CrossMark

ARTICLE   **OPEN ACCESS**

Modeling Inflation of Transportation, Communication, and Service Sectors in Indonesia Using Intervention Model

Suparti[*], Alan Prahutama, Rukun Santoso, Rita Rahmawati

Statistics Department, Diponegoro University, Semarang, Indonesia

[*]*Address of correspondence: suparti702@gmail.com*

Abstract

Modeling Inflation in the value of transportation, communication and financial services in Indonesia is experiencing fluctuating high. Fluctuation is possible due to changes in fuel prices and the presidential election of 2009. However, modeled with ARIMA will get a model that does not fit. In this research, analysis of intervention of inflation value caused by changed in fuel prices. Interventions in this study occurred twice, in June 2013 and November 2014. The first intervention model was ARIMA (1,0,0) with step function b = 2, r = 0, s = 1, while the second intervention model was ARIMA (2,0,0) follows by Pulse function with b = 1, r = 0, and s = 0.

Keywords: **Intervention; Inflation in Transportation, Communication and services sector; ARIMA**

Introduction

The inflation data is one of economic time series data that has the properties of high volatility so that if the data was modeled by a parametric model Box-Jenkins ARIMA often experienced problems because there was an assumption that was not fulfilled. The assumed of the Box-Jenkins method were the data stationer, and the residual of the model was white noise and normal distribution. According [1] the best model of inflation in Indonesia with Box-Jenkins method used inflation data year on the year 1998-2008 was AR (2) model, with predicted inflation in 2009 was 10.48%. The fact, it was exceptionally so far with actual data, which is 2.78%.

There has been researched inflation model year on year from December 2006 until December 2013.[2] It was resulting subset model which is ARIMA ([1,12],1,0) with all assumed has been fulfilled. Even though the MAPE of the model less than 10%, however, the model detected outliers. Moreover, then Suparti and Sa'adah (2015), addicting outliers to ARIMA ([1,12],1,0). It was resulting ARIMA with outlier has good results better than ARIMA without outlier. The best model was subset ARIMA ([1,12],1,0) with 19 outliers.

From the observation data for 3 years (2011, 2012 and 2013), has been a significant rise in headline inflation at the end of 2013. The increase was contributed by a significant increase in some of sectors/groups of inflation, such as transportation, communications and financial services; foodstuffs sector, and housing, water,

electricity, gas, and fuel. However, the very significant contribution occurred in transportation, communications, and financial services - a significant increase in inflation in 2013 as the effects of government policies that raise the price of electricity gradually throughout the year 2013 and the increase in fuel oil in mid-2013.[3]

With rising fuel prices mid-2013 have increased very significant changes in inflation so that the inflation target in 2013 set by the government for $(4,5 \pm 1)\%$ is not achieved by the end of 2013 inflation in Indonesia reached 8,38%. Based on preliminary research that has been done research, data modeling inflation Indonesia on Transport Sector, Communications and Financial Services using ARIMA models, residual normality assumptions were not met. Then, the addition of outliers and best model ARIMA ([2], 0.2) with one outlier but residual normality assumption remains unfulfilled.[4]

Intervention model is a time series model that influenced the events of individual external and internal which these events can lead to changes in data patterns. Intervention model able to cope with the spread of the time series data that are fluctuating up or down, that is caused by certain events (intervention). Interventions could happen one period or in the period of the incident - genesis classified interventions such as natural disasters, government policy, promotion, war, demonstration, holidays, Eid day and other important events. Intervention model is a model times series which is a linear approach. Linear modeling is a simple but very tight with the assumption. Changes in fuel prices are the price set by

government policies that result in significant changes in inflation so that changes in fuel prices is a variable intervention.

