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International Journal of Data and Network Science

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Hybrid SSA-TBATS to improve forecasting accuracy on export value data in Indonesia

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C H R O N I C L E

Article history:
Received: July 2, 2023
Received in revised format: July 26, 2023
Accepted: August 14, 2023
Available online: August 14, 2023

Keywords:
Forecasting
Singular Spectrum Analysis
TBATS
Time Series
Export

A B S T R A C T

This research aims to present the Hybrid SSA-TBATS approach as an alternate forecasting technique that does not need specific assumptions or requirements such as stationarity, linear or non-linear process, and normality. This analysis used Indonesian exports (in millions of USD) from January 1993 to July 2022. The findings of this research reveal that the Hybrid SSA-TBATS method outperforms SSA and TBATS in forecasting accuracy and defines the window length and number of groups. Therefore, it is highly recommended based on MAPE since it does not need any information on the characteristics of the data to be forecasted.

1. Introduction

According to use, exports are one of the components of the Gross Domestic Product and a source of foreign exchange for the country. Export occurs due to an excess of specific domestic products and international demand for those same commodities for which the destination nations need more supplies for their economic activities. In international trade relations, each country has a unique competitive advantage. Each location has different and diverse natural resources and industrial benefits.

Exports boost national revenue since they are a component of total spending. Export benefits national economic development by taking advantage of economies of scale and increasing efficiency through increased competition (Balassa, 1978; Helpman & Krugman, 1985; Kavoussi, 1984; Krueger, 1980; Srinivasan & Bhagwati, 1979). In addition, Jung & Marshall (Jung & Marshall, 1985) proposed four theories on the link between exports and economic growth. First, export stimulates economic growth. The second is that export decreases a nation's economic growth. Third, economic growth increases a nation's exports (internally generated exports). Meanwhile, the final hypothesis is that a country's economic growth decreases export.

The preceding explanation indicates the significance of export to the national economy; hence, export growth must be routinely monitored. Furthermore, strengthening domestic industry is required to sustain export growth considering many other short-, medium-, and long-term macroeconomic objectives; thus, future export data is necessary to make macroeconomic policies and programs. Scientific forecasting is one method via which this information can be obtained.

Forecasting with time series is a numerical approach for evaluating and analyzing data regularly utilizing the relevant procedures. The findings could be used as a benchmark for forecasting the next period's value. Singular spectrum analysis

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ISSN 2561-8156 (Online) - ISSN 2561-8148 (Print)

doi: 10.5267/j.ijdns.2023.8.012

(SSA) is one method for forecasting time series. SSA is a nonparametric method that decomposes a time series into numerous components that are then regrouped following the notion of analysis of the significant features (Golyandina et al., 2005; Golyandina & Korobeynikov, 2014; Golyandina & Zhigljavsky, 2013). The advantages of this technique do not require data stationarity requirements or particular time series assumptions. SSA has been implemented to forecasting the production index (Hassani et al., 2009), the currency exchange rate (Ghodsi & Yarmohammadi, 2014; Hassani et al., 2010), Gross domestic product (Hassani & Zhigljavsky, 2009), stocks (Menezes et al., 2012; Thomakos et al., 2002), energy consumption (Kumar & Jain, 2010), hydrological data (Marques et al., 2006; Zhang et al., 2011), commodity price (Wang & Li, 2018), and Sleep EEG (Aydln et al., 2011).

With the rapid development of computing technology, forecasting methods have experienced significant results, and SSA is no exception. The SSA method is hybridized by other methods or models, such as Hybrid SSA-ARIMA (Zhang et al., 2011) and SSA-TSR-ARIMA (Suhartono et al., 2018), and hybridized SSA with the neural network such as SSA-ELM (Fajar, 2019), SSA-NN-LSSVM (Zhang et al., 2021), SSA-NN (Wang & Li, 2018), SSA-ARIMA-ANN (Unnikrishnan & Jothiprakash, 2020), SSA-TLSNN (Sulandari et al., 2020), and SSA-SVM (Wen et al., 2014) are two methods for improving predicting accuracy. On the other hand, the TBATS method developed by de Livera et al. (2011) can be used in time series generated from linear and nonlinear processes so that it does not require specific prerequisites or assumptions. Therefore, this study proposes a Hybrid SSA-TBATS forecasting method expected to accommodate export dynamics to improve forecasting accuracy.

