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Forecasting The Number Of Tourist Arrivals To Batam Using The Singular Spectrum Analysis And Arima Methods

1st Agustinus Angelaus Ete
Department of Mathematics and Science Education
IKIP Muhammadiyah Maumere
Maumere, Indonesia
agustinus_angelaus@ikipmumaumere.ac.id

2nd Meita Fitrianawati
Faculty of Teaching Training and Education
Universitas Ahmad Dahlan
Yogyakarta, Indonesia
meita.fitrianawati@pgsd.uad.ac.id

3rd Muhammad Taufik Arifin
Department of Humanities and Social Sciences Education
IKIP Muhammadiyah Maumere
Maumere, Indonesia
taufik_arifin@ikipmumaumere.ac.id

***Abstract*— Singular Spectrum Analysis (SSA) is a time series method used to decompose the original time series into a sum of a small number of components that can be interpreted such as trends, oscillatory components, and noise. The purpose of this study is to compare the accuracy of the forecast between the SSA and ARIMA methods to obtain the best method in predicting the number of foreign tourist arrivals to Indonesia. The data used in this study is data on the number of arrival of foreign tourists to Indonesia through the Batam entrance. The forecasting results obtained using the SSA method will be compared with the ARIMA method to assess its superiority. The level of forecasting accuracy generated by each method is measured by the criteria of Mean Absolute Percentage Error (MAPE). The results of the study show that the ARIMA method produces better forecast accuracy than the SSA method for forecasting the number of tourist arrivals through the Batam's entrance. The MAPE value obtained from the results of forecasting using the ARIMA method is 9.83. The MAPE value obtained from the results of forecasting using the SSA method is 10.98.**

Keywords*— *Singular Spectrum Analysis, Trend, Oscillatory, Noise, ARIMA

I. Introduction

Forecasting is a technique for estimating future values by looking at past and current data. SSA is one of the time series analysis techniques used to decompose the original time series into a small number of components that can be interpreted as trends, oscillatory components, and noise. SSA was first applied to extract trend and harmonic components in the time series of meteorology and geophysics as in [1]. In recent years SSA has been applied to many problems. Reference [2] use SSA for feature extraction in hyperspectral imaging (HSI), leading to increased accuracy in pixel-based classification tasks. Reference [3] use SSA for forecasting U.S. trade before, during and after the 2008 recession. The SSA algorithm consists of two main stages, i.e. the decomposition and reconstruction stages as in [4]. In the decomposition stage, two main steps must be taken to obtain eigentriples, i.e. embedding and singular value decomposition. The parameter that has an important role in the decomposition stage is window length (L). During the reconstruction phase, two steps must be taken to obtain the reconstructed series, i.e. grouping and diagonal averaging. The parameter that has an important role in the reconstruction phase is effect grouping (r). The SSA method has two forecasting algorithms that can be used to obtain forecast values, i.e. repeat forecasting algorithms and vector forecasting algorithms. Vector forecasting has a greater computational cost than repeat forecasting as in [5]. Reference [6] predicted the number of US tourist arrivals using the optimal SSA, ARIMA, exponential smoothing, and Neural Network. Reference [6] use the SSA vector forecasting algorithm to obtain forecast values from US tourist arrivals. In this study, the SSA method will be used to predict the number of foreign tourist arrivals per month to Indonesia according to Batam's entrance. Batam City in Riau Islands Province is one of the cities with the fastest growth potential in Indonesia. The location of Batam City is adjacent to Singapore so that Batam City is made as one of the main destinations for business, tourism, and trade. The people of Batam City are heterogeneous societies consisting of various tribes and groups. The dominant tribes include Malay, Java, Batak, Minangkabau, and Chinese. At the forecasting stage, SSA's repeated forecasting algorithm is used to obtain forecast values. The SSA method will be compared with the ARIMA method to assess its superiority. The ARIMA method consists of four models, i.e. Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA). The SSA and ARIMA methods can be used to predict series containing seasonal components..

