Estimation Models of the Impacts of the Economic and Population Growth to Changes in CO_2 Emissions in Indonesia Using the Cobb-Douglas Production Function

Ruly Budiono and Muhamad Nurzaman
Department of Biology, Faculty of Mathematics and Natural Sciences,
Universitas Padjadjaran, Indonesia
ruly@unpad.ac.id; m.nurzaman@unpad.ac.id

Hafizan Juahir
East Coast Environmental Research Institute (ESERI),
Universiti Sultan Zainal Abidin, Malaysia
hafizanjuahir@unisza.edu.my

Mustafa Mamat
Faculty of Informatics and Computing,
Universiti Sultan Zainal Abidin, Malaysia
musmat567@gmail.com

Sukono
Department of Mathematics, Faculty of Mathematics and Natural Sciences,
Universitas Padjadjaran, Indonesia
sukono@unpad.ac.id

Abdul Talib Bon
Department of Production and Operations,
University Tun Hussein Onn Malaysia, Malaysia
talibon@gmail.com

Abstract

Economic development is done to achieve economic growth of a country. Unplanned economic development has a negative impact on environmental damage. The dynamics of economic growth and population is very potential for global warming caused by the accumulation of CO_2 emissions in the air. This paper intends to investigate the effect of economic and population growth in increasing CO_2 emissions in the air. The goal is to estimate the models that are able to illustrate the relationship between economic growth and the population towards the changes in CO_2 emissions in the air. Model estimation is done by using product function in Cobb-Douglas, meanwhile parameter estimation is done by using ordinary least square method (OLS). The results of the analysis show that the Cobb-Douglas production function can significantly illustrate the relationship of economic and population growth influence to CO_2 emission change. The strength of the relationship can be shown by the coefficient of determination which reached 98.0%. This shows the truth that the increase in CO_2 emissions is significantly influenced by economic growth and population.

Keywords
GDP, population, CO_2 emissions, Cobb-Douglas, ordinary least square.

1. Introduction

Economic development is a process of increasing total income and income per capita by taking into account the existence of population growth, and accompanied by fundamental changes in the economic structure of a country and the equitable distribution of income for a resident of a State (Knight and Schor, 2014). A country is said to experience economic growth if there is an increase in the real Gross Regional Domestic Product (GDP) in the country. Through economic development, it is possible to change the economic structure of agrarian economic structure into industrial economic structure, so that the economic activities carried out by the state will be more diverse and dynamic (Liu and Lin, 2009). The existence of economic development that is not well planned leads to environmental damage. Economic development through industrialization has brought prosperity to many nations, but has also had a profound impact on the world's ecological system (Asici, 2011). Currently in a great crisis situation, which has been perceived for its own bad effects of air pollution and global warming. Population dynamics are closely related to climate change, increasing the number of population then the potential for global warming (global warming) is also higher (Mazumder et al., 2016; Reinecke and Casey, 2017). CO_2 emissions have the greatest risk in climate change because these gases continue to accumulate in the atmosphere in large numbers (Budiono et al., 2018). Therefore, it is important to study the effect of economic growth and the population in increasing CO_2 emissions.

Phimphanthavong (2013), has tested the relationship between economic growth and environmental degradation. As a representative of environmental degradation, carbon dioxide emissions (CO_2 emissions) per capita are used. The test was conducted using time series data between 1980 and 2010. The study was conducted based on the Kuznets Curve Environmental hypothesis (EKC), that environmental degradation follows the reversed U-shaped curve of the graph in relation to economic growth. The results show that the correlation between economic growth and environmental degradation based on the EKC hypothesis, that in the early stages of economic growth increase environmental degradation, then environmental degradation decreases after reaching the level of average income per capita. Keho (2017), using quantitative regression to examine the effects of economic growth and energy consumption on CO_2 emissions based on five panel data from 59 countries. The results show that energy consumption is the cause of increased CO_2 emissions in all panels. These findings suggest that economic growth everywhere has always been the cause of pollution. Coi and Abdullah (2016), predicted an increase in CO_2 emissions using linear regression. The trend of increasing CO_2 emissions is related to economic activity and other variables, such as demand and supply in economy and energy consumption. They say that the linear model is one of the commonly used methods to explain the correlation between CO_2 emissions and related economic variables. Similar studies have also been conducted by Abdullah (2015), Asici (2011), Ayeche et al. (2016), Khobai and Roux (2017), Knight and Schor (2014), Mikayilov et al. (2018), and Mrabet et al. (2013).

