Songklanakarin J. Sci. Technol.
47 (1), 26–33, Jan. – Feb. 2025

http://www.sjst.psu.ac.th

Original Article

Prediction of inflation rate in Indonesia using Fourier series estimator and support vector regression (SVR)

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Received: 2 May 2024; Revised: 1 August 2024; Accepted: 20 November 2024

Abstract

High and low inflation rates greatly affect economic growth in Indonesia. This supports the eighth goal of the Sustainable Development Goals (SDGs), which is economic growth. One way to deal with fluctuating inflation rates is to make predictions. This is the main objective of this research so that the prediction results can be used as a reference by Bank Indonesia in setting future inflation targets. The model generated using the Fourier series estimator and Support Vector Regression (SVR) is evaluated for accuracy by comparing the Mean Absolute Percentage Error (MAPE) in estimate of inflation rate in Indonesia. The results show that the SVR model with a linear kernel had better accuracy than the Fourier series estimator containing cosine and sine rows with MAPE values of 8.40% and 0.10% for each test data. The insight gained from this research is that accurate inflation rate prediction will have a significant impact on economic, monetary policy, and market stability. Improved prediction accuracy can help Bank Indonesia make more informed decisions about maintaining price stability and economic growth.

Keywords: prediction, inflation, Fourier series estimator, support vector regression, sustainable development goals

1. Introduction

Inflation can be referred to as a monetary phenomenon, because the value of the monetary unit in purchase of a good decreases. This relates to the eighth goal of the Sustainable Development Goals (SDGs): economic growth. According to modern economists, inflation is an increase in the amount of money that must be paid for goods and services (Nabila & Anwar, 2021). The inflation rate in Indonesia is still relatively controlled because, historically, Indonesia experienced a high inflation rate of 8.5% in 2014 (Wati, Eltivia, & Djajanto, 2021). Indonesia's inflation rate fell to less than 2% between June 2020 and September 2021. Inflation has decreased due to restrictions on people's activities in fulfilling their needs (Savitri *et al*., 2021). One organization that monitors Indonesia's inflation rate is Bank Indonesia. It does this by determining whether the set target is in line with future inflation projections. Models based on specific data are used to derive predictions (Fibriyani & Chamidah, 2021).

Predictions are made to anticipate something that may be happening in the future so that suitable action can be taken. Two approaches can be used to perform forecasting on time series data, namely parametric and nonparametric approaches. The nonparametric regression approach is used if the functional relationship between the response variable and the predictor variables does not fit the form of a specific regression function. Nonparametric regression approaches are highly flexible because the regression function is not defined in a particular form but is assumed to be smooth (Eubank, 1999).

One approach that is used to estimate nonparametric regression functions is the Fourier series estimator. The Fourier series estimator has the flexibility of approximating repeating or oscillating data patterns with trigonometric function patterns. The Fourier series estimator is suitable for modeling seasonal data patterns, and trends in seasonal data patterns (Mardianto, Kartiko, & Utami, 2019). In addition to using the Fourier series estimator approach, this research uses the time series approach with Support Vector Regression (SVR). The advantage of SVR is the ability to address nonlinear data problems by using kernel

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functions to overcome the problem of overfitting, where the resulting model only produces a good model for training data and not for testing data (Su *et al*., 2019). SVR can produce high prediction accuracy with excellent generalization ability and is effectively applied in estimating real valued functions (Awad & Khanna, 2015).

Previously, research was conducted by Mardianto *et al*. (2020) regarding the prediction of strategic commodity prices in Indonesia during the COVID-19 pandemic based on a comparison between the Fourier series estimate and a kernel based estimate. The study results show that the Fourier series estimator has better prediction performance, with a small MAPE of 0.0443%. In addition, another study was conducted by Suparti *et al*. (2019) on Indonesian Inflation Analysis Using the Hybrid Fourier-Wavelet Multiscale Autoregressive Method. The results showed that the hybrid Fourier-Wavelet regression model produced a better model than the wavelet model with fewer parameters. Oktanisa *et al*. (2020) reported on inflation rate prediction in Indonesia using Support Vector Regression. Based on the tests, the SVR genetic algorithm method can predict Indonesia's inflation rate.