II. Singular Spectrum Analysis

Singular Spectrum Analysis (SSA) is a nonparametric time series analysis technique used for forecasting. SSA aims at decomposing the original series into a sum of a small number of interpretable components such as a slowly varying trend, oscillatory components and a structureless noise as in [7]. The SSA method consists of two complementary stages, i.e. the decomposition and reconstruction stages. In the decomposition stage, two main steps must be taken to obtain eigentriples, i.e. embedding and singular value decomposition. The parameter used in the decomposition stage is the window length (*L*). The value of *L* must be close to producing better separability between the components of the series as in [8]. During the reconstruction phase, two steps must be taken to obtain the reconstructed series, i.e. grouping and diagonal averaging. The parameter used in the reconstruction phase, i.e. effect grouping (*r*).

A. Embedding

Consider an original time series, $F = (f_0, \ldots, f_{N-1})$ with length *N*. Assume that $N > 2$ and *F* is a nonzero time series where there is at least one I so that $f_i \neq 0.$ In embedding step, one-dimensional series is described as a multidimensional series. The embedding procedure produces $K = N - L + 1$ lagged vectors as in [9]

$$\mathbf{X}_\mathbf{i} = (f_{i-1}, \ldots, f_{i+L-2})^T, \tag{1}$$

where $1 \le i \le K$ and $1 < L < N.$ The trajectory matrix of the series *F* described as in [10]

$$\mathbf{X} = [\mathbf{X}_1 : \ldots : \mathbf{X}_K]. \tag{2}$$

B. Singular Value Decomposition

The Singular Value Decomposition (SVD) of the trajectory matrix $\mathbf{X}$ can be written as in [11]

$$\mathbf{X} = \mathbf{X}_1 + \ldots + \mathbf{X}_d, \tag{3}$$

where $\mathbf{X}_i = \sqrt{\lambda_i}\mathbf{U}_i\mathbf{V}_i^T$ for $i = 1, \ldots, d$. $d = \max\{i : \lambda_i > 0\}$ is the rank of the matrix $\mathbf{X}$. $\mathbf{U}_i$ are the eigenvectors of the matrix $\mathbf{X}\mathbf{X}^T$. $\mathbf{V}_i = \mathbf{X}^T\mathbf{U}_i / \sqrt{\lambda_i}$ are the principal components. λ_i are the eigenvalues of $\mathbf{X}\mathbf{X}^T$. The collection $(\sqrt{\lambda_i}, \mathbf{U}_i, \mathbf{V}_i)$ is called *i*-th eigentriple of the matrix $\mathbf{X}$ as in [12].

C. Grouping

At the grouping stage, the set of indices $\{1, \ldots, d\}$ to be partitioned into *m* disjoint subsets, $I_1, \ldots, I_m$. The resultant matrix $\mathbf{X}_I$ is defined as $\mathbf{X}_I = \mathbf{X}_{i_1} + \ldots + \mathbf{X}_{i_p}$. These are computed for $I = I_1, \ldots, I_m$ and leads to the decomposition $\mathbf{X} = \mathbf{X}_{I_1} + \ldots + \mathbf{X}_{I_m}$ as in [13].

D. Diagonal Averaging

Define $\mathbf{Y}$ be a $L \times K$ matrix with elements y_{ij}, $1 \le i \le L,$ $1 \le j \le K.$ Define $L^* = \min(L, K),$ $K^* = \max(L, K),$ $y^*_{ij} = y_{ij}$ if $L < K,$ and $y^*_{ij} = y_{ji}$ if $L > K.$ The element g_k as a result of the diagonal averaging of $\mathbf{Y}$ is given by [9]

$$g_k \begin{cases} \dfrac{1}{k+1}\displaystyle\sum_{m=1}^{k+1} y^*_{m,k-m+2} & \text{for } 0 \le k < L^* - 1, \\ \dfrac{1}{L^*}\displaystyle\sum_{m=1}^{L^*} y^*_{m,k-m+2} & \text{for } L^* - 1 \le k < K^*, \\ \dfrac{1}{N-k}\displaystyle\sum_{m=k-K^*+2}^{N-K^*+1} y^*_{m,k-m+2} & \text{for } K^* \le k < N. \end{cases} \tag{4}$$

If diagonal averaging is applied a resultant matrix $\mathbf{X}_{I_k}$, then the reconstructed series will be obtained. The reconstructed series can be written with the notation $\tilde{F}^{(k)} = \left(\tilde{f}_0^{(k)}, \ldots, \tilde{f}_{N-1}^{(k)}\right),$ where $f_n = \sum_{k=1}^{m} \tilde{f}_n^{(k)},$ for $n = 0, 1, \ldots, N-1$ as in [9].

