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HYBRID MODEL OF SINGULAR SPECTRUM ANALYSIS WITH AUTOREGRESSIVE INTEGRATED MOVING AVERAGE AND FUZZY TIME SERIES FOR INDONESIAN CRUDE PRICE FORECASTING

Etik Zukhronah[1*], Winita Sulandari[2], Esa Permata Sari Putri Ilahi[3]

[1,2,3]Statistics Study Program, Faculty of Mathematics and Natural Science, Universitas Sebelas Maret
Jl. Ir. Sutami 36A, Surakarta, 57126, Indonesia

*Corresponding author's e-mail: * **etikzukhronah@staff.uns.ac.id***

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ABSTRACT

This study discusses a hybrid model of Singular Spectrum Analysis (SSA) with Autoregressive Integrated Moving Average (ARIMA) and Fuzzy Time Series (FTS) for forecasting the Indonesian Crude Price (ICP). SSA is considered to capture the deterministic component of the data while the ARIMA and FTS are to represent the stochastics one. The data that used in this study are ICP per month from January 2017 to May 2023. The data from January 2017 to December 2022 are used as insample data, while the data from January to May 2023 are used as outsample data. The insample data is firstly modeled by SSA and the residuals are then modeled by ARIMA, referred to as the hybrid SSA-ARIMA. By the same procedure, the hybrid SSA-FTS model is also constructed to the insample data. Based on the experiment, the hybrid SSA-ARIMA produces Mean Absolute Percentage Error values 8.08% for an insample and 7.10% for an outsample data. These values are less than those obtained by hybrid SSA-FTS. Therefore, the hybrid SSA-ARIMA is recommended for forecasting the monthly ICP.

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1. INTRODUCTION

SSA is a mathematical method employed in modeling time series data and signal processing. Developed during the 1980s, SSA proves to be a valuable tool for breaking down a time series into its fundamental elements, allowing for the detection of trends, seasonal variations, and random fluctuations (noise). SSA modeling is a nonparametric method that is more flexible in its use and does not rely on certain assumptions, such as stationarity, independence and normality of residuals [1]. Previous research indicates that SSA could extract the various components of the time series effectively and could also forecast the daily rainfall time series pertaining to Koyna watershed in Maharashtra, India, for one year with reasonable accuracy [2]. Another research study, conducted by [3] shows that the SSA technique gives a much more accurate forecast than Box-Jenkins SARIMA, ARAR algorithm and Holt-Winter algorithm for forecasting the data of monthly accidental deaths in the USA. According to [4], the SSA model produces forecasts which perform (statistically) significantly better than ARIMA, exponential smoothing and neural network to forecast monthly data for tourist arrivals into the Unites States over the period 1996 to 2012. The other researchers have used the SSA model and have good performance in forecasting that are forecasting the number of tourist arrivals to Batam [5], forecasting stochastic processes [6], analyzing and forecasting economic and financial time series [7], forecasting the average price of rice [8], studying of filtering and parameter estimation of surface-NMR data [9].

SSA hybrid model with other time series models has been done by several researchers. Hybrid SSA-ARIMA models have been used by [10]-[12] for annual runoff data, for daily maximum ambient O3 concentration data and for seasonal time series data, respectively. [13] conducted hybrid SSA-TSR-ARIMA for forecasting water demand. [14] applied hybrid SSA-TLSNN and SSA-TLCSNN models for forecasting complex seasonal time series data. Meanwhile, hybrid SSA-LRF-FTS and SSA-LRF-NN models have been applied by [15], [16]. One of their findings is that hybrid models generally yield superior outcomes compared to single models. On the other words, hybrid models can improve forecasting accuracy.

All studies utilizing the above hybrid model do not apply it to Indonesian Crude Price (ICP) data. On the other hand, the studies indicated that hybrid models yield better forecasting accuracy than single model. Based on this, we utilize the hybrid SSA-ARIMA and SSA-FTS models for forecasting Indonesian Crude Price (ICP) data. MAPE is used to assessed the model performance. There are other studies using ICP data conducted by [17] and [18], however, they employ different methods, namely ARIMA-GARCH and multiple linear regression algorithm, respectively.

The organization of this study includes a concise overview of the procedures involved in SSA, hybrid SSA-ARIMA, and SSA-FTS modeling presented in section 2. Additionally, we offer a brief explanation of the fundamental concepts behind SSA, ARIMA, and fuzzy time series. Moving on to Section 3, we present the data analysis and the resulting findings. Lastly, Section 4 contains the conclusions drawn from our study.