Based on that description, the novelty of this research is to compare the classical nonparametric time series based on the Fourier series and the modern nonparametric time series based on Support Vector Regression (SVR) to forecast the inflation rate in Indonesia. The combination of a Fourier series estimator and the SVR method is proven to be a reliable forecasting technique for predicting Indonesia's inflation rate. The method demonstrates accuracy through commonly used measures such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

In this article, the research introduction has been discussed in general. Next, in Section 2, Materials and Methods are presented, providing a more detailed explanation of data sources, time series regression, nonparametric regression, Fourier series estimator, oscillation parameter, Support Vector Regression, model accuracy using MAPE, and steps of data analysis. Section 3, Results and Discussion, presents the main findings of the inflation rate prediction analysis using the Fourier Series Estimator and Support Vector Regression (SVR). Finally, the conclusion is presented in Section 4.

2. Materials and Methods

2.1 Data and data sources

The data used are secondary data related to Indonesia's inflation rate. The data used are monthly from 2013 to 2022, consisting of 120 observations collected. The data in question are divided into two categories, namely training data (2013-2019) consisting of 84 observations used to build the model, and testing data (2020-2022) consisting of 36 observations used to test prediction ability. The data are taken from the Bank Indonesia's website: https://www.bi.go.id/id/default.aspx. In this case, the response variable (y) is the Inflation Rate, and the observation time (t) is the predictor variable.

2.2 Data analysis method

2.2.1 Nonlinearity test

The first step in applying a nonlinear model is to perform a nonlinearity test on the time series data. This is done to ensure that the method to be used is suitable for the characteristics of the data. One test that can be used to determine the nonlinear relationship between variables is the Terasvirta Test. The hypothesis formula tested in the Terasvirta test is as follows: if the quadratic and cubic components are 0, then H_0 fails to be rejected so that a linear model is obtained. The Terasvirta test can be performed using the chi-square and F distributions (Terasvirta, 1994).

2.2.2 Time series regression

A time series observation data set can be described as a random variable y_t, with t as the time index of the observation sequence (Satrio, Darmawan, Nadia, & Hanafiah 2021). Time series analysis can be applied to time series regression. In time series regression modeling, there are two common approaches to estimating regression curves namely parametric regression and nonparametric regression. The geometry of the regression curve which can be a line, a curve segment, or any other shape, must be known to perform parametric regression. In contrast to parametric regression, nonparametric regression uses a specific regression curve shape that cannot be estimated and is in a specific functional domain (Asrini & Budiantara, 2014).

2.2.3 Nonparametric regression

Nonparametric regression analysis is a subset of statistical methods used to model the relationship between predictor and response variables. If the data pattern cannot fulfill the assumption test or if many parameters are not significant, then one solution that can be used is nonparametric regression. Nonparametric regression has great flexibility in modeling data patterns that are not known or recognized so that the regression curve looks for the data pattern (Takezawa, 2005). Suppose then the relationship between (x_i, y_i) can be expressed as follows (Ramli, Budiantara, & Ratnasari, 2023).

$$y_i = f(x_i) + \varepsilon_i \; ; i = 1,2, \dots, n \tag{1}$$

with,

$f(x_i)$: regression curve
ε_i : random error
x_i : predictor variable
y_i : response variable

2.2.4 Fourier series estimator

A trigonometric polynomial with a lot of flexibility is the Fourier series. A curve that represents the sine and cosine functions is called the Fourier series. A periodic function can be defined as a combination of many harmonic functions, such as sine and cosine functions, including sinusoidal functions, when represented in Fourier form (Faisol *et al*., 2022).