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Forecasting with time series is a numerical approach for evaluating and analyzing data regularly utilizing the relevant procedures. The findings could be used as a benchmark for forecasting the next period's value. Singular spectrum analysis (SSA) is one method for forecasting time series. SSA is a nonparametric method that decomposes a time series into numerous components that are then regrouped following the notion of analysis of the significant features (Golyandina et al., 2005; Golyandina & Korobeynikov, 2014; Golyandina & Zhigljavsky, 2013). The advantages of this technique do not require data stationarity requirements or particular time series assumptions. SSA has been implemented to forecasting the production index (Hassani et al., 2009), the currency exchange rate (Ghodsi & Yarmohammadi, 2014; Hassani et al., 2010), Gross domestic product (Hassani & Zhigljavsky, 2009), stocks (Menezes et al., 2012; Thomakos et al., 2002), energy consumption (Kumar & Jain, 2010), hydrological data (Marques et al., 2006; Zhang et al., 2011), commodity price (Wang & Li, 2018), and Sleep EEG (Aydln et al., 2011).

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2. Materials and Methods

2.1. Singular Spectrum Analysis (SSA)

A nonparametric time series technique called singular spectrum analysis breaks down a time series into its trend, periodic, quasi-periodic, and noise components. There are four stages to the SSA approach.

Stage 1. Embedding

Time series $z_1.z_2.\dots.z_{\mathcal{T}}$, select a $\mathcal{L}$ stands for window length, and $\mathcal{L}$ parameter is determined in interval $\left[2.{}^{\mathcal{T}}/_{2}\right]$ and set $\mathcal{K} = \mathcal{T} - \mathcal{L} + 1$. $\boldsymbol{Z}$ has been defined:

$$\boldsymbol{Z} = (Z_1.\dots.Z_{\mathcal{T}}) = \begin{pmatrix} z_1 & z_2 & \cdots & z_{\mathcal{K}} \\ z_2 & z_3 & \cdots & z_{\mathcal{K}+1} \\ \vdots & \vdots & \ddots & \vdots \\ z_{\mathcal{L}} & z_{\mathcal{L}+1} & \cdots & z_{\mathcal{T}} \end{pmatrix},$$

Since $\boldsymbol{Z}$ is a Hankel matrix, every element on the major antidiagonal is equal. Consequently, $\boldsymbol{Z}$ can be thought of as multivariate data, the covariance matrix is $\boldsymbol{S} = \boldsymbol{Z}\boldsymbol{Z}'$ based on $\boldsymbol{Z}$.

Stage 2. Singular Value Decomposition (SVD)

$\boldsymbol{S}$ has an eigenvalue $(\gamma_1.\dots.\gamma_L.\gamma_1 \geq \gamma_2 \geq \cdots \geq \gamma_{\mathcal{L}})$ and eigenvector $(\mathcal{U}_1.\dots.\mathcal{U}_L)$. SVD of $\boldsymbol{Z}$ was obtained as follows.

$$Z = \sum_{i=1}^{h} E_i. \tag{1}$$

where $E_i = \sqrt{\gamma_i}\mathcal{U}_i\mathcal{V}_i'$, $i = 1.2.\dots.h$, is known as the principal component and the number of eigenvalues γ_i, and $\mathcal{V}_i = \boldsymbol{Z}'\,\mathcal{U}_i/\sqrt{\gamma_i}$.

Stage 3. Grouping

The grouping step divides stage $\boldsymbol{Z}$ into subgroups depending on time series creating patterns. Index set divides $\{1.2.\dots.h\}$ into groups $I_1.I_2.\dots.I_n$, and $\boldsymbol{Z}_I$ corresponds to group $\mathcal{I} = \{i_1.i_2.\dots.i_{\ell}\}$ which is defined as:

$$\boldsymbol{Z}_I = M_{i_1} + M_{i_2} + \cdots + M_{i_{\ell}}\ , \tag{2}$$

So that decomposition is represented:

$$\boldsymbol{Z} = \boldsymbol{Z}_{I_1} + \boldsymbol{Z}_{I_2} + \cdots + \boldsymbol{Z}_{I_n}. \tag{3}$$

where $\boldsymbol{Z}_{\mathcal{I}_j}(j = 1.2.\dots.n)$ denotes the reconstruction component. Component contributions $\boldsymbol{Z}_{\mathcal{I}}$, as assessed by the corresponding eigenvalue contribution: $\sum_{i\in\mathcal{I}}\gamma_i/\sum_{i=1}^{h}\gamma_i$. The minimum mean absolute percentage error (MAPE) is utilized in this research to figure out how to calculate the group number. If the frequency magnitudes of numerous primary components are similar, they are blended into a single reconstruction component. Thus, on till $\boldsymbol{Z}_{I_1}.\boldsymbol{Z}_{I_2}.\dots.\boldsymbol{Z}_{I_n}$ are produced.

