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Research Paper

Dynamic Modeling and Forecasting Data Energy Used and Carbon Dioxide (CO_2)

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Abstract
The model of Vector Autoregressive (VAR) with cointegration is able to be modified by Vector Error Correction Model (VECM). Because of its simpilicity and less restrictions the VECM is applied in many studies. The correlation among variables of multivariate time series also can be explained by VECM model, which can explain the effect of a variable or set of variables on others using Granger Causality, Impulse Response Function (IRF), and Forecasting. In this study, the relationship of Energy Used and CO_2 will be discussed. The data used here were collected over the year 1971 to 2018. Based on the comparison of some criteria: Akaike Information Criterion Corrected (AICC), Hannan-Quin Information Criterion (HQC), Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) for some VAR(p) model with p= 1,2,3,4,5, the best model with smallest values of AICC, HQC, AIC and SBC is at lag 2 (p= 2). Then the best model found is VECM (2) and further analysis such as Granger Causality, IRF, and Forecasting will be based on this model.

Keywords
Carbon Dioxide (CO_2), Energy Used, Cointegration, VAR Model, VECM Model

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1. INTRODUCTION

Currently, studies on the phenomenon of global warming caused by the use of fossil fuels, Energy Used, the use of electricity consumption, and the increment of the steel industry have been conducted by many scientists (Anjana and Kandpal, 1997; Sakamoto and Tonooka, 2000; Di Lorenzo et al., 2013; Aye and Edoja, 2017; Balsalobre et al., 2018; Mahmood et al., 2019; Wasti and Zaidi, 2020; Munir et al., 2020). Developed countries have sought to reduce the amount of CO_2 emissions (known as one of the representative greenhouse gases) (UN UNCED, 1992; UN UNCED, 1996; Mahmood et al., 2019). Developed countries that use a lot of fossil fuels, use more electricity to produce CO_2 emissions, for example, Japan contributed about 5% of world CO_2 emissions in 1990 (OECD, 2005).

Since the era of the industrial revolution began in the early 19^{th} century, the growth in the use of fuels (fossil), the discovery and increasing of electricity consumption, and the increase in the steel industry have caused substantial climate change and global warming. CO_2 emissions to the atmosphere have caused an increase in the greenhouse effect and caused the surface temperature of the earth to increase (EPA, 2017). Therefore, industrialization growth, intensive use of fossil fuels, and electricity use have damaged the environment and stimulated global warming (Dong et al., 2018; Al Araby, 2019). Carbon Dioxide (CO_2) is considered to be one of the most dominant causes of increasing global warming and climate change (IPCC, 2014; Al Araby, 2019; Hasnisah et al., 2019). Increasing energy use and concerns about global warming and climate change, have encouraged many developed countries and companies to apply strategies in order to cut energy use and increase clean energy production (Benedetti et al., 2017; Faizah, 2018).

Economic growth in many developed countries is closely related to increasing CO_2 emissions (Mirza and Kanwal, 2017; Charfeddine, 2017; Hanif, 2018). Increased CO_2 emissions are positively correlated with energy consumption, the use of fossil fuels and electricity, which causes an increase in pollution. Thus, many developed countries have targeted using renewable energy sources to reduce CO_2 emissions in an effort to reduce pollution (Balogh and Jámbor, 2017; Ito, 2017; Balsalobre et al., 2018). Abolhosseini et al. (2014) have investigated the effect of renewable energy on reducing the emission of CO_2. The studies about the correlation between the emission of CO_2 and the use of electricity have been conducted by many scientists, including (Tamba et al., 2017; Bah and Azam, 2017; Akpan and Akpan, 2012).

The VAR or VECM model for modeling energy and economics have been used by many researchers because of too many problems concerning energy, climate change, CO_2 and renewable energy (Forero, 2019; Warsono et al., 2019a, Warsono et al., 2019b; Wang et al., 2018; Ito, 2017). The used of VECM modeling to find the correlation between food price index and crude oil price had been investigated by Aynur (2013). Yu et al. (2006) investigated the correlation between the price of vegetable oil and higher crude oil using causality approach and cointegration. The correlation and Forecasting between index's prices coal of two coal companies using VAR model was discussed by Warsono et al. (2019a).

In order to analyze macroeconomic data, Sims (1980) introduced VAR model. In economy and finance, VAR model plays an important role (Kirchgässner et al., 2012; Hamilton, 1994). VAR model are natural tool for Forecasting (Lütkepohl, 2013). Vector Error Correction Model (VECM) will be used by modifying VAR model if the data has cointegration. If the variables have a common stochastic's trend, then they are called cointegrated (Engle and Granger, 1987; Granger, 1981). The VAR model is not convenient to be used if cointegration occurs in the variables. In this case specific parameterizations will be considered, and VECM is the commonly used model to elaborate the cointegration among the variables.

There are a lot of researchs that have been done concerning the effect on Forecasting by cointegration (Lütkepohl, 2005; Campiche et al., 2007; Yu et al., 2008; Hunter et al., 2017). The comparison the forecasts generated from an estimated VECM model by assuming that the cointegrating rank and the lag order are known, with those from an estimated Vector Autoregressive (VAR) model in levels with the correct lag was investigated by Engle and Yoo (1987). The result is that VECM model is better than VAR model, because VECM allows us to explain the correlation of the long-run and the short-run of nonstationary variables.