E. Singular Spectrum Analysis Forecasting

In the SSA method, there are two forecasting algorithms that can be used to obtain forecast values from each component, i.e. repeat forecasting algorithm and vector forecasting algorithm. Repeated forecasting algorithms can be formulated as in [9]

1. The time series $F_{N+M} = (f_0, \ldots, f_{N+M-1})$ is defined by

$$f_i = \begin{cases} \tilde{f}_i & \text{for } i = 0, \ldots, N-1, \\ \sum_{j=1}^{L-1} a_j f_{i-j} & \text{for } i = N, \ldots, N+M-1, \end{cases} \tag{5}$$

where the vector of coefficients $\mathbf{A} = (a_1, \ldots, a_{L-1})$ can be expressed as $\mathbf{A} = \frac{1}{1-v^2} \sum_{i=1}^{r} \pi_i \mathbf{U}_i^{\nabla}$. For an eigenvector $\mathbf{U} \in \mathbb{R}^L$, the vector of the first $L-1$ components of the vector $\mathbf{U}$ can be expressed as $\mathbf{U}^{\nabla} \in \mathbb{R}^{L-1}$. Define $v^2 = \pi_1^2 + \ldots + \pi_r^2 < 1$, where π_i is the last component of the eigenvector $\mathbf{U}_i$, for $i = 1, \ldots, r$.

2. The numbers $f_N, \ldots, f_{N+M-1}$ form the *M* terms of the recurrent forecast.

III. ARIMA METHOD

The ARIMA method can be used to predict data that has nonseasonal and seasonal patterns. The ARIMA model $(P, D, Q)^s$ for the seasonal data pattern is formulated as in [14]

$$\Phi(B^m)\phi(B)(1-B^m)^D (1-B)^d y_t^* = c + \Theta(B^m)\theta(B)a_t. \tag{6}$$

ARIMA models can be used for short-run estimation based on annual, quarterly, monthly or even weekly, daily or hourly data as in [15]. If a good ARIMA model is obtained more than one model, then the best model can be determined using in-sample criteria and out-sample criteria. If the best model selection is based on out-sample criteria, then the criterion that can be used is the *Mean Absolute Percentage Error* (MAPE) as in [16]

$$MAPE = \left(\frac{1}{M} \sum_{l=1}^{M} \left(Z_{n+l} - \hat{Z}_n(l) \right)^2 \right) 100\%. \tag{7}$$

The best model has the smallest MAPE value.

IV. RESEARCH METHODOLOGY

The data used in this study is data about the number of foreign tourist arrivals per month according to Batam's entrance in the period January 1996 until December 2017. Data obtained from [17]. Data is divided into two parts, i.e. in-sample data and out-sample data. Data about the number of tourist arrivals in the period January 1996 to December 2016 was used as in-sample data. While data about the number of tourist arrivals in the period January 2017 to December 2017 was used as out-sample data. The variables used in this study is defined as follows

$Y_{1,t}$ = *The number of foreign tourist arrivals per month through Batam's entrance*,

The forecasting stage using the SSA method is explained as follows:

1. Embedding.
2. SVD.
3. Grouping.
4. Diagonal Averaging.
5. Forecasting out-sample data.
6. Calculate the MAPE value of out-sample data.

The forecasting stage using the ARIMA method is explained as follows

1. Create a time series chart to detect stationarity of data. If data are not stationary on its variance, then data need to be transformed. The type of transformation used is the Box-Cox transformation. If data are not stationary on mean, then data need to be done differencing operations.

2. If data have been stationary, then the ARIMA model can be identified based on ACF and PACF pattern.
3. Test the significance of the parameters.
4. Test the assumption of normality and white noise on the residual.
5. Forecasting out-sample data.
6. Calculate the MAPE value of out-sample data.

V. Results

The general description of foreign tourist arrivals through the Batam's entrance can be explained using descriptive statistics and boxplot. Based on data about the number of foreign tourist arrivals per month according to the Batam's entrance in the period from January 1996 until December 2017, it is known that the average number of foreign tourist arrivals through Batam's entrance reaches 100652 with a standard deviation of 20182. The minimum number of foreign tourist arrivals through Batam's entrance reaches 64421 people. The maximum number of foreign tourist arrivals through Batam's entrance reaches 192796 people.