Stage 4. Reconstruction

In the last stage, we performed transformations on $\boldsymbol{Z}_{\mathcal{I}_j}$ into a new series $(y_1.y_2.\dots.y_{\mathcal{T}})$ with length $\mathcal{T}$ determined by diagonal averaging. Let's assume $\boldsymbol{\mathcal{Y}}$ is a matrix with $\mathcal{L} \times \mathcal{K}$ size, which element $y_{\ell k}$. interval $\ell{:}\,[1.\mathcal{L}]$. $k{:}\,[1.\mathcal{K}]$, Then $\dot{\mathcal{L}}$ is minimum of $\mathcal{L}$ and $\mathcal{K}$, $\dot{\mathcal{K}}$ is maximum of $\mathcal{L}$ and $\mathcal{K}$. If $\mathcal{L} < \mathcal{K}$, $y_{ij}^{*} = y_{ij}$ and if $\mathcal{L} > \mathcal{K}.\,y_{ij}^{*} = y_{ji}$. $\boldsymbol{\mathcal{Y}}$ transferred into a series $y_1.y_2.\dots.y_{\mathcal{T}}$ by using the formula (4).

$$y_k = \begin{cases} \dfrac{1}{k}\displaystyle\sum_{\ell=1}^{k} y_{\ell.k-\ell+1}^{*}\,; 1 \leq k \leq \mathcal{K}^{*} \\ \dfrac{1}{\mathcal{L}^{*}}\displaystyle\sum_{\ell=1}^{\mathcal{L}^{*}} y_{\ell.k-\ell+1}^{*}\,; \mathcal{L}^{*} \leq k \leq \mathcal{K}^{*} \\ \dfrac{1}{\mathcal{T}-k+1}\displaystyle\sum_{\ell=k-\mathcal{K}^{*}+1}^{\mathcal{T}-\mathcal{K}^{*}+1} y_{\ell.k-\ell+1}^{*}\,; \mathcal{K}^{*} \leq k \leq \mathcal{T} \end{cases}, \tag{4}$$

It is essentially averaging the matrix elements along the antidiagonals $i + j = k + 1$; for example, suppose $k = 1$ interpret $y_1 = y_{1.1}.\,k = 2$ as $y_2 = (y_{1.2} + y_{2.1})/2$. Diagonal averaging on Eq. (4) is performed on all components of the matrix $\boldsymbol{Z}_{\mathcal{I}_j}$ in Eq. (3) produces a series $\widetilde{\boldsymbol{Z}}^{(k)} = \left(\check{z}_1^{(k)}.\check{z}_2^{(k)}.\dots.\check{z}_{\mathcal{T}}^{(k)}\right)$, hence series $z_1.z_2.\dots.z_{\mathcal{T}}$ decomposed into a summation of the reconstruction ℓ series:

$$z_t = \sum_{k=1}^{\ell} \check{z}_t^{(k)} . t = 1.2. \dots . \mathcal{T} , \tag{5}$$

This SSA forecasting uses the SSA recurrent, where the calculation algorithm refers to Golyandina & Zhigljavsky (2013).

2.2. TBATS

de Livera et al. (2011) developed an ESSS with a Cox Box transformation, an ARMA error, trends, and a trigonometric equation with seasonal components dubbed TBATS. The trigonometric equation is based on the Fourier model in this model. The TBATS model includes seasonal ingredients with integers and non-integers that are periodic, double or single, or spring seasonal.

TBATS has the following equation:

$$\check{z}_t^{(\omega)} = \begin{cases} \dfrac{\check{z}_t^{\omega} - 1}{\omega}, \omega \neq 0 \\ \ln \check{z}_t \quad , \omega = 0 \end{cases} \tag{6}$$

$$\check{z}_t^{(\omega)} = l_{t-1} + \vartheta b_{t-1} + \sum_{i=1}^{\mathcal{M}} \mathfrak{s}_{t-m_i}^{(i)} + \sigma_t \tag{7}$$

$$l_t = l_{t-1} + \vartheta b_{t-1} + a\sigma_t \tag{8}$$

$$b_t = (1-\vartheta)b^* + \vartheta b_{t-1} + \mathfrak{b}\sigma_t \tag{9}$$

$$\sigma_t = \sum_{i=1}^{v} \vartheta_i \sigma_{t-i} + \sum_{j=1}^{w} \phi_j \epsilon_{t-j} + \epsilon_t \tag{10}$$

