www.ijemr.net ISSN (ONLINE): 2250-0758, ISSN (PRINT): 2394-6962

Vandana Publications
IJEMR

Volume-8, Issue-2, April 2018
International Journal of Engineering and Management Research
Page Number: 96-102

Vector Autoregressive (VAR) for Rainfall Prediction

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ABSTRACT

Weather and climate information is useful in a variety of areas including agriculture, tourism, transportation both land, sea and air. For that, up to date weather and climate data and its forecasting are essential. This study aims to create rainfall modeling with Vector Auto Regressive (VAR) using circular data and linear data. The data used comes from the station climatology Darmaga Bogor period 2006-2017. The VAR model (2) of the rainfall variables in the *t*-month is affected by the *t*-1 moisture air moisture, the *t*-2 moisture air and the air temperature at *t*-2. This VAR model (2) is used to forecast the next period. The mean absolute percentage error (MAPE) VAR (2) obtained was 42.18. The novelty of the study is (1) VAR modeling for rainfall prediction, (2) Use of circular data for wind direction data.

***Keywords*--** Vector Auto Regressive (VAR); Circular Data; Rainfall

Type of Paper: Empirical.
MSC Classification: 62P99
JEL Classification: C32, C51, C53.

I. INTRODUCTION

Weather is a state of air at any given moment and in a relatively narrow area and in a short period of time in hours or days (Tjasjono, 2004). Climate is the average weather condition within a year that the investigation is done for a long time (minimum 30 years) and covers a large area (Tjasjono, 2004). Weather and climate have elements such as light, air humidity, air temperature, air pressure, wind (wind direction and speed) and rainfall. Information on weather and climate is useful in a variety of areas including agriculture, tourism, transportation both land, sea and air.

Up-to-date climate data and its forecast for several future periods are important. Forecasting method for rainfall time series data, air humidity, air temperature, air pressure, wind direction and wind speed can be done by single time series model forecasting technique and can be simultaneously done. This is because the movement of time series data can occur together or follow the movement of other time series data. One of the most commonly used forecasting methods is Vector Autoregressive (VAR). VAR is widely used mainly in the field of econometrics. In VAR the system of equations shows that each variable as a linear function of the constant and the past value (lag) of the variable itself and the lag value of the other variables present in the system (Enders, 1995).

The dynamic relationship between the movement of interrelated variables and the reciprocal effect of the weather is an interesting topic to examine. The choice of six variables namely rainfall, air humidity, air temperature, air pressure, wind direction and speed in this study because it is assumed there is a reciprocal relationship and relationship between six variables. In addition, Tjasjono (2004) also states that rain is a symptom or a weather phenomenon that is seen as a non-free variable formed from various elements of the weather.

Based on the explanation above, in this research will be formed a VAR model using six variables, namely rainfall, air humidity, air temperature, air pressure, wind direction and wind speed. The wind direction is a circular variable, ie a variable measured in units of degrees that can be represented in a circle of radius of one unit. The position of each data in the circle depends on the selection of the zero point and the direction of rotation. Therefore, in the data analysis the variable of wind direction is divided into component sin direction and cos direction.

II. RESEARCH OBJECTIVES

The purpose of this research is to use VAR model to build rainfall modeling using circular and linear data. The novelty of this study vis-à-vis comparators in the literature stems from its combination of both of these data. In addition, although many studies focus on VAR, no extant study is devoted to use rainfall prediction.

III. DATA AND METHODOLOGY

Data

The data used in this research is secondary data of monthly weather element that is rainfall, air humidity, air temperature, air pressure, direction and wind speed of Darmaga Bogor region from January 2006 to December 2017. In this research, the data is divided into two, namely January data 2006- December 2015 used for VAR modeling and data from January 2016- December 2017 as validation data.