Referring to the description above, it appears that it generally does not consider the variable of population growth. Therefore in this study variable population growth along with economic growth is considered to have an effect in increasing CO_2 emissions, so that the production function Cobb-Douglas model is considered very appropriate to apply in this study. Thus, this study aims to estimate the impact model of economic and population growth on increasing CO_2 emissions, where the model used is the Cobb-Douglas production function. As a case study, analyzing of GDP growth data is based on prevailing prices and population growth, as well as data on CO_2 emissions in Indonesia.

2. Methodology

The methodology in this section include: Cobb-Douglas production function, parameter estimation method, goodness of fit test, and forecasting.

2.1. Cobb-Douglas production function

Referring to Wang (2013) in general the Cobb-Douglas production function with more than two independent variables can be stated as follows:

$$G = \phi Z_1^{\beta_1} Z_2^{\beta_2} Z_3^{\beta_3} \ldots Z_n^{\beta_n} e^{\varepsilon}, \tag{1}$$

where G is the dependent variable (output); ϕ is multiplier coefficient; $Z_1, Z_2, Z_3, \ldots, Z_n$ are independent variables (input); $\beta_1, \beta_2, \beta_3, \ldots, \beta_n$ are elasticity of the independent variable; e = 2.7182818285 natural number; and ε is error (residual).

The sum of elasticity is the size of the returns to scale. There are 3 possible returns to scale, as follows:

a) Decreasing returns to scale, when $\sum_{i=1}^{n} \beta_i < 1$

   It is an additional condition of results that decreases the scale of production, where output increases with a smaller proportion of inputs.

b) Constant returns to scale, when $\sum_{i=1}^{n} \beta_i = 1$

   It is an additional condition that has a constant result on the scale of production, when all inputs rise in certain proportions, and the produced output rises in exact proportion to the proportion of the input.

c) Increasing returns to scale, when $\sum_{i=1}^{n} \beta_i > 1$

   It is an additional condition that results in increased production scale, where output increases with a greater proportion than input.

When the left and right sides of equation (1) are transformed by natural logarithms, then equation (2) is obtained, and resulting in the following linear regression equation:

$$\ln G = \ln \phi + \beta_1 \ln Z_1 + \beta_2 \ln Z_2 + \beta_3 \ln Z_3 + ... + \beta_n \ln Z_n + \varepsilon. \tag{2}$$

If we give $Y = \ln G$, $\beta_0 = \ln b$, $X_1 = \ln Z_1$, $X_2 = \ln Z_2$, $X_3 = \ln Z_3$, ..., $X_n = \ln Z_n$, then equation (2) is a multiple linear regression equation as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + ... + \beta_n X_n + \varepsilon. \tag{3}$$

Estimator of equation (3) is as follows:

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + ... + \beta_n X_n. \tag{4}$$

So it can be determined that the residual values $\varepsilon = Y - \hat{Y}$.

