1 (Gustriansyah, 2017):

Table 1 MAPE value accuracy

MAPE Value	Prediction Accuracy
MAPE ≤ 10%	High
10% < MAPE ≤ 20%	Good
20% < MAPE ≤ 50%	*Reasonable*
MAPE > 50%	Low

2.5. *Farmer Exchange Rate (FER)*

Farmers Terms Of Trade (FER) is the ratio between the index received by farmers and the index paid by farmers. From the index received by farmers can be seen the development of commodity prices / agricultural products sold by farmers periodically. While the price index paid by farmers can be seen from the development of the price of goods and services consumed by farmers in rural areas as well as the development of the price of goods and

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services needed to produce agricultural commodities/products. FER is a measure of price relations that provides a general indication of the purchasing power of agricultural commodities/products against goods and services currently purchased by farmers both for daily living needs and for production costs and additional capital goods (BPS, 2022)

3. Research Method and Materials [11pt, Garamond, Bold, Justified]

The type of research used is research with a quantitative approach. The quantitative approach is research whose analysis focuses more on numerical data that will be processed using statistical methods, using Singular Spectrum Analysis. The data used in this research is the Farmers Terms Of Trade (FER) data in Indonesia obtained from the publication of the Central Statistics Agency (BPS), which is accessed via the link https://www.bps.go.id/, with a data period of January 2014 to June 2021. The flow chart of this research is shown in Figure 1.

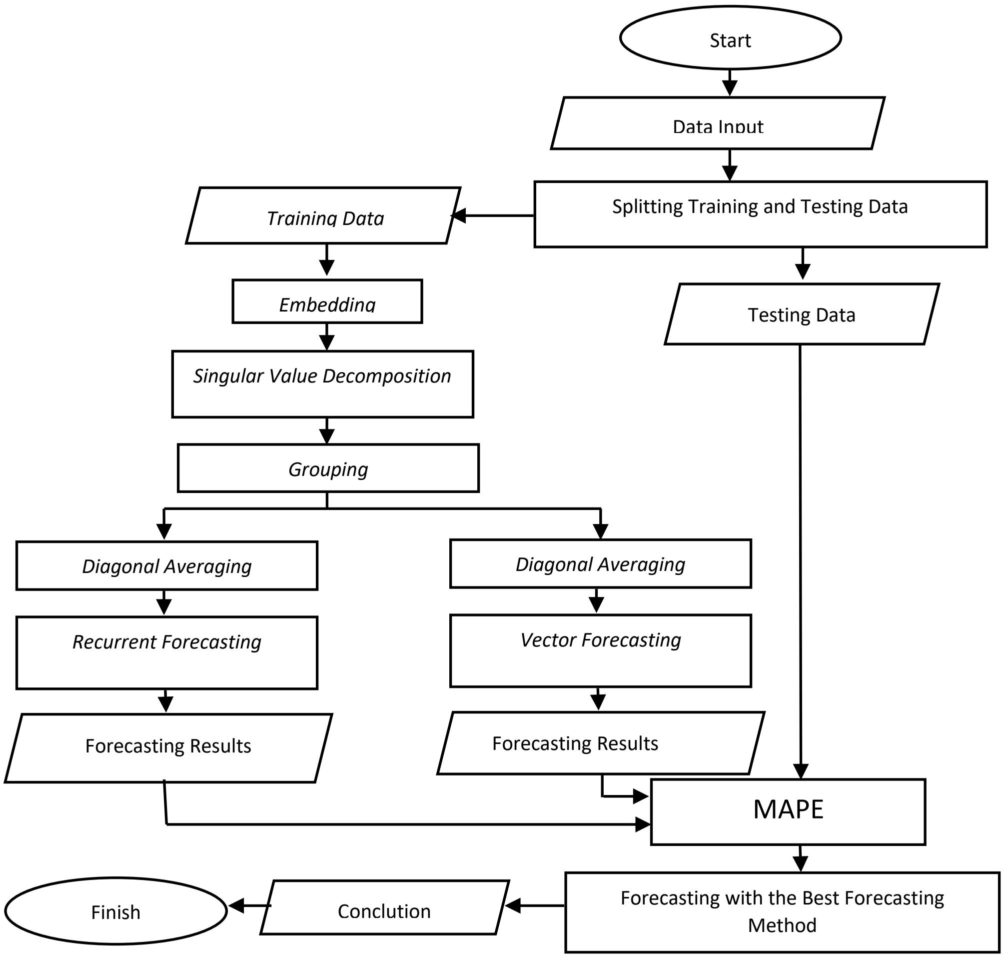

Figure 1 Research Flow Chart

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4. Results and Discussion

4.1. Descriptive Analysis

The following is a graph of the FER data in Indonesia from January 2014 to June 2021.