2. RESEARCH METHODS

The data used is Indonesian crude price per month from January 2017 to May 2023. The ICP is taken from website https://databoks.katadata.co.id/datapublish/2022 /04/08 /tertinggi-sejak-2013-icp-maret-2022-capai-us1135-per-barel and https://databoks.katadata.co.id/datapublish/2022/12/05/harga-minyak-indonesia-turun-ke-us875-per-barel-pada-november-2022. Insample data are from January 2017 to December 2022, while outsample data are from January to May 2023. The insample data are modelled using SSA, and we get the residual of SSA. Then, the residual of SSA is modelled using ARIMA and FTS. Here are the steps involved in data analysis.

Step 1: Modelling SSA for insample data

1.1 Select the parameter of window length ($\boldsymbol{L}$).
1.2 Form the trajectory matrix ($\boldsymbol{X}$).
1.3 Decompose the matrix $\boldsymbol{X}$ using Singular Value Decomposition.
1.4 Group the eigentriple to find trends, seasonal and noise components.
1.5 Reconstruct sub component of series using diagonal averaging algorithm, into the signal series and the noise time series.
1.6 Calculate the forecast values for the signal using the linear recurrent formula.

Step 2: Hybrid SSA-ARIMA model

2.1 Obtain the residuals of SSA as described in Step 1.
2.2 Check the stationary of the SSA residual. Doing the differencing when the residual is not stationary.
2.3 Plot ACF and PACF of the residual.
2.4 Define the order of AR and MA models by using ACF and PACF plots.
2.5 Check the significance of parameter model.
2.6 Check the diagnostics of the ARIMA model, i.e., whether the residuals follow a normal distribution using the Kolmogorov-Smirnov test and LBQ test for a white noise process. Choose the model which satisfies a diagnostics test.
2.7 Calculate the forecast values for the residual of SSA using the ARIMA model obtained in step 2.6.
2.8 Calculate the final forecast values of hybrid SSA-ARIMA by adding the forecast values obtained by SSA in step 1.6 and the forecast values obtained by ARIMA in step 2.7.
2.9 Calculate the performance of model using MAPE and choose the model with the lowest MAPE.

Step 3: Hybrid SSA-FTS model

3.1 The residuals of SSA as described in Step 1 is modelled using FTS.
3.2 Determine the maximum, minimum and universe set of $\boldsymbol{U}$ of the SSA residual.
3.3 Determine the interval length.
3.4 Partition the universe set $\boldsymbol{U}$ into several intervals and determine the middle value.
3.5 Define a fuzzy set on $\boldsymbol{U}$ and perform fuzzification.
3.6 Determine a fuzzy logic relation (FLR).
3.7 Determine a FLR group (FLRG).
3.8 Determine defuzzification.
3.9 Calculate the forecast values for the residual of SSA using FTS model obtained in step 3.8.
3.10 Calculate the final forecast values of hybrid SSA-FTS by adding the forecast values obtained by SSA in step 1.6 and the forecast values obtained by FTS in step 3.9.
3.11 Evaluate the model using MAPE and choose the model with the lowest MAPE.

2.1 Method of SSA

SSA decomposes the time series into several smaller components, allowing us to classify each subseries as either a trend, seasonal pattern, or random noise. The SSA method involves a pair of interconnected phases: the decomposition and the reconstruction stage [19]. There are embedding and SVD in decomposition stage, while grouping and performing diagonal averaging are in reconstruction stage. In the embedding process, a one-dimensional series $\mathbf{X} = (x_1, x_2, \dots, x_N)$ is transformed into multiple-dimensional series $(X_1, X_2, \dots, X_K)$ with each vector $\mathbf{X} = (X_i, X_{i+1}, \dots, X_{i+L-1})^T \in R^L$, where i ranges from 1 to K and $K = N - L + 1$. The window length L, determines how the embedding is carried out, with the restriction that $2 < L < (\frac{N}{2})$. The time series X is used to construct a Hankel trajectory matrix $\mathbf{X}$ with dimensions $L \times K$,