Methodology

Stages of Data Analysis:

- Conducting exploration of data on each variable. Exploration of data conducted among them determine the descriptive statistics that is the measure of central symptoms (average), the size of the spread (minimum value, maximum value, and standard deviation).
- Conduct a test of data kestasioneran for each variable. The kestasioneran of each variable can be checked through the Dickey Fuller test (Enders, 1995). The test kestasioneran data following the order autoregresi process 1. Suppose the time series data y_t single variable is written:

$$y_t = a_0 + a_1 y_{t-1} + e_t$$

with a distinction model can be written as:

$$\Delta y_t = a_0 + \gamma y_{t-1} + e_t$$

The hypothesis to be tested is:

$H_0 : \gamma = 0$ (data is not stationary)

$H_1 : \gamma \neq 0$ (data is stationary)

The value γ is assumed by the least squares method by making the regression between Δy_t and y_{t-1} as well as the tests performed using *t*-test. Test statistics can be written as follows:

$$t_{stat} = \frac{\hat{\gamma}}{\sigma_{\hat{\gamma}}}$$

where $\hat{\gamma}$ indicates the value of conjecture γ and $\sigma_{\hat{\gamma}}$ indicates the standard deviation from $\hat{\gamma}$.

Decision:

If the t_{stat} value < is critical value in the Dickey Fuller table, then reject Ho which means the data is stationary.

- Selects the lag of the VAR model

If the VAR order is denoted by *p*, then each n equation contains $n \times p$ coefficient coupled with an intercept. According to Enders (1995), the VAR order can be determined by using AIC (Akaike Information Criterion). The AIC measures the goodness of the model that improves the loss of degrees of freedom when additional lag is included in the model. The order of VAR is determined by the value of *p* which produces the smallest AIC.

According to Enders (1995), the test criteria for determining the order of VAR with AIC statistics are:

$$\mathrm{AIC} = T \log|\Sigma| + 2N$$

where $|\Sigma|$ indicates the determinant of the covariance variance matrix error, T indicates number of observations, N indicates the expected number of parameters of all equations. If each equation in n variables VAR has plag and intercept, then $N = n^2p + n$ (Enders, 1995).

- Make predictions of model parameters

Vector Autoregressive (VAR) is a system of equations involving each variable as a linear function of the constants and lag (past) of the variable itself and the lag value of other variables present in the system (Enders 1995). How to estimate the VAR model with the least squares method (Ordinary Least Square, OLS) in each equation separately.

In general the model VAR of order *p* for *n* variables can be formulated as follows (Enders, 1995):

$$\boldsymbol{y_t} = \boldsymbol{A_0} + A_1\boldsymbol{y_{t-1}} + A_2\boldsymbol{y_{t-2}} + A_3\boldsymbol{y_{t-3}} + \cdots + A_p\boldsymbol{y_{t-p}} + \boldsymbol{e_t}$$

where $\boldsymbol{y_t}, \boldsymbol{y_{t-i}}$ indicates $n \times 1$ sized vector containing *n* variables included in the VAR model at time *t* and *t-i*, *i* = 1,2, ... *p*, $\boldsymbol{A_0}$ indicates intercept vector of $n \times 1$ size, A_i $n \times n$ coefficient matrix for each i = 1,2, ... *p*, $\boldsymbol{e_t}$ indicates the $n \times 1$ sized vector sizes are e_{1t}, e_{2t}, ..., e_{ntT}, *p* indicates order VAR, *t* indicates observation period.

- Assesses the impulse response and decomposition response functions

IRF informs the effect of shock change or shock of a variable on the forecast of the variable itself and other variables (Enders, 1995). Decomposition of variance decomposes the change of values of a variable caused by the shock of the variable itself and the shock of other variables.

