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APPLICATION OF SINGULAR SPECTRUM ANALYSIS METHOD IN FORECASTING INDONESIA COMPOSITE DATA

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ABSTRACT

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The wellbeing of the public is a key state objective. To attain this objective, developments are required, including economic development. Economic development can be initiated by enhancing a state's economic growth, as it describes its economic conditions. Forecasting future economic conditions is one of the things that may be done to ensure economic stability. Investment businesses can be utilized as indicators, with the Indonesia Composite Index (ICI) being one of them. Singular Spectrum Analysis (SSA) is one of the available techniques for forecasting. Due to the fact that SSA is non-parametric, no assumptions must be met, resulting in high performance and adaptability. Thus, SSA will be utilized for forecasting ICI. The ICI data utilized is obtained from Yahoo Finance. On the basis of the forecasting result for the closing price of ICI from March 2, 2020, to March 28, 2022, using SSA, which yielded MAPE values of 1.59% for training data and 4.84% for testing data, it can be inferred that this method is accurate. The outcome also revealed that the tendency tends to rise over the next few periods.

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1. INTRODUCTION

The wellbeing of the public is a key state objective. According to Hariwijaya [1], advancements are necessary for the public good. Economic growth is one of the developments that has significant ramifications for public wellbeing. Economic development can be initiated by accelerating economic expansion. A state's economic conditions can be characterized by its economic growth. According to the page of Badan Koordinasi Penanaman Modal, home consumption, the investment business sector, and the sector abroad that performs export and import are the three most influential factors in determining the economic state of Indonesia.

Considering the current state of globalization, the community finds investment to be highly intriguing. According to data from Kustodian Sentral Efek Indonesia (KSEI), the number of investors on the capital market in Indonesia reached 8.62 million at the end of April 2022. Not only did the capital market facilitate the exchange of securities, but it also promoted capital formation and sustained economic expansion [2]. Neither the increase (bullish) nor decrease (bearish) of the capital market can be determined from the movement of the index nor the rise and fall of stock prices.

The Indonesia Composite Index (ICI) maintained by the Indonesia Stock Exchange (IDX) provides a summary of the capital market's activity, growth, and global status. When ICI increases, it may be claimed that the economy is in good condition, but when ICI decreases, it can be argued that the economy is in turmoil or distress [3].

Darmadji and Fakhrudin [4] list seven terms commonly used for stock price monitoring: previous price (closing price of the previous day), opening price (the first price of the day at the start of the trading session), highest price (the highest price of the day), lowest price (the lowest price of the day), last price (the last price that occurred of the day), change (the difference between the opening price and the occurring price), and closing price (the last price of the day at the closing of the trading session). According to Gemilang [5], the closing price is significant because it can be used as a benchmark for the next day's opening price; hence, the closing price is typically utilized to estimate future stock prices. In addition, the government can use forecasting ICI data as one of the pillars and references for determining policies relating to the stability of the financial system and early prediction of economic stability [6].

The ICI data closing price is an example of time series data. According to Dani, Wahyuningsih, and Rizki [7], time series data is a collection of data that is successively based on time with a specified time interval. Forecasting is analysis that is related to time series data. Forecasting can be defined as the correct estimation of future events based on available information, such as historical data and knowledge or systematic scientific approach [8].

There are numerous techniques for forecasting time series data, one of which is Singular Spectrum Analysis (SSA). According to Hidayat, Wahyuningsih, and Nasution [9], SSA is a time series analysis approach with good performance. This method is very flexible because it is a non-parametric method, thus no assumptions must be met. According to Utami et al [10], the SSA approach is a forecasting tool that may be used to decompose time series data into trend, seasonal, and cyclical components, so making it easier to comprehend. With the expansion of science, the SSA approach may now be used to study econometrics and consumer price index data in addition to climate, meteorological, and geophysical information [10].

Basari and Achmad [11] conducted research on forecasting the Consumer Price Index (CPI) for 2019 and obtained a MAPE of 0.24%. Previous research employs the SSA approach. Using the farmer exchange rate in Bali, Andhika, Sumarjaya, and Srinadi [12] conducted research employing the same methodology. The study obtained a modest MAPE of 0.49%. In the same year, Shafira, Utami, and Arum [13] also conducted research in which they predicted the amount of tourists visiting Bali and acquired a MAPE of 10.79%. In 2019, Utami et al [10] conducted study using the same methodology and termed it Peramalan Beban Listrik Daerah Istimewa Yogyakarta Dengan Metode Singular Spectrum Analysis. The study utilized monthly electrical load data from 2008 to 2018 to calculate a MAPE of 1.90%. Because Indonesia is still in the midst of a pandemic, researchers are interested in future economic conditions during a pandemic. This is what distinguishes it from prior study.