2. Materials and Methods

2.1. Autoregressive Integrated Moving Average (ARIMA)

In time series for ARIMA methods, in general, some models can be used is the model Autoregressive (AR), Moving Average (MA), Processes Autoregressive Moving Average (ARMA) and Integrated Autoregressive Processes Moving Average (ARIMA). Model AR (Autoregressive) or Autoregressive Process as the name suggests is implicit call with regression but in this case the regression with itself. In general, the model AR (p) are as follows[5]:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + a_t.$$

Model moving average (MA) order q states that a model of the observation time t affected all past mistakes. Model of the moving average order q in the equation is written as follows:

$$Y_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} \dots - \theta_q a_{t-q}.$$

Model mixture autoregressive and moving average can be written ARMA (p, q) or ARIMA (p, 0, q) is a combination of AR (p) and MA (q), the model forms as follows:

$$Y_t = \phi_1 Y_{t-1} + \dots + \phi_p Y_{t-p} + a_t - \theta_1 a_{t-1} - \dots - \theta_q a_{t-q}.$$

Model Autoregressive Integrated Moving Average Processes used on data that is already stationary by the differencing process that is $(1 - B)^d Y_t$. So we get the forecasting model as follows:

$$\phi_p(B)(1 - B)^d Y_t = \theta_0 + \theta_q(B) a_t.$$

with

$\phi_p(B) = 1 - \phi_1 B - \dots - \phi_p B^p$; $\theta_q(B) = 1 - \theta_1 B - \dots - \theta_q B^q$; $\phi_1, \phi_2, \dots, \phi_p$ are coefficients of AR order p-th; $\theta_1, \theta_2, \dots, \theta_q$ are coefficients of MA orde q-th; $(1 - B)^d$ shows differencing order d-*th*.

Table 1. The pattern of ACF and PACF for Stationary Process[6]

Model	ACF	PACF
AR(p)	Dies down exponential	Cut off after lag p
MA(q)	Cut off after lag q	Dies down exponential
AR(p) or MA(q)	Cut off after lag q	Cut off after lag q
ARMA (p,q)	Fast down after lag (q-p)	Fast down after lag (q-p)

2.2. Intervention Model

At a time series or time series data are often influenced by specific events such as changes in government policy, labor strikes, financial crisis, ad campaigns, environmental legislation, natural disasters, and other events. This is referred to as the incidence of early intervention with the assumption of knowing when the event happened intervention.[7] Intervention model is a model that is used during special events (external) unexpected variables that affect forecasted. This analysis has the main goal to measure the effects of an intervention on a time series. The general form of the intervention model is:

$$Y_t = \frac{\omega_s(B) B^b}{\delta_r(B)} X_t + N_t ,$$

with

$$\omega_s(B) = \omega_0 - \omega_1 B - \dots - \omega_s B^s$$

$$\delta_r(B) = 1 - \delta_1 B - \dots - \delta_r B^r$$

Y_t : Respond variable at t while it stationary

b : delay time when intervention time

X_t : Intervention variable, 0 (before intervention) or 1 (after intervention)

N_t : model "*noise*" (as a model of ARIMA before intervention events)

Generally, there are two types of intervention variables is a step function and pulse. The step function is a form of intervention that the occurrence of a long period or continue at a later time. Mathematically, this form of intervention step function denoted as follows

$$X_t = S_t^{(T)} = \begin{cases} 1 & , t \geq T \\ 0 & , t < T \end{cases}$$

T is the start time of intervention. Pulse function is the only form of intervention within a particular time and does not continue at a later time form of intervention pulse function denoted by

$$X_t = P_t^{(T)} = \begin{cases} 1 & , t = T \\ 0 & , t \neq T \end{cases}$$

3. Results and Discussion

3.1. Modelling Data with ARIMA Models

Based on Figure 1. The value of inflation seen in the sectors of transport, communications, and financial services from the period January 2009 to March 2016. Changes in fuel prices occurred four times, i.e., changes to January 15, 2009, decreased by 10% in fuel. The second change occurred on June 22, 2013, increased by 44% from the previous price. A third change on 18 November 2014 an increase of 31% from the previous price. Then on January 1, 2015, decreased by 11.8%. In this study, researchers ignore price changes in January 2009 because there was no analysis of previous data. In this figure, it appears that the data has not been stationary so needs differencing. The results of the data differencing inflation in the transport sector, communications and financial services.
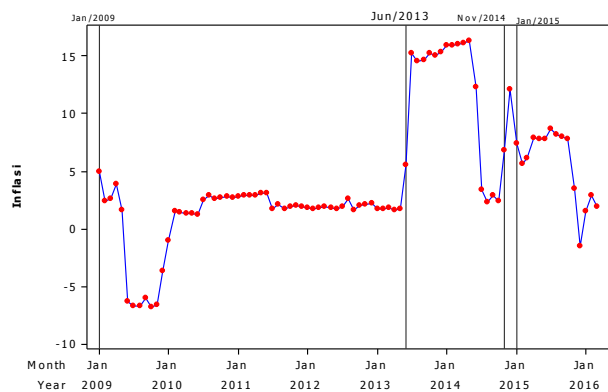
Figure 1. Scatterplot of Inflation of Transportation, Communication, and Services in Indonesia from Jan 2093 – Jan 2016.

