Prediction of Inflation Rate in Indonesia Using Local Polynomial Estimator for Time Series Data

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Abstract. Inflation prediction is needed to determine strategies and policies to control a country's economic stability. Inflation is one of the important macroeconomic indicators. Fluctuating inflation rates can disrupt a country's economy, so this is a particular concern. In this paper, inflation prediction was carried out through two approaches: the parametric regression model approach based on the Autoregressive Integrated Moving Average (ARIMA) model and the nonparametric regression approach based on the local polynomial estimator. The model's accuracy is determined based on prediction results using the mean absolute percentage error (MAPE) value. We obtained a MAPE value of 9.0% for the ARIMA model approach and MAPE values of 4.0% and 1.778% for first and second orders, respectively, of local polynomial nonparametric regression model approach. It means that the best model for predicting Indonesia's inflation rate is the second order of local polynomial nonparametric regression model because it has the smallest MAPE value.

Keywords: prediction; inflation rate; local polynomial estimator; times series

1. Introduction
The economy of a country is one of the important factors in creating people's welfare. As a developing country, Indonesia has an agrarian-style economic structure that is very vulnerable to shocks to financial stability [1]. One economic phenomenon that is always interesting to discuss is inflation. This is because inflation has broad impacts on the macroeconomy, such as economic growth, competitiveness, and income distribution.

Bank Indonesia is one of the agencies that control Indonesia's inflation rate by evaluating whether the targets still set future inflation projections. Predictions are made through a model based on several information that can describe inflation in the future [2]. The forecast of future inflation rates is needed for the government and business as a basis for determining policies and strategies in the economic field. Some researchers have conducted studies related to the projected future inflation rate by forecasting time series, as has been done by Saluza [3].

Forecasting is used to predict something likely to happen in the future to take appropriate action. Two approaches can be used to predict, namely the parametric approach and the nonparametric approach. One of the parametric approaches used to predict is the Autoregressive Integrated Moving Average (ARIMA) method, as has been done by Nyoni [4] in predicting the value of inflation in Burundi. Some other researchers who use ARIMA in predicting the value of inflation include Abdulrahman et al. [5], Fahrudin, and Sumitra [6].

If the functional relationship between the response variable and the predictor variable does not follow a certain form of the regression function, the researcher can use a nonparametric regression approach. This approach has high flexibility because the regression function is not specified in a particular form but is assumed as smooth so that it can be estimated using certain smoothing methods based on data patterns as described in [13]. Some previous studies have made predictions by using nonparametric regression approach; for example, Suparti et al. [14] used the B-Spline estimator in modeling inflation.
rates, Chamidah et al. [15] used the least square spline estimator to predict blood pressures based on stress score. Oktavitri et al. [16] predicted a suspended and attached process behavior in anaerobic batch reactors using spline estimators.

In the nonparametric regression approach, several smoothing techniques that are often used include Kernel estimator ([17],[18]), local linear estimator [19-21], local polynomial estimator [22-24], and Spline estimators [25-27]. According to Chamidah et al. [22], local polynomial estimators are a popular new approach. Local polynomial estimators have exceptional cases that are if the degree of local polynomial equals zero. It is called the Kernel estimator, and if the polynomial degree equals one, then it is called a local linear estimator. Local linear estimators are used if data patterns are generally monotonous [28]. According to Loader [29], each differentiable function can be approached locally with a straight line.

Both parametric and nonparametric regression approaches are not only used in cross-section and longitudinal data but can also be used in time-series data. Time series data (time series) is a set of observational data taken at different times and collected periodically at a certain time interval [30]. Time series data includes one research object or individual, such as stock prices, currency rates, or inflation rates in several periods, such as daily, weekly, monthly, or yearly. Time series data modeling usually uses classical models such as Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA). These models are linear models in the time series, which are very commonly used in economics. Some previous studies that have predicted the inflation rate include Stephani et al. [8], and Nyoni [9], used ARIMA and Garch to model inflation rates in Kenya. Besides, another parametric method that can be used to predict inflation rates is Neural Network Backpropagation, as done by Amrin [10], Sukono et al. [11], and Sari et al. [12].