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

The window length parameter L is must be selected and is addressed in [20], [21]. In the subsequent step, the trajectory matrix $\mathbf{X}$, as defined in **Equation (1)**, is subjected to decomposition using SVD,

$$\mathbf{X} = \sum_{i=1}^{d} \sqrt{\lambda_i}\, U_i\, V_i' \quad (2)$$

where $\lambda_1 \ \geq \ \lambda_2 \ \geq \dots \geq \lambda_d > 0$ are eigenvalues of matrix $\mathbf{XX}$', U_i are left eigen vectors and $V_i = X'\, U_i/\sqrt{\lambda_i}$ are right eigen vectors. The term of $\sqrt{\lambda_i}$, U_i and V_i are called eigentriples. The third stage is to group the eigentriple into m disjoint subset I_k, where k ranges from 1 to m, with m being no greater than d. This arrangement is carried out the **Equation (2)** as

$$\mathbf{X} = \mathbf{X}_{\boldsymbol{I_1}} + \mathbf{X}_{\boldsymbol{I_2}} + \dots + \mathbf{X}_{\boldsymbol{I_m}},$$

where $\mathbf{X}_{I_k} = \sum_{j \in I_k} \sqrt{\lambda_j}\, U_j\, V_j'$. The grouping process involves categorizing matrix X into distinct sets, which are referred to as trend, seasonal, and noise patterns. The final step is to convert each element of $\mathbf{X}_{I_k}$ into a time series through a process known as diagonal averaging that can be found in [22]-[24]. To predict the trend or seasonal component, the Linear Recurrent Formula (LRF) can be employed. The recurrent forecasting, also known as R-forecasting [3], can be expressed as follows

$$\hat{X}_{t+d} = \sum_{k=1}^{d} a_k \; X_{t+d-k} \tag{3}$$

where t ranges from 1 to $T - d$, $\hat{X}_{t+d}$ represents forecasted value at future time $t + d$ and T denotes size of sample.

2.2 Method of ARIMA

The popularity of the ARIMA model in time series forecasting arises from its effectiveness in prediction. This model is a linear model with the ability to capture both stationary and nonstationary time series data. The ARIMA (p, d, q) model [25] is expressed as Equation (4)

$$\psi_p(B)(1 - B)^d X_t = \eta_q(B)\varepsilon_t \tag{4}$$

where ψ_p represents a parameter associated with the Moving Average of order p, η_q corresponds to a parameter related to the Autoregressive component of order q, B is a mathematical operator for backward shift, d is the difference order, X_t denotes the observed data at time t, and ε_t represents the error at time t where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$ and this errors are also assumed to be independent of each other. The order of p and q can be ascertained by examining the ACF and PACF patterns within the data [26]. The Least Squares method is employed to estimate the parameters ψ_p and η_q in the ARIMA (p, d, q) model, as written in Equation (4). It is important to check that the residuals of the ARIMA model meet the assumption. In this study, we use Kolmogorov-Smirnov to examine whether the residuals follow a normal distribution [27] and Ljung-Box Q-statistics to assess the randomness of a white noise process within an ARIMA model [28], [29].

2.3 Method of FTS

The FTS is a forecasting technique that relies on fuzzy principles as its fundamental framework. The inception of FTS was initially presented by Song and Chissom [30], [31]. The following definitions are used in FTS.

Definition 1: *If there is relationship between* $F(t-1) = A_j$ *and* $F(t) = A_i$ *then FLR can be written by* $A_j \rightarrow A_i$.

Definition 2: *If* $A_i \rightarrow A_{j1}, A_i \rightarrow A_{j2}, \dots, A_i \rightarrow A_{jl}$ *then FLRG of those FLRs can be written as* $A_i \rightarrow A_{j1}, A_{j2}, \dots, A_{jl}$.

Fuzzification is the process of converting numerical variables into linguistic variables which are usually presented in the form of fuzzy sets with their respective membership functions [32]. Furthermore, it performs defuzzification, which aims to convert each fuzzy set result into a real number. Forecasting using Chen's fuzzy time series method is discussed in [33].

3. RESULTS AND DISCUSSION

The plot of insample data for ICP from January 2017 to December 2022 is shown in Figure 1. The presence of an upward trend in the insample data is clear. However, in January 2020, a downturn commences, which is linked to the onset of the COVID-19 pandemic. From May 2020 onwards, there is an increase.