The aim of this research is to explain the patterns of the relationship between Carbon Dioxide (CO_2) and Energy Used using VECM approach in an Indonesian case. Studies on modeling the correlation between CO_2 and Energy Used using multivariate time series data by means of VECM modeling are relatively rare. Therefore, this study is an attempt to fill this gap by analyzing the data Energy Used and Carbon Dioxide (CO_2) using VECM approach.

2. THE METHOD

In this study, the method to analyze the data Energy Used and Carbon Dioxide (CO_2) is a VECM model, with the following steps: first, the assumptions stationary data will be checked; second, the optimal lag will be determined for the Vector Autoregression (VAR) model using the AICC, HQC, AIC, and BSC criterion information; third, after the optimal lag has been obtained, the cointegration test will be carried out by using the Johansen test; fourth, after obtaining rank cointegration, the VECM model is built. Based on the best VECM model obtained, the analysis of IRF, Granger Causality and Forecasting is carried out (Hamilton, 1994; Lütkepohl, 2005; Tsay, 2014; Wei, 2019).

2.1 Dynamic Modeling

In studying time series data, we often face with many variables, Y_{it}, where i= 1, 2, ..., p and the data are taken in a sequence of time, t. Let Y_t= [Y_{1t}, Y_{2t}, ..., Y_{pt}]', where Y_{it} is the ith component variable at time t and it is a random variable for each i and t (Wei, 2019). Because most of standard method of statistical theory on random samples are not applicable, so different methods are needed (Tsay, 2014; Wei, 2019). In decision making, we need to get accurate prediction of those variables, and it require understanding the relationships among those variables.

It is assuming that the data is stationar. By checking the plot of the data we know the stationary of the data. If the data are fluctuating around certain number then it is stationary, if not then the data are nonstationary. Besides, we also can use Augmented Dickey-Fuller (ADF) test. Autocorrelation Function (ACF) graph also can be used. The ADF-test with lag-p, is defined as:

$$\Delta Y_t = \alpha + \phi Y_{t-1} + \sum_{i=1}^{p-1} \phi_i * \Delta Y_{t-i} + u_t \quad (1)$$

ΔY_t= Y_t-Y_{t-1} and u_t is white noise. Ho: ϕ= 0 is the null hypothesis, and Ha: ϕ<0 is the alternative hypothesis, α= 0.05 is level of significance. If τ<-2.57, then it rejects Ho, or if the p value<0.05 (Tsay, 2005; Brockwell and Davis, 2002). The test statistic is

$$\text{ADF} \quad \tau = \frac{\phi}{\text{Se}(\phi)} \quad (2)$$

2.2 Cointegration

Granger (1983) who first stated the term cointegration. Granger (1983) has investigated of how the relationship between cointegration and modeling with error correction. This study has attracted much attention in econometric, financial and in various fields of science involving multivariate time series data that has a cointegration between variables (Johansen, 1995; Engle and Granger, 1987). Over the past 25 years, this approach has contributed a lot to various scientific studies, for example in the fields of finance, business, and environment. Cointegration is the key concepts of in econometrics and modern time series analysis.

The development of method of inferential and estimation is given by Johansen (1988). In general, Y_t is nonstationary with order d, I(d) process, if $(1\text{-}B)^d Y_t = Z_t$, where Z_t is stationary and invertable (Mittnik et al., 2007; Tsay, 2005, Tsay, 2014). If there is a cointegration, then the rank of the cointegration should be tested (Tsay, 2005; Tsay, 2014), and to test the rank of cointegration we can use Trace test and test of maximum eigenvalues. For Trace test, the null hypothesis: there are at most r positive eigenvalues, and the test:

$$Tr(r) = -T \sum_{i=r+1}^{k} \ln(1-\hat{\lambda}_i) \tag{3}$$

The test for maximum eigen value: the null hypothesis: there are r positive eigen values, and the test statistics:

$$\lambda_{max}(r, r+1) = -T \ln(1-\hat{\lambda}_i) \tag{4}$$

$\hat{\lambda}_i$= estimate of eigenvalue, T= total number of observations, and k= total number of endogeneous variables.