Suppose the order VAR model 1 with the equation:

$$\boldsymbol{y_t} = \boldsymbol{A_0} + A_1\boldsymbol{y_{t-1}} + \boldsymbol{e_t}$$

and the number of endogenous variables 2 (x_t and z_t), then the forecast for the next step is (Enders, 1995):

$$E(\mathbf{y}_{t+m}) = (I + A_1 + A_1^2 + \dots + A_1^{m-1})\mathbf{A_0} + A_1^m\mathbf{y}_t$$

with forecast error of:

$$\mathbf{y}_{t+m} - E(\mathbf{y}_{t+m}) = \sum_{i=0}^{m-1} A_1^i e_{t+m-i} = \sum_{i=0}^{m-1} \phi_i e_{t+m-i}$$

where $\phi_i = \begin{bmatrix} \phi_{11}(i) & \phi_{12}(i) \\ \phi_{21}(i) & \phi_{22}(i) \end{bmatrix}$

The coefficient ϕ_i can be used to generate the effect of the shock of the variable x_t or z_t (e_{x_t} or e_{z_t}) to the series x_t or z_t. For example, the coefficient $\phi_{12}(0)$ is the direct influence of a unit of change e_{z_t} to x_t. In the same way, elements $\phi_{11}(1)$ and $\phi_{12}(1)$ are the response of unit changes e_{x_t} and e_{z_t} at x_{t+1}. In the n^{th} period, the effect of e_{z_t} on the value of x_{t+n} is $\phi_{12}(n)$. The coefficients $\phi_{11}(i)$, $\phi_{12}(i)$, $\phi_{21}(i)$ and $\phi_{22}(i)$ are referred to as impulse response functions. The effect of the shock can be seen visually by ploting the coefficients $\phi_{jk}(i)$ with *i*.

- Forecasting / validating models

The model obtained is used to predict the data in the period to come. The precision of forecasting is calculated using MAPE (Mean Absolute Percentage Error) or the percentage average of absolute error. The formula used to determine the MAPE value is (Makridakis & Wheelwright, 1999):

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

where y_t indicates actual data and $\hat{y}_t$ indicates forecast data. The smaller the MAPE value, the data forecasting results closer to the actual value.

In summary the above steps are presented in Figure 1.

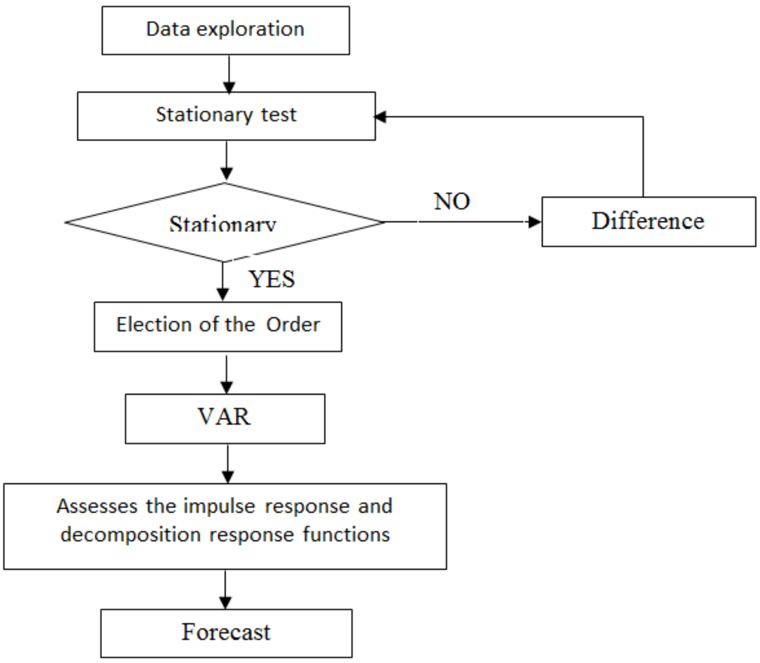

Figure 1 Stages of modeling

IV. RESULTS AND DISCUSSION

Data Exploration

Results Exploration of data on all variables are as follows:

Table 2. Descriptive Statistics of Linear Variables

Variables	Rainfall (mm)	Humidity (%)	Air Temperature (^{0}C)	Air pressure (mb)	Wind velocity (knot)
Mean	303,9378	82,8141	25,8448	1012,1160	6,4248
Max	855,0000	90,0000	27,1000	1017,1000	14,0000
Min	2,0000	70,0000	24,4400	1009,1000	3,1000
Deviation Standar	168,9247	4,4259	0,4628	1,4755	2,0451

Descriptive statistics of wind direction variables are separate from other variables. This is due to the wind direction variable is the circular data, so to determine the descriptive statistics and the graph is different from the variables with the linear scale. The descriptive statistics of wind direction variables are presented in Table 3.