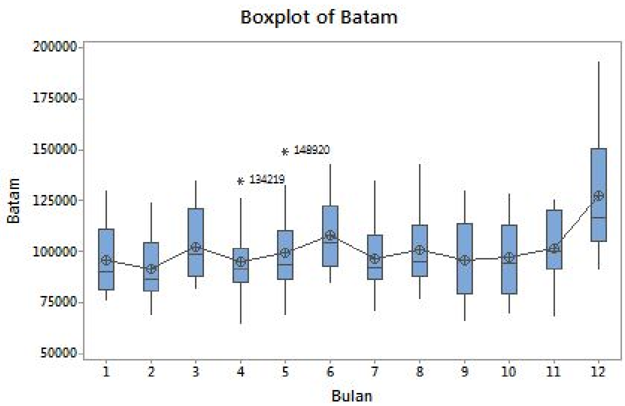


Fig. 1. The Boxplot of the Number of Foreign Tourist Arrivals through Batam's Entrance.

Based on Fig. 1, it is known that data about the number of foreign tourist arrivals through the Batam Entrance contain outliers identified as observation data in May 2015 and April 2017. In May 2015, there was an increase in the number of foreign tourist arrivals through the Batam's entrance due to the application of visa-free by the government in a number of countries. In April 2017, there was a significant increase in the number of foreign tourist arrivals compared to the same period in 2016. Expansion of marketing of Indonesian tourist destinations is also expected to continue to be carried out by the government to attract foreign tourist arrivals from other countries.

A. Forecasting Using The SSA Method

In the SSA method, there are two stages used to separate the trend components, seasonality components, and noise components from the initial time series, i.e. the decomposition and reconstruction stages. Window length (L) is the parameter used in the decomposition stage. The value of the window length (L) parameter taken is 96. In the decomposition stage, the trajectory matrix $\mathbf{X}$ is decomposed into 50 eigentriples, which consists of 50 eigenvalues, 50 eigenvectors, and 0 vectors factor. The reconstruction phase is used to obtain the trend components, seasonality components, and noise components from eigentriples produced in the decomposition stage. Effect grouping (r) is a single parameter at the grouping stage. Effect grouping (r) is used to limit the number of eigentriples that will be used to identify trend components and seasonality components. The value of the effect grouping (r) parameter is determined based on the number of eigentriples that do not reflect noise in the plot of singular value. The sequence of singular values that decreases slowly in the plot of singular value reflects the noise components.

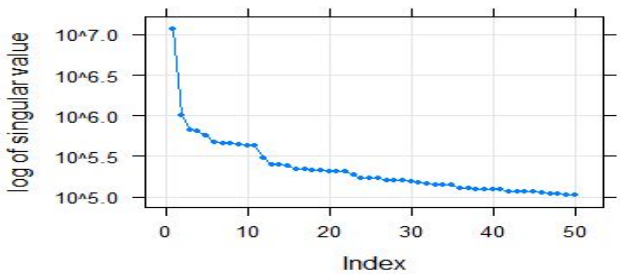


Fig. 2. The Plot of 50 Singular Values on Case Number of Foreign Tourist Arrivals through Batam's Entrance.

Based on Fig. 2, it is known that the parameter value of effect grouping (r) for Batam's entrance is 11. The 12th eigentriple to the 50th eigentriple was identified as a noise component because singular values began to decline slowly in 12th eigentriple to the 50th eigentriple. Although eigentriples that reflect the noise component has been identified, it is possible that the number of eigentriples that reflect the noise component can increase. The rest of the eigentriples that are not related to the trend component and the seasonality component of the r eigentriple will be grouped into noise groups. The next step is to group eigentriples related to trend component and seasonality component. The plot of the reconstructed series can be used to identify eigentriples that are related to the trend component and seasonality component. In the plots of the reconstructed series, all the components that very slowly are identified as trend component as in [18]. Grouping of eigentriples related to seasonality component is carried out based on the similarity of singular values from two sequential eigentriples. The similarity of singular values from two successive eigentriples result in the series reconstructed by each eigentriple having the same seasonal pattern and the same seasonal period. Two eigentriples that have similar singular values can be grouped into seasonality groups if the seasonal periods of the series reconstructed by the two eigentriples are 12 months, 6 months, 4 months, 3 months, 2.4 months, and 2 months as in [19]. Fig. 3 shows the number of reconstructed series based on the value of the effect grouping parameter obtained at the Batam's entrance.