The next step is the ARIMA model the overall data. Here is presented ACF plot data that has differencing one. Based on the plot of ACF and PACF seen that the resulting model is ARIMA (2,1,1).
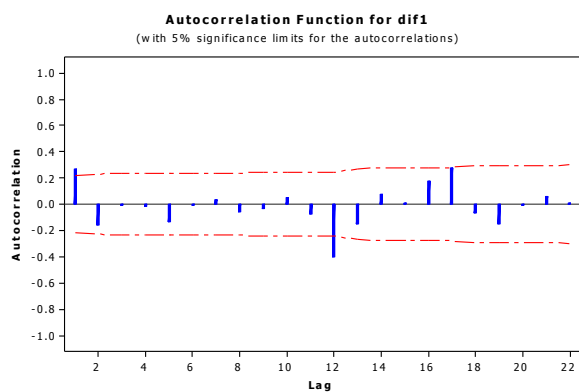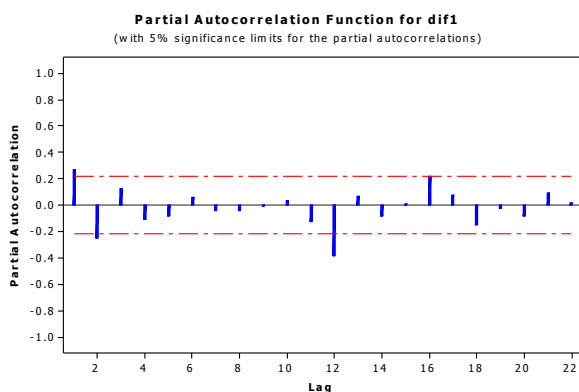

Figure 2a: ACF of Yt

Figure 2b: PACF of Yt

Table 2. Estimation of ARIMA (2,1,1) for Inflation in Transportation, Communication, and Services sectors

Parameter	Coefecient	t-value	p-value
ϕ_1	1.2014	11.43	0.00
ϕ_2	-0.3521	-3.37	0.001
θ	0.9716	23.7	0.000

Based on table 2, It is seen that the coefficient parameter AR and MA are all significant. In the ARIMA (2,1,1) based on the testing of L-Jung Box Pierce showed that the model white noise for all lag. While testing the normality of the residuals using Kolmogorov Smirnof test showed that the residual ARIMA (2,1,1) is not normal. After ARIMA modeling all the data, the next step is ARIMA modeling before the first intervention.

3.2. Modeling 1-st Intervention

Based on Figure 1, can be seen that in January 2010 through 2013, it appears that the data is already stationary. However the data from January 2009 until January 2010, the data experiences fluctuating.

Parameter estimation models produced before the first intervention is ARIMA (1,0,0). Parameter AR worth 0.9018. AR Parameter is significant at the 5% significance level. Based on testing of L-Jung Box Pierce showed that the residual ARIMA (1,0,0) white noise, but not normal. The next step is modeling the first intervention.