On the basis of the argument presented, researchers are interested in SSA-based research on anticipating the closing price of ICI data. The consequence of this research undertaken by researchers is a level of accuracy and the ability to predict future results using the SSA approach.

2. RESEARCH METHODS

The researcher utilizes secondary data retrieved from Yahoo Finance. The study was conducted utilizing daily historical data for ICI's closing price between March 2, 2020 and March 28, 2022. The research structure utilized to perform this study is depicted in the flowchart appended to Figure 1.

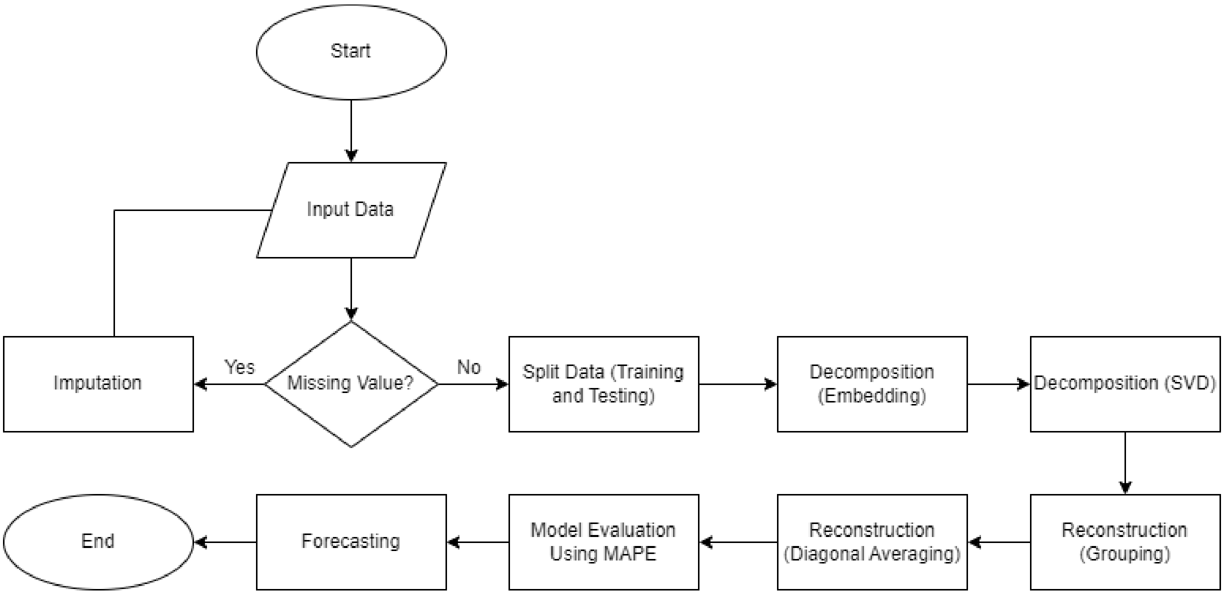

Figure 1. Flowchart of Research

2.1 Forecasting

Forecasting can be defined as the correct estimation of future events based on available information, such as historical data and knowledge or a systematic scientific approach [8]. Forecasting is the estimation of upcoming events. If there are sufficient time series data and the forecasting method chosen is appropriate or produces a small error value and a high accuracy value, a good forecasting result can be attained [14].

According to Saputro and Asri [15], forecasting is classified into two categories based on the arrangement of forecast data types. First, qualitative forecasting, which is based on qualitative data typically derived from the outcomes of investigations, opinions, or surveys. The forecasting findings depend on the researcher because they are dependent on the researcher's opinion, intuition, experience, and expertise. Second, quantitative forecasting, which is based on historical quantitative data. The outcomes rely on the method chosen by the researcher for forecasting.

In addition to the types of forecast data which are arranged, forecasting is also divided into three types based on the time horizon: short term forecasting, which covers a period of time less than three months; medium term forecasting, which has coverage forecasting period of approximately three to eighteen months; and long term forecasting, which covers a longer period of time than short and medium term forecasting, which is greater than eighteen months [16].

2.2 Singular Spectrum Analysis (SSA)

According to Hidayat, Wahyuningsih, and Nasution [9], SSA is a time series analysis approach with good performance, and this method is very flexible because it is a non-parametric method, thus no assumptions must be met. According to Utami et al [10], the SSA approach is a forecasting tool that may be used to decompose time series data into trend, seasonal, and cyclical components, making interpretation considerably simpler. The SSA approach is commonly applied to climate, meteorological, and geophysical data, but with the advancement of research, it may also be used to evaluate economic and consumer price index data [10].

