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COMPARISON OF LEAST SQUARE SPLINE AND ARIMA MODELS FOR PREDICTING INDONESIA COMPOSITE INDEX

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ABSTRACT

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The Indonesian Composite Index (ICI) reflects Indonesia's economic growth. ICI predictions are significant considerations for investors when making investment decisions. Two approaches can be used to predict ICI: parametric and nonparametric approaches. Therefore, this study compares parametric and nonparametric approaches to predict ICI. In its application, the parametric approach requires several assumptions to be met, such as linearity. This differs from analysis with a nonparametric approach that does not require certain assumptions. The parametric approach in this study uses the ARIMA model. ARIMA is widely used to predict time series data. In the nonparametric approach, in this study, we used nonparametric regression based on the least square spline. Spline is chosen because it can handle data that tends to fluctuate by placing knot points when data changes occur. In this study, ICI monthly data obtained from the website investing.com was used. Investing.com is a website that financial analysts often use as a data source to monitor world economic conditions, including the ICI. The Mean Absolute Percentage Error (MAPE) value is determined to assess the accuracy of the prediction. The study results indicate that the analysis with ARIMA cannot meet the assumptions, so ARIMA modeling cannot be continued. Different results were obtained in nonparametric regression modeling based on the least square spline estimator. Prediction of ICI using nonparametric regression based on the least square spline estimator has a MAPE value of 2.613% (less than 10%), which means the model is a highly accurate prediction, meaning modeling using nonparametric regression based on the least square spline estimator is better than the ARIMA model for predicting ICI.

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1. INTRODUCTION

The capital market is one of the leading indicators of a country's economic growth. The capital market provides a forum for exchanging information for investors and companies [1]. Companies can obtain long-term funding through the capital market. Apart from this, investors can profit from their investment results. The Composite Stock Price Index (CSPI) indicates capital market development. It reflects the average performance of all shares listed on the stock exchange. The combined stock price in Indonesia has numerous capital market indices divided into several industrial sectors. The combination of all these industrial sectors is called the ICI [2]. ICI can evaluate the effectiveness of Indonesian businesses. Moreover, the stock market's overall performance is reflected in increases or reductions in ICI. According to Apituley [3], ICI is seen as a representation of the Indonesian economy. Investors and financial analysts frequently use ICI to track the stock market's performance. To decide whether to purchase or sell shares, investors must predict the rise and fall of stock prices. Several studies by Xiu et al. [4] to predict the New York Stock Exchange, Hikmah et al. [5] also performed ICI predictions with the C-D Vine Copula Approach which produced an accurate prediction model, and Huang [6] investigated the prediction of Shanghai Securities Composite Index using ARMA and ARIMA model.

Predictions of upcoming events can be made by analyzing historical data [7]. The two types of predicting methods are parametric and nonparametric. One of the potential parametric strategies is the application of the Autoregressive Integrated Moving Average (ARIMA). According to Siami-Namini et al., the ARIMA model is frequently employed for predicting [8]. For instance, Latif et al. [9] onducted research utilizing the ARIMA model to predict Bitcoin prices. Additionally, Benvenuto et al. [10] employ ARIMA model on COVID-19 data.

The connection between the predictor and response variables is occasionally linear or consistent with a specific pattern. A nonparametric approach can be employed if a particular connection pattern between the two variables does not exist. Since the nonparametric procedure requires that the nonparametric curve follows the data, it is considered more flexible than parametric regression. Techniques for smoothing data are essential to estimate nonparametric models. Kernel, linear local, local polynomial, spline, penalized spline, and Fourier series are examples of smoothing techniques [11]. Zhou et al. [12] utilized smoothing kernels to predict wind power in one of the earlier nonparametric research. Feriel and Elias [13] discuss nonparametric regression using a local linear estimator on twice-censored data.

Modeling utilizing nonparametric techniques with local polynomials outperforms the typical multiple polynomial regression strategies on data on avocado fruit sweetness level [14]. Chamidah et al. [15] employ a spline estimator to evaluate growth charts for kids in East Java. In addition, Orbe and Virto [16] and Pusporani et al. [17] implemented penalized spline and Fourier series estimators in their investigation.

