Vol. 20 No.2, Oktober 2015, p: 60-63

# MODELLING OF FORECASTING MONTHLY INFLATION BY USING VARIMA AND GSTARIMA MODELS

Andi Setiawan<sup>1</sup>, Muhammad Nur Aidi<sup>2</sup>, I Made Sumertajaya<sup>3</sup>

Department of Statistics, Bogor Agricultural University E-mail: setiawandi@yahoo.co.id<sup>1</sup>, nuraidi@yahoo.com<sup>2</sup>,imsjaya@yahoo.com<sup>3</sup>

#### **ABSTRACT**

The model parameters could be different form the well to the factors of time and location. A general model of GSTAR can be used to establish model the inflation in some locations by using GSTARIMA model if time series data is self-contained autoregressive, differentiation, and moving averages. This study examines whether the effect of such locations on the GSTARIMA model is better than the VARIMA model that regardless of the location influences. The aim of this study is to establish two models of inflation six provincial capitals in Java using VARIMA model and GSTARIMA model with inverse distance weighting. Dummy variables have been used to overcome normality and white noise problems. The best forecasting of monthly inflation in provincial capitals in Java Island is GSTAR(1;1) with inverse distance weighting. It has smallest RMSE value of 0.9199.

Key words: GSTARIMA, Inverse Distance, RMSE, VARIMA

### INTRODUCTION

Low inflation rate and stable to represent the especial target of monetary policy. High inflation rate affect to social and economic condition of society. Increasing of price level of goods and services cause decrease real income of society so that can increase poorness and unemployment rate. In long term, it can decrease Human Development Index (HDI). Hyper inflation happened when governance commutation from old order to new order in the year 1966 with the inflation rate equal to 636 percent. Governance commutation from new order to reform order in the year 1998 also with the high inflation rate equal to 77.63 percent.

Research concerning on regional inflation express the happening of related inflation inter provinces (Wimanda 2006). According to GDRP at current market prices in the year 2013, Provinces in Java Island gave contribution to GDP that is reach 57.99 percent (1,637 trillion rupiah). This matter cause the economic growth in Java Island very having an effect to national economic growth. Low inflation and in control become the especial prerequisite to reach the expected of economic growth. Forecasting inflation of provincial capitals in Java Island needed to

anticipate the high inflation shock and also correct policy to control the inflation.

Modelling of inflation at some location can be come near with VARIMA (Vector Autoregressive Integrated Moving Average) model by assuming location mentioned as variables of time series data. GSTARIMA (Generalized Space-Time Autoregressive Integrated Moving Average) model representing development analyse time series data which not only give attention to related of previous time but also give attention to related of its location.

## MATERIALS AND METHODS

## Data

The data used in this research is secondary data that is rate monthly inflation in 2001-2014 at six provincial capitals in Java Island, obtained from publications at BPS-Statistics Indonesia. There are Jakarta  $(Z_1)$ , Bandung  $(Z_2)$ , Semarang  $(Z_3)$ , Yogyakarta  $(Z_4)$ , Surabaya  $(Z_5)$ , and Serang  $(Z_6)$ . The data were divided into two part, training data (in the year 2001-2013) used to build the model and testing data (in the year 2014) to see the effectiveness of forecasting results.

## **VARIMA**

VARIMA model explain related among observation and error of a variable at certain time with the observation and error of variable itself and other variable previously. VARIMA (p,d,q) model with p, d, and q each representing order autoregressive, differentiation, and moving average defined as follows (Wei 2006):

$$\mathbf{\Phi}_{p}(B)\mathbf{D}(B)\mathbf{Z}_{t} = \mathbf{\Theta}_{q}(B)\mathbf{a}_{t}$$
(1)

with,

 $\mathbf{Z}_t$  : observation vectors with  $\mathbf{Z}_t = [\mathbf{Z}_{1,t}, \mathbf{Z}_{2,t}, \dots, \mathbf{Z}_{n,t}]'$ 