SSA is a data forecasting technique that combines classical principles of time series analysis, multivariate statistics, multivariate geometry, dynamic system, and signal processing in order to deconstruct time series data into small, interpretable components [17]. Two steps comprise the SSA forecasting method: decomposition and reconstruction. Each of these processes consists of two distinct steps. Two phases comprise decomposition: embedding and Singular Value Decomposition (SVD). Reconstruction method consisting on grouping and diagonal averaging. An excerpt from Anita Kaimuddin's research on the SSA analysis procedure is presented as theory [17].

2.2.1 Decomposition

The first step in the SSA approach is decomposition. The two steps of decomposition are embedding and SVD. Embedding step is carried out to convert one dimensional data into multidimensional data. This phase then generates a trajectory matrix, also referred to as a Hankel matrix. The SVD phase follows the embedding phase. This phase consists of operations performed to separate components with distinct properties.

1. Embedding

Embedding is the initial phase of decomposition process. This phase is carried out to convert one dimensional data into multidimensional data or trajectory matrix X [18]. Process of changing the dimensions of time series data with N period length also does not contain missing values and vector x_i with $i = 1,2,\dots,N$ this will produce X trajectory matrix. This matrix also known as hankel matrix. This matrix with $L \times K$ dimensions has the same values on the anti diagonal elements. The values of L or also known as windows length shows the number of rows of trajectory matrix. There is not any yet theory that explains the determination for value of L, so that the determination of the value of L is done by trial and error, but L value must be in the range $2 < L < \frac{N}{2}$ with assuming the value of L must be large but should not exceed $\frac{N}{2}$. The value of K shows the number of columns of trajectory matrix. This value is obtained from the calculation $K = N - L + 1$. The following is a form of trajectory matrix or hankel matrix where the anti diagonal elements has the same value [19].

$$X = (x_i)_{L\times K} = \begin{bmatrix} x_1 & x_2 & x_3 & \cdots & x_K \\ x_2 & x_3 & x_4 & \cdots & x_{K+1} \\ x_3 & x_4 & x_5 & \cdots & x_{K+2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & x_{L+2} & \cdots & x_N \end{bmatrix} \quad (1)$$

2. Singular Value Decomposition (SVD)

Singular Value Decomposition (SVD) phase is continuation of embedding phase. This phase contains steps that are carried out to separate components with different characteristics. The separation components process was done based on eigentriple. According to Kaimuddin [17], SVD begins with forming S matrix that obtained from multiplication of matrices XX^T. This multiplication matrices obtained S matrix with $L \times L$ dimensions. After obtaining S matrix, conducted determination of eigenvalues λ_i for $i = 1,2,\dots L$, then conducted calculation of singular values which is the positive root value of eigenvalues. Eigenvalues from S matrix then sorted from the largest to the smallest, so that $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L \geq 0$. Then determine the eigenvector $U_i = U_1, U_2, \dots, U_L$ from S matrix. After obtaining eigenvector, then determine V_i which $V_i = \frac{X^T U_i}{\sqrt{\lambda_i}}$ for $i = 1,2,\dots,L$ and V_i is the principal component of S matrix. These processes then produce singular values ($\sqrt{\lambda_i}$), eigenvectors (U_i), and principal components (V_i) which is called an eigentriple [9].

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2.2.2 Reconstruction

Reconstruction process is done to reconstruct the existing data into a new time series data. Reconstruction process divided into two phases, grouping and diagonal averaging. Grouping phase is process to grouping the data components into several groups. This phase conducted based on the characteristics of each component. After grouping phase, then proceed with diagonal averaging phase, which canges the results of grouping that has been done into time series data with size of N.

1. Grouping

Grouping phase is process to separate components with different characteristics. The grouping is conducted to separate the components that have been obtained in the previous phase, SVD, into several sub groups consisting of trends, seasonality, and noise. This phase is done by grouping index sets $i = \{1,2, \dots L\}$ into m disjoint subset $I_1, I_2, \dots, I_L$. This process is carried out by trial and error. The determination of members of each group is done by using a graph, if there are components that have the same pattern, it can be interpreted that the characteristics of these components are almost the same. According to Ete [20], there are two ways that can be used to grouping components, which is

a). View one dimensional graph of reconstructed series to be able to identify both trend and seasonal components. Components that have slow variation on the graph are included in trend group, meanwhile if there is pattern and same seasonal period, the components are combined into seasonal group.
b). Checking the graph of singular values. If the sequence decreases slowly and slopingly, it usually related to noise component of the existing data.