2.3 Vector Autoregressive

In the modeling with Vector Autoregressive (VAR) models means that the future values of the process are weighted sum of present and past values with some noises (Mittnik et al., 2007). Tsay (2014) and Wei (2019) stated that this model is used comprehensively in business, financial and econometric studies because: (1) the model is easy to estimate; (2) the VAR model have been investigated expansively in the literature (Warsono et al., 2019a, Warsono et al., 2019b; Wei, 2006; Lütkepohl, 2005; Lütkepohl, 2013), and (3) Vector Autoregression models in multivariate analysis are like multivariate linear regression. The k-dimensional VAR process with order p, VAR(p) is:

$$\mathrm{Y}_t = \mu_0 + \Phi_1 \mathrm{Y}_{t-1} + \ldots.. + \Phi_p \mathrm{Y}_p + \mathrm{u}_t \tag{5}$$

or

$$\Phi_p(\mathrm{B})\mathrm{Y}_t = \mu_0 + \mathrm{u}_t \tag{6}$$

Where u_t is k-dimensional vector white noise process with mean vector 0_{kxl} and variance covariance matrix $\sum$, VWN(0, $\sum$),

$$\Phi_p(\mathrm{B}) = \mathrm{I} - \Phi_1\mathrm{B} - \ldots - \Phi_p B^p. \tag{7}$$

If the roots of $|\gamma^p\mathrm{I}$-$\gamma^{p-1}\Phi_1$- ...-$\Phi_p|$= 0 are all lie inside the unit circle, then VAR model is invertible and it will be stationary.

2.4 Vector Error Correction Model

A modified VAR model which has cointegration among the variables. If r≤k is the rank of cointegration, p is the lag of endogeneous variable, the general form of VECM(p) is:

$$\Delta\mathrm{Y}_t = \Pi\mathrm{Y}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta\mathrm{Y}_{t-i} + \mathrm{u}_t \tag{8}$$

Some advantages of VECM(p) model's applications: (1) The multicollinearity is reduced, (2) All information about long-run impacts is summarized in the level matrix (denoted by Π), (3) The easier of the interpretation of estimates, and (4) VECM model is easier to interprete (Juselius, 2006). The criteria of information AIC, SBC, are used to find the best model of VECM(p).

2.5 Normality Test

To check the normality of residual, the Jarque-Bera (JB) test is used. Besides, the residuals plot's performance will be considered. The JB Test is:

$$\mathrm{JB} = \frac{\mathrm{n}-\mathrm{k}}{6}\left[\mathrm{S}^2 + \frac{(\mathrm{K}\text{-}3)^2}{4}\right] \tag{9}$$

where:

n = Number of Samples

$$\mathrm{S} = \text{Expected Skewness} = \frac{\frac{1}{\mathrm{n}}\sum_{i=1}^{n}(\mathrm{Y}_i - \bar{\mathrm{Y}})^3}{(\frac{1}{\mathrm{n}}\sum_{i=1}^{n}(\mathrm{Y}_i - \bar{\mathrm{Y}})^2)^{3/2}} \tag{10}$$

$$\mathrm{K} = \text{Expected Excess Kurtosis} = \frac{\frac{1}{\mathrm{n}}\sum_{i=1}^{n}(\mathrm{Y}_i - \bar{\mathrm{Y}})^4}{(\frac{1}{\mathrm{n}}\sum_{i=1}^{n}(\mathrm{Y}_i - \bar{\mathrm{Y}})^2)^2} \tag{11}$$

k = The Number of Independent Variables

Jarque-Bera test has x^2 distribution (Jarque and Bera, 1987).

2.6 Test for Granger Causality

Many researchers have argued concerning the meaning and nature of causality, and the important role of casuality in the study economic (Sampson, 2001). Consider a VAR(p) model (Wei, 2019).

$$\Phi_p(\mathrm{B})\mathrm{Y}_t = \theta_0 + \mathrm{u}_t \tag{12}$$

The vector Y_t is partitioned into two components, Y_t= $|Y'_{it}, Y'_{2t}|$', then the Equation (12) can be written as:

$$\begin{bmatrix}\Phi_{11}(\mathrm{B}) & \Phi_{12}(\mathrm{B}) \\ \Phi_{21}(\mathrm{B}) & \Phi_{22}(\mathrm{B})\end{bmatrix}\begin{bmatrix}\mathrm{Y}_{1t} \\ \mathrm{Y}_{2t}\end{bmatrix} = \begin{bmatrix}\theta_1 \\ \theta_2\end{bmatrix} + \begin{bmatrix}\mathrm{u}_{1t} \\ \mathrm{u}_{2t}\end{bmatrix} \tag{13}$$

If the value of Φ_{12}(B)= 0, then Equation (13) can be written as follows:

$$\begin{aligned}\Phi_{12}(\mathrm{B})\mathrm{Y}_{1t} &= \theta_1 + \mathrm{u}_{1t} \\ \Phi_{22}(\mathrm{B})\mathrm{Y}_{2t} &= \theta_2 + \Phi_{21}(\mathrm{B})\mathrm{Y}_{1t} + \mathrm{u}_{2t}\end{aligned} \tag{14}$$

The interpretation is as follows: the future values of Y_{2t} are impacted by its own past and the past of Y_{1t}. The future values of Y_{1t} are impacted by its own past. This idea is called as the Granger Causality, because it is first introduced by Granger (1969).

2.7 Impulse Response Function

Consider the VAR model as follows (Hamilton, 1994):

$$Y_t = \mu + \mu_t + \Psi_1 u_{t-1} + \Psi_2 u_{t-2} + ...$$

The interpretation of matrix Ψ_s is as follows: $\frac{\partial Y_{t+s}}{\partial \varepsilon_t'} = \Psi_s$.