 $\Phi_p$ : autoregressive matrix polynomials of orders p

 $\mathbf{\Theta}_q$  : moving average matrix polynomials of orders q

 $\mathbf{D}(B)$ : differencing operator

 $a_t$ : white noise random vectors, with  $a_t \sim MN(0, \Sigma)$ 

# **GSTARIMA**

GSTARIMA model represent the general form of GSTAR. If  $\mathbf{Z}_t$  represent observation vectors nonstationary hence done a differentiation so that  $\dot{\mathbf{Z}}_t = (1-B)^{\mathrm{d}}\mathbf{Z}_t$  have stationary. GSTARIMA  $(p_{\lambda_k}, d, q_{\nu_k})$  defined as follows:

 $\dot{\mathbf{z}}_{t} = \sum_{k=1}^{p} \sum_{l=0}^{\lambda_{k}} \mathbf{\Phi}_{kl} \mathbf{W}^{(l)} \dot{\mathbf{z}}_{t-k} - \sum_{k=1}^{q} \sum_{l=0}^{\nu_{k}} \mathbf{\Theta}_{kl} \mathbf{W}^{(l)} \mathbf{a}_{t-k} + \mathbf{a}_{t}$ (2) with,

 $\mathbf{Z}_t$  : observation vectors with  $\mathbf{Z}_t = [\mathbf{Z}_{1,t}, \mathbf{Z}_{2,t}, \dots, \mathbf{Z}_{n,t}]'$ 

 $\mathbf{\Phi}_{kl}$  : diagonal matrix of autoregressive parameter at time lag-k and spatial lag-l

 $W^{(1)}$ : spatial weighting matrix lag-l with  $W^{(0)}$  is identity matrix

 $\mathbf{\Theta}_{kl}$ : diagonal matrix of moving average parameter at time lag-k and spatial lag-l

 $a_t$ : white noise random vectors, with  $a_t \sim MN(0, \Sigma)$ 

# **Inverse Distance Weighting**

Value of inverse distance weighting obtained based on real distance inter locations which its calculation can use latitude and longitude coordinate distance between center the location perceived. Nerby location get the weighting value bigger ones and contrary:

$$w_{ij} = \begin{cases} \frac{w_{ij}^{*}}{\sum_{j=1}^{n} w_{ij}^{*}}, for \ i \neq j \\ 0, for \ i = j \end{cases}$$
 (3)

with,

 $w_{ij}^* = 1/d_{ij}$  where  $d_{ij}$  distance between location-i and location-j.

#### RESULTS AND DISCUSSION

Based on plot of data of monthly inflation that data have stationary at level and there are not seasonally. This case strenghtened with the statistically significant of result the Augmented Dickey-Fuller test in each location. By multivariate, stationarity data shown with the value of modulus smaller than one. The best VARIMA model after done by overfitting is VAR(1). This case is relied on smallest value of AICC that is equal to – 9.6474. There are a lot of outliers affecting do not fulfill normality and uncorrelated residuals.

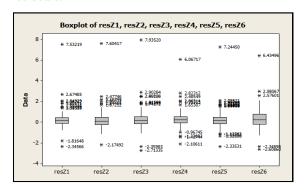


Figure 1 Boxplot diagram residuals of VAR(1) model

One of way to overcome nonnormality residuals is include the outliers into forecasting model. Outlier category done by as base of addition dummy variable in the model. D1 has value one for extreme positive outliers, D2 has value one for positive outliers, and D3 has value one for negative outliers. While to be other as refference has value zero. Because of forecasting model formed represent the model of space-time, hence dummy variables in model valid for all location. For case, high inflation happened on July 2013 in all provincial capitals in Java Island reach 2.58-3.56 percent. It is pushed by increase price of oil fuel subsidize, group of food-stuff, and group transpor, communications and finance service.

Table 1. Identification residuals of VAR(1) early model

t=T	$\mathbf{D}_1$	$\mathbf{D}_2$	$\mathbf{D}_3$
7	0	1	0
8	0	0	1
23	0	1	0
51	0	1	0
58	1	0	0
59	0	0	1
61	0	1	0
85	0	1	0
90	0	1	0
151	0	1	0

The best VARIMA model with the addition of dummy variables after done overfitting is VAR(1). This case is relied on smallest value of AICC that is equal to -11.1260.