The main concept that contained in SSA method is separability. This concept indicates how well components with different characteristics can be separated from each other. Decomposition process of time series data is successful only if the additive components of the sequence can be separated from each other. The measurement of success can be seen from W-correlation plot. The plot can be used to describe how strong correlation between groups is. The higher correlation value, the color displayed on W-correlation plot will be darker, if the color that shown on W-correlation plot is light, the correlation value is small [12].

According to Kaimuddin [17], the smaller correlation value between two components or grouups (correlation value approach zero), two components can be separated. W-correlation value can be obtained using the following **Equation (2)**.

$$\rho_{12}{}^{(w)} = \frac{\left(Y_N{}^{(i)}.Y_N{}^{(j)}\right)_w}{\sqrt{\left(Y_N{}^{(i)}.Y_N{}^{(i)}\right)_w \left(Y_N{}^{(j)}.Y_N{}^{(j)}\right)_w}} \tag{2}$$

with

$$\left(Y_N{}^{(i)}.Y_N{}^{(j)}\right)_w = \sum_{p=1}^{N} w_p^{L,N} . y_p{}^{(i)} . y_p{}^{(j)} \tag{3}$$

and

$$w_p^{L,N} = \frac{N+1}{2} - \frac{\left|\frac{N+1}{2} - L\right|}{2} - \frac{\left|\frac{N+1}{2} - p\right|}{2} - \frac{\left|\left|\frac{N+1}{2} - L\right| - \left|\frac{N+1}{2} - p\right|\right|}{2} \tag{4}$$

2. Diagonal Averaging

According to Anita Kaimuddin [17], the last process of SSA analysis is diagonal averaging, which is changing the grouping results into a new time series with N length. Suppose Y is matrix with $L \times K$ dimension with y_{lk} elements for $1 \le l \le L$ and $1 \le k \le K$ which $L \le K$, the quantity of Y matrix that formed will be equal to the number of the groups that have been determined at grouping phase. The values of y_{lk} obtained from singular value $(\sqrt{\lambda_i})$ multiplied by the product of U_i and V_i, so that

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_K \\ y_{21} & y_{22} & \cdots & y_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_L & y_{L+1} & \cdots & y_N \end{bmatrix} \tag{5}$$

The Y matrix in **Equation (5)** then converted into $g_1, g_2, \dots, g_N$ sequences, through diagonal averaging phase using the following **Equation (6)**

$$g_k = \frac{\sum_{(l,k)\in A_S} y_{lk}}{|A_S|} \tag{6}$$

with $|A_S|$ states the number of members of the set A_S for $A_S = \{(l,k): l + k = s, 1 \le l \le L, 1 \le k \le K\}$ and $i + j = s$ [21].

Based on **Equation (6)**, suppose Y matrix for $k = 1$ give $g_1 = y_{11}$, for $k = 2$ give $g_2 = \frac{y_{1,2}+y_{2,1}}{2}$, $g_3 = \frac{y_{1,3}+y_{2,2}+y_{3,1}}{3}$, and so on **[18]**. According to Basari & Achmad **[11]**, reconstruction data $(\widehat{x_i})$ obtained from the sum of diagonal averaging values for each component of the group that has been formed.

2.3 Linear Reccurent Formula (LRF)

According to Asrof et al **[18]** SSA forecasting method using Linear Recurrent Formula (LRF) also known as R-forecasting. Time series that used in the forecasting is a results from reconstruction process which is obtained from diagonal averaging phase then determined M new data points that will be predicted. The following is forecasting model used

$$g_i = \begin{cases} \widehat{x_i}, & for\ i = 1,2,\dots,N \\ \sum_{j=1}^{L-1} a_j g_{i-j}, & for\ i = N+1,\dots,N+M \end{cases} \tag{7}$$

R-forecasting related to LRF estimate $a_1, a_2, \dots, a_{L-1}$ using eigenvector which is the result of SVD phase. Suppose $U = (U_1, U_2, \dots, U_{L-1}, U_L), U^{\bar{v}} = (U_1, U_2, \dots, U_{L-1})$ and π_q is the last component of eigenvector U or can be written with $\pi_q = U_L$ so the coefficient of LRF can be calculated by using equation (8).