If the value of u_t is changed by δ_1, at the same time u_{t-1} is changed by δ_2, ..., and the u_{t-n} is changed by δ_n, so that the combined impact to the value of vector Y_{t+s} is as follows:

$$\Delta Y_{t+s} = \frac{\partial Y_{t+s}}{\partial \varepsilon_{1t}}\delta_1 + \frac{\partial Y_{t+s}}{\partial \varepsilon_{2t}}\delta_2 + \ldots + \frac{\partial Y_{t+s}}{\partial \varepsilon_{nt}}\delta_n = \Psi_s \delta \quad (15)$$

Where $\delta = (\delta_1, \delta_2, ..., \delta_n)'$ and the graph of the row i, column j element of Ψ_s

$$\frac{\partial Y_{i,t+s}}{\partial \varepsilon_{jt}}$$

as a function of s is called Impulse Response Function.

3. RESULTS AND DISCUSSION

To analysis the data Energy Used and CO_2, the SAS program is used (SAS/ETS 13.2, 2014). The assumption of stationarity will be checked by: (1) evaluate the behavior of the plot of data, (2) ACF plot of data, and (3) Augmented Dickey Fuller test. The data used in this research are the use of Energy (ENR) and Carbone Dioxide (CO_2) emission. The plot of the data is shown in Figure 1.

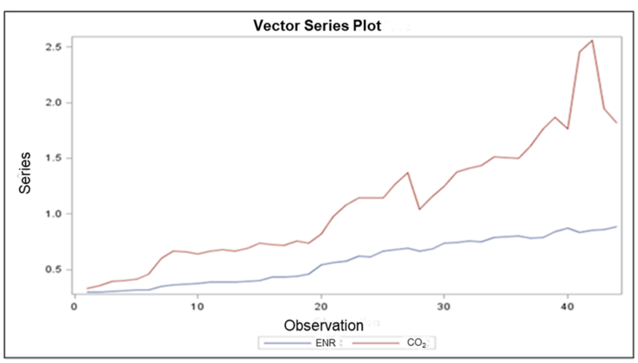

Figure 1. Plot of Energy Used (ENR) and CO_2 Emission

Table 1. Unit Roots Test or ADF Test for Energy Used and CO_2

Variable	Type	Lags	Rho	p-Value	Tau	p-Value
Energy (ENR)	Zero Mean	2	0.8776	0.8835	3.30	0.9996
	Single Mean	2	-0.0717	0.9497	-0.12	0.9401
	Trend	2	-8.2149	0.5260	-1.90	0.6384
CO_2	Zero Mean	2	1.4082	0.9545	2.80	0.9983
	Single Mean	2	0.5399	0.9752	0.49	0.9843
	Trend	2	-9.9202	0.3909	-1.82	0.6779

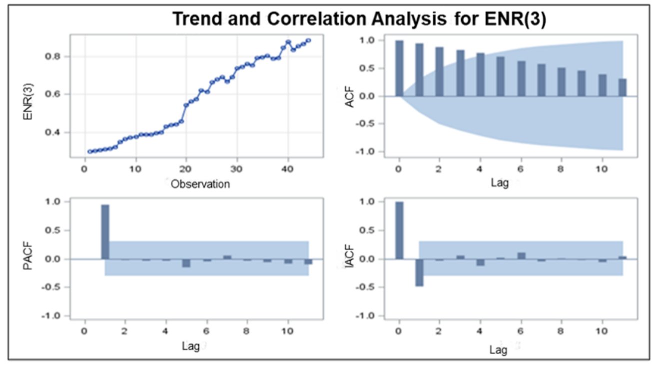

Figure 2. Trend and Correlation Analysis of Energy Used (ENR)

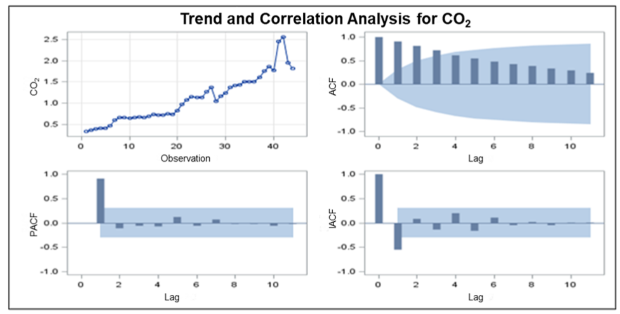

Figure 3. Trend and Correlation Analysis of CO_2

From Figure 1, we can see that Energy Used and CO_2 emission, the trend are increase and fluctuative. Figure 2 and 3 the plot of Autocorrelation Function (ACF) for Energy and CO_2 the autocorrelations are decrease very slowly. From Table 1, ADF test for Energy (ENR) and CO_2 the Tau-test for single mean at lag 2 not significant with p-values= 0.9401 and 0.9843, respectively. These means that Energy Used and CO_2 are non-stationary. To attain the stationary data, the differencing method is used.