Table 3 Descriptive statistics of wind direction variables

Variables	Wind direction
Mean Directions ($\bar{\theta}$)	300,417°
Mean Length of Response Vector ($\lvert\bar{R}\rvert$)	0,702
Concentration ($\hat{k}$)	2,019
Circular Variance	0,298

According to Table 3, the average of wind direction variables (θ ̅) is 271.219 °. This shows during 2001-2008 the direction of wind tends to come from the northwest. The average resultant vector length ($\lvert\bar{R}\rvert$) shows a value of 0,702. This shows that the data has a high concentration on the average direction. The resulting concentration value is 2.019. Low concentration values indicate that during the period

2006-2015 the wind direction varies or does not converge to a particular value (Fisher, 2000). The value of circular variance of 0.298 gives the meaning that the circular data (wind direction) is quite varied. For wind direction data for the last eight years, *cos* component direction and *sin* direction correlate closely (r = 1) or in other words multicollinearity occurs. So in making the VAR model, the wind direction component used is chosen one. In this study the wind direction component used is *cos* direction.

Stationary Data

There is an assumption that must be met in VAR analysis that is checking kestasioneran data. The kestasioneran data checking is done by Dickey Fuller test. The data analysis is conducted to test whether the variables of rainfall, humidity, air temperature, air pressure, wind speed and cos wind direction are stationary or not. The results of the test kestasioneran data presented in Table 4.

Table 4. Dickey Fuller test for the stationary data

Variables	I(0) *t*-stat	Critical value	Explanation
Rainfall	-8,2048	-2,8859	Stationary
Air Humidity	-6,6108	-2,8867	Stationary
Air Temperature	-6,3041	-2,8859	Stationary
Air pressure	-3,6154	-2,8859	Stationary
Wind velocity	-3,7082	-3,4483	Stationary
Cos direction	-3,2150	-2,8861	Stationary

Based on Table 4, all variables are stationary at the level with a real level $\alpha = 0{,}05$ so there is no need for differencing. The model used is a standard VAR model.

Determination of Order of VAR

The determination of the order or length of the VAR model lag is done by examining the AIC (Akaike Information Criteria) value. The AIC value calculation results are presented in Table 5.

Table 5. AIC calculation results for selection of VAR order

Lag (*p*)	AIC
0	28,149
1	24,783
2	24,603*
3	24,709
4	24,904
5	25,011

* Indicates selected order or song based on AIC criteria

Based on Table 5, when p = 1 obtained the smallest AIC value so that the order of VAR model is order 2 or written VAR (2). The VAR model (2) can be written as follows:

$$\boldsymbol{y_t} = \boldsymbol{A_0} + A_1\boldsymbol{y_{t-1}} + A_2\boldsymbol{y_{t-2}} + \boldsymbol{e_t}$$

where $\boldsymbol{y_t}$ indicates vector size 6×1 containing 6 variables included in the VAR model in month *t*, $\boldsymbol{y_{t-1}}$ indicates vector size 6×1 containing 6 variables included in the VAR model in month *t-1*, $\boldsymbol{A_0}$ indicates intercept vector 6×1, $A_{\boldsymbol{1}}, A_{\boldsymbol{2}}$ indicates coefficient matrix measuring 6×6, $\boldsymbol{e_t}$ indicates the remaining vector is 6×1 in month *t*.