$$\Re = (a_{L-1}, a_{L-2}, \dots, a_1)^T = \frac{1}{1-v^2} \sum_{q=1}^{r} \pi_q U^{\bar{v}} \tag{8}$$

with

$$v^2 = \sum_{q=1}^{r} \pi_q^{\ 2}.$$

2.4 Forecasting Ability

Forecasting data analysis contains the chance of error or mistake. According to Heizer and Render **[22]**, the forecast error is often calculated using a variety of metrics. Mean Absolute Percentage Error (MAPE) is one metric of error employed by researchers in this study. MAPE is the calculation of the difference between actual data and predicted or fitted value. The absolute value of the difference between the actual data and the fitted value is then utilized to calculate the percentage. The average value of these percentage results is then determined. The MAPE value may be determined using the following formula:

$$MAPE = \frac{1}{N} \sum_{t=1}^{N} \frac{|x_i - \hat{x}_i|}{x_i} \times 100\% \tag{9}$$

According to Nurvianti et al **[23]**, a model's performance is exceptional if the MAPE value is below 10%. On the basis of the MAPE value generated from a method, the forecasting performance of a method can be classified into multiple categories. The categories listed in **Table 1 [23]**.

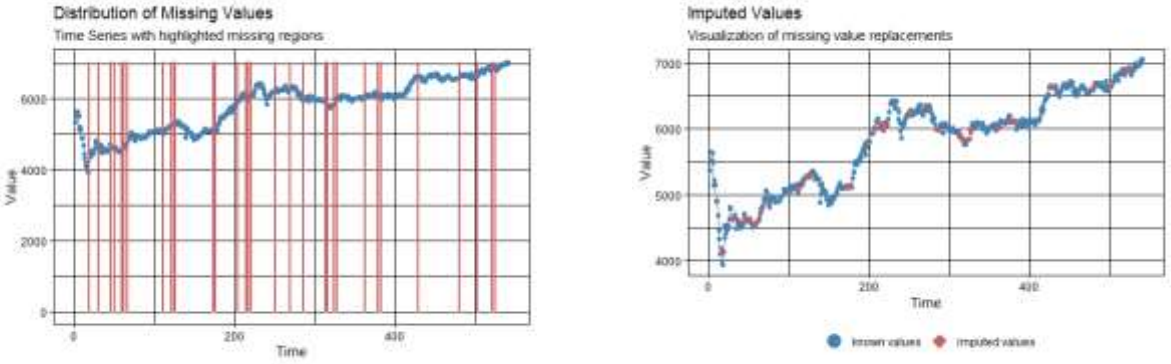
Table 1. Categories of Forecasting Ability

Range of MAPE	Category
$MAPE \leq 10\%$	Forecasting ability is very good
$10\% < MAPE \leq 20\%$	Forecasting ability is good
$20\% < MAPE \leq 50\%$	Forecasting ability is quite good
$MAPE > 50\%$	Forecasting ability is bad

3. RESULTS AND DISCUSSION

3.1 Descriptive Analysis

Researcher first checked there was a missing value or not in the data used. This process conducted because if there is missing value, imputation process is needed to complete the data so it does not affect the process and result of analysis. Based in **Figure 2(a)** it is known that there are missing values in daily data of ICI closing price which is indicated by red line. Then the researcher carried out imputation process to fill missing data. Imputation results can be seen in **Figure 2(b)**.



(a) (b)

Figure 2. Check Missing Value and Imputation Result

Researcher conducted descriptive analysis on ICI closing price daily data which had been imputed. The results of descriptive analysis are obtained in **Table 2**.

Table 2. Descriptive Statistics

	ICI
Min	3.937,63
Max	7.049,69
Median	6.035,54
Mean	5.826,21
St. Dev	721,69

Researcher displays the ICI closing price plot to find out the pattern of the data used. Based on **Figure 3**. it can be seen that the data shows an upward trend pattern and there was a drastic decline in early March 2020 due to COVID-19 pandemic.

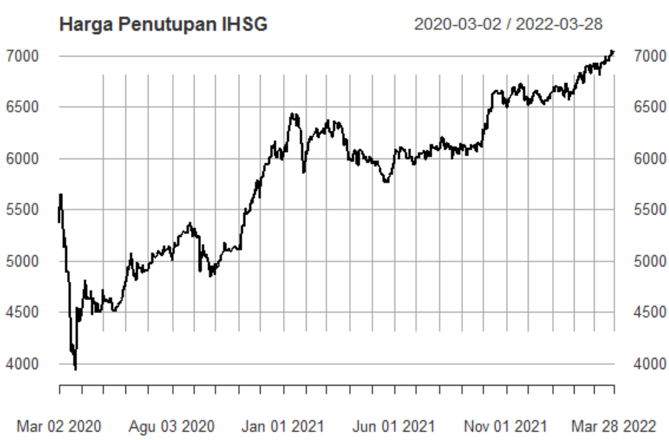


Figure 3. ICI closing price plot data

3.2 Split Dataset

The next process is split the dataset into training and testing data. The distribution of training and testing data is carried out with percentage of 80% : 20%. The amount of training data is 433 and testing data is 108.