Figure 2 FER in Indonesia January 2014 – June 2021

From the graph in Figure 2, it can be seen that the FER in Indonesia fluctuates from time to time. In January to May 2020, it experienced a downward trend, this was due to the production price being smaller than the consumption price and production costs.

Table 2 Descriptive Analysis

Variable	Mean	Standard Deviation	Min	Max
FER	102.11	1.106	99.47	104.46

From Table 2, it can be seen that the highest FER in Indonesia occurred in December 2019, amounting to 104.46 and the lowest FER occurred in May 2020, amounting to 99.47.

4.2. SSA Analysis

Before entering the analysis stage with the SSA method, the data is first divided into two parts, so that out of 90 time series data will be divided into two parts, namely 78 as training data for model formation and the last 12 data as testing data in measuring the accuracy of the forecasting model formed.

In the Singular Spectrum Analysis (SSA) method, there are two stages before forecasting, namely the decomposition stage and the reconstruction stage.

4.2.2. Decomposition

In the embedding stage, the trajectory matrix will be generated by first determining the window length (L) value. Determination of the L value is based on the results of trial and error. In this study, the amount of data used was 78 data. So that the L value that meets is $2 < L < 39$.

The value of $L = 34$ is obtained as the best window length based on the smallest MAPE value compared to other window lengths, based on the value of L, the dimension $K = N - L + 1 = 45$. The X trajectory matrix can be arranged as follows:

$$\boldsymbol{X} = (x_{i,j})_{34\times 45} = \begin{bmatrix} 101.95 & 101.79 & \cdots & 102.22 \\ 101.79 & 101.86 & \cdots & 102.78 \\ \vdots & \vdots & \ddots & \vdots \\ 101.71 & 101.31 & \cdots & 99.6 \end{bmatrix}$$

4.2.3. Singular Value Decomposition (SVD)

The initial step at the SVD stage is to form an S matrix by multiplying the trajectory matrix with the transpose of the trajectory matrix itself so that the S matrix is obtained as follows.

$$\boldsymbol{S} = (x_{i,j})_{34\times 34} = \begin{bmatrix} 464058.5 & 464138.0 & \cdots & 466770.0 \\ 464138.0 & 464228.4 & \cdots & 466844.0 \\ \vdots & \vdots & \ddots & \vdots \\ 466770.0 & 466844.0 & \cdots & 469638.3 \end{bmatrix}$$

The next step in the SVD stage is to obtain eigentriple values consisting of singular value, eigenvector, and principal component. The eigentriple values are shown in the following table:

Table 3 *Singular Value*

i	*Eigenvalues*	*Singular Values*
1	15875474.4383	3984.4039
2	339.7201	18.4315
3	247.3982	15.7289
4	212.6813	14.5836
5	147.8510	12.1594
⋮	⋮	⋮
34	0.0649	0.2549

Singular value is obtained from the square root calculation operation of the eigenvalue. Based on Table 3, the singular value for L1 = 3984.4039 is the largest value, meaning that it provides the greatest influence of the time series component on data characteristics. While the singular value of L36 = 0.2549 is the smallest value, which means it gives the least influence on the characteristics of the data.

After getting the singular value, the next step is to get the eigenvector value. The eigenvector values are shown in Table 4.

Table 4 *Eigenvector*

i	U_1	…	U_{34}
1	-0.1709	…	0.0737
2	-0.1709	…	-0.1898
3	-0.1710	…	0.2864
⋮	⋮	⋮	⋮
34	-0.1719	…	0.0482

Based on Table 4, it is found that the eigenvector value is L = 34 starting from U1 with components -0.1709 to 0.0737 and U34 with components -0.1719 to 0.0482. The components of each eigenvector will form a plot in Figure 4.2.

The singular values and eigenvectors obtained are used to calculate the principal component value using the formula $V_1 = \frac{X^T U_i}{\sqrt{\lambda_i}}$.. From the calculation results, the main components are obtained as follows.

Table 5 Principal Component

i	V_1	V_2	…	V_{34}
1	-0.1489	0.1006	…	-0.0304
2	-32.1922	0.2306	…	-0.0082
⋮	⋮	⋮	⋮	⋮
45	-205.3697	-4.7196	…	0.1527

The eigentriple value obtained is used to represent the entire decomposition process that has been carried out. This is based on the value of each component so that it can be used in the grouping stage.