$$\mathfrak{s}_t^{(i)} = \sum_{j=1}^{k_i} \mathfrak{s}_{j,t}^{(i)}$$

$$\mathfrak{s}_{j,t}^{(i)} = \mathfrak{s}_{j,t-1}^{(i)} \cos \psi_j^{(i)} + \mathfrak{s}_{j,t-1}^{*(i)} \cos \psi_j^{(i)} + \xi_1^{(i)} \sigma_t \tag{11}$$

$$\mathfrak{s}_{j,t}^{*(i)} = -\mathfrak{s}_{j,t-1}^{(i)} \cos \psi_j^{(i)} + \mathfrak{s}_{j,t-1}^{*(i)} \cos \psi_j^{(i)} + \xi_2^{(i)} \sigma_t \tag{12}$$

$$\psi_j^{(i)} = \frac{2\pi j}{m_i} , \pi = 3.14 \dots,$$

where $m_1, \dots, m_{\mathcal{M}}$ represent the seasonal period, l_t is the local level in period t, b_{t-1} is the short-run trends period t, $\mathfrak{s}_t^{(i)}$ represents the i-th seasonal component at time t, d_t implies ARMA (v, w), ϵ_t is an error term, $a, \mathfrak{b}, \xi_1^{(i)}, \xi_2^{(i)}$ are smoothing parameters. Eq. (6) is a Box-Cox transformation, Eq. (7) represents a seasonal pattern, Eq. (8) and (9) are global and local trends, Eq. (10) is an error modeled with ARMA, and Eq. (11) and (12) are seasonal patterns modeled by the Fourier model. Estimating and forecasting TBATS follows as de Livera et al. (2011).

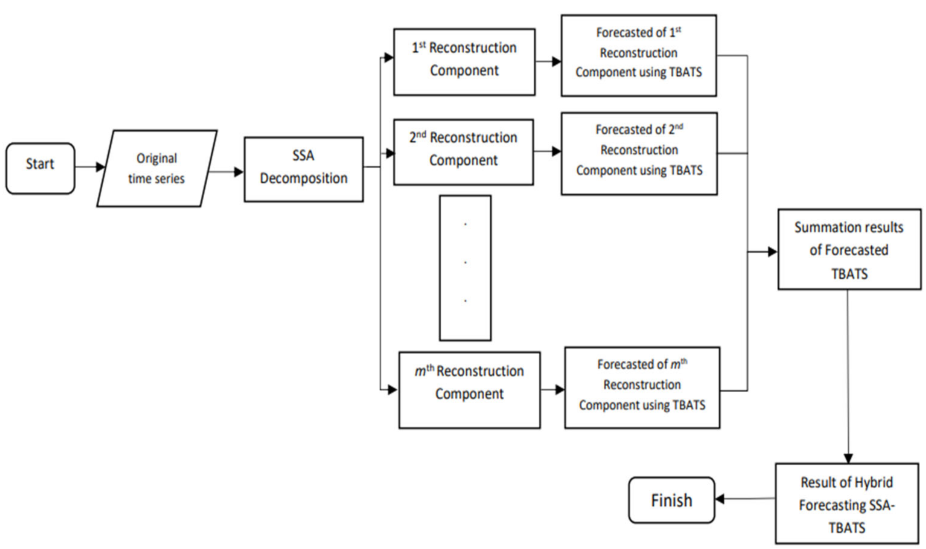


Fig. 1. Hybrid SSA – TBATS

2.3. Hybrid Singular Spectrum Analysis and TBATS

The following is our proposal for the Hybrid SSA-TBATS forecasting method:

(1) SSA disassembled the original time series into their principal components.
(2) The results of Stage 1 principal component are susceptible to being classified as trend, periodic, quasi-periodic, or noise.
(3) The reconstruction component is divided into many primary components based on frequency proximity.
(4) TBATS is utilized in all components of the reconstruction.
(5) The aggregate of the projections for various reconstruction components constitutes the Hybrid SSA-TBATS's ultimate forecasting output. Figure 1 depicts the prior described phases.

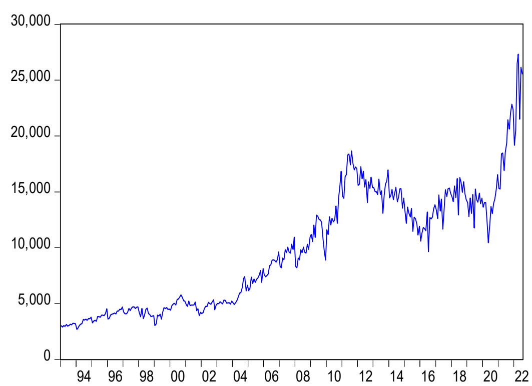
2.4 Data Set

The overall export value, which is the sum of the importance of oil and gas exports and the importance of non-oil and gas exports in millions of US dollars from January 1993 to July 2022 ($\mathcal{T}$ = 355), was used in the research. These numbers were obtained from the Ministry of Finance's Directorate General of Customs and Excise. The Hybrid SSA-TBATS method's performance is evaluated using 1, 3, 5, 7, 9, 12, 24, 36, and 48 observations. The least MAPE of the testing data forecast is used to establish the window length and the number of groups using hybrid SSA-TBATS. The length of the window and the number of groups are calculated by scanning the ranges $[(\mathcal{T}-p)/\Bbbk], \Bbbk = 2,3,\dots,10$, and 2, 3, …, 30, respectively.