Estimation of Order VAR Model 2

The VAR model estimation is done by the least squares method. The VAR model used in this research is the order VAR 2. The result of the assumption of the parameter of the order VAR model 2 is as follows:

$Rain_t$ = 17865,79 + 0,0859 $Rain_{t-1}$ – 0,1032 $Rain_{t-2}$ + 19,1994 $Humid_{t-1}$* – 19,6022 $Humid_{t-2}$* + 73,3649 $Temp_{t-1}$ – 99,0169 $Temp_{t-2}$* – 15,1756 $Press_{t-1}$ – 1,5177 $Press_{t-2}$ + 14,5238 $Veloc_{t-1}$ – 8,7751 $Veloc_{t-2}$ – 19,3487 Cos_{t-1} + 0,9104 Cos_{t-2}.

$Humid_t$ = 453,958 + 0,0031 $Rain_{t-1}$ + 0,0004 $Rain_{t-2}$ + 0,6939 $Humid_{t-1}$* – 0,1345 $Humid_{t-2}$ + 2,0189 $Temp_{t-1}$* – 0,8754 $Temp_{t-2}$ – 0,6154 $Press_{t-1}$ + 0,1722 $Press_{t-2}$ + 0,0203 $Veloc_{t-1}$ + 0,1244 $Veloc_{t-2}$ – 1,6043 Cos_{t-1}* + 0,2705 Cos_{t-2}.

$Temp_t$ = –48,6209 + 0,0001 $Rain_{t-1}$ + 0,0000 $Rain_{t-2}$ – 0,0141 $Humid_{t-1}$ – 0,0056 $Humid_{t-2}$ + 0,4365 $Temp_{t-1}$* – 0,1688 $Temp_{t-2}$ + 0,0384 $Press_{t-1}$ + 0,0297 $Press_{t-2}$ + 0,0392 $Veloc_{t-1}$ – 0,0127 $Veloc_{t-2}$ + 0,2229 Cos_{t-1}* – 0,1758 Cos_{t-2}.

$Press_t$ = 157,7907 – 0,0002 $Rain_{t-1}$ – 0,0003 $Rain_{t-2}$ – 0,0932 $Humid_{t-1}$* + 0,1078 $Humid_{t-2}$* – 0,5939 $Temp_{t-1}$* + 0,7657 $Temp_{t-2}$* + 0,6115 $Press_{t-1}$* + 0,2269 $Press_{t-2}$* + 0,0319 $Veloc_{t-1}$ + 0,0398 $Veloc_{t-2}$ – 0,3887 Cos_{t-1}* – 0,1102 Cos_{t-2}.

$Veloc_t$ = –37,8283 – 0,0001 $Rain_{t-1}$ + 0,0004 $Rain_{t-2}$ + 0,0062 $Humid_{t-1}$ – 0,0590 $Humid_{t-2}$ + 0,0285 $Temp_{t-1}$ – 0,5986 $Temp_{t-2}$* – 0,0770 $Press_{t-1}$ + 0,1338 $Press_{t-2}$ + 0,4769 $Veloc_{t-1}$* + 0,4411 $Veloc_{t-2}$* + 0,6394 Cos_{t-1}* – 0,0179 Cos_{t-2}.

Cos_t = –2,3248 – 0,0000 $Rain_{t-1}$ – 0,0003 $Rain_{t-2}$ + 0,0029 $Humid_{t-1}$ +0,0250 $Humid_{t-2}$ + 0,0411 $Temp_{t-1}$ + 0,0843 $Temp_{t-2}$ + 0,0939 $Press_{t-1}$ – 0,0578 $Press_{t-2}$ + 0,0627 $Veloc_{t-1}$ - 0,0578 $Veloc_{t-2}$ + 0,4139 Cos_{t-1}* + 0,2985 Cos_{t-2}*.

* Indicates the variables that have a significant effect on $\alpha = 0{,}05$.