Table 2. The result of parameter estimates VAR(1) model by addition dummy variables

Parameter	Z <sub>1,t</sub>	Z <sub>2,t</sub>	Z <sub>3,t</sub>	Z <sub>4,t</sub>	Z <sub>5,t</sub>	Z <sub>6,t</sub>
$\beta_{i1}$	7.5872ª	7.7194ª	7.9517ª	6.0932 a	7.3160 a	6.3934ª
$\beta_{i2}$	1.7319ª	1.7754 a	1.9871 ª	1.7729 a	1.6696 a	1.9840 a
$\beta_{i3}$	-2.3981 a	-1.5609 a	-3.0206 a	-1.9740 a	-2.0415 a	-3.0138 a
$\phi_{i1}^1$	-0.1090	0.0072	-0.0808	-0.0556	-0.1968	0.0752
$\phi_{i2}^1$	-0.0361	0.0022	-0.1030	-0.1606	-0.0681	-0.0616
$\phi_{i3}^{1}$	-0.1770	-0.0780	-0.3116ª	-0.2080	-0.2565	-0.1605
$\phi_{i4}^1$	0.3769ª	0.4330 a	0.5791ª	0.5781 a	0.6235 a	0.4869 a
$\phi_{i5}^1$	0.4022ª	0.1841	0.4117ª	0.3380 a	0.2738ª	0.2409
$\phi_{i6}^{1}$	0.1339	0.0983	0.1991ª	0.1379	0.2123 a	0.0917

<sup>a</sup>Statistically significant at level 5%

For example, VAR(1) model that obtained for rate inflation of Jakarta as follows:

$$\begin{split} Z_{1,t} &= 7.5872D_1 + 1.7319D_2 - 2.3981D_3 \\ &\quad - 0.1604Z_{1,t-1} \\ &\quad - 0.1770Z_{3,t-1} \\ &\quad + 0.3769Z_{4,t-1} \\ &\quad + 0.4022Z_{5,t-1} \\ &\quad + 0.1339\ Z_{6,t-1} + a_{1,t} \end{split}$$

The result of Kolmogorov-Smirnov test for each location obtained p-value bigger than 0.05 meaning assumption residual have normal distribution is fullfiled. Others, residual distribution come near symmetrical form. Based on Ljung-Box test, assumption residual have the character of the white noise fullfiled.

Order determination of GSTARIMA model based on spatial and time order. In this research, spatial order limited at first order, while time order alighted from chosen VARIMA model that is VAR(1). Thereby, chosen GSTARIMA model is GSTAR(1;1).

Table 3 showed that value of inverse distance weighting is bigger for the nearby location. This case have been estimated related inflation for the nearby location is bigger than further location.

Table 3. Matrix of inverse distance weighting

Wii	Zı	<b>Z</b> <sub>2</sub>	Z3	$Z_4$	Zs	$Z_6$
$Z_1$	0.0000	0.3116	0.0887	0.0838	0.0541	0.4619
$Z_2$	0.3912	0.0000	0.1448	0.1403	0.0791	0.2446
$Z_3$	0.1100	0.1431	0.0000	0.4829	0.1717	0.0924
$Z_4$	0.1061	0.1415	0.4927	0.0000	0.1694	0.0903
$Z_5$	0.1236	0.1440	0.3161	0.3057	0.0000	0.1106
$Z_6$	0.5429	0.2290	0.0875	0.0838	0.0569	0.0000

The result of parameter estimates GSTAR(1;1) model by inverse distance weighting and addition three dummy variables most statistically significant at level 5 percent (Table 4).

Table 4. Parameter estimates GSTAR(1;1) model by inverse distance weighting

Parameter	Estimate	Approx std error	t-value	p-value
$\beta_1$	7.2153	0.2171	33.24	0.00
$\beta_2$	1.7717	0.0830	21.35	0.00
$\beta_3$	-2.3635	0.1880	-12.57	0.00
$\phi_{10}^1$	0.1604	0.0850	1.89	$0.06^{a}$
$\phi_{10}^*$	0.0771	0.0728	1.06	0.29 a
$\phi_{10}^{3}$	-0.5252	0.0956	-5.49	0.00
$\phi_{10}^{4}$	0.4959	0.0956	5.19	0.00
$\phi_{10}^4 \ \phi_{10}^5$	0.2193	0.0807	2.72	0.01
$\phi_{10}^{6}$	0.2179	0.0886	2.46	0.02
$\phi_{11}^{1}$	0.3664	0.1792	2.04	0.04
$\phi_{11}^{2}$	-0.2223	0.2100	-1.06	0.29 a
$\phi_{11}^{3}$	-0.5823	0.1822	-3.20	0.00
$\phi_{11}^{4}$	1.6165	0.1793	9.01	0.00
$\phi_{11}^{5}$	2.3445	0.4425	5.30	0.00
$\phi_{11}^{6}$	0.5332	0.1406	3.79	0.00

<sup>a</sup>Statistically not significant at level 5%

This case showed the model obtained good enough. Value of parameter estimate have negative sign show inflation rate city at period previously have an effect on the negativity to inflation rate now.