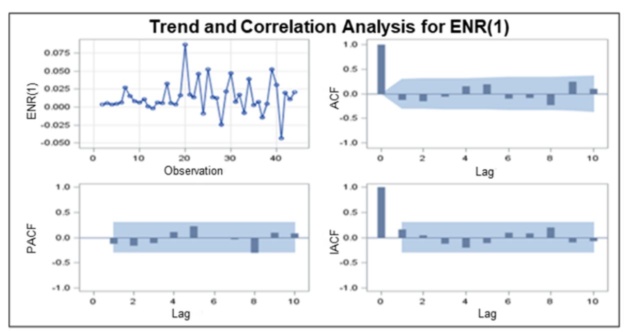

Figure 4. Trend and Correlation Analysis of Energy Used after Differencing, d=1

From Figures 4 and 5 of data ENR and CO_2 after differencing with d= 1, the data are fluctuated around certain

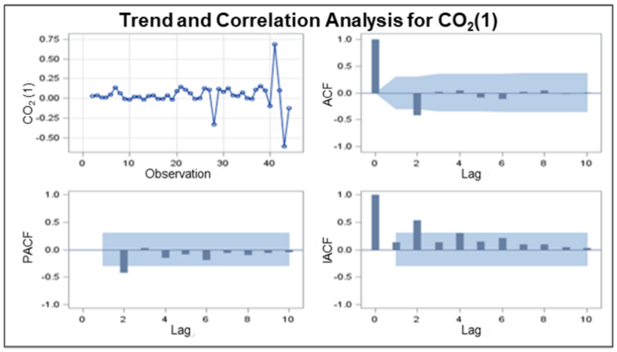

Figure 5. Trend and Correlation Analysis of CO_2 after Differencing, d=1

Table 2. ADF Unit Roots Test of Energy (ENR) and CO_2 after Differencing, d=1

Variable	Type	Lags	Rho	p-Value	Tau	p-Value
Energy (ENR)	Zero Mean	2	-51.8104	<0.0001	-3.42	0.0011
	Single Mean	2	-1962.80	0.0001	-4.57	0.0007
	Trend	2	320.6803	0.9999	-4.66	0.0030
CO_2	Zero Mean	2	-14.7087	0.0050	-2.33	0.0205
	Single Mean	2	-98.1031	0.0003	-4.50	0.0008
	Trend	2	-98.1986	<0.0001	-4.43	0.0055

number, the data are stationary. The ADF test for data ENR and CO_2 the Tau-test= -4.57 with p-value= 0.0007, Tau-test= -4.57 with p-value= 0.0008, respectively. Thus, after the first differencing, the data ENR and CO_2 are stationary.

3.1 Test for Lag Optimum

By using criteria AIC, SBC, HQC and AICC, we find the best VAR model from endogeneous variables that are ENR and CO_2, where the results are as follows:

Table 3. Criteria to Select of Lag VAR Model for All Endogeneous Variables

	VAR(p) Lag Order Selection Criteria				
Criteria	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
AICC	-10.9638	-11.2889*	-11.0036	-10.7606	-10.5612
HQC	-10.8947	-11.2045*	-10.9383	-10.7620	-10.6956
AIC	-10.9857	-11.3567*	-11.1520	-11.0375	-11.0329
SBC	-10.7375	-10.9387*	-10.5609	-10.2697	-10.0848

From Table 3, at lag 2, the smallest information criteria (*) of AICC, AIC, and HQC occur. Thus, the test of cointegration is conducted at lag 2.

3.2 Test for Cointegration

Table 4 is the result of cointegration testing with the null hypothesis: rank= r, no cointegration with the alternative: rank>r, there is cointegration. From Table 4 we can conclude that the test results are that rank>r= 1, or rank r= 2. Based on these results, the VECM model with cointegration rank= 2 will be used.

3.3 The Estimation of Parameters VECM(2) Model

Based on the above analysis, we have chosen the model for Energy Used (ENR) and CO_2 data is VECM(2) with the cointegration rank= 2 as the best model. Table 5 is the estimate parameter of (β), the long-run parameter Beta Estimate. Table 6 give an estimate parameter (α), Adjustment Coefficient Alpha Estimates, and Table 7 give the estimate parameter $\Pi= \alpha * \beta'$.

The estimate parameters of VECM(2) is:

$$\Delta Y_t = \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \varepsilon_t \quad (16)$$

$$\Delta\left[Y_t\right] = \begin{bmatrix} -0.7393 & 0.0355 \\ 4.5149 & -1.6776 \end{bmatrix} Y_{t-1} + \begin{bmatrix} -0.1151 & -0.0130 \\ -3.1509 & 0.6297 \end{bmatrix} \Delta Y_{t-1} + \begin{bmatrix} \varepsilon_{t1} \\ \varepsilon_{t2} \end{bmatrix} \quad (17)$$

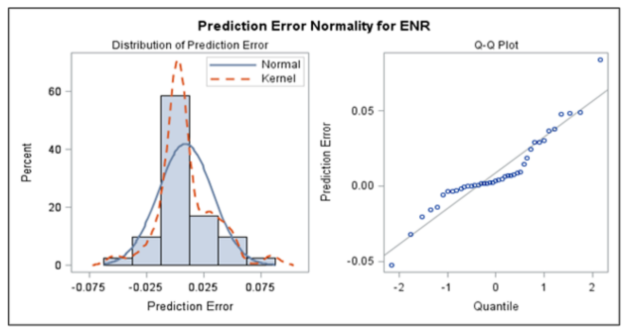

Figure 6. Prediction Error Normality for Energy (ENR)