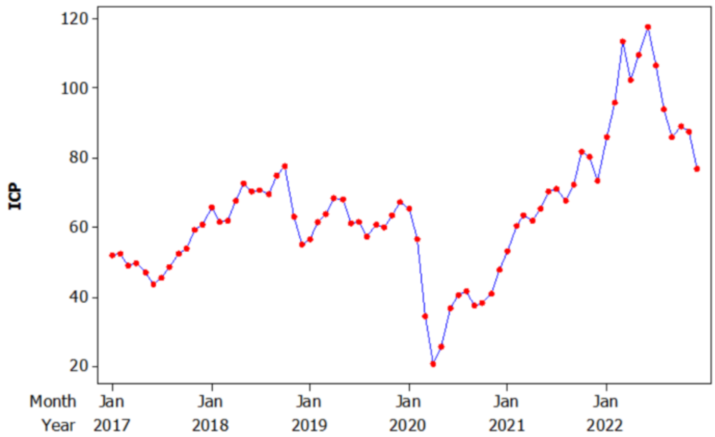
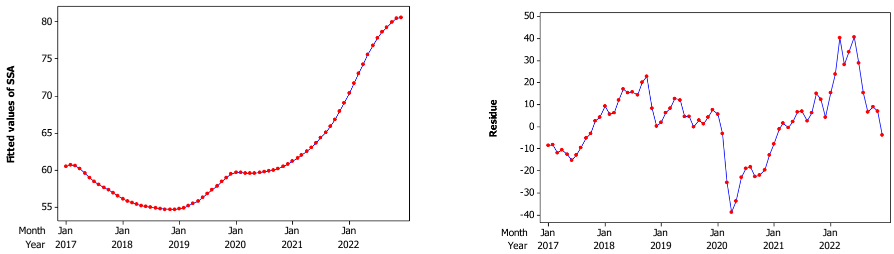


Figure 1. Plot of ICP insample data

The insample data of ICP is modelled using SSA. A window length of $L = 36$ is chosen because it results in the most distinct separation between the trend and noise. The first eigentriple is identified as the trend component, while eigentriples 2 to 36 are identified as noise as they do not exhibit a trend or seasonal pattern. Figure 2 shows the fitted values of SSA and its residues.



(a) (b)

Figure 2. The fitted value of SSA and its residues,
(a) Fitted values, (b) Residues

The residual of SSA (see Figure 2) is modelled by using ARIMA and then using FTS, namely hybrid SSA-ARIMA and SSA-FTS models.

3.1 Hybrid SSA-ARIMA

In this section, we modelled the residual of SSA using ARIMA. The data that modelled using ARIMA must be stationary. In this case, the residual is not stationary (see Figure 2 (b) and Figure 3).

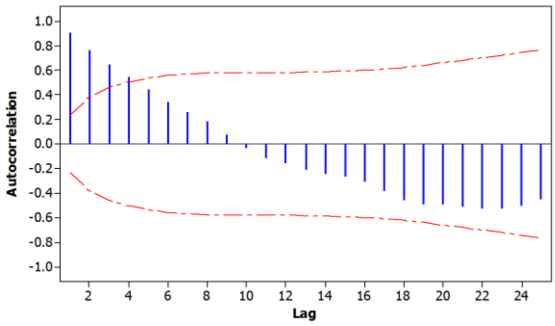
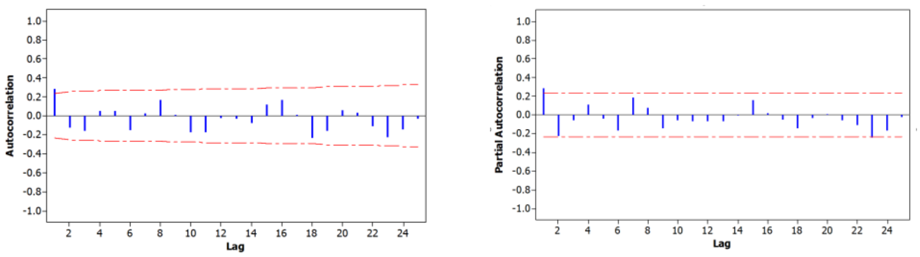


Figure 3. ACF plot of SSA residue

It shows that Figure 3 is not stationary and has a trend pattern. Furthermore, differencing of order 1 is performed, and the ACF and PACF plots are shown in Figure 4.



(a) **(b)**

Figure 4. ACF and PACF plots of diff 1 of SSA residue, (a) ACF, (b) PACF

Based on Figure 4, it shows that the data has a stationary pattern and we can see that lag one is outside the confidence interval, it suggests the order of $p = 1$ and $q = 1$. The alternative ARIMA models are ARIMA(1,1,0), ARIMA(0,1,1) and ARIMA(1,1,1). There are just two models in which the parameters are significant: ARIMA (0,1,1) that written as,

$$y_t = y_{t-1} + \varepsilon_t + 0.3608\, \varepsilon_{t-1}$$

and ARIMA (1,1,0) that represented as

$$y_t = 1.2945\, y_{t-1} - 0.2945\, y_{t-2}$$

The residuals of both models are normal and white noise. Next, we compute the MAPE of insample and outsample data of hybrid SSA with $L = 36$-ARIMA model. The forecasting of hybrid SSA with $L = 36$-ARIMA model is obtained by summing the forecasts from SSA, which is the trend component, with the forecasts from ARIMA. The MAPE value of hybrid SSA with $L = 36$-ARIMA(0,1,1), and SSA with $L = 36$-ARIMA(1,1,0) models are presented in Table 1.