In time-series data, nonparametric regression approach has been developed by several researchers, for example, Gao and Gijbels [31], Chen et al. [32], Gao, and King [33] carried out modeling based on the Kernel estimator. Also, some researchers such as Fernandez and Cao [34], Wang and Phillips [35], and Li et al. [36] developed a nonparametric regression approach to time series data based on local linear estimators. Dong and Gao [37] have used the Truncated Least Square estimator to model time series data. Nottingham and Cook [38] explain the related comparison between the parametric approach using ARIMA with the nonparametric approach using local linear regression (LLR) and Fattahi [39] comparing the ARIMA method with MARS.

The nonparametric regression approach is more complicated than parametric approach. There is no guarantee that a complex approach causes a better model. Local polynomial estimators are a popular new approach. Local polynomial estimator depends on two parameters: the order of local polynomial fit and the smoothing parameter, namely bandwidth. The effect of those parameters is increasing variance and reducing bias if a higher-order fit and smaller bandwidth. But it's reducing variance and increasing if a lower order fit and large bandwidth. This is appropriate and can be a solution to the pattern of inflation rate data with high fluctuations. Local polynomial estimators have a special case; if the order is equal to zero, it is called the Kernel estimator. If the order is similar to one, it is called a local linear estimator [19].

This paper discusses the nonparametric regression approach using local polynomial of the first order (local linear) and second-order (local quadratic) estimators, and parametric regression approach using ARIMA. Also, we compare them based on MAPE criteria to obtain the best model which will be used for predicting inflation rate in Indonesia.

2. Materials and Analysis Methods

The data used in this study are secondary data related to inflation rate in Indonesia. The data were taken monthly from September 2004 to August 2019, which consists of 180 observations. The data is divided into two parts, i.e., in-sample (from September 2004 to August 2016), which will be used to estimate the model, and out-sample (from September 2016 to August 2019) will be used for predicting. The data was taken from the website of Bank Indonesia. In this study, observation time (t) in months is a predictor, and inflation rate is a response variable.
### 2.1. Nonparametric Regression Model Based on Local Polynomial Estimator

Given a nonparametric regression model [40]:

\[ y_i = m(t_i) + \varepsilon_i, \quad i = 1, 2, \ldots, n \]  

(1)

where \( y \) as response variable \( m(\cdot) \) is an unknown smooth function and \( \varepsilon_i \) is zero mean and \( \sigma^2 \) variance random error. To estimate function \( m(t_i) \) in equation (1), we use local polynomial estimator. Function \( m(t_i) \) can be approximated by Taylor expansion as follows:

\[ m(t_i) \approx \sum_{k=0}^{p} \frac{m^{(k)}(t_0)}{k!}(t-t_0)^k = \sum_{k=0}^{p} \beta_k (t_0)(t-t_0)^k \]  

(2)

where \( m^{(k)}(t_0) \) is the \( k \)-derivative of \( m(t_0) \) at \( t \in (t_0 - h, t_0 + h) \) and \( \frac{m^{(k)}(t_0)}{k!} = \beta_k (t_0) \).

If equation (2) is written in matrix notation, we obtain

\[ m(t_i) = \mathbf{t}_0 \mathbf{\beta}(t_0) \]  

(3)

where \( \mathbf{t}_0 = \begin{bmatrix} 1 & (t-t_0) & \ldots & (t-t_0)^p \end{bmatrix}, t \in (t_0 - h, t_0 + h) \) and

\[ \mathbf{\beta}(t_0) = \begin{bmatrix} \beta_0 (t_0) & \beta_1 (t_0) & \ldots & \beta_p (t_0) \end{bmatrix}^T. \]