4.2.4. Reconstruction

The first step in the reconstruction stage is to group the eigentriples into trend, seasonal and noise components. To limit the number of eigentriples to be used when identifying trend and seasonal components, the grouping effect (r) is used, which is determined based on the number of eigentriples that do not reflect noise in the singular value plot.

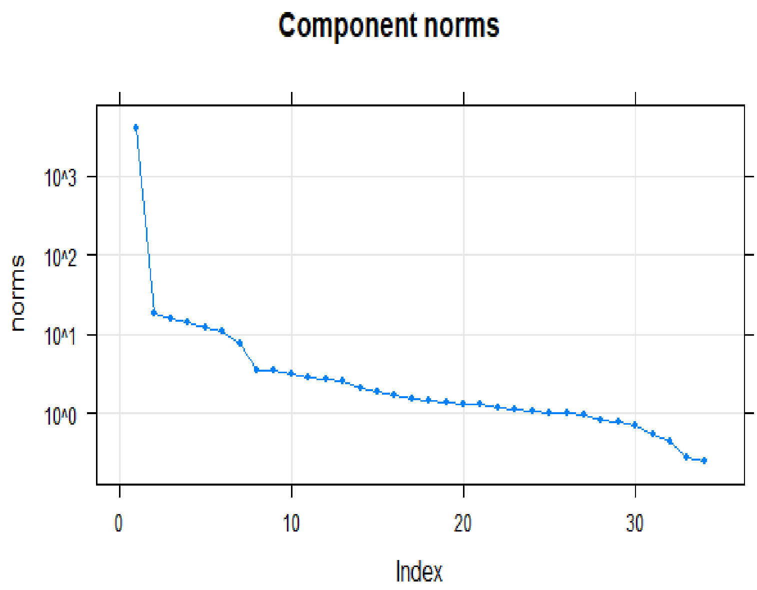

Figure 3 Plot of Singular Value

Figure 3 shows the singular value plot of 34 eigentriples. It can be seen that the singular value starts to decrease slowly from eigentriple 14. This causes eigentriple 14 to eigentriple 34 to be identified as a noise component, so the value of r is 13. Thus, the number of eigentriples that will be used to identify trend and seasonal components is 13 eigentriples. Of the 13 eigentriples, there may be eigentriples that reflect the noise component, this can be known from the remaining eigentriples that are not included in the trend and seasonal components. In identifying eigentriples related to trends and seasonality can use the reconstructed series plot. The reconstructed sequence plot is shown in Figure 4.

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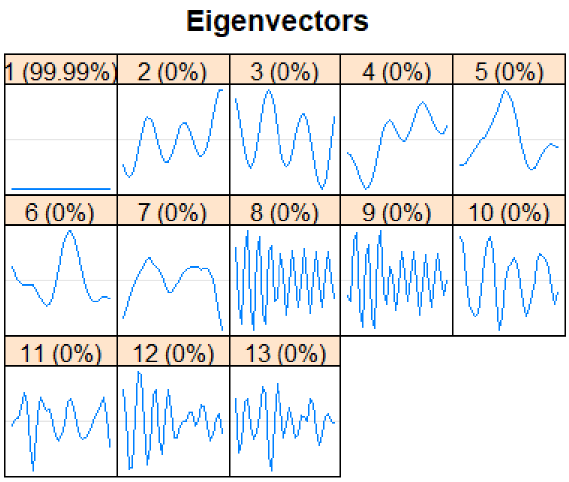

Figure 4 Eigenvector Graph

Figure 4 shows that the series reconstructed by eigentriple 1 contains a slowly varying component. Therefore, eigentriple 1 is identified into the trend component. Furthermore, the grouping of eigentriples into seasonal components is done based on the similarity of consecutive eigentriples. The figure shows several pairs of consecutive eigentriples that have similar patterns, namely eigentriples 2 and 3, and eigentriples 8 and 9.

Table 6 Eigentriple Pairs

Component	Eigentriple
Tren	1
Seasonal 1	2 and 3
Seasonal 2	8 and 9
Noise	4,5,6,7,11,12, and 13

Based on the groups that have been formed, weak separability between groups will be checked to ensure that there is no strong correlation between groups using the w-correlation matrix (separability plot) (Golyandina & Korobeynikov, 2014; Lubis et al., 2017).