Based on the VAR model for rainfall above, it is found that the variables that have significant influence on rainfall in month t are the air humidity variables in month *t*-1, the humidity of air in month *t*-2 and the air temperature in month *t*-2. Tjasjono (2004) says that rainfall is seen as one of the most important forecasts of weather and climate variables. This is because rainfall affects human life activities in various sectors such as agriculture, transportation, trade, health, environment and so on and has a very high diversity both by time and place. Therefore, for the next variables that will be discussed more deeply is the variable of rainfall.

Impulse Response Function

The Impulse Response Function (IRF) function informs the effect of the shock of a variable on the forecast of the variable itself and other variables (Enders 1995). The IRF results from the rainfall variables are presented in Table 6 below:

Table 6. Function of Impulse Response variables Rainfall

Period	Rainfall	Humidity	Temperature	Pressure	Velocity	*Cos*
1	156,0692 (10,1592)	0,0000 (0,0000)	0,0000 (0,0000)	0,0000 (0,0000)	0,0000 (0,0000)	0,0000 (0,0000)
2	45,2685 (15,3131)	35,0272 (15,6737)	26,0048 (14,8699)	-16,9032 (14,2158)	13,9239 (13,4530)	-7,1931 (14,2843)
3	-8,6939 (16,1640)	-8,3478 (12,9710)	0,0441 (14,8027)	-18,2957 (10,2595)	1,2658 (9,7359)	-2,9838 (13,7519)
4	-7,1027 (10,9056)	-15,0699 (8,9749)	-19,8007 (12,8916)	-6,9739 (8,2893)	5,1185 (7,3694)	-0,3139 (9,8352)
5	-8,2136 (8,6892)	-7,9477 (6,8330)	-14,7777 (8,36201)	-4,7935 (6,0334)	-0,5723 (6,9049)	2,8308 (7,4546)
6	-5,9585 (7,2671)	-3,8855 (5,4599)	-5,1057 (8,0958)	-3,1058 (4,7091)	-1,0581 (5,9476)	5,1138 (5,9135)
7	-2,2771 (5,2973)	-0,5617 (4,4712)	2,1253 (7,4221)	-2,4384 (3,8097)	-2,2808 (5,3678)	6,7730 (5,0425)
8	0,7430 (4,1345)	1,3834 (3,9464)	4,8807 (5,6513)	-2,0382 (3,1672)	-1,8924 (4,8222)	6,5224 (4,4465)
9	1,9993 (3,4989)	2,2949 (3,3053)	5,0899 (4,3041)	-2,0570 (2,7483)	-1,8998 (4,5145)	5,6997 (4,0555)
10	2,3526 (2,9995)	2,3352 (2,6507)	4,1229 (3,5417)	-2,0479 (2,5141)	-1,6442 (4,3234)	4,5676 (3,7858)

The table above shows how the six variables in the VAR system respond when a standard 1 deviation shock occurs in rainfall. Shock of 1 standard deviation on rainfall in month t resulted in a standard deviation error 156,0692 of the unit against forecasting rainfall one month ahead, but did not give effect to the standard deviation error other weather elements in forecasting one month ahead (standard deviation error other variables zero). For forecasting for the next two months, the standard deviation of the rainfall error will be 45.2685 above the average. While the effect on other variables is to give rise of standard deviation of air humidity error error of 35,0272 above average, the increase of standard deviation of error of temperature variable is 26,0048 above average, decrease of standard deviation error of air pressure variable of 16, 9032 above the average, the standard deviation of the wind speed variation error by 13.9239 above the mean and the standard deviation of the wind direction deviation error of 7.1931 below the mean.

In general, the shock on the rainfall of all variables gives an influence big enough until the sixth month. After that period the effect of rainfall shock on other variables tends to be constant and convergent to zero after a period of six months.

Variance Decomposition

Variance Decomposition (VD) informs the proportion of diversity forecasting errors of a variable described by the error of each variable and other error variables (Enders, 1995). Here is the result of the decomposition of variations of the rainfall variables.