For example, GSTAR(1;1) model that obtained for rate inflation of Jakarta as follows:

$$\begin{split} Z_{1,t} &= 7.2153D_1 + 1.7717D_2 - 2.3635D_3 \\ &\quad + 0.1604Z_{1,t-1} \\ &\quad - 0.2223Z_{2,t-1} \\ &\quad - 0.5823Z_{3,t-1} \\ &\quad + 1.6165Z_{4,t-1} \\ &\quad + 2.3445Z_{5,t-1} \\ &\quad + 0.5332\ Z_{6,t-1} + a_{1,t} \end{split}$$

The result of Shapiro-Wilk W test for each location obtained p-value bigger than 0.05 meaning assumption residual have normal distribution is fullfiled. Based on Ljung-Box test, assumption residual have the character of the white noise fullfiled.

GSTAR(1;1) model by inverse distance weighting is the best model with the smallest value of RMSE equal to 0.9199 like shown by Table 5.

Table 5. Value of RMSE based on forecasting model at each location

	Forecasting model			
Location	VAR(1)	GSTAR(1;1) Inverse distance		
Jakarta	1.0535	1.0103		
Bandung	0.9089	0.8594		
Semarang	0.9403	0.9035		
Yogyakarta	0.7674	0.7197		
Surabaya	0.8837	0.8459		
Serang	1.2221	1.1809		
Mean	0.9626	0.9199		

# CONCLUSION

The best modelling of forecasting monthly inflation provincial capitals in Java Island is GSTAR(1;1) by inverse distance weighting with smallest value of RMSE. Inflation at a location not only influenced by inflation the previous period but also previous period in other locations. Rate of monthly inflation has fluctuate pattern at certain month as impact of significant increase for price of goods and services. Anticipation require to be done and surely if high inflation disseminate widely so that influence inflation in other region.

For further research, it is suggested to group the outlier become the Additive Outlier, Innovational Outlier, Level Shift, and Transitory Change. Addition transfer function model and intervention model as exogenous variables can be used to yield the better model accuration.

## REFERENCES

- Anselin L. 2009. Spatial Regression.

  Fotheringham AS, Rogerson PA, editor, Handbook of Spatial Analysis.

  London: Sage Publications.
- Borovkova S, Ruchjana BN, Lopuhaa H. 2008. Consistency and Asymptotic Normality of Least Squares Estimators in Generalized STAR Model. *Statistica Neerlandica, Vol. 62 (4):482-508*.
- Box, GEP. et al. 2008. Time Series Analysis: Forecasting and Control. Fourth Edition. New Jersey: John Wiley &Sons, Inc.
- Cryer JD. 2008. *Time Series Analysis. Second Edition*. Boston: PWS-Kent Publishing Company.
- Mankiw NG. 2007. *Teori Makroekonomi*. Edisi Keenam. Iman N [penerjemah]. Jakarta (ID): Erlangga
- Nainggolan N. 2010. Pengembangan Model GSTAR dengan Galat ARCH dan Penerapannya pada Inflasi [disertasi]. Bandung: Universitas Padjadjaran.
- Solikin. 2007. Karakteristik Tekanan Inflasi di Indonesia: Pengaruh Dinamis Sisi Permintaan-Penawaran dan Prospek ke Depan. Buletin Ekonomi Moneter dan Perbankan (BEMP), Januari. Bank Indonesia.
- Wei WWS. 2006. Time Series Analysis
  Univariate and Multivariate Methods.
  Canada: Addison Wesley Publishing
  Company, Inc.
- Wutsqa, D.U., Suhartono dan Sutijo, B. 2010.
  Generalized Space-Time Autoregressive Modeling. Proceedings of the 6th IMT-GT Conference on Mathematics, Statistics and its Applications (ICMSA2010). Kuala Lumpur, Malaysia: 752-761.