Spline is a smoothing technique widely employed in nonparametric modeling [18]. The advantage of using a spline is dealing with data that tends to fluctuate randomly by placing knot points [19]. The fittest knot point is selected based on the lowest Generalized Cross Validation (GCV) value [20]. Previous studies have utilized the spline smoothing technique for nonparametric regression [21].

Time series, longitudinal, and cross-sectional data are all studied using parametric and nonparametric methods. Data collected at predetermined intervals is referred to as a time series. Research items such as stock prices, currency exchange rates, and inflation are included in time series data over various timescales, including daily, monthly, and yearly [22]. One widely implemented method to predict time series data is the Autoregressive Integrated Moving Average (ARIMA) model. Amry and Siregar used the ARIMA model approach to research time series data to predict the ICI data from 2000 to 2017 [23]. Furthermore, the ARIMA model predicts ICI in Gunawan, Astika [24] and Adyatama [25].

The researchers use nonparametric analysis for time series data. Several studies of time series data using nonparametric regression have utilized a kernel estimator, including Stoppa et al.[26] and Yan et al. [27]. In addition to the kernel estimator, time series data research was carried out using the least square spline estimator by Dong et al. [28]. Fibriyani and Chamidah also operate local polynomials and compare them with the ARIMA model to predict the inflation rate in Indonesia [29]. This study obtained more accurate inflation prediction results based on a nonparametric model using a local polynomial estimator compared to the ARIMA model.

Using estimators in nonparametric regression depends on the data pattern between the predictor and response variables. Due to fluctuating inflation data, previous studies compared ARIMA and local polynomial estimators in nonparametric regression. This study compares ARIMA versus nonparametric regression based on the least squares spline estimator model applied to ICI data. The least square spline estimator was used because it may segment the curve by positioning knot points, allowing the estimated curve to shift by the actual data, which can be a solution for frequently fluctuating data. Comparing the analytical results to the MAPE criteria is necessary to determine the most appropriate model for ICI forecasting. The results of this study are expected to contribute to understanding each method for predicting ICI. They can help investors make long-term investment decisions using more accurate ICI predictions.

2. RESEARCH METHODS

This section describes the materials and methods used in this research. The material includes nonparametric regression based on the least square spline estimator, ARIMA, and data from the ICI.

2.1 Nonparametric Regression Models Based on Least Square Spline Estimator

Given the nonparametric regression model:

$$Y_t = g(x_t) + \varepsilon_t, t = 1,2,\cdots,T \tag{1}$$

Functions $g(x)$ on the spline with order p and knot points $k_1, k_2, \cdots, k_m$ can be written in **Equation (2) [30]**:

$$g(x_t) = \sum_{j=0}^{p} \beta_j {x_t}^j + \sum_{j=1}^{m} \beta_{j+p}(x_t - k_j)_+^p \tag{2}$$

where $(x_t - k_{j-p})_+^p = \begin{cases} (x_t - k_{j-p})^p; x_t \geq k_{j-p} \\ 0 \qquad\qquad\quad ; x_t \geq k_{j-p} \end{cases}$

If given, $\lambda = (p, k_1, k_2, \cdots, k_m)$ which is the smoothing parameter represented by knots $k_1, k_2, \cdots, k_m$ and p is the spline order. Then the parameter estimation is:

$$\hat{\beta} = (X_\lambda^T X_\lambda)^{-1} X_\lambda^T y \tag{3}$$

where $\boldsymbol{X_\lambda} = \begin{pmatrix} 1 & x_1^1 & x_1^2 & \cdots & x_1^p & (x_1 - \tau_1)_+^p & \cdots & (x_1 - \tau_m)_+^p \\ 1 & x_2^1 & x_2^2 & \cdots & x_2^p & (x_2 - \tau_1)_+^p & \cdots & (x_2 - \tau_m)_+^p \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_T^1 & x_T^2 & \cdots & x_T^p & (x_T - \tau_1)_+^p & \cdots & (x_T - \tau_m)_+^p \end{pmatrix}$.