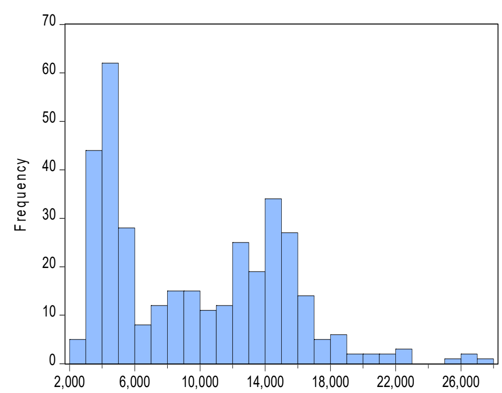
Before the forecasting process is executed, the data is examined for plots, histograms, and stationarity checks using the Phillips-Perron Test (Phillips & Perron, 1988), long memory process investigations based on the Qu Test (Qu, 2011), and nonlinearity verifications based on the Tsay Test (Tsay, 1986). These examination results provide additional information for data analysis.

3. Results and Discussion

Throughout the observation period, Indonesia's exports showed a rising trend. However, structural fractures occurred at many periods in time (See Fig.2).(a)), such as in December 2009 as a result of the global financial crisis, and in May 2020 as a result of decreased worldwide travel or economic activity to control the spread of the COVID-19 pandemic. (See Figure 2.b.) The histogram of Indonesian exports reveals two forms of export data. This graph illustrates that the export data follows a mixture of probability distributions due to structural breaks.



(a) The plot of export, January 1993 – July 2022



) Histogram of export, January 1993 – July 2022

Fig. 2. Visualization of Indonesia's Export Periods January 1993 – July 2022

Table 1
Results of Phillips-Perron Test, Qu Test, and Tsay Test on export data

Statistical Test	Statistic	Decision (using alpha 5%)
Phillips-Perron Test (with intercept and trend) H_0: time series is stationary H_1: time series is stationary	-2.991483 [0.1361]	H_0 is not rejected
Qu Test H_0: time series is a long memory process H_1: time series is a spurious long-memory process	0.1053545 (1.155)	H_0 is not rejected
Tsay Test H_0: time series follows AR (1) process H_1: time series does not follow AR (1) process	5.45326 [0.02009482]	H_0 rejected

Note: […] represents p-value, and (…) represents critical value.

The Indonesian export data across the observation period has a unit root, as shown in Table 1, indicating that the data are unstable. It is caused by structural breaks and trend components with rather large magnitudes. According to the results of the Qu test, export data follows a long memory process. As a result, it tends to retain a pattern over a more extended period. Furthermore, the Tsay Test results show that Indonesia's export data is a nonlinear pattern.

Table 2

MAPE produced by SSA, TBATS, and Hybrid SSA-TBATS according to the length of the ahead period in Indonesia's export forecasting