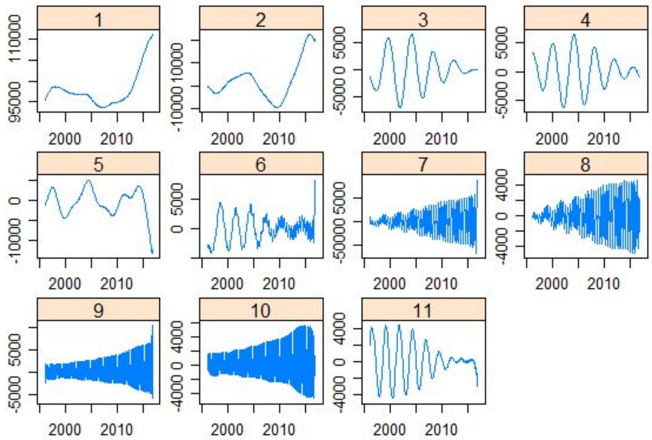


Fig. 3. The plot of the Reconstructed Series on the Case of Number of Foreign Tourist Arrivals through Batam's Entrance.

Based on Fig. 3, it is known that the reconstructed series by 1st eigentriple, 2th eigentriple, and 5th eigentriple contain components that very slowly so that the three eigentriples are grouped into trend groups. According to Fig. 3, it is known that the 9th eigentriple has a singular value similarity with the 10th eigentriple because the series reconstructed by the 9th eigentriple has the same seasonal pattern as the reconstructed series by 10th eigentriple. The reconstructed series by 9th eigentriple has the same seasonal period as the reconstructed series by 10th eigentriple, which is 3 months. Thus the 9th eigentriple and 10th eigentriple are grouped into seasonality groups. The 3rd eigentriple, 4th eigentriple, 6th eigentriple, 7th eigentriple, 8th eigentriple, and 11th eigentriple are grouped into noise groups.

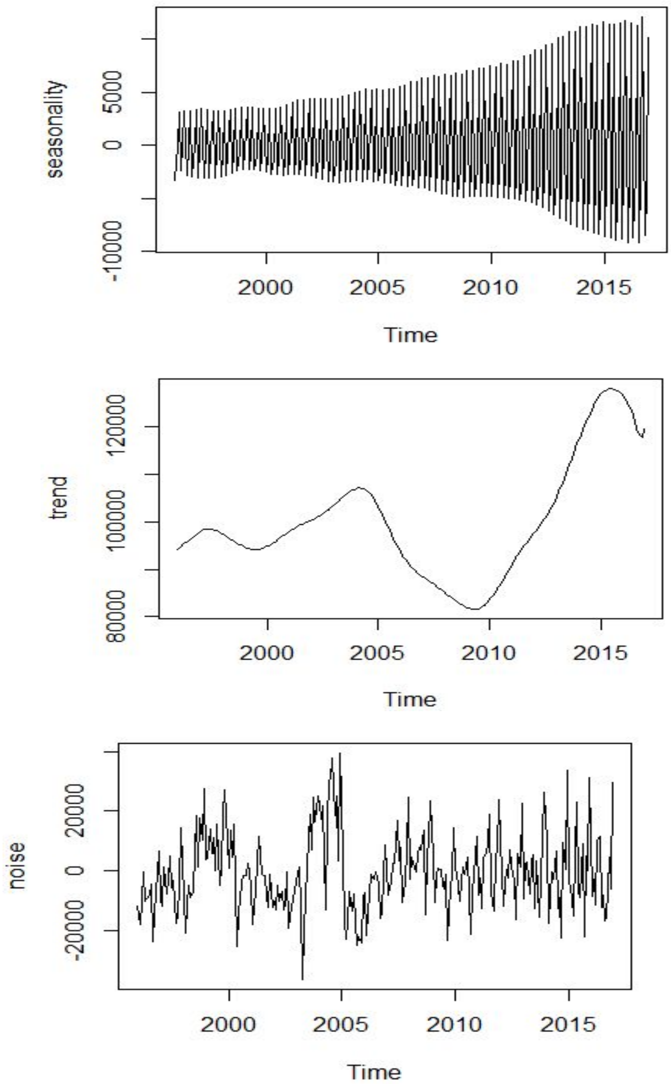


Fig. 4. Tourist Series and Reconstructed Components on Cases Number of Foreign Tourist Arrivals Through Batam's Entrance