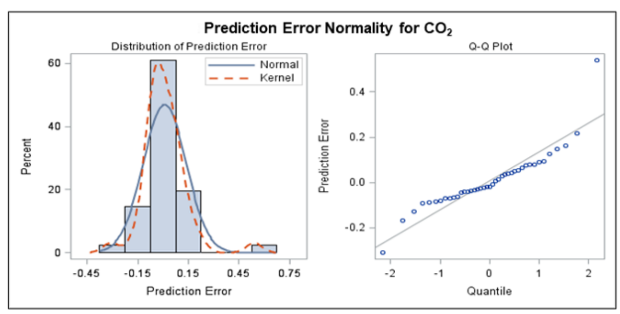

Figure 7. Prediction Error Normality for CO_2

3.4 Normality of Residual

Table 9 is the result of testing with the null hypothesis: the residuals are not correlated. The results for models AR(1), AR(1,2), AR(1,2,3) and AR(1,2,3,4), the null hypothesis was not rejected. So the residuals are not correlated. Table 10 is the result of the normality distribution test for residual ENR and CO_2 data, the results show that the JB test for both ENR and CO_2 data is rejected with p-value<0.0001. So the residuals are not normally distributed. However, if we look at the results

Table 4. Cointegration Rank Test Using Trace Statistics

H_0:Rank= r	H_1:Rank>r	Eigenvalue	Trace	p-Value	Drift in ECM	Drift in Process
0	0	0.6653	67.5644	<0.0001	Constant	Linear
1	1	0.4250	22.6894	<0.0001		

Table 5. The Long-Run Parameter Beta Estimate (β) when Rank= 2

Variable	1	2
ENR(3)	-3.04277	15.87431
CO_2	1.00000	1.00000

Table 6. Adjustment Coefficient Alpha (α) Estimates when Rank= 2

Variable	1	2
ENR(3)	0.06894	-0.03336
CO_2	-1.64649	-0.03118

of Figures 6 and 7, it shows that the residual distribution for the ENR and CO_2 data is not far enough from the normal distribution. Table 10 also shows that the ARCH effect where the results conclude that there is no ARCH effect with p-values for ENR and CO_2 data are 0.4890 and 0.8696, respectively.

3.5 Test for Stability Model

Table 11 is the result of the analysis of the root AR characteristic polynomial and it is found that all modulus<1. So the VECM(2) model has high stability.

3.6 Test for The Fitness of Model

Model VECM(2) given in (17) can be written as follows:

$$\Delta Y_{t1} = -0.7393Y_{t1-1} + 0.0355Y_{t2-1} - 0.1151Y_{t1-1} - 0.0130Y_{t2-1} + \varepsilon_{t1} \quad (18)$$

$$\Delta Y_{t2} = 4.5142Y_{t1-1} - 1.6776Y_{t2-1} - 3.1509Y_{t1-1} + 0.6297Y_{t2-1} + \varepsilon_{t2} \quad (19)$$

The VECM(2) model in Equation (17) if described in the form of two univariate models with dependent variables ENR and CO_2 (model (18) and model (19)), respectively. Table 12 is a test of significance for models (18) and (19) and both models are significant with p-values of 0.0001 and <0.0001. The R-square for ENR is 0.4258, this means that 42.58% the variance of ENR is explained by the model (18) and the R-square for CO_2 is 0.7115. This means that 71.15% the variance of CO_2 is explained by the model (19).

Table 7. The Estimate Parameter $\Pi = \alpha * \beta'$

Variable	ENR(3)	CO_2
ENR(3)	-0.73932	0.03558
CO_2	4.51488	-1.67767

Table 8. Model Parameter Estimates

Equation	Parameter	Estimate	Standard Error	t Value	p-Value	Variable
D_ENR	AR1_1_1	-0.73932	0.20510			ENR(t-1)
	AR1_1_2	0.03558	0.03844			CO_2(t-1)
	AR2_1_1	-0.11508	0.15586	-0.74	0.4650	D_ENR(t-1)
	AR2_1_2	-0.01300	0.02941	-0.44	0.6611	D_CO_2(t-1)
D_CO_2	AR1_2_1	4.51488	1.02976			ENR(t-1)
	AR1_2_2	-1.67767	0.19301			CO_2(t-1)
	AR2_2_1	-3.15094	0.78252	-4.03	0.0003	D_ENR(t-1)
	AR2_2_2	0.62977	0.14766	4.26	0.0001	D_CO_2(t-1)

3.7 Analysis Granger-Causality

One of a key question about VAR model or VECM model is how useful some variables are for Forecasting others, and this question usually addressed when we study about the relationship and Forecasting among economic variables (Hamilton, 1994). The null hypothesis of the Granger Causality test is that Group 1 is induced only by itself and not by Group 2 (SAS/ETS 13.2, 2014).