Ahead period (p): 1 month			
Method of forecasting:	**window length**	**number of groups**	**MAPE** (%)
SSA	floor[$(\mathcal{T}-p)/7$]	7	0.039793
TBATS	-	-	0.013373
Hybrid SSA-TBATS	floor[$(\mathcal{T}-p)/7$]	7	**0.000380**
Ahead period (p): 3 months			
Method of forecasting:	**window length**	**number of groups**	**MAPE** (%)
SSA	floor[$(\mathcal{T}-p)/9$]	7	0.074732
TBATS	-	-	0.100926
Hybrid SSA-TBATS	floor[$(\mathcal{T}-p)/9$]	7	**0.055808**
Ahead period (p): 5 months			
Method of forecasting:	**window length**	**number of groups**	**MAPE** (%)
SSA	floor[$(\mathcal{T}-p)/4$]	2	0.340999
TBATS	-	-	0.149767
Hybrid SSA-TBATS	floor[$(\mathcal{T}-p)/4$]	2	**0.139109**
Ahead period (p): 7 months			
Method of forecasting:	**window length**	**number of groups**	**MAPE** (%)
SSA	floor[$(\mathcal{T}-p)/2$]	25	0.168274
TBATS	-	-	0.111956
Hybrid SSA-TBATS	floor[$(\mathcal{T}-p)/2$]	25	**0.085608**
Ahead period (p): 9 months			
Method of forecasting:	**window length**	**number of groups**	**MAPE** (%)
SSA	floor[$(\mathcal{T}-p)/3$]	20	0.380655
TBATS	-	-	0.116839
Hybrid SSA-TBATS	floor[$(\mathcal{T}-p)/3$]	20	**0.080221**
Ahead period (p): 12 months			
Method of forecasting:	**window length**	**number of groups**	**MAPE** (%)
SSA	floor[$(\mathcal{T}-p)/10$]	8	0.147367
TBATS	-	-	0.172067
Hybrid SSA-TBATS	floor[$(\mathcal{T}-p)/10$]	8	**0.071747**
Ahead period (p): 24 months			
Method of forecasting:	**window length**	**number of groups**	**MAPE** (%)
SSA	floor[$(\mathcal{T}-p)/6$]	19	0.344298
TBATS	-	-	0.316312
Hybrid SSA-TBATS	floor[$(\mathcal{T}-p)/6$]	19	**0.073157**
Ahead period (p): 36 months			
Method of forecasting:	**window length**	**number of groups**	**MAPE** (%)
SSA	floor[$(\mathcal{T}-p)/8$]	15	0.219868
TBATS	-	-	0.195695
Hybrid SSA-TBATS	floor[$(\mathcal{T}-p)/8$]	15	**0.115008**
Ahead period (p): 48 months			
Method of forecasting:	**window length**	**number of groups**	**MAPE** (%)
SSA	floor[$(\mathcal{T}-p)/8$]	15	0.386902
TBATS	-	-	0.162403
Hybrid SSA-TBATS	floor[$(\mathcal{T}-p)/8$]	15	**0.143382**

$\mathcal{T} = 355$

window length $= [(\mathcal{T}-p)/\mathbb{k}], \mathbb{k} = 2,3,\ldots,10$

Table 2 shows that the SSA, TBATS, and Hybrid SSA-TBATS yield MAPE values of less than 10% based on the duration of the forward periods. Regarding Indonesian export forecasting, the three techniques demonstrate outstanding predictive ability. The hybrid SSA-TBATS has the lowest MAPE value compared to SSA and TBATS. It happens because the Hybrid SSA-TBATS combines the advantages of both SSA and TBATS. They are appropriate for stationary or non-stationary data, have complicated seasonal components, and follow linear or nonlinear processes.

For the month ahead, the MAPE generated by Hybrid SSA-TBATS is 0.000380%. Instead, for forwarding periods of more than one month, the MAPE value of the Hybrid SSA-TBATS remains less than 0.14 percent. The absence of an increase or throw in window length and group size results from rising forward periods or decreasing MAPE. It means that the data's qualities determine the window length and the number of groups. The use of MAPE or equivalent measures as a guide for determining window length and group size is an alternative strategy that can be used regardless of the nature of the data or the need for additional supporting information. This technique is consistent with the proposal developed by Khan and Poskitt (2012). Furthermore, the window length determination proposed by Khan and Poskitt (2013) and Yang et al. (2016) correlates to the data autocovariance function and spectral information for each principal component in SSA, respectively. These methods, however, still necessitate prior comprehension of the data.

MAPE generated by Hybrid SSA-TBATS tends to increase when the forward time is more than or equal to 12 months (12, 24, 36, and 48 months). It suggests that forecast uncertainty increases as the forward time lengthens. It means that the Hybrid SSA-TBATS is only effective for a limited time.