When the trend, seasonality, and noise components are successfully separated, the next step is to make predictions on each component except the noise component. The forecast values generated by the SSA model of each component consists of forecast values for in-sample data and forecast values for out-sample data. The SSA model used in forecasting trend components can be written as follows

1. Model for in-sample data

   - SSA generates a reconstructed trend, i.e. $\tilde{y}_0^T, \tilde{y}_1^T, \ldots, \tilde{y}_{251}^T$.

- $\hat{y}_i^T = \tilde{y}_i^T$, for $i = 0,1,2,...,94$.
- $\hat{y}_i^T = 0.07\tilde{y}_{i-1}^T + 0.07\tilde{y}_{i-2}^T + ... + 0.01\tilde{y}_{i-95}^T$, for $i = 95,96,97,...,251$.

2. Model for out-sample data
   - SSA generates a reconstructed trend, i.e. $\tilde{y}_0^T, \tilde{y}_1^T, \ldots, \tilde{y}_{251}^T$.
   - $\hat{y}_{251+k}^T = 0.07\check{y}_{251+k-1}^T + 0.07\check{y}_{251+k-2}^T + ... + 0.01\check{y}_{251+k-95}^T$, where

$$\check{y}_{251+k-j}^T = \begin{cases} \tilde{y}_{251+k-j}^T, & \text{for } j \geq k \\ \hat{y}_{251+k-j}^T, & \text{for } j < k \end{cases}$$

The SSA model used in forecasting seasonal components can be written as follows

1. Model for in-sample data
   - SSA generates a reconstructed seasonal, i.e. $\tilde{y}_0^S, \tilde{y}_1^S, \tilde{y}_2^S, \ldots, \tilde{y}_{251}^S$.
   - $\hat{y}_i^S = \tilde{y}_i^S$, for $i = 0,1,2,...,94$.
   - $\hat{y}_i^S = -0.02\tilde{y}_{i-1}^S - 0.02\tilde{y}_{i-2}^S + ... - 0.01\tilde{y}_{i-95}^S$, for $95,96,97,\ldots,251$.

2. Model for out-sample data
   - SSA generates a reconstructed seasonal, i.e. $\tilde{y}_0^S, \tilde{y}_1^S, \tilde{y}_2^S, \ldots, \tilde{y}_{251}^S$.
   - $\hat{y}_{251+k}^S = -0.02\check{y}_{251+k-1}^S - 0.02\check{y}_{251+k-2}^S + ... - 0.01\check{y}_{251+k-95}^S$, where

$$\check{y}_{251+k-j}^S = \begin{cases} \tilde{y}_{251+k-j}^S, & \text{for } j \geq k \\ \hat{y}_{251+k-j}^S, & \text{for } j < k \end{cases}$$

The SSA model used to obtain forecast values for in-sample data and out-sample data as a whole can be written as follows

1. In-sample data

$$\hat{y}_i = \hat{y}_i^T + \hat{y}_i^S, \text{ for } i = 0,1,2,\ldots,251.$$

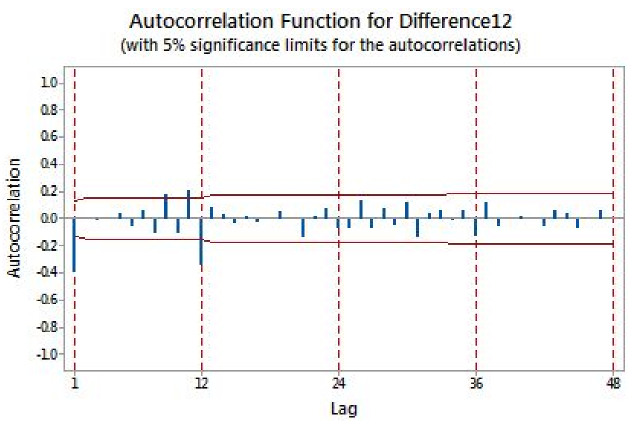
2. Out-sample data

$$\hat{y}_{251+k} = \hat{y}_{251+k}^T + \hat{y}_{251+k}^S, \text{ for } k = 1,2,\ldots,12.$$

The result of forecasting the number of foreign tourist arrivals using the SSA model is shown in Fig. 5.