3.3 Decomposition

3.3.1 Embedding

The embedding process begins with determining $\boldsymbol{L}$ first. This research using $\boldsymbol{L} = \mathbf{150}$ and the value of $\boldsymbol{K}$ which is obtained by formula $\boldsymbol{K} = \boldsymbol{N} - \boldsymbol{L} + \mathbf{1}$, so $\boldsymbol{K} = \mathbf{284}$. Based on **Equation (1)**, this process caried out to produce trajectory matrix as follows

$$X = (x_i)_{150\times 284} = \begin{bmatrix} 5.361,25 & 5.518,63 & 5.650,14 & \dots & 6.011,46 \\ 5.518,63 & 5.650,14 & 5.638,13 & \dots & 5.990,87 \\ 5.650,14 & 5.638,13 & 5.498,54 & \dots & 5.970,29 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 4.917,96 & 4.842,76 & 4.945,79 & \dots & 6.625,70 \\ 4.842,76 & 4.945,79 & 4.906,55 & \dots & 6.656,94 \\ 4.945,79 & 4.906,55 & 4.879,10 & \dots & 6.602,21 \end{bmatrix}$$

3.3.2 Singular Value Decomposition

The next phase in SVD is find the eigentriple of trajectory matrix that has been obtained. The first step is form $\boldsymbol{S}$ matrix with $\boldsymbol{L} \times \boldsymbol{L}$ dimensions as follows

$$S = \begin{bmatrix} 8225572784 & 8228313773 & \dots & 9107912575 \\ 8228313773 & 8232720360 & \dots & 9112474638 \\ 8229949290 & 8234494265 & \dots & 9116112357 \\ \vdots & \vdots & \ddots & \vdots \\ 9089906164 & 9094401890 & \dots & 10169751414 \\ 9098884861 & 9103420648 & \dots & 10180198547 \\ 9107912575 & 9112474638 & \dots & 10190670315 \end{bmatrix}$$

The next process is looking for the components that make up SVD, it consisting of eigenvector $(\boldsymbol{U_i})$, singular value $(\sqrt{\boldsymbol{\lambda_i}})$, and principal component $(\boldsymbol{V_i})$ that called eigentriples. The following is attached eigenvalue in **Table 3(a)** and singular value in **Table 3(b)**. The greater eigenvalue and singular value, the greater effect of time series component.

Table 3. Eigenvalue and Singular Value

(a)

No	Eigenvalue (λ_i)
1	$1,377990 \times 10^{12}$
2	$1,673319 \times 10^{9}$
3	$7,758692 \times 10^{8}$
⋮	⋮
148	$4,229763 \times 10^{4}$
149	$3,010157 \times 10^{4}$
150	$2,870334 \times 10^{4}$

(b)

No	Singular Value $(\sqrt{\lambda_i})$
1	1.173.878,19
2	40.906,22
3	27.854,43
⋮	⋮
148	205,66
149	173,50
150	169,42

Then compiling the eigenvector value $(\boldsymbol{U_i})$ that obtained from $\boldsymbol{S}$ matrix. The following is attached eigenvector in **Table 4**.

Table 4. Eigenvector

No	U_1	U_2	...	U_{150}
1	-0,07706	-0,08735	...	1,08822 x 10^{-2}
2	-0,07710	-0,08956	...	-2,82415 x 10^{-2}
3	-0,07713	-0,09175	...	4,02306 x 10^{-2}
⋮	⋮	⋮	⋱	⋮
148	-0,08568	0,08752	...	-0,04021
149	-0,08577	0,08650	...	0,03357
150	-0,08585	0,08550	...	-0,01533

The next step is calculate principal component (V_i) that obtained from calculation $V_i = \frac{X^T U_i}{\sqrt{\lambda_i}}$. The following is attached eigenvector in Table 5.

Table 5. Principal Component

No	V_1	V_2	...	V_{150}
1	-0,05109	0,02263	…	-0,02017
2	-0,05105	0,02406	…	0,02161
3	-0,05101	0,02568	…	-0,01952
⋮	⋮	⋮	⋱	⋮
282	-0,06355	-0,01943	…	0,05880
283	-0,06360	-0,01794	…	-0,03723
284	-0,06363	-0,01674	…	0,01949

After obtaining the components of eigentriple, then researcher proceed to the next process, namely reconstruction.