At this stage will be determined the order of the model's first intervention by making a residual plot of forecasting data based on the initial ARIMA model. Forecasting is done as the data from the time of the intervention (T = 55) until before the second intervention (T = 72) some 16 observations.
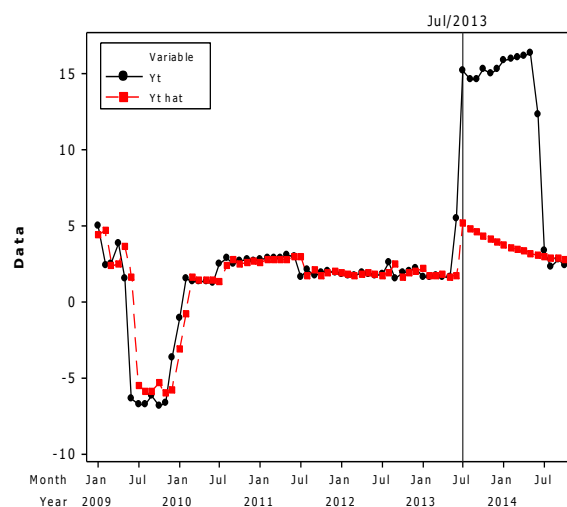

Figure 2. Scatter plot of Inflation in Transportation, Communication and services before 2nd Intervention

Based on Figure 2. It is seen that the results forecast before the first intervention, by the original data. Alternatively, it can be said that the forecast results approaching the actual data for ARIMA (1,0,0). However, after the intervention, the inflation rate in the transport sector and financial services has increased significantly, so that the results forecast ARIMA (1,0,0) after the intervention was very much with the actual data. To find out how much and duration of the effects of the monetary crisis than to identify the order of the model of intervention by making a diagram of the residuals of the model as follows
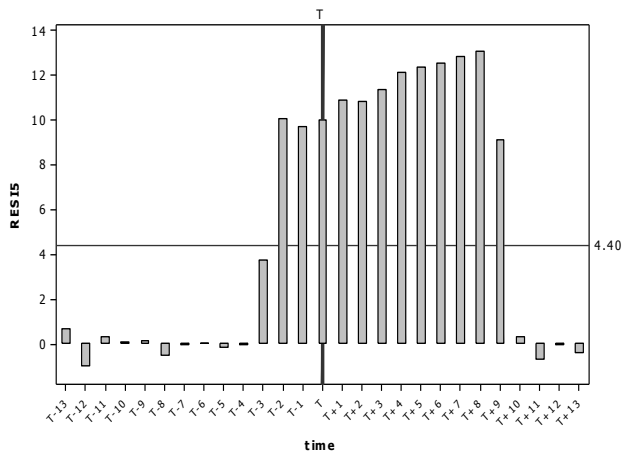
Figure 3. Residual Diagram after 1-st intervention and before 2-nd intervention
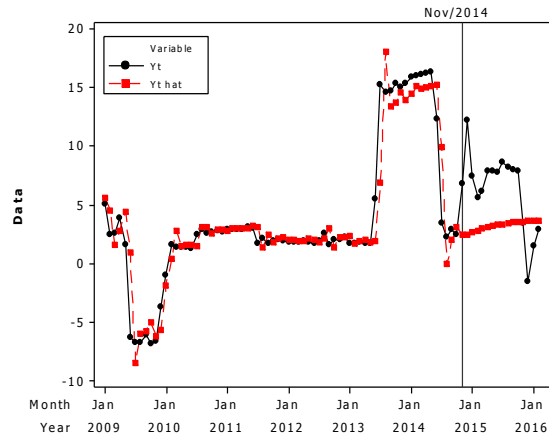
Figure 3. The incident shows that the first intervention that the fuel price hike in June 2013 led to residual of forecasting data is out of bounds. Based on these images can be determined first-order model of intervention that is b = 1, s = 2, and r = 0. It is seen that the first intervention are likely permanent, then the function used is a step function. The next step alleged order of the intervention models used to estimate the model parameter first intervention. The Estimation Parameter of 1-st Intervention as follows as:

Table 3. Estimation Parameter of 1-st Intervention

Parameter	Coefficient	t-value	p-value
μ	2.938	1.76	0.0025
θ_1	0.938	16.31	< 0.001
ω_{01}	9.206	5.12	< 0.001
ω_{11}	0.536	0.3	0.7669

Based on Table 3 shows that ω_{11} the parameter is not significant for a significance level of 5%. Based on testing of L-Jung Box test indicates that the first intervention modeling with b = 1, r = 0, and s = 2 indicates that the residual white noise, but did not meet the assumptions of normality. The next step is to model the 2nd intervention.