Table 1. MAPE of Hybrid SSA-ARIMA

Model	Insample	Outsample
Hybrid SSA with $L = 36$-ARIMA(0,1,1)	8.08	7.10
Hybrid SSA with $L = 36$-ARIMA(1,1,0)	8.34	7.44

Based on Table 1, it shows that both models have MAPE values of less than 10%. However, the hybrid SSA with $L = 36$-ARIMA(0,1,1) model has a smaller MAPE value. This indicates that both models are very suitable for forecasting ICP.

3.2 Hybrid SSA-FTS

The noises of SSA are modelled using FTS. The first step is formed the universe $U = [-40, 50]$ which then divided into three different lengths of intervals, i.e., 5, 10 and 15. Based on the analysis on each length of intervals, we can obtain FLRG and defuzzification that described in Table 2, especially for interval length 5.

Table 2. FLRG And Defuzzification with Interval Length 5

Group	FLRG	Defuzzification $F(t)$	
1	$A_1 \to A_2$	m_2	-32.5
2	$A_2 \to A_4$	m_4	-22.5
3	$A_3 \to A_1$	m_1	-37.5
4	$A_4 \to A_4, A_5$	$\frac{(m_4 + m_5)}{2}$	-20
5	$A_5 \to A_4, A_5, A_6$	$\frac{(m_4 + m_5 + m_6)}{3}$	-17.5
6	$A_6 \to A_5, A_6, A_7$	$\frac{(m_5 + m_6 + m_7)}{3}$	-12.5
⋮	⋮	⋮	⋮
16	$A_{16} \to \emptyset$	m_{16}	37.5
17	$A_{17} \to A_{14}$	m_{14}	27.5
18	$A_{18} \to \emptyset$	m_{18}	47.5

The result of defuzzification can be used to forecast the residual of SSA. The forecasted values of hybrid SSA-FTS model are found by adding the SSA forecast and FTS forecast, and the value of MAPE are calculated, as shown in **Table 5**.

Table 5. The MAPE Value of Hybrid SSA With $L = 36$-FTS

SSA with $L = 36$-FTS	Insample	Outsample
Interval length 5	7.50	11.89
Interval length 10	9.51	9.08
Interval length 15	14.70	9.10

Table 5 clearly indicates that the top-performing model is the SSA with $L = 36$-FTS model, particularly with an interval length of 10. This preference is driven by the fact that it exhibits MAPE values below 10% for both of insample and outsample data ICP.

The MAPE values of SSA with $L = 36$-ARIMA(0,1,1) for insample data is 8.08% and for outsample data is 7.10%. Meanwhile, the MAPE value of SSA with L=36-FTS with interval length 10 for insample data is 9.51% and for outsample data is 9.08%. The study conducted by **[17]** utilized ICP data with a different time period compared to the researcher's study. In that research, an ARIMA(1,2,1)-GARCH(1,3) model was obtained and employed for forecasting one period ahead. However, forecasting errors, such as MAPE, were not calculated in that study, making it impossible to compare with the results of the researcher's study. The same applies to the study conducted by **[18]**.

The hybrid model combines two methods for forecasting time series data. Insample data is modeled using SSA, then residuals from SSA are modeled using ARIMA and FTS. Forecasting of the hybrid SSA-ARIMA is obtained by adding up the forecasting results using SSA and the forecasting results using ARIMA. Likewise, for forecasting the hybrid SSA-FTS, it is obtained by adding up the forecasting results using SSA and the forecasting results using FTS. SSA can capture deterministic models, while ARIMA and FTS can capture stochastic models. Thus, the hybrid model can increase the accuracy of forecasting results.

4. CONCLUSIONS

The analysis of ICP was conducted using the hybrid SSA-ARIMA and hybrid SSA-FTS models. Both models produce MAPE values of less than 10%. However, the hybrid SSA-ARIMA model yields a smaller MAPE value. This shows that the ARIMA model can capture the stochastic model better than the FTS model, so that forecasting results using the hybrid SSA-ARIMA are closer to the actual data. In light of these findings, the hybrid SSA-ARIMA model is more suitable choice than hybrid SSA-FTS for ICP value forecasting.

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