2.2. Model parameter estimation method

In this section we discuss the method of estimating these multiple regression parameters in general. Using the matrix equation approach, multiple linear regression equations (3) can be expressed as follows:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e} \tag{5}$$

with

$$\mathbf{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix};\ \mathbf{X} = \begin{bmatrix} 1 & X_{12} & X_{13} & \cdots & X_{1k} \\ 1 & X_{22} & X_{23} & \cdots & X_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{n2} & X_{n3} & \cdots & X_{nk} \end{bmatrix};\ \boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix};\ \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix},$$

where **Y** is matrix of ($n \times 1$), **X** is matrix of ($n \times k$), **β** is matrix of ($k \times 1$), and **ε** is matrix of ($k \times 1$).
According to Anghelache et al. (2015) and Gogtay et al. (2017) to obtain the parameter estimator value of the matrix **β**, can be determined by minimizing the residual squares amount or otherwise known as the ordinary least square method (OLS), as follows:

$$\min \sum \varepsilon_i^2 = \boldsymbol{\varepsilon}^T \boldsymbol{\varepsilon} = (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})^T (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}) \tag{6}$$

where $\boldsymbol{\varepsilon}^T = (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})^T$ transpose of **ε**. Because $\boldsymbol{\beta}^T \mathbf{X}^T \mathbf{Y}$ is a scalar, therefore equal to its transpose, that is $\mathbf{Y}^T \mathbf{X}\mathbf{B}$.
For the minimizing process of the equation (6) is obtained as follows:

$$\frac{\partial \sum \varepsilon_i^2}{\partial \boldsymbol{\beta}} = -2\mathbf{X}^T \mathbf{Y} + 2\mathbf{X}^T \mathbf{X}\boldsymbol{\beta} = 0 \tag{7}$$

Solving equation (7) can be obtained parameter estimator matrix:

$$\boldsymbol{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} \tag{8}$$

where the matrix $(\mathbf{X}^T \mathbf{X})^{-1}$ is the inverse of the matrix $(\mathbf{X}^T \mathbf{X})$.

Of course, this approach can be used if $(\mathbf{X}^T \mathbf{X})$ has an inverse, but if there is multicollinearity, inverse matrix calculations can be doubted.

2.3. Goodness of fit test

The goodness of fit test is to determine that the model is significantly able to describe the actual data. Goodness of fit test to model parameter estimator is done by using partial significance test, simultaneous significance test, assumption of residual normality test, and coefficient of determination test.

a) Significance test of parameters individually
The significance test of individual parameter estimators is intended to test each parameter β_i (i = 0, 1, 2, ..., k), from equation (8), in affecting the dependent variable. To test the parameters β_i, arranged the hypothesis $H_0 : \beta_i = 0$ with alternative hypothesis $H_1 : \beta_i \neq 0$. Testing is done using statistic t_{stat}, the equation is:

$$t_{stat} = \frac{\theta_i}{SE(\theta_i)}, \tag{9}$$

where $SE(\beta_i)$ is the standard error of parameter β_i.
The criterion is to reject the hypothesis H_0 if statistic $|t_{stat}| > \left|t_{(n-2,\frac{1}{2}\alpha)}\right|$, or statistic $\Pr[t_{stat}] < \alpha$, where $t_{(n-2,\frac{1}{2}\alpha)}$ the critical value of the distribution-at the level of significance $100(1-\alpha)\%$ and n is the number of data (Anghelache et al., 2015; Sukono et al., 2016).

b) Significance test of parameters simultaneously
Test the significance of parameter estimators simultaneously, is to test together parameter estimator β_i (i = 0, 1, 2, ..., k), from equation (4), in influencing the dependent variable. In this test arranged the hypothesis $H_0 : \beta_0 = \beta_1 = \beta_2 = \cdots = \beta_k = 0$ with alternative hypothesis $H_0 : \exists \beta_0 \neq \beta_1 \neq \beta_2 \neq \cdots \neq \beta_k \neq 0$. Testing is done using statistic F, the equation is:

$$F_{stat} = \frac{\mathrm{MS_{Reg}}}{\mathrm{MS_{Error}}}, \tag{10}$$

where $\mathrm{MS_{Reg}}$ mean square due to regression, and $\mathrm{MS_{Error}}$ mean square due to residual variation.
The criterion is to reject the hypothesis H_0 when the statistic $F_{stat} > F_{(1,n-2,1-\alpha)}$, or statistic $\Pr[F_{stat}] < \alpha$, where $F_{(1,n-2,1-\alpha)}$ the critical value of the distribution of F at the level of significance $100(1-\alpha)\%$, and n is the number of data (Gogtay et al., 2017; Sukono et al., 2016).