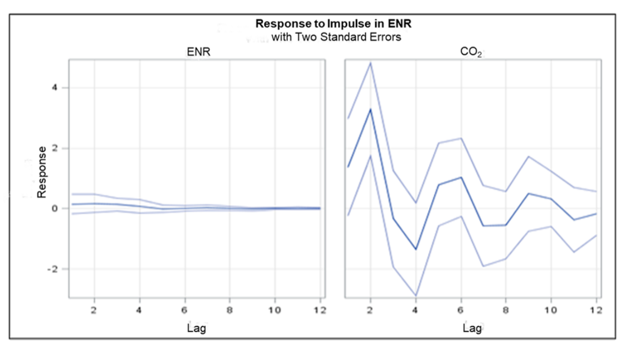

Figure 8. Impulse Response Function for Shock in Variabel Energy (ENR)

Table 13 shows that the ENR as Group 1 and CO_2 as Group 2 (test 1). The result with Chi-square test=1.09 with p-value is 0.5808>0.05, thus we can conclude that there is no evidence to reject the null hypothesis. Therefore, ENR is induced by itself and not by CO_2. This means that past information on CO_2 does not affect current Energy Used (ENR). From the test

Table 9. Univariate Model AR Diagnostics

Variable	AR1		AR2		AR3		AR4	
	F Value	p-value	F Value	p-value	F Value	p-value	F Value	p-value
ENR	1.17	0.2861	2.19	0.1264	2.48	0.0777	1.70	0.1745
CO_2	0.35	0.5594	0.21	0.8077	0.15	0.9316	0.41	0.8031

Table 10. Univariate Model White Noise Diagnostics

Variable	Durbin Watson	Normality		ARCH	
		Chi-Square	p-Value	F Value	p-Value
ENR	2.02723	21.81	<0.0001	0.49	0.4890
CO_2	2.12368	93.22	<0.0001	0.03	0.8696

Table 11. Test for Stability Model

Index	Real	Imaginary	Modulus	Radian	Degree
1	0.54588	0.00000	0.5459	0.0000	0.0000
2	-0.07088	0.82042	0.8235	1.6570	94.9380
3	-0.07088	-0.82042	0.8235	-1.6570	-94.9380
4	-0.30641	0.00000	0.3064	3.1416	180.0000

results for test 2 shows that the CO_2 as Group 1 and ENR as Group 2, the results show where Chi-square test= 21.78 with p-value is <0.0001, the null hypothesis is rejected. Therefore, CO_2 is influenced not only by past information from itself (CO_2), but also by information of the past of Energy Used (ENR). So, there is Granger Causal of ENR to CO_2.

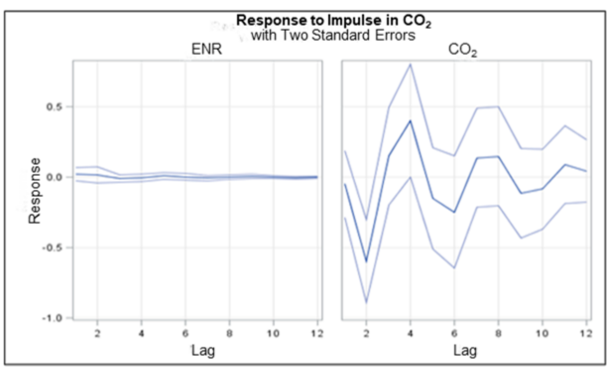

Figure 9. Impulse Response Function for Shock in Variabel CO_2

3.8 Impulse Response Function (IRF)

Figure 8 is the graph of Impulse Response Function if there is a shock 1 standard deviation in ENR and its effect to the variable ENR and CO_2. If there is a shock of one standard deviation in ENR, this causes the ENR gives response positively for the first four years and after that the effect getting smaller and smaller. The response of ENR itself from the first year

Table 12. Test for Significant of The Model

Variable	R-Square	Standard Deviation	F Value	p-Value
ENR	0.4258	0.02513	9.14	0.0001
CO_2	0.7115	0.12619	30.42	<0.0001

to the fourth year are: 0.1456, 0.1671, 0.1329, and 0.0738, respectively. If there is a shock of one standard deviation in ENR, this causes the CO_2 gives response fluctuatively from the first year up to the twelf year, in the first and second year the response are positive, the three and fourth year the response are negative, in the fifth and sixth year the response are positive. In the seventh and eight year the responses are negative. After the tenth year the impact are getting smaller toward to the equilibrium condition. The response of CO_2 from the first year to the eight years are: 1.3639, 3.2842, -0.3296, -1.3446, 0.7917, 1.0298, -0.5649, and -0.5514, respectively.