3.4 Reconstruction

3.4.1 Grouping

Reconstruction process begins with grouping phase based on the results of SVD phase that have been obtained. According to Andhika, Sumarjaya, and Srinadi [12], grouping effects (r) is an important parameter besides L. This parameter used to limit the number of components that will be used in grouping phase. The determination of r value can be seen from singular values plot which does not reflect noise component. Based on Fig. 4. it can be seen that after the 23rd component, the singular value plot shows there is slow decline, so the researcher used r value of 23, while the 24th to 150th components were considered as noise.

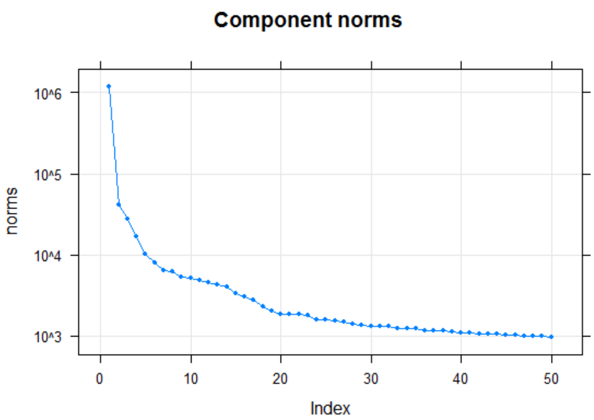


Figure 4. Singular Value Plot

Then the grouping phase is carried out by looking at the eigenvector of 1st to 23rd components as shown in **Figure 5**. Then after going through several trial and error, the best grouping results are obtained as in **Table 6**.

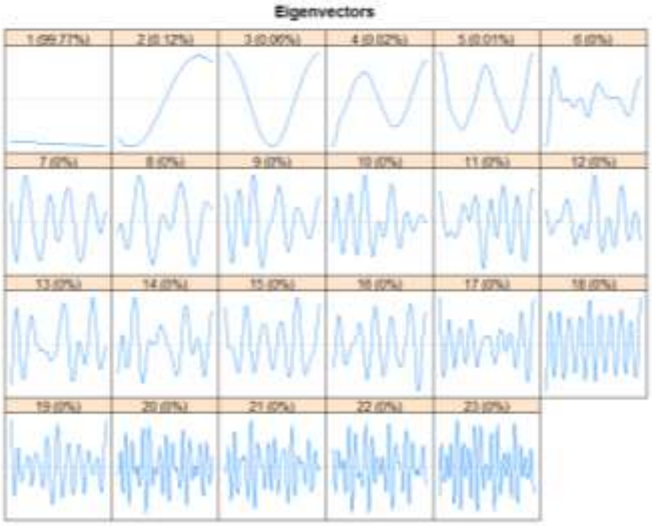


Figure 5. **Eigenvector Plot**

Table 6. **Grouping Results**

Group	Component	Pattern
1	1	Trend
2	2, 3, 4	Trend
3	13, 14, 15	Seasonal

The researcher then checked W-correlation values and plot with the results as shown in **Table 7** and **Figure 6**. Based on these results, it can be seen that each group only has strong correlation with itself and has no correlation with other groups.

Table 7. **W-correlation Values**

	G1	G2	G3
G1	1,0000	0,0108	0,0001
G2	0,0108	1,0000	0,0105
G3	0,0001	0,0105	1,0000

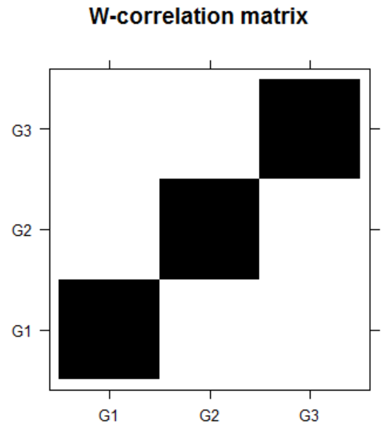


Figure 6. **Eigenvector Plot**

3.4.2 Diagonal Averaging

The last phase in SSA is diagonal averaging. This phase transforms the grouping results into new one dimensional data with N length. Reconstruction data is obtained from the sum of diagonal averaging results. The following is attached in Table 7 the diagonal averaging results that obtained.