3.3. Modeling 2nd Intervention

Just as in the previous step, to model a second intervention, we should to modeled using data before the second intervention of ARIMA. The model obtained is ARIMA (2,0,0). Parameter AR (1) 1.302 and the parameters AR (2) -0.39, and both were significant. ARIMA (2,0,0) satisfies the assumption of white noise, but the residuals are not normally distributed. To model the 2nd intervention, first plotted the residuals of ARIMA (2,0,0) to get the order of interventions.

Based on Figure 4a shows that the forecasting results after the 1st intervention is very far from the actual data. Based on Figure 4b, visible order of the intervention is b = 1, r = 0, s = 0.

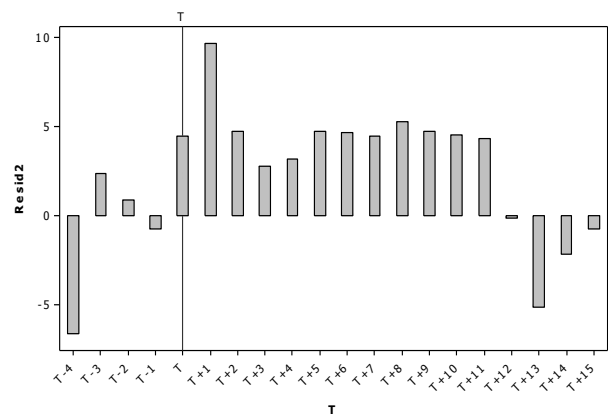**Figure 4a: Scatter plot of Forecast Inflation data with ARIMA (2,0,0)**

Figure 4b: Residual Plot after 2nd Intervention

Table 4. Estimation Parameter of 2-st Intervention

Parameter	Coefecient	t-value	p-value
μ	-0.0193	-0.01	0.9921
θ_1	0.892	16.34	< 0.001
ω_{01}	9.213	3.42	0.001
ω_{11}	-4.178	-1.55	0.1247
ω_{02}	8.156	3.5	0.0008

Table 4 shows the parameter values of the 2-nd intervention. Based on the table shows that the model parameters are not significant - however, other significant variables. Model 2nd intervention does not meet the assumption of white noise and normal distribution.

Conclusion

Based on the analysis that has been done can be concluded that the modeling of inflation in the transportation sector, communications and financial services do intervention analysis. Interventions based on changes in fuel prices. The first intervention model shows the step function of the order of b = 2, r = 0, and s = 1. While the second shows the intervention order b = 1, r = 0, s = 0. The first intervention is a step function while the second intervention is the pulse function.

Acknowledgments

References

[1] Bunyamin dan Danila, N.(2011). Estimasi Inflasi di Indonesia dengan Menggunakan Metodologi Box-Jenkins. *National Journals*. Volume 18 No.2.

[2] Suparti, Warsito, B., and Mukid, M.A., (2014). The analysis of Indonesia Inflation Data using Box-Jenkins Models. The 4th ISNPINSA Proceeding, FSM Undip Semarang

[3] Suparti, Warsito, B., and Mukid, M.A., (2015). Analisis Data Inflasi di Indonesia Menggunakan Model Arima Box-Jenkins, Kernel dan Spline. Prosiding Seminar Nasional Matematika Saintekinfo, MIPA UNS, hal. 150-156

[4] Suparti, Yasin, H., Prahutama, A., dan Sa'adah, 2016, Analisis Data Inflasi Indonesia pada Sektor Transportasi, Komunikasi dan Jasa Keuangan Menggunakan ARIMA dengan Outlier, Prosiding Seminar Nasional Pendidikan Matematika, Unissula, Semarang.

[5] Wei, W.W.S. (2006). *Time Series Analysis, Univariate and Multivariate Methods*, Addison Wesley Publishing Company, Canada.

[6] Bowerman, B.L., and O'Connel, R.T., 1993, Forecasting and Time Series: An applied Approach 3rd edition, Belmont, California: Duxbury Press.

[7] Box, G.E.P, Jenkins, G.M., and Reinsel, G.C., 1994, Time Series Anlysis Forecasting and Control, 3rd edition, Englewood Cliffs: Prentice Hall.