The estimation of the function $g(x_t)$ in **Equation (2)** can be expressed as follows using **Equation (3)**:

$$\hat{g}_\lambda(x_t) = H(\lambda)y \tag{4}$$

where $H(\lambda) = X_\lambda(X_\lambda^T X_\lambda)^{-1} X_\lambda^T y$. Subsequently, $\hat{g}_\lambda(x_t)$ refers to a least square spline estimator.

2.2 Autoregressive Integrated Moving Average (ARIMA)

Autoregressive Integrated Moving Average (ARIMA) is a time series method non-stationary series. If the data is not stationary, it is necessary to do differencing by taking the differentiating term $(1 - B)^d$. ARIMA *(p,d,q)* is the ARMA model *(p,q)* which has through the differencing process *d* times **[31]**. The general ARIMA can be expressed as follows:

$$\phi_p(B)(1 - B)^d = \theta_0 + \theta_q(B)\alpha_t \tag{5}$$

where is stationary operator of AR, $\phi_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ is the invertible MA operator, and $\theta_0 = \mu(1 - \phi_1 - \phi_2 - \cdots - \phi_p)$ is deterministic trend term.

2.3 Data of Indonesia Composite Index

The secondary data in this research was gathered from ICI data collected through the website investing.com, which is a trusted source of financial data and widely used by investors and financial analysts as a source of information. On the website, information is provided regarding the source of the data presented so that users can verify the accuracy of the data. Moreover, the ICI data used in this study include monthly data with about 120 observations from September 2014 to August 2024. The data in this study are separated into the sample used for modeling (September 2014 to August 2023) and the sample used for predicting (September 2023 to August 2024). Time (t) is the predictor variable, while the response variable is ICI.

2.4 Analysis Method

This study is a study that compares two models that are built, namely nonparametric regression based on least square spline estimator and ARIMA model. The steps of analysis using nonparametric regression based on least square spline estimator are as follows:

a. Determine descriptive statistics on ICI data

b. Plot the ICI data with time *(t)*

c. Employ the following Generalised Cross Validation (GCV) criterion two select the optimal knot points in the in-sample data:

$$GCV(\lambda) = \frac{MSE(\lambda)}{\left[\frac{1}{n}trace(I-H(\lambda))\right]^2} \quad (6)$$

with $\lambda = p, \tau_1, \tau_2, \cdots, \tau_k$is smoothing parameter p is spline order, τ is the total knot points, and $H(\lambda) = X_\lambda\left(X_\lambda^T X_\lambda\right)^{-1} X_\lambda^T y$.

d. Create the nonparametric regression model based on optimal knot points.

e. Determine the goodness of the model criteria of nonparametric regression model based on least square spline estimator by calculate MAPE value with the following formula in **Equation (7)**:

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\hat{y}_t - y_t}{y_t}\right| x100 \quad (7)$$

with n is total observation, $\hat{y}_t$the estimated value at time *t*, and $y_t$denotes the response value at time *t*. These are the MAPE accuracy level categories **[32]**:

Table 1. Interpretation of MAPE Value

MAPE Value	Interpretation
MAPE > 50	Inaccurate
20 < MAPE ≤ 50	Reasonable
10 < MAPE ≤ 20	Good Prediction
MAPE ≤ 10	High Accurate Prediction

Next, the stages in analysis using ARIMA are as follows:

a. Plot the ICI data.

b. Identifying data stationary.

c. Differentiate and transform the data to ensure they are stationary.

f. Plot of ACF and PACF.

g. Select a tentative model based on ACF and PACF.

h. Decide the most suitable ARIMA model.

i. Calculate the MAPE value of the ARIMA model.

After obtaining the model and MAPE values based on the nonparametric regression model based on the least square spline estimator and ARIMA, the next step is comparing MAPE values so that a better method is obtained. The stages of the methodology in this research are depicted in the flowchart in **Figure 1**.