c) Test of the normality assumption of the residuals
Test normality assumption is to determine that the data is spread residuals follow a normal distribution. Normality assumption test can be done using Kolmogorov-Smirnov (KS) statistic. In this test a hypothesis is prepared are H_0 : data is normally distributed, with alternative hypothesis H_1 : data is not normally distributed. Testing is done by determining residual standard deviation by using equation:

$$S_{\varepsilon_i} = \sqrt{\frac{\sum_{i=1}^{n} (\varepsilon_i - \bar{\varepsilon})^2}{n-1}}. \tag{11}$$

Then, transformed value ε_i into z_i using equation $z_i = (\varepsilon_i - \bar{\varepsilon}) / S\varepsilon_i$. Determine the probability value $P(z_i)$ using a standard normal distribution table. While the probability $S(z_i)$ determined using the equation $S(z_i) = randl(z_i)/n$. Next, we calculate the values of absolute difference $|S(z_i) - P(z_i)|$. The statistical value of Kolmogorov-Smirnov KS_{stat} is determined using the equation:

$$KS_{stat} = \max\{|S(z_i) - P(z_i)|\}. \tag{12}$$

Then we determine the critical value of statistic $KS_{(\alpha,n-1)}$, at the level of significance α = 0.05. The criteria of testing is to reject the hypothesis H_0 if the statistic $KS_{stat} > KS_{(\alpha,n-1)}$.

d) Coefficient of determination
Referring to Anghelache et al. (2015) and Gogtay et al. (2017), the coefficient of determination R^2 is to measure how much the variability of independent variables to the dependent variable, based on the level of correlation power. So the coefficient of determination is the ability or the power of independent variables X_i

(i = 0, 1, 2, ..., k) in affecting the dependent variable Y. Coefficient of determination R^2 determined using the equation:

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{Y}_i - \overline{Y})^2}{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}. \tag{13}$$

The value of determination coefficient is between 0 and 1. The value of determination is small close to 0 which means the variation of free variables is very weak, and a value close to 1 means that the variation of independent variables is very strong in influencing the dependent variable.

2.4. Forecasting (Prediction)

Forecasting (prediction) is done because of the complexity and uncertainty faced by the model maker, so it takes a great degree of accuracy. There are many methods that can be used to measure the accuracy of a forecasting model, one of them is Mean Absolute Percentage Error (MAPE). The MAPE value is determined by using the equation as follows:

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{|Y_i - \hat{Y}_i|}{Y_i}\right) \times 100\%. \tag{14}$$

The smaller the MAPE value, the smaller the value of error, which means the greater the accuracy of the model in predicting an event.

3. Result and Analysis

In this section we will discuss the results which include: data analyzed, multiple linear regression model estimation, and estimation of Cobb-Douglas model estimator and forecasting.

3.1. Data Analyzed

In this study the data used include: data of GDP based on prevailing prices, population, and CO_2 emissions in Indonesia for the period 1967 to 2014. The data is obtained from the official website of World Bank (https://data.worldbank.org/). Suppose G is CO_2 emissions; Z_1 is GDP at current prices; and Z_2 is the total population. Descriptive statistical data of this research are presented in Table 1.

Table 1. Statistic Descriptive

Statistic	G Unit	Z_1 Unit	Z_2 People
Mean	1.02753743	974.481835	181,239,285
Median	0.89894000	584.263600	183,000,000
Maximum	2.55975023	3,687.9540	255,000,000
Minimum	0.23191548	53.5161517	105,907,403
Std.Dev	0.57736700	1011.15700	446,693,252

As for the graph of GDP based on the current price data is given as Figure 1, the graph of population data as Figure 2, and the graph of CO_2 emission data as Figure 3.