Suppose we have pairs of observational data (t_r, y_r) that follow the general regression model as follows:

$$y_r = m(t_r) + \varepsilon_r \,, \qquad r = 1,2,\dots,n$$

The regression function $m(t_r)$ is of unknown form and will be estimated by a nonparametric regression approach using the Fourier series estimator. Suppose it is assumed that $m(t_r) \in L_2[a,b]$ which is a Hilbert space so that $m(t_r)$ can be expressed as a linear combination of basis elements of $L_2[a,b]$. Therefore, if $\{x_j\}_{j=1}^{\infty}$ is a complete orthonormal system of $L_2[a,b]$ then $m(t_r)$ can be expressed as follows:

$$m(t_r) = \sum_{j=1}^{\infty} \beta_j x_j(t_r), \quad r = 1,2,\dots,n \qquad (2)$$

if β_j is a scalar and λ is an integer then the model can be expressed as follows:

$$y_r = \sum_{j=1}^{\lambda} \beta_j x_j(t_r) + \varepsilon_r \,, \qquad r = 1,2,\dots,n \qquad (3)$$

If expressed in the form of a matrix:

$$y = X_\lambda \beta_\lambda + \varepsilon \qquad (4)$$

with,

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, X_\lambda = \begin{pmatrix} e^{2\pi i(-\lambda)t_1} & e^{2\pi i(-\lambda+1)t_1} & \dots & e^{2\pi i\lambda)t_1} \\ e^{2\pi i(-\lambda)t_2} & e^{2\pi i(-\lambda+1)t_2} & \dots & e^{2\pi i\lambda)t_2} \\ \vdots & \vdots & \dots & \vdots \\ e^{2\pi i(-\lambda)t_n} & e^{2\pi i(-\lambda+1)t_n} & \dots & e^{2\pi i\lambda)t_n} \end{pmatrix}, \beta_\lambda = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{pmatrix}, \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

$$Q = \varepsilon'\varepsilon = (y - X_\lambda\beta_\lambda)'(y - X_\lambda\beta_\lambda) = y'y - 2\beta_\lambda' X_\lambda' y + \beta_\lambda' X_\lambda' X_\lambda \beta_\lambda$$

Since the least squares method is to minimize the sum of the squares of the errors, therefore:

$$\frac{\partial Q}{\partial \beta_\lambda} = 0 - 2X_\lambda' y + 2X_\lambda' X_\lambda \beta_\lambda = 0$$
$$\hat{\beta}_j = (X_\lambda' X_\lambda)^{-1} X_\lambda' y$$

Where X_λ' denotes the transposition of X_λ, therefore:

$$X_\lambda' X_\lambda = \begin{pmatrix} n & 0 & \dots & 0 \\ 0 & n & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \dots & n \end{pmatrix} = n \times I$$
$$(X_\lambda' X_\lambda)^{-1} = \frac{1}{n} I$$
$$X_\lambda' y = \sum_{r=1}^{n} y_r e^{-2\pi i j t_r}$$

The Fourier series estimator for $m(t_r)$ is:

$$\hat{m}(t_r) = \sum_{j=-\lambda}^{\lambda} (n^{-1} \sum_{i=1}^{n} y_i \, e^{-2\pi i j t_i}) e^{-2\pi i j t_i} \qquad (5)$$