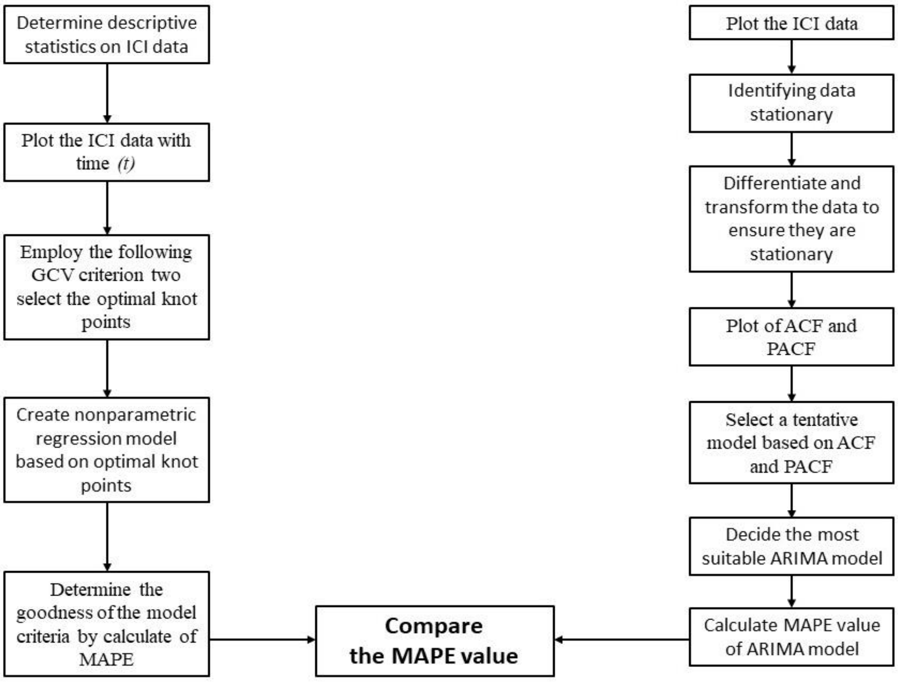


Figure 1. Flowchart of Analysis Stages

3. RESULTS AND DISCUSSION

ICI represents the Indonesian stock market. Its movement depends on the economic conditions of the country. Therefore, it reflects Indonesia's financial conditions. The descriptive statistic for ICI data from September 2014 to August 2024 is explained in Table 2.

Table 2. Descriptive Statistic of ICI variable

Min	Max	Mean	Variance
4223.91	7670.73	5996.34	688986.72

Table 2 shows that from September 2014 to August 2024, the average ICI was 5996.34, with a variance of 688986.72. The lowest ICI was in September 2015, and the highest ICI was 7670.73 in April 2022. ICI tends to rise and fall each year. Indonesia's economic performance is indicated by the rise and fall of ICI.

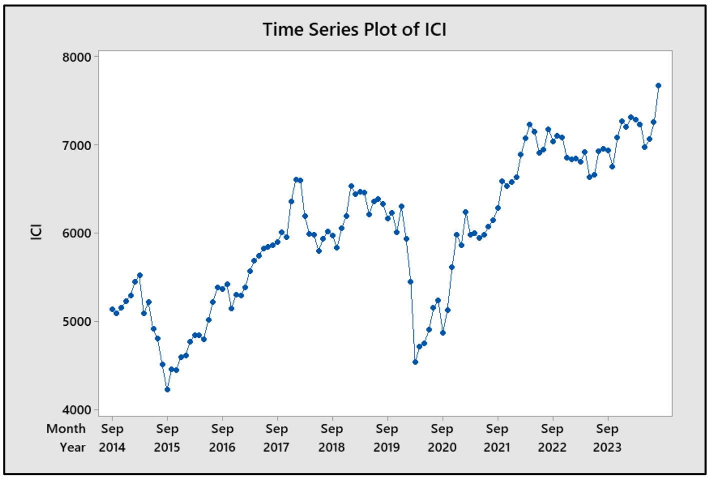


Figure 2. ICI from September 2014 until August 2024

Figure 2 illustrates the increase and decrease in ICI from September 2014 to August 2024. The horizontal axis demonstrates the time (t), and the vertical axis indicates the ICI in this period.