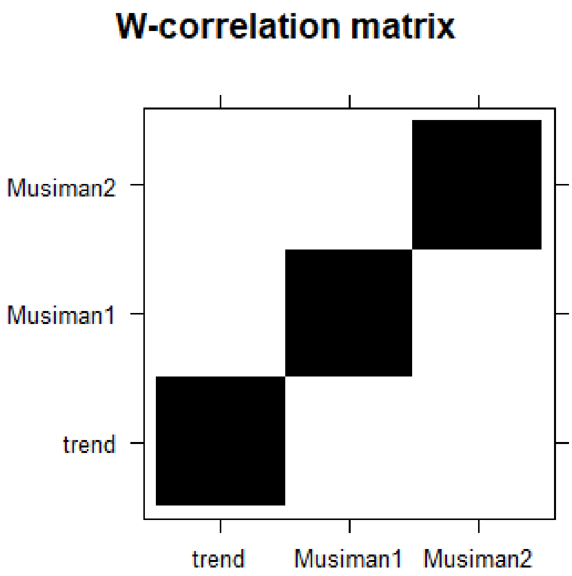

Figure 5 Separability Plot

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Figure 5 shows the separability plot of the trend component (eigentriple 1), seasonal 1 (eigentriple pairs 2 and 3), and seasonal 2 (eigentriple pairs 8 and 9). In the figure, it appears that there is no relationship between the groups as indicated by the absence of colors indicating correlation between the groups.

The next step is diagonal averaging. At this stage, the transformation of the grouping results into a new sequence is performed. Each component is reconstructed using the corresponding eigentriple. In this study, the trend component is reconstructed by eigentriple 1. While the seasonal component is divided into two seasons, for seasonal one is reconstructed by eigentriple 2 and 3, and for seasonal 2 is reconstructed by eigentriple 8 and 9. Diagonal averaging is obtained by calculation using Equation (2.3) and the results are shown in Table 7.

Table 7 *Diagonal Averaging*

Time-	Reconstruction			Diagonal Averaging
	Trend	Seasonal 1	Seasonal 2	
1	101.45	0.62	-0.06	102.01
2	101.45	0.34	0.17	101.98
3	101.46	0.07	0.00	101.55
…	…	...	...	...
78	102.88	-2.16	-0.01	100.69

The next stage is to perform forecasting from a series of models formed through solving the time series data above with recurrent forecasting and vector forecasting methods in SSA.

4.2.5. Forecasting

After all components have been successfully separated, the next step is to perform forecasting on the trend and seasonal components. In this research, forecasting is done with two forecasting methods in the SSA method, namely recurrent forecasting and vector forecasting. The training data used is 78 data, so that forecasting with testing data at interval h = 12, namely $\tilde{X}_{79}, \dots, \tilde{X}_{90}$.

4.2.5.1. Recurrent Forecasting

After obtaining the SSA model for forecasting, the next step is to forecast the testing data based on the model obtained. The overall testing data forecast value is obtained from the sum of the testing data forecast values from the trend component and the seasonal component. Mathematically, the SSA model to obtain the overall testing data forecast value can be written as follows:

$$\hat{Z}t = \hat{Z}_i^T + \hat{Z}_i^S \text{ for } i = 79, \cdots, 90.$$

The results of forecasting testing data for the next twelve months in the recurrent forecasting method are shown in Table 8.

Table 8 R-Forecasting Results against Testing Data

Month	Forecasting			Forecasting Result	Actual Data	Percentage of Error
	Trend	Seasonal 1	Seasonal 2			
July	102.79	-1.187	-0.023	101.58	100.09	0.01497
August	102.82	-0.444	0.028	102.40	100.65	0.01747
September	102.84	0.427	0.020	103.29	101.66	0.01610
October	102.87	1.204	-0.028	104.05	102.25	0.01761
November	102.89	1.684	-0.017	104.56	102.86	0.01658
December	102.92	1.729	0.028	104.68	103.25	0.01387

January	102.94	1.312	0.014	104.27	103.26	0.00983
February	102.97	0.520	-0.028	103.46	103.10	0.00355
March	102.99	-0.454	-0.011	102.53	103.29	0.00733
April	103.02	-1.358	0.028	101.69	102.93	0.01202
May	102.04	-1.944	0.009	101.11	103.39	0.02202
June	103.07	-2.034	-0.027	101.01	103.59	0.02491
MAPE						0.01469

4.2.5.2. Vector Forecasting

After obtaining the SSA model for forecasting, the next step is to forecast the testing data based on the model obtained. Table 9 presents the results of forecasting with the vector forecasting method of testing data for the next twelve months.

Tabel 9 V-Forecasting Results against Testing Data

Month	Forecasting Results	Actual Data	Percentage Error
July	102.33	100.09	0.02239
August	102.22	100.65	0.01557
September	102.22	101.66	0.00547
October	102.27	102.25	0.00019
November	102.42	102.86	0.00425
December	102.71	103.25	0.00524
January	103.03	103.26	0.00220
February	103.28	103.10	0.00179
March	103.46	103.29	0.00166
April	103.58	102.93	0.00634
May	103.59	103.39	0.00195
June	103.44	103.59	0.00143
MAPE			0.00570

4.2.5.3. Comparison of Forecasting Accuracy with MAPE

The accuracy of the forecasting results on the testing data is measured by the MAPE value which is the average percentage error value of several periods. Table 10 presents a comparison of the MAPE values of each forecasting method.