If $[a,b] = [0,1]$ and t_r is equidistant at $[0,1]$ t_r can be written as follows:

$$t_r = \frac{r-1}{n}\,, \qquad r = 1,2,\dots,n$$

Let $a_j = \hat{\beta}_j + \hat{\beta}_{-j}$ and $b_j = i(\hat{\beta}_j + \hat{\beta}_{-j})$ where $\hat{\beta}_{(-j)}$ is a complex number of $\hat{\beta}_j$, $e^{ix} = \cos(x) + i\sin(x)$ and $e^{-ix} = \cos(x) - i\sin(x)$ so the Fourier-series estimator of $\hat{m}(t_r)$ is:

$$\hat{m}(t_r) = \hat{\beta}_0 + \sum_{j=1}^{\lambda} \left[a_j \cos\left(\frac{2\pi j(r-1)}{n}\right) + b_j \sin\left(\frac{2\pi j(r-1)}{n}\right) \right] \qquad (6)$$

with,

$$\hat{\beta}_0 = (\textstyle\sum_{i-1}^{n} y_i)/n$$
$$a_j = \frac{2}{n} \sum_{r=1}^{\lambda} y_r \, cos\left(\frac{2\pi j(r-1}{n}\right)$$
$$b_j = \frac{2}{n} \sum_{r=1}^{\lambda} y_r \, sin\left(\frac{2\pi j(r-1}{n}\right)$$

2.2.5 Selection of optimal oscillation parameters

The parameter λ in the Fourier assumption represents the disparity control between the smooth functions. If λ is large, the estimation of the regression function will have a large bias and be smoother (Liang & Chen, 2005). On the other hand, if λ is small, it will make it a coarse function. For this reason, we need a rather large and a rather small number to get the best estimator function results. Thus there is an optimal λ value. One method that is often used to determine the λ parameter is Generalized Cross Validation (GCV) (Asrini & Budiantara, 2014). According to Wu and Zhang (2006) the optimal bandwidth is obtained by minimizing GCV:

$$\text{GCV}(k) = \frac{n^{-1}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{(n^{-1} trace(I - H(\lambda)))^2} = \frac{\text{MSE}(\lambda)}{(1 - (2\lambda + 1)/n)^2} \qquad (7)$$

with,

$$\text{MSE}(\lambda) = \frac{1}{n} \sum_{r=1}^{n} [y_r - \hat{m}_\lambda(t_r)]^2 \qquad (8)$$

2.2.6 Support vector regression (SVR)

Support Vector Regression (SVR) is a modified version of the SVM method specifically designed to handle regression problems. In SVR, the outputs are represented as real and continuous numbers (Smola & Schölkopf, 2004). The main principle of SVR is to create a separating model close to most of the data while minimizing the distance between the separating line and the data. This is done by minimizing risk that is estimating the function by minimizing the upper bound of the generalization error so that SVR can overcome overfitting (Pradnyandita, 2022).

The concept of the SVR method is to have training data $\{(x_1, y_1), (x_2, y_2), \dots, (x_i, y_i)\}$ where $x_i \in \mathbb{R}^d$ is the i-th input vector with $i = 1,2,\dots,n,$ d is the dimension and y_i is the goal or target value (Ho & Lin., 2012). According to Zhang and O'Donnell (2020) the general equation of the SVR model can be written as follows:

$$f(x) = w'\varphi(x) + b \quad (9)$$

with,

w : n dimensional weight vector
$\varphi(x)$: function that corresponds x in n-dimensional space
$f(x)$: the output value of prediction
b : bias

To obtain a good generalization with the regression function $f(x)$, the next step is to find the smallest w. One way is to minimize the norm $\|w\|^2 = \langle w, w\rangle$. We can write the solution to the optimization problem as follows (Smola & Schölkopf, 2004):

$$min_w \frac{1}{2}\|w\|^2 \; with \begin{cases} y_i - w'x_i - b \le \varepsilon \\ w'x_i + b - y_i \le \varepsilon \end{cases} \quad (10)$$

In the regression function f, it is assumed that all points within the range $f(x) \pm \varepsilon$ are feasible, and points outside the range are infeasible, so the *slack* ξ and ξ^* are added to overcome the inappropriate constraints of the optimization problem. Furthermore, according to Awad and Khanna (2015), equation (10) can be transformed in the following form:

$$min_w \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad (11)$$

The optimization problem has the following constraint function:

$$y_i - w'x_i - b \le \varepsilon + \xi_i, \quad i = 1, \dots, n$$
$$w'x_i + b - y_i \le \varepsilon + \xi_i^* \quad i = 1, \dots, n$$
$$\xi_i, \xi_i^* \ge 0 \quad i = 1, \dots, n$$