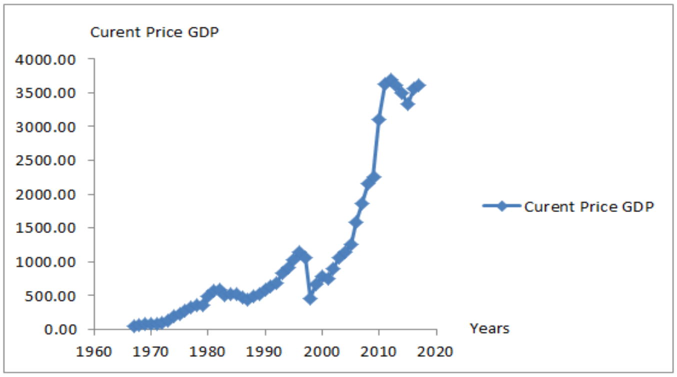

Figure 1. Graph of Current Price GDP

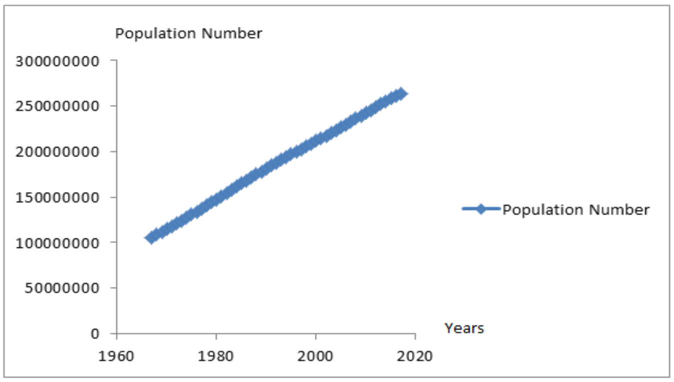

Figure 2. Graph of Population

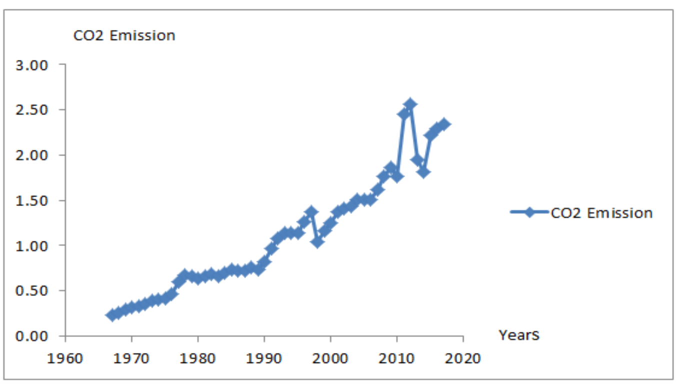

Figure 3. CO_2 Emission in Indonesia

3.2. Multiple linear regression modeling

In this section we estimate multiple linear regression models of natural logarithms data of GDP at current prices, population, and CO_2 emissions. The estimation is done by using Ordinary Least Square (OLS) method which refers to equations (2) and (3). The estimation of multiple linear regression models is done by using Minitab 16 software, and the result of estimation as given in Table 2.

Table 2. Results of multiple linear regression model estimates of CO_2 emissions

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The regression equation is
ln(CO2 Emissions) = - 31.0 + 0.196 ln(Curent GDP) + 1.56 ln(population)

Predictor            Coef   SE Coef       T      P
Constant          -30.967     2.868  -10.80  0.000
ln(Curent GDP)    0.19552   0.03840    5.09  0.000
ln(population)     1.5580    0.1633    9.54  0.000

S = 0.0890152   R-Sq = 98.0%   R-Sq(adj) = 97.9%

Analysis of Variance

Source          DF       SS      MS        F      P
Regression       2  17.6619  8.8309  1114.50  0.000
Residual Error  45   0.3566  0.0079
Total           47  18.0184