B. Forecasting Using ARIMA Method

The Box-Jenkins procedure for obtaining the best ARIMA model consists of four stages, i.e. model identification, parameter estimation, diagnostic check, and application of models for forecasting as in [20]. The first step in the identification stage is checking the stationary data in variance and the stationery data in mean. Based on the Box-Cox plot of data about the number of foreign tourist arrivals through Batam's entrance, it is known that the estimated value obtained for λ is -0.65. The data has not been stationary in variance because the confidence interval of the estimated value for λ does not contain the value 1 so data need to be transformed. In-sample data are also not stationary in mean because autocorrelation value is close to one and tends to fall slowly. Because autocorrelation value on nonseasonal lag tends to fall slowly, then the first nonseasonal difference operation $(d=1)$ needs to be done on data that has been transformed. The results of the first nonseasonal difference operation on data that has been transformed show that autocorrelation value on seasonal lag tends to fall slowly. Therefore, the first seasonal difference operation $(D=1)$ needs to be done on data that has been transformed. Fig. 5 shows ACF and PACF diagrams of data after the first seasonal difference operation.



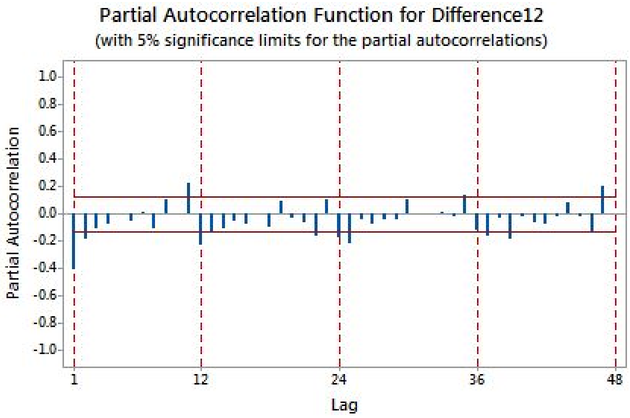


Fig. 5. ACF and PACF Diagrams of Data After The First Seasonal Difference Operation.

Based on the results of identification of significant lags in the ACF and PACF diagrams, the best ARIMA model was obtained, i.e. ARIMA $(0,1,1)(1,1,1)^{12}$.

VI. Comparison of Forecasting Results SSA and ARIMA Methods

After the SSA and ARIMA models used for forecasting have been obtained, the next step is to predict the in-sample data and out-sample data based on the model obtained. The accuracy of forecast results on in-sample data and out-sample data is measured by MAPE value. If the MAPE value in the in-sample data is smaller, then the model is better used for forecasting. If the MAPE value in the out-sample data is smaller, then the result of the prediction obtained from the model is more accurate. The MAPE value obtained from forecasting in-sample data using the SSA model is 11.17%. The MAPE value obtained from forecasting in-sample data using the ARIMA model is 8.47%. Thus the ARIMA model is better if used for forecasting compared to the SSA model. In forecasting out-sample data, the MAPE value obtained using the SSA model is 10.98%. The MAPE value obtained using the ARIMA model for forecasting out-sample data is 9.83%. The accuracy of the forecast obtained in the out-sample data using the ARIMA model is better than the accuracy of the forecast obtained in the out-sample data using the SSA model. ARIMA method provides better forecast results than the SSA method. Comparison of the results of out-sample data forecasting using the SSA model and the ARIMA model can be seen in Fig. 6.

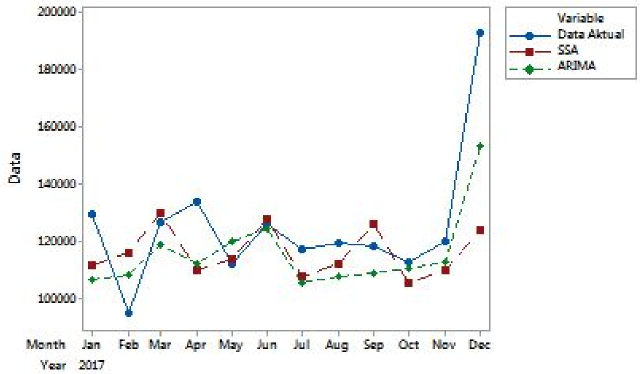


Fig. 6. Comparison of The Results of Out-Sample Data Forecasting Using The SSA Model and The ARIMA Model.