By solving the optimization problem, it is obtained that:

$$w = \sum_{i=1}^{n}(\alpha_i^* - \alpha_i)\varphi(x_i) \quad (12)$$

The data contained in the vector x from the input space can be mapped to a higher-dimensional feature space with a function φ which is approximated by a kernel function, so that the SVR function can be defined as follows:

$$f(x) = \sum_{i=1}^{n}(\alpha_i^* - \alpha_i)K(x_i, x) + b \quad (13)$$

The kernel function used in this study is the linear kernel that based on Pradnyandita (2022) is defined as follows:

$$K(x_i, x) = x_i' x \quad (14)$$

2.2.7 Measurement of estimation model accuracy using MAPE as metric

Mean Absolute Percentage Error (MAPE) is used to measure the error in estimating model values and is expressed as the average absolute percent of the residuals. The MAPE criterion has the advantage of stating the percentage error of the projection results against the actual observations over a certain period, which will provide information on whether the percentage error is too high or too low. The MAPE calculation can be written as follows (De Myttenaere *et al*., 2016)

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100\% \quad (15)$$

The number of data points or observations is denoted by n. y_t is the true information. The predicted data are denoted by $\hat{y}_t$. The model with the lowest MAPE value is considered good and MAPE levels can be categorized according to Moreno, Pol, Abad, and Blasco (2013).

2.2.8 Steps of data analysis and flowchart of the research

The procedure or stages of the analysis method in this study are systematically explained in the form of a research flowchart shown in Figure 1.

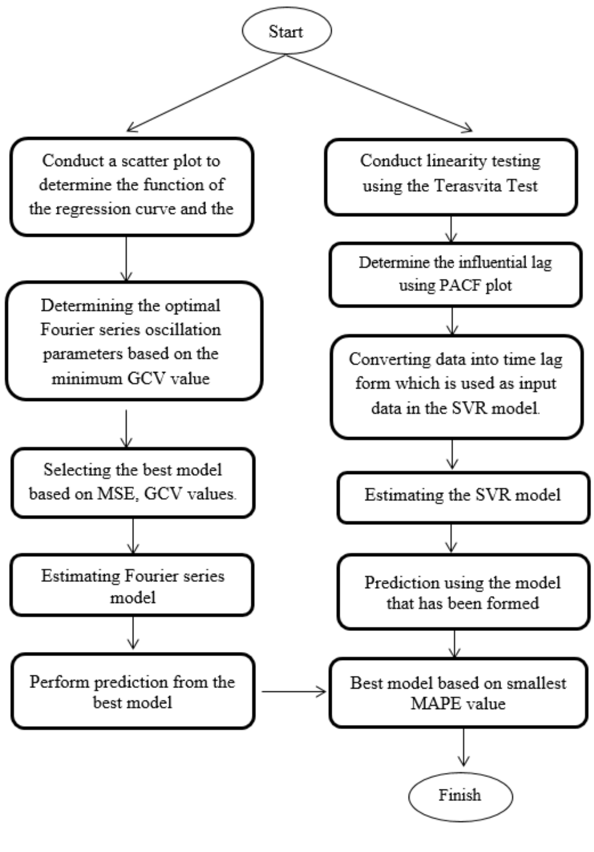

Figure 1. Flowchart of Research

3. Results and Discussion

3.1 Exploratory data analysis

Descriptively, the inflation rate in Indonesia every month from January 2013 to December 2022 can be seen in Figure 2. In 120 monthly data points on the inflation rate in Indonesia, the average rate is 4.113 with a standard deviation