Based on equation (3), we can write equation (1) as:

\[ y_i = \mathbf{t}_0 \mathbf{\beta}(t_0) + \varepsilon_i \]  

(4)

By giving \( n \) samples, paired data \( \{t_i, y_i\}_{i=1}^{n} \), equation (4) can be written as follows:

\[
\begin{align*}
y_1 &= \beta_0 (t_0) + \beta_1 (t_0)(t_1-t_0) + \beta_2 (t_0)(t_1-t_0)^2 + \ldots + \beta_p (t_0)(t_1-t_0)^p + \varepsilon_1 \\
y_2 &= \beta_0 (t_0) + \beta_1 (t_0)(t_2-t_0) + \beta_2 (t_0)(t_2-t_0)^2 + \ldots + \beta_p (t_0)(t_2-t_0)^p + \varepsilon_2 \\
&\vdots \\
y_n &= \beta_0 (t_0) + \beta_1 (t_0)(t_n-t_0) + \beta_2 (t_0)(t_n-t_0)^2 + \ldots + \beta_p (t_0)(t_n-t_0)^p + \varepsilon_n \\
\end{align*}
\]  

(5)

Hence, equation (5) can be expressed in matrix notation:

\[
\mathbf{y} = \mathbf{t}_0 \mathbf{\beta}(t_0) + \mathbf{\varepsilon}
\]  

(6)

where

\[
\mathbf{t}_0 = \begin{bmatrix} 1 & (t_1-t_0) & \ldots & (t_1-t_0)^p \\ \vdots & \vdots & \ddots & \vdots \\ 1 & (t_n-t_0) & \ldots & (t_n-t_0)^p \end{bmatrix}, \mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}, \mathbf{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{bmatrix}
\]  

(7)

To estimate \( \mathbf{\beta}(t_0) \), we apply the weighted least square (WLS) optimization as follows:

\[
\text{Min } Q(t_0) = \text{Min} \left( \mathbf{y} - \mathbf{t}_0 \mathbf{\beta}(t_0) \right)^T \mathbf{K}_n(t_0) \left( \mathbf{y} - \mathbf{t}_0 \mathbf{\beta}(t_0) \right)
\]  

(8)

where
$K_h(t_0) = \begin{bmatrix} K_h(t_1-t_0) & 0 & \ldots & 0 \\ 0 & K_h(t_2-t_0) & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & K_h(t_n-t_0) \end{bmatrix}$

In equation (9) $K_h(.)$ is Kernel function with bandwidth $h$ defined by [13] as follows:

$K_h(t) = \frac{1}{h} K\left(\frac{t}{h}\right); -\infty < t < \infty$ and $h > 0$

In this study, we use the Gaussian Kernel defined as follows [32]:

$K(t) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right)$

Next, we take the derivative of equation (8) concerning $\beta(t_0)$ and then equalizing to zero, such that we get:

$$\frac{\partial Q(t_0)}{\partial \beta(t_0)} = -2T_v^T K_h(t_0) y + 2T_v^T K_h(t_0) T_v \beta(t_0) = 0$$

$$T_v^T K_h(t_0) T_v \beta(t_0) = T_v^T K_h(t_0) T_v \beta(t_0) y$$, so

$$\beta(t_0) = (T_v^T K_h(t_0) T_v)^{-1} T_v^T K_h(t_0) y$$

Based on equations (3) and (10), the local polynomial estimator for $\hat{m}(t)$ is:

$$\hat{m}(x_t) = t_0 \left(T_v^T K_h(t_0) T_v\right)^{-1} T_v^T K_h(t_0) y$$

2.2. Autoregressive Integrated Moving Average (ARIMA) model

In the time series model, a notation $Y_t$ is used, which states the observation at time $t$. It shows an unobserved white noise sequence, independent random variables with identical distribution with zero mean [41]. The Integrated Moving Average Autoregressive Model (ARIMA) is a model for non-stationary series. A series $Y_t$ is said to be an ARIMA model if it experiences the $d$th differentiation, $W_t = \nabla^d Y_t$ is a stationary Moving Average (ARMA) process, which $W_t$ is the ARMA model $(p,q)$, and $Y_t$ is the ARIMA model $(p,d,q)$. ARIMA$(p,d,q)$ can be written as follows [42]:

$$Y_t = (1 + \phi_1 Y_{t-1} + (\phi_2 - \phi_1) Y_{t-2} + (\phi_3 - \phi_2) Y_{t-3} + \ldots$$

$$+ a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-q}$$

ARMA model is a combination between autoregressive (AR) model with the order $p$ and moving average (MA) model with the order $q$. Generally, it can be written as follows:

$$Y_t = \phi Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-q}$$

Based on equation (13), especially case for $p = 1$ and $q = 1$, ARIMA$(1,1)$ model has an equation:

$$Y_t = \phi Y_{t-1} + a_t - \theta a_{t-1}$$

Autocorrelation function from equation (14) is

$$\rho_k = \frac{(1-\theta \phi)(\phi - \theta)}{1-2\phi + \theta^2} \phi^{k-1}, \text{ for } k \geq 1$$
Equation (15) has the exponential function of the decreasing function as the k becomes larger.

2.3. Analysis Method

The stages of analysis in this research are as follows:
1. Determining descriptive statistics of inflation rate data;
2. Plotting inflation rate versus time;
3. Choosing the optimal bandwidth of in-sample data based on Cross-Validation (CV) criteria as follows:

\[ CV(h) = \frac{1}{n} \sum_{i=1}^{n} \left( y_i - \hat{m}_{h_{,i}}(t_i) \right)^2 \]  

(16)

4. Determining the accuracy of predicting based on MAPE from nonparametric regression model, with the following mathematical expression:

\[ MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{\hat{y}_t - y_t}{y_t} \right| \times 100 \]  

(17)

Following this is a table of typical MAPE values and their interpretation:

| MAPE   | Interpretation |
|--------|---------------|
| < 10   | Highly Accurate |
| 10 – 20| Accurate       |
| 20 – 50| Reasonable    |
| > 50   | Inaccurate    |

5. Differencing and transforming data so that it is stationary to mean.
6. Calculating ACF and PACF values.
7. Determining a tentative model based on ACF and PACF
8. Determining the best ARIMA model.
9. Determining the accuracy of predicting is use MAPE from ARIMA model
10. Comparing ARIMA and local polynomial models based on MAPE value

3. Result and Discussion

Inflation is a macroeconomic indicator that has an important role in a country, so that inflation caused a much influence in economic growth. The following are descriptive statistics inflation for the period 2004 – 2019.

| Table 2. Descriptive Statistic of Variable |
|------------------------------------------|
| Variable | Mean | Variance | Min. | Max. |
| Inflation (%) | 6.302 | 11.920 | 2.410 | 18.380 |

Based on Table 2, it is known that the average inflation rate since the beginning of the reformation era up to date is 6.302%, with a relatively high diversity of 11.920%. Indonesia’s highest inflation rate as 18.380% happened in November 2005, where there has been an increase in oil prices worldwide and international interest rates, putting pressure on domestic monetary stability. This condition resulted in domestic fuel prices and decreasing in rupiah [43]. Indonesia was at the lowest inflation level of 2.410% in November 2009.
Figure 1 shows the pattern of inflation rate from September 2004 until August 2019. Horizontal axis represents times, and vertical axis represents inflation rate. Also, it appears increasing and decreasing in the period.