3.1 Prediction of ICI using Nonparametric Regression-Based on Least Square Spline Estimator

Nonparametric regression using a spline estimator has been employed in this investigation, with 120 observations in the modeling data (in-sample) from September 2014 to August 2023. Choosing the most appropriate knot point according to the lowest GCV value is crucial when utilizing a spline estimator and nonparametric regression. These are the results of the GCV and MAPE calculations:

Table 3 Estimation Result using Nonparametric Regression based on Least Square Spline Estimator

Number of Knot Points	Knot Points	Order of Spline	GCV	MAPE
4	42; 46; 54; 67	1	150126.9	5.338
		2	183657.4	5.657
5	13; 42; 46; 54; 67	1	98124.92	3.935
		2	182912	5.592
6	13; 42; 46; 54; 67; 92	1	69403.96	3.303
		2	136580.1	4.893
7	7; 13; 42; 46; 54; 67; 92	**1**	**59650.41**	**2.841**
		2	125243.5	4.503

Based on Table 3, the lowest GCV value is obtained by modeling order 1 with 7-knot points with a GCV value of 59650.41. The MAPE value obtained from in-sample data is 2.841%, and the MAPE value from out-sample data is 2.385%, which means that overall MAPE is 2.613%. The MAPE value of 2.613% (<10%) indicates that the model produced is a highly accurate prediction. The following Equation (9) shows the Prediction of ICI model estimation using nonparametric regression based on the least square spline estimator:

$$\begin{aligned}\hat{y} = 4993.649 + 66.36t - 250.237(t-7)_+ + 253.93(t-13)_+ - 254.104(t-42)_+ \\ + 323.69(t-46)_+ - 274.06(t-54)_+ + 212.79(t-67)_+ - 87.662(t-92)_+\end{aligned} \tag{9}$$

The Equation (9) is elaborated as follows.

$$y_t = \begin{cases} 4993.649 + 66.36t & ; t < 7 \\ 6745.308 - 183.877t & ; 7 \le t < 13 \\ 3444.218 + 70.053t & ; 13 \le t < 42 \\ 14116.586 - 184.051t & ; 42 \le t < 46 \\ -773.154 + 139.639t & ; 46 \le t < 54 \\ 14026.086 - 134.421t & ; 54 \le t < 67 \\ -230.844 + 78.369t & ; 67 \le t < 92 \\ 7834.06 - 9.293t & ; 92 < t \end{cases} \tag{10}$$

Based on Equation (10), the relationship between t and ICI fluctuates, indicating that the movement of the ICI depends on conditions that influence time, such as in 2019, when the pandemic occurred, causing the ICI to fall and gradually improve; in this case, the ICI value slowly rose along with the pandemic conditions, which gradually improved. In the model described in Equation (10), if t is less than 7 and t increases by one unit, then the ICI will also increase by 66.36. If t is more than equal to 7 and less than 13 and t increases by one unit, then the ICI will decrease by 183.877. If t is more than equal to 13 and less than 42 and increases by one unit, then the ICI increases by 70,053. If t is between 42 and 46, the ICI decreases by 184.051. ICI will increase by 139.639 if t is more than equal to 46 and less than 54. If t is more than equal to 54 and less than 67 and t increases by one unit, then ICI decreases by 134.421. ICI increases by 78.369 if t is more than equal to 67 and less than 92 and increases by one unit. If t is more than 92 and increases by one unit, then ICI decreases by 9.293. The plot of observational data and estimates of the ICI using nonparametric regression based on the least square spline estimator is shown in Figure 3.