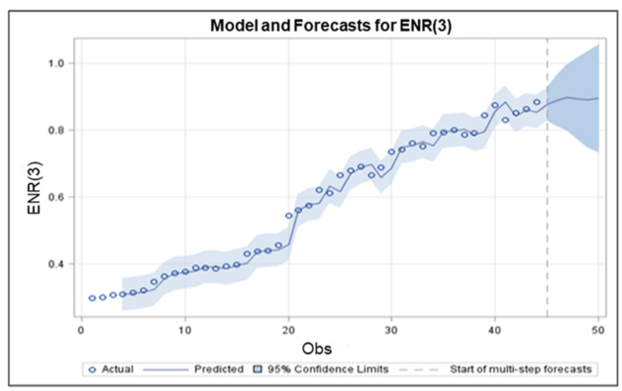

Figure 10. Model and Forecasts for ENR

Figure 9 is the graph of Impulse Response Function if there is a shock 1 standard deviation in CO_2 and its impact to the variables Energy (ENR) and itself CO_2. Shock of one standard deviation in causes the ENR gives a response fluctuatively, but only has small impact. In the first and second year the response is positive, in the third year to the fourth year the response is negative. For Energy (ENR) the response from the first year to the third year are: 0.0226, 0.0152, and -0.0093. After the fourth year the response getting smaller tend to the zero poin (equilibrium point). Shock of one standard deviation in CO_2, causes the CO_2 itself gives a response fluctuatively. In the first

Table 13. Test for Granger-Causality

Test	Group Variable	Null hypotheses (H_0)	Chi-Square	p-Value	Conclusion
1	Group 1. variables: ENR Group 2. variables: CO_2	H_{01} : ENR is affected by itself and not by CO_2	1.09	0.5808	Do not reject H_0
2	Group 1. variables: CO_2 Group 2. variables: ENR	H_{02} : CO_2 is affected by itself and not by ENR	21.78	<0.0001	Reject H_0

year to the second year the responses are negative, in the third and fourth year the response is positive, in the fifth and sixth year the response is negative. The response of CO_2 from the first year to the eight years are: -0.0479, -0.5967, 0.1506, 0.4038, -0.1488, -0.2467, 0.1391, and 0.1494.

Table 14. Forecasting for The Next Sixth Periods of Energy (ENR) and CO_2

Variable	Obs	Forecast	Standard Error	95% Confidence Limits	
ENR3	45	0.87741	0.02513	0.82815	0.92667
	46	0.88757	0.03827	0.81255	0.96258
	47	0.89682	0.05068	0.79750	0.99614
	48	0.89405	0.06241	0.77173	1.01636
	49	0.89052	0.07319	0.74707	1.03397
	50	0.89437	0.08252	0.73264	1.05610
CO_2	45	2.27649	0.12619	2.02917	2.52381
	46	2.39082	0.17699	2.04393	2.73772
	47	2.09083	0.21615	1.66718	2.51449
	48	2.07781	0.24947	1.58886	2.56676
	49	2.29274	0.28385	1.73640	2.84909
	50	2.27709	0.31352	1.66259	2.89158

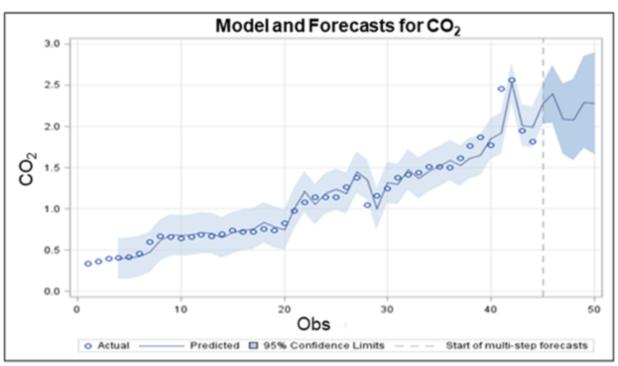

Figure 11. Model and Forecasts for CO_2

3.9 Forecasting

In Forecasting data for Energy Used (ENR) and CO_2, we used model given in Equation (18) and (19), the models are significant with p-values 0.0001 and <0.0001 and with R-squares 0.4258 and 0.7115. These univariate models will be used for Forecasting. Figures 10 and 11 show that the univariate models (18) and (19) fit very well with the ENR and CO_2 data where the observation values are very closed to their predictive values. So, the models used are very reliable and sound good. The Forecasting for the next six years, the values are not to much variation, but the confidence interval of Forecasting are bigger as the period longer (Table 14).

4. CONCLUSIONS

This research has investigated and examined the correlation between Energy Used (ENR) and CO_2 emission. There is cointegration correlation between Energy used and CO_2 emission with the rank=2. By using smallest criteria of information of AICC, HQC, AIC and HQC, the best model is VAR(p) with lag p=2. By cointegration test and smallest criteria of information the best model is VECM(p) with lag p=2. From the Granger Causality it was found that there is unidirection effect namely there is causal effect of Energy Used to CO_2 emission. From Impulse Response Function analysis shows that if there is shock of one standard deviation of Energy Used, the impact on Energy Used itself is small, but the impact on CO_2 emission is fluctuated and relatively long periode of time to attain the stability condition. if there is shock of one standard deviation of CO_2 emission, the impact on Energy Used is small, but the impact on CO_2 emission itself is fluctuate and relatively long periode of time to attain the stability condition. The Forecasting result for the next six period by using model VECM(2) the Energy Used showed ther trend is increase, while the emission fluctuate.

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