3.1. Prediction of Inflation using Nonparametric Regression

Researcher using a nonparametric regression approach based on local polynomial estimator to predict an inflation rate in Indonesia. The data used for modeling are 144 observations. In this study, the researcher makes a nonparametric regression model based on local polynomial estimator with the degree of polynomial $p = 0, 1, 2$. If $p = 0$ then obtained a local constant model. If $p = 1$ it is called local linear model and $p = 2$ is called local quadratic model. Furthermore, a researcher has a bandwidth optimal for local constant model as 0.214 for local linear model as 0.267, and local quadratic model as 0.394. After that, the researcher calculates the accuracy of prediction using MAPE criteria. The best model of nonparametric regression is a model that has a minimum of MAPE.

| Optimal Bandwidth | Degree | Namely          | MAPE  |
|------------------|--------|-----------------|-------|
| 0.214            | 0      | Local Constant  | 6.082 |
| 0.267            | 1      | Local Linear    | 5.967 |
| 0.394            | 2      | Local Quadratic | 6.050 |

Shown in Table 3, local constant model has a MAPE value as 6.082%. For local linear model has a MAPE value as 5.967%. In local quadratic model has a MAPE value 6.050%. MAPE of nonparametric regression approach is smaller than 10; it's mean that model has a highly accurate prediction, as explained by Moreno et al. [44]. Based on the MAPE value, local linear model is better than the other two nonparametric regression models based on local polynomial estimators. Modeling inflation using a local linear, as follows:

\[
\hat{y} = 3.115 + 1.127(t - 144), \quad t \in (143.733; 144.267)
\]

Based on equation (18), if $t = 144$ then an inflation as 3.789.

3.2. Prediction of Inflation using ARIMA

After knowing a plotting data to find out whether there are trends from the data patterns, furthermore, the data stationarity test, the stationarity test for variants is carried out by Box-Cox transformation while the stationarity test for the mean is carried out a different process. In this case, the process
becomes stationary for both variance and mean after differencing of 1. Time series plot of before and after differencing is shown in Fig.2. The next step is to observe the ACF and PACF patterns to determine the order of the AR process and the MA process. The ACF and PACF plots of this case can be seen in Fig. 3; it is known that the lag that comes out both in ACF and PACF is lag 1.

![Time Series Plot of Trans](image1)

![Time Series Plot of Diff](image2)

**Figure 2.** (a) Time Series Plot; (b) Output of Differencing

![Autocorrelation Function for Diff](image3)

![Partial Autocorrelation Function for Diff](image4)

**Figure 3.** (a) Plot ACF of Inflation; (b) Plot PACF of Inflation

| Table 4. Tentative Model |
|--------------------------|
| Model       | Parameter |   P-value   |   MSE   | White Noise Assumptions |
| ARIMA (1,1,0) | AR (1)   | 0.021       | 1.483   | No                   |
| ARIMA (0,1,1) | MA (1)   | 0.005       | 1.470   | No                   |
| ARIMA (1,1,1) | AR (1)   | 0.488       | 1.464   | No                   |
| ARIMA (1,0)   | MA (1)   | 0.140       | 1.464   | No                   |
| ARIMA (1,1,1) | AR (1)   | 0.034       | 1.104   | Yes                  |
| SAR (12)     |           | 0.000       |         |                     |
| ARIMA (0,1,1) | MA (1)   | 0.025       | 0.858   | Yes                  |
| SMA (12)     |           | 0.000       |         |                     |

Based on Table 4, it is known that model ARIMA (0,1,1) (0,0,1)\(^{12}\) has significant parameters, meets the white noise assumptions, and has minimum MSE so that the model is used to predict. A comparison of MAPE values between model ARIMA (0,1,1) (0,0,1)\(^{12}\) and local linear model is shown in Table 5.
Based on Table 5, it is known that the predicted value of the local linear model and ARIMA both assess the actual value, which MAPE values are less than 10%. It means that both of them have high accuracy for predicting. A local linear model is better than ARIMA (0,1,1) (0,0,1)12 because local linear model has a smaller MAPE value.

4. Conclusion
Based on the analysis results, we conclude that nonparametric regression model approach by using local polynomial estimator is better than ARIMA model approach for the prediction inflation rate in Indonesia because local linear model has a smaller MAPE value than ARIMA (0,1,1) (0,0,1)12 model, and it has a highly accurate prediction.

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