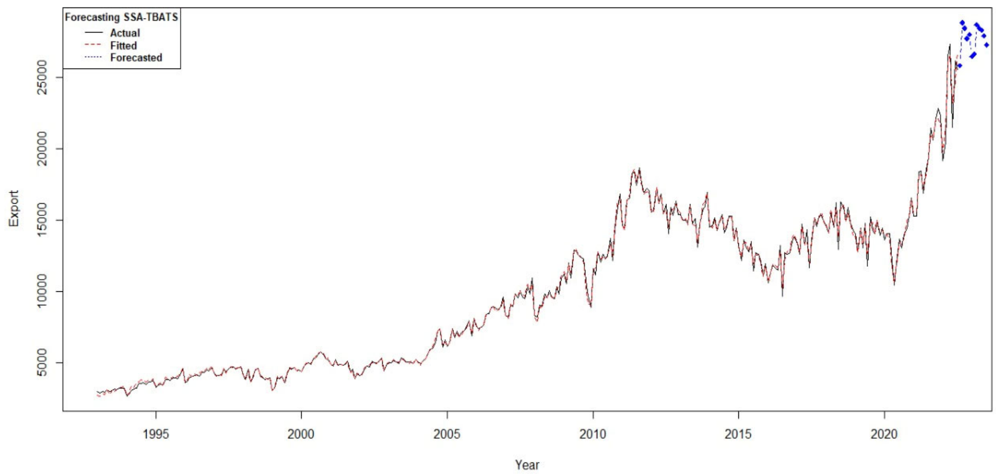


Fig. 3. Indonesian Export Movement (Actual Data) for the Period of January 1993 – July 2022 (In-sample) and Export Forecasting for the Period of August 2022 – July 2023 (Out-sample)

The forecasting observations produced by SSA-TBATS are quite accurate, despite their short-term character, and are particularly useful to the appropriate authorities in establishing trade and monetary policies. Indonesia's export estimate for August 2022-July 2023 reveals that developments are slowly improving, with an average growth rate of 0.61132%, indicating that exports could assist the economy (See Figure 3 and Table 3).

Table 3
Export Forecasting and Growth, Period August 2022 – July 2023.

Year	Month	Forecasted of Export (millions of U.S. dollars)	Export Growth (%)
2022	Aug	25817.80349	-
	Sept	28844.08428	11.72168
	Oct	28452.97149	-1.35595
	Nov	27737.99135	-2.51285
	Dec	28029.10227	1.04950
2023	Jan	26467.72493	-5.57056
	Feb	26646.08767	0.67389
	Mar	28693.13021	7.68234
	Apr	28473.00562	-0.76717
	May	28313.74722	-0.55933
	June	27923.76943	-1.37734
	July	27292.78674	-2.25966
		Average of Growth (%)	0.61132

This finding corresponds with Sumiyarti (2015) and Ginting (2017) findings that support the "export-led growth" hypothesis, but in Indonesia, the influence of exports is less dominant in GDP compared to household consumption, which has an average share of 60.29291%, exports, and imports, which have average shares of 27.75517% and 24.93603%, respectively. Throughout the period 1992Q2 - 2022Q2, the movement of the consumption share has always been greater than the movement of the export and import shares (see Fig. 4). Because imports are a declining component of GDP, the net export component has an average GDP share of 2.8191448%. The Indonesian economy's tiny percentage of net exports has an advantage in that it is not affected as severely when there is a foreign shock, such as the Russian-Ukrainian war, reduced demand for certain goods, and so on. This highlights how important the household consumption expenditure component is to the Indonesian economy. Furthermore, the SSA-TBATS forecast for Indonesian exports shows a rising trend, implying that the Rupiah will weaken against the USD between August 2022 and July 2023. This is typical since exporters are paid in USD and profit gradually when the Rupiah's exchange rate against the USD declines, meaning that the country's foreign exchange in the form of foreign currency rises. However, rupiah depreciation against the USD must be controlled and stabilized so that it does not set a precedent for an economic crisis through various policy packages in both the real and monetary sectors, such as from the real side: controlling prices of necessities, providing business stimulus through business assistance and business loans, improving investment licensing flows, and from the monetary side, namely the policy mixed of Bank Indonesia (Bank Indonesia, 2022): (a) Expand monetary policy by raising the interest rate structure in the money market to conform to the BI7DRR rate hike in order to lower inflation expectations and guarantee core inflation returns to goal as promptly as feasible; (b) Improving rupiah stability in the exchange rate by maintaining it in the market as part of initiatives to mitigate inflation, particularly importing it through foreign exchange market interventions such as observing financial transactions, Domestic Non-Deliverable Forward (DNDF), and the aftermarket purchase or sale of government securities (SBN); (c) Sustaining SBN sales and purchases in the secondary market in order to boost BI7DRR transmission improves SBN yield competitiveness for global portfolio investors and strengthens rupiah currency stability; (d) Publishing Bank Indonesia sukuk instruments (SukBI) based on underlying securities (SukBI inclusive) and designated as inclusive financing securities (SBPI), in accordance with Bank Indonesia's obligation to continue to support inclusive financing and the growth of the Islamic economy and finance; (e) Extending the Basic Lending Rate Transparency Policy by enhancing the examination of the bank's rate of interest receptivity to the policy rate; (f) Keep encouraging the use of QRIS and improving QRIS features and services, including extending the reach of QRIS beyond borders, in order to meet the goal of 15 million new QRIS users by October 2022; (g) Support payment system inventiveness, such as preserving the general acceptance of BI-FAST through expanded engagement, channels of service, and regular communication with the public.