VII. Conclusions

The conclusion that can be obtained based on the research conducted is the ARIMA method produces better forecast accuracy than the SSA method for forecasting the number of tourist arrivals through the Batam's entrance. In forecasting out-sample data, the MAPE value obtained using the SSA model is 10.98%. The MAPE value obtained using the ARIMA model for forecasting out-sample data is 9.83%. The result of forecasting on out-sample data using ARIMA method is closer to actual data when compared with SSA method.

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References

[1] H. Hassani, S. Heravi, and A. Zhigljavsky, "Forecasting European industrial production with singular spectrum analysis," International Journal of Forecasting, vol. 25, pp. 103-118, 2009.

[2] J. Zabalza, J. Ren, Z. Wang, H. Zhao, J. Wang, and S. Marshall, "Fast implementation of singular spectrum analysis for effective feature extraction in hyperspectral imaging," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 8, pp. 2845-2853, 2015.

[3] E. S. Silva and H. Hassani, "On the use of singular spectrum analysis for forecasting U.S. trade before, during and after the 2008 recession," International Economics, vol. 141, pp. 34-49, 2015.

[4] X. Mi, H. Liu, and Y. Li, "Wind speed prediction model using singular spectrum analysis, empirical mode decomposition and convolutional support vector machine," Energy Conversion and Management, vol. 180, pp. 196-205, 2019.

[5] N. Golyandina and A. Zhigljavsky, Singular Spectrum Analysis for Time Series. New York, Springer, 2013.

[6] H. Hassani, A. Webster, E. S. Silva, and S. Heravi, "Forecasting U.S. tourist arrivals using optimal singular spectrum analysis," Tourism Management, vol. 46, pp. 322-335, 2015.

[7] A. Zhigljavsky, “Singular spectrum analysis for time series: introduction to this special issue,” Statistics and Its Interface, vol. 3, pp. 255-258, 2010.

[8] T. Alexandrov, N. Golyandina, and A. Spirov, "Singular spectrum analysis of gene expression profiles of early Drosophila embryo: exponential in distance patterns," Research Letters in Signal Processing, pp 1-5, 2008.

[9] N. Golyandina, V. Nekrutkin, A. Zhigljavsky, Analysis of Time Series Structure: SSA and Related Techniques. Florida, Chapman & Hall/CRC, 2001.

[10] J. Gillard and V. Knight, “Using singular spectrum analysis to obtain staffing level requirements in emergency units,” Journal of the Operational Research Society, vol. 65, pp. 735-746, 2014.

[11] N. Golyandina and D. Stepanov, “SSA-based approaches to analysis and forecast of multidimensional time series,” Proceedings of the 5th St. Petersburg Workshop on Simulation, pp. 293-298, 2005.

[12] X. Xu, M. Zhao, and J. Lin, “Detecting weak position fluctuations from encoder signal using singular spectrum analysis,” ISA Transactions, pp. 1-8, 2017.

[13] J. L. Vile, J. W. Gillard, P. R. Harper, and V. A. Knight, “Predicting ambulance demand using singular spectrum analysis,” Journal of the Operational Research Society, vol. 63, pp. 1556-1565, 2012.

[14] R. J. Hyndman and Y. Khandakar, “Automatic time series forecasting: the forecast package for R,” Journal of Statistical Software, vol. 27, pp. 1-22, July 2008.

[15] B. Petrevska, “Predicting tourism demand by ARIMA models,” Economic Research, vol. 30, pp. 939-950, 2017.

[16] W. W. S. Wei, Time Series Analysis Univariate and Multivariate Methods. Pearson Education, 2006.

[17] Indonesian Central Bureau of Statistics, “The number of tourist arrivals to Indonesia according to the entrance,” unpublished.

[18] H. Hassani, “Singular spectrum analysis: methodology and comparison,” Journal of Data Science, vol. 5, pp. 239-257, 2007.

[19] N. Golyandina and A. Korobeynikov, Basic Singular Spectrum Analysis and Forecasting with R. St. Petersburg, St. Petersburg State University, 2013.

[20] Aswi and Sukarna, Analisis Deret Waktu. Makasar, Andira Publisher, 2006.