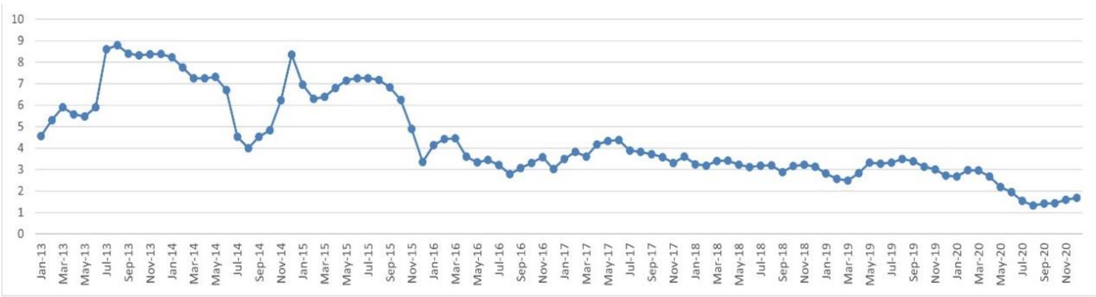

Figure 2. Plot of Inflation Rate Data in Indonesia for the Period January 2013 - December 2022

of 2.010071. In general, the inflation rate tends to fluctuate every year until it reaches its highest value in August 2013 at 8.79% and reaches its lowest value in August 2020, which is 1.32%.

Before determining the model with the Fourier series estimator and SVR, to determine the pattern of time series data, the linearity test is carried out using the Terasvirta test. In this case, it is represented by a nonparametric function on inflation rate data in Indonesia during the period January 2013 to December 2022 using the calculation in the results show that the linearity test using the Terasvirta test obtained a $p > 0{,}05$. Thus, H_0 is accepted. This indicates that the relationship between variables x and y is linear, or that the inflation rate data in Indonesia contains a linear pattern.

3.2 Fourier series estimator result

The nonparametric regression model with a Fourier series estimator has an optimal Fourier coefficient (λ). The GCV method is used to determine the optimum value. The results of the optimum GCV calculation using R software for the sample data are presented in Table 1. Based on the optimum Fourier coefficient (λ) value in the cosine function, which is 6, it can be concluded that the data has an optimum λ value of 6 with a minimum GCV value of 0.421.

Table 1. GCV Value

Function	λ	GCV Value
sin	4	1.129
cos	1	3.643
cos sin	6	0.42

Furthermore, the value of the Fourier parameter is obtained as a cosine function and b_j as a sine function of the Fourier series estimator model. The values of λ, a_j, and b_j are given in Table 2 below:

Table 2. Values of λ, a_j, and b_j

Lambda (λ)	a_j	b_j
1	0.456	2.021
2	0.383	0.679
3	0.304	0.650
4	0.767	0.458
5	0.255	0.248
6	0.459	0.184

The Fourier series estimator model obtained by nonparametric regression is as follows:

$$\begin{aligned}\hat{m}(t_r) = 4.761 &+ 0.456\cos(2\pi t_r) + 2.021\sin(2\pi t_r)\\ &- 0.383\cos(4\pi t_r) + 0.679\sin(4\pi t_r)\\ &+ 0.304\cos(6\pi t_r) + 0.650\sin(6\pi t_r)\\ &- 0.767\cos(8\pi t_r) + 0.458\sin(8\pi t_r)\\ &- 0.255\cos(10\pi t_r) - 0.248\sin(10\pi t_r)\\ &+ 0.459\cos(12\pi t_r) - 0.184\sin(12\pi t_r)\end{aligned}$$

In general, the movement of the inflation rate in Indonesia can be predicted using the Fourier series estimator model. The prediction results using the Fourier series estimator method on the Inflation Rate in Indonesia for the period January 2020 to December 2022 can be seen in Table 3. Based on Table 3 which is a table of predicted values of testing data, the RMSE value is 0.548 and MAPE is 8.400% which is classified as a very accurate prediction result.