Source          DF   Seq SS
ln(Curent GDP)   1  16.9402
ln(population)   1   0.7216
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Based on the values in Table 2, and with reference to equation (3) multiple linear regression models the estimation results can be expressed as equations:

$$Y = -30.967 + 0.19552X_1 + 1.5580X_2 + \varepsilon,$$

Where Y is ln(CO_2 emissions), X_1 ln(GDP at current prices), and X_2 ln(population), and ε is residual. Furthermore, equation (15) needs to be tested goodness of fit. First, the individual significance test is performed on the parameter estimators of $\hat{\beta}_0$ = -30.967, $\hat{\beta}_1$ = 0.19552, and $\hat{\beta}_2$ = 1.5580. The test is performed by referring to equation (9), using a significance level $\alpha = 0.05$. Based on the test results presented in Table 2, it shows that parameter estimator $\hat{\beta}_0$ is significant. The significance test also needs to be done for the parameter estimator $\hat{\beta}_1$ and $\hat{\beta}_2$. Testing is also done in the same way, and each result also significantly affects the variable Y (CO_2 emissions). Second, the simultaneous significance test of the parameter estimators of $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\beta}_2$. The test is performed by referring to equation (10), using a significance level $\alpha = 0.05$. Based on the test results presented in Table 2, it shows that parameter estimators of $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\beta}_2$, has simultaneously significant effect on the variable Y (CO_2 emissions).

Third, the assumption of residual normality test ε, the point is to ensure that residual ε normal distribution. Testing is done by referring to equation (12), also by using the level of significance $\alpha = 0.05$. Based on the results of testing using Minitab 16 software, it shows that residual $\varepsilon \sim N(0.001143, 0.007586)$. Fourth, the determination coefficient test is useful to control the level of strength of the relationship between the independent variable with the dependent variable. Determination of coefficient value of determination is done by referring to equation (13). Based on the test results presented in Table 2, it is found that the value of determination $R^2 = 98.0\%$. This shows that the relationship between the independent variable and the dependent variable is very strong.

After a goodness of fit test and all test results are significant, thereby obtaining an estimator of multiple linear regression models of CO_2 emissions given in equation (15) can be expressed as equations:

$$\hat{Y} = -30.967 + 0.19552X_1 + 1.5580X_2. \tag{15}$$

Furthermore, based on the estimator model of regression equation (15), with reference to equation (1) can be obtained Cobb-Douglas production function as follows:

$$\hat{G} = e^{-30.967} Z_1^{0.19552} Z_2^{1.5580} \tag{16}$$

where G is the output variable (CO_2 emissions); e = 2.7182818285 is a natural number as a multiplier; Z_1 is a variable of GDP based on current price; and Z_2 is the variable of population number.

Furthermore, Cobb-Douglas production function estimator (16) is used for forecasting. First, forecasting is done by using in-sample data which results are shown as forecasting graphs as shown in Figure 4.