Table 7. Diagonal Averaging Results

No.	Actual Data	Diagonal Averaging			Reconstruction
		G1	G2	G3	
1	5.361,25	4.620,74	298,02	-106,66	4.812,10
2	5.518,63	4.620,58	276,50	-66,45	4.830,64
3	5.650,14	4.619,89	250,18	-30,67	4.839,40
⋮	⋮	⋮	⋮	⋮	⋮
431	6.625,70	6.402,30	65,57	4,41	6.472,28
432	6.656,94	6.407,56	74,64	-8,62	6.473,58
433	6.602,21	6.412,88	82,08	-22,55	6.472,41

3.4 Forecasting Ability

Forecasting ability or accuracy is calculated by comparing actual data with fitted value or predicted data. Researcher used MAPE value as a measurement of SSA method ability in forecasting. The following attached in Table 8 and Table 9 the MAPE results of training and testing data. Based on the calculation results, the MAPE values for training and testing data less than 10%, so SSA method has a very good ability in forecasting ICI closing price data.

Table 8. MAPE values of training data

No.	Actual Data	Reconstruction	Error
1	5.361,25	4.812,10	0,1141
2	5.518,63	4.830,64	0,1424
3	5.650,14	4.839,40	0,1675
⋮	⋮	⋮	⋮
432	6.656,94	6.473,58	0,0283
433	6.602,21	6.472,41	0,0201
Average			0,0159
MAPE			1,59%

Table 9. MAPE values of testing

No.	Actual Data	Prediction	Error
1	6.524,08	6.625,21	0,0153
2	6.591,35	6.631,17	0,0060
3	6.552,89	6.637,70	0,0128
⋮	⋮	⋮	⋮
106	7.049,69	6.651,48	0,0599
107	7.002,53	6.645,56	0,0537
108	7.049,60	6.638,51	0,0620
Average			0,0484

No.	Actual Data	Prediction	Error
	MAPE		4,84%

3.4 Forecasting

The next step is performs daily data of ICI closing price forecasting for next several periods using all the data (training and testing) to make forecast. Forecasting is conducted using $L = 150$ and $r = 3$. The LRF coefficient or denoted by α_j is used to form forecasting model. The amount of LRF coefficients is $L - 1$, so in this research there will be 149 LRF coefficients. The following is equation of forecasting model.

$$g_i = -0{,}0056 g_{i-1} - 0{,}0067 g_{i-2} + \cdots + 0{,}0908 g_{i-149}$$

Based on the forecasting model, the forecast results are obtained as in Table 10.

Table 10. Forecasting Results

Data	Forecast	Data	Forecast
542	7.052,53	557	7.123,74
543	7.063,34	558	7.125,69
544	7.073,36	559	7.128,33
545	7.082,50	560	7.131,75
546	7.090,64	561	7.136,00
547	7.097,73	562	7.141,10
548	7.103,71	563	7.146,82
549	7.108,60	564	7.153,14
550	7.112,45	565	7.159,80
551	7.115,36	566	7.166,56
552	7.117,49	567	7.173,15
553	7.119,02	568	7.179,29
554	7.120,18	569	7.184,73
555	7.121,20	570	7.189,23
556	7.122,31	571	7.192,63

Attached to Figure 7, the plot of actual data, reconstruction or prediction data, and forecast results. Based on Figure 7, it can be seen that the overall pattern of reconstructed data almost resembles with actual data pattern. In addition, it can be seen that the forecast data shows an upward trend.

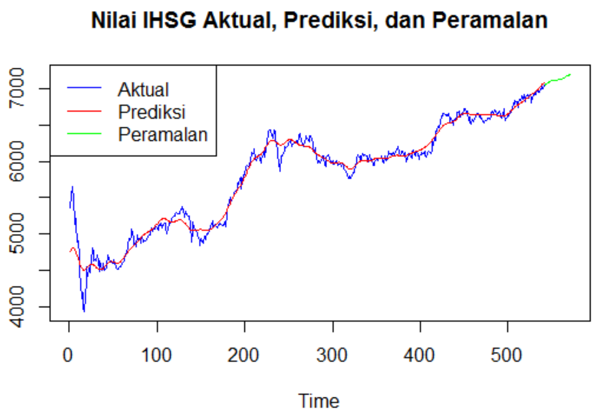


Figure 7. Eigenvector Plot

4. CONCLUSIONS

Following are some concluding remarks from the investigation based on the research conducted. The daily closing price data for ICI from March 2, 2020 to March 28, 2022 was quite variable, and there was a significant fall in March 2020. The findings of daily data of ICI closing price forecasts using the SSA approach indicated an upward tendency for the following several periods. The application of the SSA approach to daily data of ICI's closing price for the period 2 March 2020 to 28 March 2022 is deemed excellent because the MAPE value for training and testing data is less than 10%.

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