3.3 Support vector regression (SVR) model

Before starting modeling with SVR, the first step is to convert the Indonesian inflation rate data into a time lag form based on the PACF scheme. The PACF plot for the inflation rate in Indonesia is shown in Figure 3.

Based on the PACF plot in Figure 3, lags 1 and 2 are significant lags, so there are 2 significant lags of SVR data as time lags. The SVR model evaluation results show that the SVR model has very high accuracy in predicting the training data, with an RMSE of 0.126 and MAPE of 2.896%. The comparison graph between the predicted value and actual data on modeling training data with the SVR model is presented in Figure 4.

The training model is used to predict the testing data. Furthermore, the prediction results of the inflation rate in Indonesia for the period January 2020 to December 2022 are presented in Table 4.

The SVR model has very high accuracy in predicting testing data with RMSE of 0.202 and MAPE of 0.104%.This is a result of the testing data's prediction results having a minimal RMSE value and a MAPE of less than 10%. Based on Table 4, the prediction results with the testing data show a very high level of accuracy in modeling the inflation rate in Indonesia, so the SVR method can be used as a comparison with other methods such as nonparametric regression on time series data with the Fourier series estimator. Furthermore, comparing the performance of the Fourier series estimator method and SVR can be done. The comparison results are presented in Table 5.

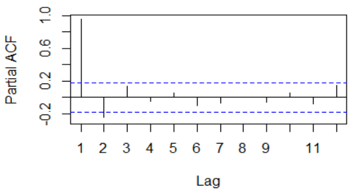

Figure 3. PACF plot of inflation rate data for Indonesia

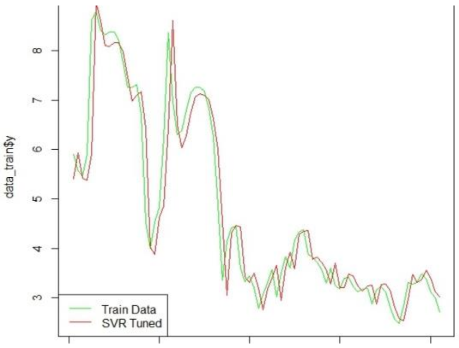

Figure 4. Comparison of training data with SVR model prediction results

Table 3. Comparison of actual data with predictions by Fourier series

Month	Actual data	Predicted data
January 2020	2.65%	3.58%
February 2020	2.98%	3.38%
March 2020	2.96%	3.19%
April 2020	2.67%	3.03%
May 2020	2.19%	2.90%
June 2020	1.96%	2.82%
July 2020	1.54%	2.79%
August 2020	1.32%	2.81%
September 2020	1.42%	2.86%
October 2020	1.44%	2.95%
November 2020	1.59%	3.06%
December 2020	1.68%	3.18%
January 2021	1.55%	3.29%
February 2021	1.38%	3.37%
March 2021	1.37%	3.43%
April 2021	1.42%	3.45%
May 2021	1.68%	3.43%
June 2021	1.33%	3.37%
July 2021	1.52%	3.28%
August 2021	1.59%	3.16%
September 2021	1.60%	3.02%
October 2021	1.66%	2.89%
November 2021	1.75%	2.76%
December 2021	1.87%	2.66%
January 2022	2.18%	2.59%
February 2022	2.06%	2.56%
March 2022	2.64%	2.59%
April 2022	3.47%	2.66%
May 2022	3.55%	2.77%
June 2022	4.35%	2.93%
July 2022	4.94%	3.12%
August 2022	4.69%	3.34%
September 2022	5.95%	3.57%
October 2022	5.71%	3.82%
November 2022	5.42%	4.07%
December 2022	5.51%	4.32%