Table 7. Decomposition of Various Rainfall Variables

Period	S.E.	Rainfall	Humidity	Temperature	Pressure	Velocity	*Cos* A
1	156,0692	100,0000	0,0000	0,0000	0,0000	0,0000	0,0000
2	169,8274	91,5589	4,2541	2,3447	0,9907	0,6722	0,1794

3	171,2654	90,2855	4,4205	2,3055	2,1153	0,6664	0,2068
4	173,4255	88,2182	5,0662	3,5520	2,2246	0,7371	0,2019
5	174,5186	87,3381	5,2103	4,2247	2,2723	0,7289	0,2257
6	174,8437	87,1297	5,2403	4,2943	2,2954	0,7299	0,3105
7	175,0353	86,9559	5,2299	4,2996	2,3098	0,7453	0,4595
8	175,2539	86,7409	5,2231	4,3664	2,3175	0,7551	0,5969
9	175,4691	86,5413	5,2274	4,4399	2,3256	0,7649	0,7009
10	175,6279	86,4028	5,2356	4,4869	2,3349	0,7723	0,7673

Decomposition of various variables of rainfall indicates that for the forecasting of 1 month ahead, the full diversity of rainfall errors (100%) is explained by the shock of rainfall itself. As time went on, the other five variables began to contribute even small.

In the medium term (next 6 months), the diversity of rainfall errors besides explained by the shock of rainfall itself (87.1297%) is also explained by the shock of the other five variables (air humidity 5,2403%, air temperature 4,2943%, air pressure 2.2954%, wind speed 0.7299% and wind direction 0.3105%).

Based on the result of decomposition of variance, generally it can be said that the contribution of other variables to the variation of rainfall forecasting error is relatively constant and small, except the variable of air humidity and air temperature. The humidity and air temperature variables provide a substantial and constant role for the diversity of rainfall forecasting errors. This is consistent with the VAR model for rainfall which states that only the moisture variables of t-1 and t-2 moons and the t-2 moon air temperature significantly affect rainfall in month t. The variable that has the greatest role in the diversity of rainfall errors is the variable of the rainfall itself.

Validation of VAR Model

Forecasting is not the only final goal in a time series model, but many argue that forecasting is an inseparable part of many time series models. To determine the accuracy of forecasting the VAR model used the mean absolute percentage error (MAPE) value of the model for the rainfall variables. The results of rainfall forecast for the last 2 years 2016-2017 are presented in table 8.

Table 8. Rainfall Forecast Results Data using VAR (2)

Month	Rainfall actual (mm)	Rainfall prediction (mm)
1	423	285,53
2	612	308,03
3	435	321,89
4	548	259,48
5	330	293,26
6	373	208,47
7	296	173,70
8	318	207,84
9	442	237,52
10	397	333,10
11	355	256,59
12	116	337,84
13	133	209,39
14	529	314,50
15	355	352,01
16	283	297,26
17	319	275,83
18	401	256,08
19	404	206,70
20	180	172,27
21	281	175,11

22	333	281,45
23	206	369,64
24	180	359,35
MAPE		42,18

Based on table 3, obtained MAPE value for rainfall of 42.18. The MAPE value obtained is relatively large. There are several things that cause large MAPE value, such as rainfall data used for modeling has high fluctuations and from modeling only humidity and temperature variables that have a significant effect on rainfall.

V. CONCLUSIONS AND RECOMMENDATIONS

Conclusions

Based on the results obtained VAR model for elements of rainfall weather, air humidity, air temperature, air pressure, wind direction and speed. For the VAR model the rainfall variables in the t-month are affected by the t-1 moisture air moisture, the t-2 moisture air and the air temperature at t-2.

The VAR model (2) used is used to forecast the next period. MAPE values obtained are influenced by several things such as rainfall data used for modeling has high fluctuations, and many other variables that have significant effect on rainfall.

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