Tabel 10 MAPE Value Comparison

Forecasting Method	MAPE
Recurrent Forecasting	1.46%
Vector Forecasting	0.57%

Based on the results of the analysis using the recurrent forecasting method as shown in Table 10 from the testing data, the MAPE is 0.01469 or 1.46%. While the results of the analysis with the vector forecasting method from the testing data shown in Table 4.6 obtained a MAPE of 0.00570 or 0.57%. From the MAPE results obtained in each of these methods, vector forecasting has a smaller MAPE value, which means that the vector forecasting method is the best method in forecasting the exchange rate of farmers in Indonesia. Therefore, the forecasting of farmers' exchange rate in Indonesia for the next twelve months is done using vector forecasting.

4.2.5.4. Forecasting Using the Best Forecasting Method

The last stage is forecasting using the best forecasting method based on the smallest MAPE value. Forecasting is done to predict the Farmers Terms Of Trade for the next 12 months using vector forecasting. The data used is the overall data which includes training data and testing data, in this study used as much as 90 data. Table 11 presents the results of forecasting for the next twelve months.

Tabel 11 Forecasting Results

Month	Forecasting Result
July 2021	102.28
August 2021	101.97
September 2021	101.80
October 2021	101.82
November 2021	102.01
December 2021	102.35
January 2022	102.78
February 2022	103.21
March 2022	103.56
April 2022	103.77
May 2022	103.79
June 2022	103.62

The visualization of the results of forecasting the exchange rate of farmers in Indonesia is shown in Figure 6.

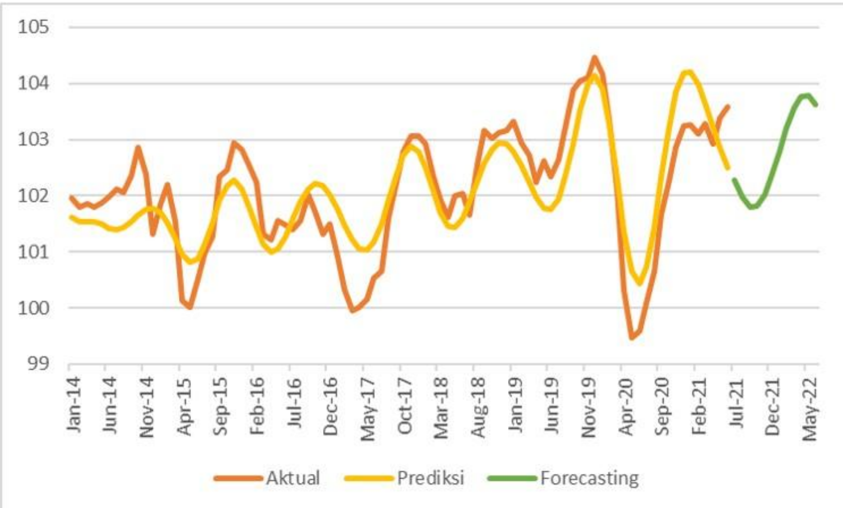

Figure 6 Forecasting Result Chart for Farmers Terms Of Trade in Indonesia

5. Conclusion

Based on the results of the research that has been carried out, forecasting the Farmers Terms Of Tradedata in Indonesia using the singular spectrum analysis (SSA) method has the following conclusions:

(1). Forecasting using the recurrent forecasting method on testing data gets the highest Farmers Terms Of Tradein December 2020, which is 104.68 and the lowest in June

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2021, which is 101.01 with a MAPE value of 1.46%, which means that forecasting has very good accuracy.

(2). Forecasting using the vector forecasting method on testing data gets the highest Farmers Terms Of Tradein May 2021, which is 103.59 and the lowest in September 2020, which is 102.22 with a MAPE value of 0.57%. So it can be said that forecasting the Farmers Terms Of Tradein Indonesia using the vector forecasting method has very good accuracy.

(3). Based on the MAPE value, it is found that the vector forecasting method has better forecasting accuracy than using the recurrent forecasting method. The results of forecasting with the vector forecasting method for the next twelve months show that the Farmers Terms Of Tradein Indonesia tends to increase and has the highest value in May 2022 which is 103.79 but has decreased again in June 2022 to 103.62.

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