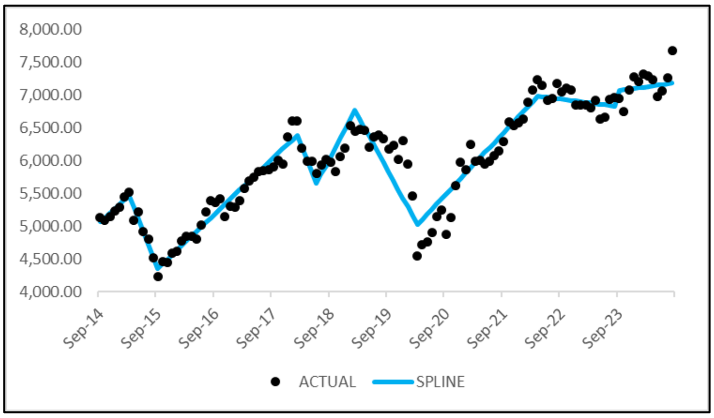
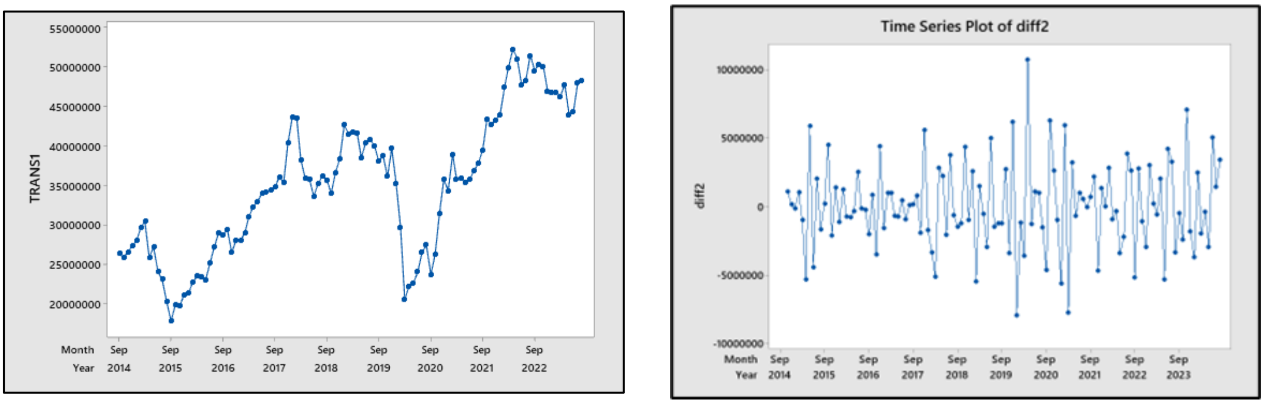


Figure 3. **The Plot of Estimated Data Utilizing Nonparametric Regression Approach using Least Square Spline Estimator.**

Figure 3 reveals that the approach with nonparametric regression using the least square spline estimator for ICI data is divided into eight segments based on knot points. The resulting model estimation results are an approach to the actual value. In the model obtained using nonparametric regression based on the least square spline, the MAPE value obtained on in-sample data was 2.841%, and on out-sample data was 2.385%. So, the overall MAPE was 2.613% (less than 10%), which means the resulting model is a highly accurate prediction.