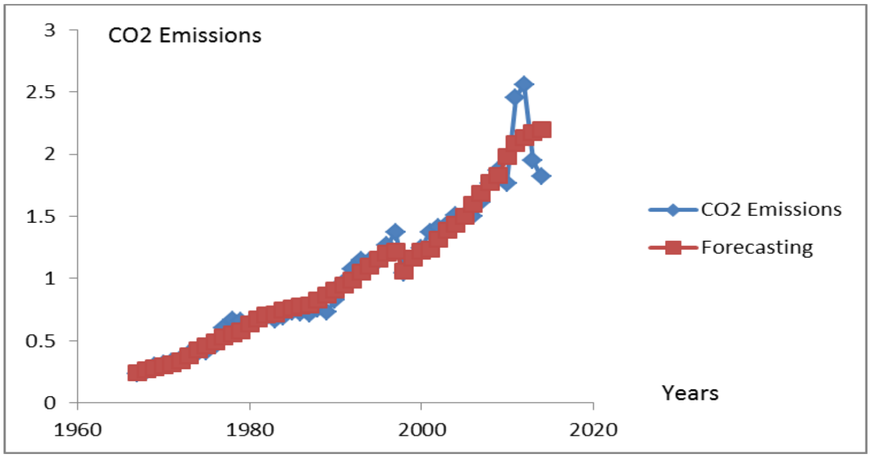

Figure 4. Forecasting and actual data of CO_2 emissions

Considering Figure 4, it can be seen that the forecasting graph (prediction) coincides with actual data (CO_2 emissions), and forecasting using the in-sample data gives a MAPE error rate of 0.070712817%. This means that the model estimator has an accuracy level for forecasting of 99.99241%. Second, forecasting based on out-sample data by estimating GDP values at current prices and the number of people in the future. For example in certain years, it is estimated that the value of GDP at current prices reaches 3552.63777, and the number of residents reached 258262222. Using Cobb-Douglas production function estimator (16) obtained the forecast of CO_2 emissions which reach 2.245935876 million tons.

5. Conclusion

In this paper, research has been conducted to estimate the impact model of economic and population growth in increasing CO_2 emissions in Indonesia, using Cobb-Douglas production function. Based on the analysis results, it can be concluded that the growth of economist and population to increase CO_2 emission in Indonesia, from year to year significantly follows the Cobb-Douglas production function, with the deterministic coefficient value of 98.0%. The estimated model of Cobb-Douglas production function has an insurance rate for forecasting of 99.99241%. Using the estimated Cobb-Douglas production model estimator, it can be CO_2 emissions in future periods, by estimating the variable values of GDP at current prices and population. If at any given period the estimated GDP at current prices reaches 3552.63777 and the number of residents reaches 258262222, then CO_2 emissions will reach 2,245935876 million tons. Therefore, the results of this study are expected to be taken into consideration in the wise economic development, in order to make efforts to decrease CO_2 emissions in the air.

Acknowledgements

Acknowledgments are conveyed to the Rector, Director of Directorate of Research, Community Involvement and Innovation, and the Dean of Faculty of Mathematics and Natural Sciences, Universities Padjadjaran, with whom the Internal Grant Program of Universitas Padjadjaran was made possible to, fund this research. The grant is a means of enhancing research and publication activities for researchers at Universitas Padjadjaran.

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Biographies

Ruly Budiono is a lecturer in the Department of Biology, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran. He is focusing his research topic on Environmental Modelling.

Muhamad Nurzaman is a lecturer in the Department of Biology, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran. He is also Manager of Academic and Student Affairs of Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran.

Hafizan Juahir is a professor in East Coast Environmental Research Institute (ESERI), Universiti Sultan Zainal Abidin, Malaysia. His research interest include Chemometrics, Climate Change and Environmental Modelling.

Mustafa Mamat is Professor at Universiti Sultan Zainal Abidin (UniSZA), Malaysia since 2013. His research interests include conjugate gradient methods, steepest descent methods, Broyden's family and quasi-Newton methods.

Sukono is a lecturer in the Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran. Chair of the Research Collaboration Community (RCC), the field of applied mathematics, with a field of concentration of financial mathematics and actuarial sciences.

Abdul Talib Bon is a professor of Production and Operations Management in the Faculty of Technology Management and Business at the Universiti Tun Hussein Onn Malaysia since 1999. He has a PhD in Computer Science, which he obtained from the Universite de La Rochelle, France in the year 2008. His doctoral thesis was on topic Process Quality Improvement on Beltline Moulding Manufacturing. He studied Business Administration in the Universiti Kebangsaan Malaysia for which he was awarded the MBA in the year 1998. He's bachelor degree and diploma in Mechanical Engineering which his obtained from the Universiti Teknologi Malaysia. He received his postgraduate certificate in Mechatronics and Robotics from Carlisle, United Kingdom in 1997. He had published more 150 International Proceedings and International Journals and 8 books. He is a member of MSORSM, IIF, IEOM, IIE, INFORMS, TAM and MIM.