Table 4. Comparison of actual data and SVR predicted data

Month	Actual data	Predicted data
January 2020	2.68 %	2.86 %
February 2020	2.98 %	3.14 %
March 2020	2.96 %	3.12 %
April 2020	2.67 %	2.85 %
May 2020	2.19 %	2.40 %
June 2020	1.96 %	2.18 %
July 2020	1.54 %	1.79 %
August 2020	1.32 %	1.58 %
September 2020	1.42 %	1.67 %
October 2020	1.44 %	1.69 %
November 2020	1.59 %	1.83 %
December 2020	1.68 %	1.92 %
January 2021	1.55 %	1.80 %
February 2021	1.38 %	1.64 %
March 2021	1.37 %	1.63 %
April 2021	1.42 %	1.67 %
May 2021	1.68 %	1.92 %
June 2021	1.33 %	1.59 %
July 2021	1.52 %	1.77 %
August 2021	1.59 %	1.83 %
September 2021	1.6 %	1.84 %
October 2021	1.66 %	1.90 %
November 2021	1.75 %	1.98 %
December 2021	1.87 %	2.10 %
January 2022	2.18 %	2.39 %
February 2022	2.06 %	2.28 %
March 2022	2.64 %	2.82 %
April 2022	3.47 %	3.60 %
May 2022	3.55 %	3.68 %
June 2022	4.35 %	4.43 %
July 2022	4.94 %	4.98 %
August 2022	4.69 %	4.75 %
September 2022	5.95 %	5.93 %
October 2022	5.71 %	5.71 %
November 2022	5.42 %	5.43 %
December 2022	5.51 %	5.52 %

Table 5. Comparison of Fourier series and SVR performances

Method	Function	MAE	MAPE	RMSE	R^2
Fourier series	Cos sin	0.393	8.400%	0.548	91.388%
SVR	Linear kernel	0.379	0.104%	0.202	93.200%

Based on Table 5, both Fourier series estimator and SVR methods are able to predict with accurate results the inflation rate in Indonesia. However, the SVR method shows better prediction accuracy with minimum RMSE, MAE, and lower MAPE compared to the Fourier series method. The results in Table 5 support the visualization of testing data between Fourier series and SVR in Figure 5.

4. Conclusions

Inflation is one of the indicators that affects economic growth in Indonesia. In the analysis results using nonparametric time series regression to predict the inflation rate in Indonesia using the Fourier series estimator method and Support Vector Regression (SVR), it was found that the Support Vector

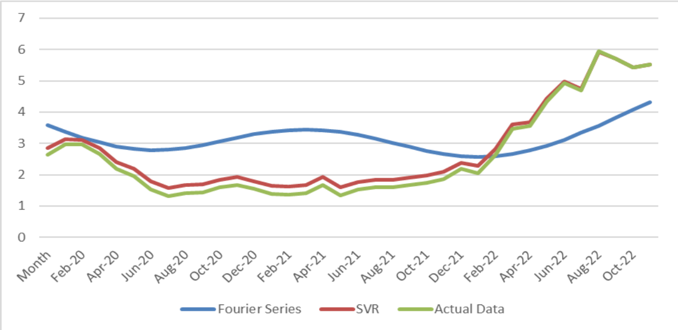

Figure 5. Comparison graph of actual data and prediction results by Fourier series and SVR

Regression (SVR) with linear kernel showed a better prediction accuracy compared to the Fourier series estimator, with Mean Absolute Percentage Error (MAPE) values of 0.104% and 8.400%, respectively. In addition, appropriate recommendations for government entities can be made based on the results of the Support Vector Regression (SVR) estimation with the smallest MAPE value.

Thus, the prediction results can be used as a basis for government policy-making in anticipating future economic activity as well as to determine exactly which policies significantly contribute to future inflation trends. In future research, we recommend considering hybridization techniques, such as combining wavelet transforms or predicting residuals using alternative algorithms.

Acknowledgements

The authors thank Indonesia Bank for providing research data. In addition, the authors also thank Universitas Airlangga for supporting this research activity.

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