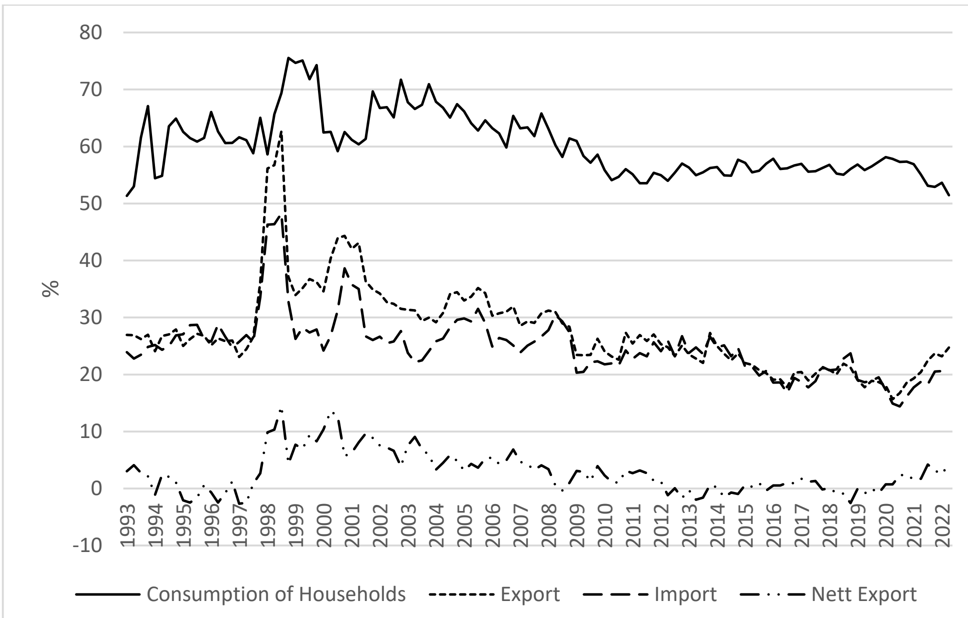


Fig. 4. Visualization of household consumption expenditure share, exports, and imports, Indonesia for the period 1992Q2-2022Q2

4. Conclusions

Forecasting Indonesia's exports, as previously stated, provides evidence that: (1) the Hybrid SSA-TBATS method has superior forecasting performance compared to SSA and TBATS, (2) the determination of window length and several groups based on MAPE criteria is highly recommended because it does not require information about the characteristics of the data to be forecasted, (3) the Hybrid SSA-TBATS method has excellent performance for an upcoming period of fewer than 12 months.

Further research necessitates a simulation investigation of the Hybrid SSA-TBATS forecasting performance on data from long memory, nonlinear, random walk, and chaotic processes by defining the window length and the number of groups based on MAPE.

Monitoring export developments is critical for the government because it can be used as an early warning system indicator to anticipate economic shocks from internal and external factors, allowing economic policy packages to be developed that strengthen the foundation of the domestic economy.

Author Contributions: "Conceptualization, S.S. and M.F.; methodology, M.F. and S.S.; software, H.Y., and M.F.; validation, H.S., M.F. and H.Y.; formal analysis, M.F., C.R.L., and S.S..; investigation, M.F., and S.S.; resources, M.F.; data curation, M.F..; writing—original draft preparation, S.S., M.F., H.Y., and C.R.L.; writing—review and editing, S.S., and C.R.L.; visualization, H.Y., and M.F.; supervision, S.S., M.F., and C.R.L.; All authors have read and agreed to the published version of the manuscript".

Funding: "This research was supported by LEMBAGA PENGELOLA DANA PENDIDIKAN (LPDP) UNDER THE MINISTRY OF FINANCE OF THE REPUBLIC OF INDONESIA and CENTRAL FOR HIGHER EDUCATION FUNDING or BALAI PEMBIAYAAN PENDIDIKAN TINGGI (BPPT) UNDER THE MINISTRY OF EDUCATION, CULTURE, RESEARCH, AND TECHNOLOGY (KEMENDIKBUDRISTEK) OF THE REPUBLIC OF INDONESIA".

Acknowledgments

The authors sincerely acknowledge the financial assistance granted by the Lembaga Pengelola Dana Pendidikan (LPDP) under the Ministry of Finance of the Republic of Indonesia. We gratefully acknowledge the funding from Central for Higher Education Funding or Balai Pembiayaan Pendidikan Tinggi (BPPT) under the Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia.

Conflicts of Interest

The funders were not involved in the design of the study, data collection, analysis, interpretation, manuscript development, or the decision to publish the findings.

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