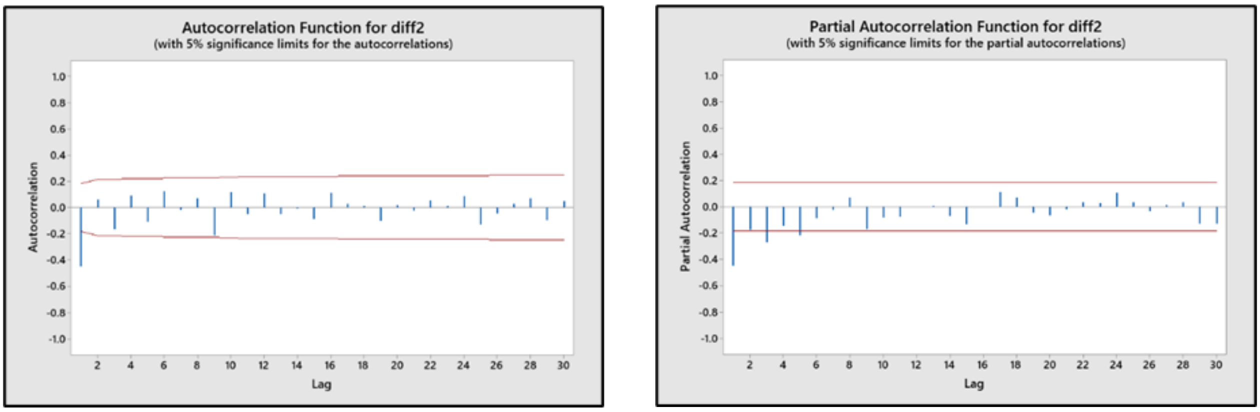
3.2 Prediction of ICI using ARIMA Model

The step of the ARIMA technique is to identify whether the trend of the input data is stationary in terms of variance and average. The Box-Cox test was completed for the stationary test in variance, while the stationary test in the standard was carried out by looking at the ACF plot. After carrying out the transformation and difference of 2 in this investigation, the data have evolved stationary in terms of variance and average. **Figure 4** portrays the plots of time series data before and after differentiating. Explore the ACF and PACF sequences utilized to create the model. **Figure 5** illustrates the plot of ACF and PACF.



(a) **(b)**

Figure 4. **(a) Time Series Plot; (b) Output Differencing**



(a) **(b)**

Figure 5. **(a) Plot ACF; (b) Plot PACF**

Based on Figure 4, it can be seen that the data is stationary in the second differencing. The following phase is to develop a tentative model relying on the ACF and PACF in Figure 5. Table 4 presents the tentative model-based ARIMA.

Table 4. Tentative Model-based ARIMA

ARIMA Model	P-Value (parameter)	MSE	White Noise Assumptions
ARIMA (1,2,1)	AR1 = 0.146 MA 1 = 0.000	43487.9	Lag 12 = 0.207 Lag 24 = 0.594 Lag 36 = 0.490 Lag 48 = 0.433 White Noise
ARIMA (3,2,1)	AR 1 = 0.181 AR 2 = 0.555 AR 3 = 0.085 MA 1 = 0.000	43383.6	Lag 12 = 0.438 Lag 24 = 0.891 Lag 36 = 0.569 Lag 48 = 0.685 White Noise

The results of the ARIMA model estimation shown in Table 4 show that there are still insignificant parameter coefficients for all possible ARIMA models. Thus, the testing process cannot be carried out because assumptions in the parametric time series are not met. These results prove that the nonparametric regression model based on the least square spline estimator is better than the ARIMA model in predicting ICI. The results of this research strengthen research related to the application of nonparametric regression, which produces a better model than the model created by the ARIMA method. This is based on research conducted by Fibriyani et al. [22] and Pratama et al. [33], which compares nonparametric regression based on local polynomial estimators with the ARIMA method. A similar thing was also found in research conducted by Wisisono et al. [34], who stated that the nonparametric regression model based on the Fourier series estimator produces a better model than the ARIMA model. Therefore, the model generated by nonparametric regression based on the least square spline estimator in Equation (9) can be a consideration for investors to make ICI predictions in the future. Based on nonparametric regression, investors can get more accurate ICI prediction values when making investment decisions.

4. CONCLUSIONS

Based on the study's results, the nonparametric regression model based on the least square spline estimator is more appropriate for predicting ICI than the ARIMA model. Because in the ARIMA model, a parametric time series assumption is not met. The MAPE value obtained based on the analysis results with nonparametric regression based on the least square spline is 2.613% (less than 10%), which means this model is a highly accurate prediction. Thus, this study has implications for further research plans. Based on the study's results, nonparametric regression using least square spline is more appropriate for prediction. The model produced by the least square spline is better than the ARIMA model. The results of this study can be used as a consideration in predicting ICI for investors so that more accurate ICI predictions can be obtained. In this study, we only investigated ICI based on previous ICI data. In the future, it is hoped that this study can be developed by considering other factors that influence ICI. In addition, it can be developed with other methods such as ARIMAX.

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