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The Effect of Gross Domestic Product and Population Growth on CO_2 Emissions in Indonesia: An Application of the Ant Colony Optimisation Algorithm and Cobb-Douglas Model

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ABSTRACT

Gross domestic product (GDP) is one indicator for measuring a country's economic growth. However, the increase in GDP and population growth are affecting CO_2 emissions. This study analyses the effects of GDP and population density on CO_2 emissions in Indonesia. To this end, it used the Cobb-Douglas model, and parameter estimation using Ant Colony Optimisation algorithm. The analysis of the results reveals that GDP and population density influence CO_2 emissions in Indonesia significantly, and significantly follows the Cobb-Douglas model with increasing return to scale characteristics. Thus, an increase in GDP and population density will lead to increased CO_2 emissions in Indonesia.

Keywords: Economic Growth, Gross Domestic Product, Population Growth, CO_2 Emission, Ant Colony Optimisation Algorithm, Cobb-Douglas Model

JEL Classifications: C61, O47, O150, Q530

1. INTRODUCTION

Gross domestic product (GDP) is the total production value in the form of goods and services produced by production units within the boundaries of a country (domestic) for 1 year. GDP shows a country's flow of income and expenditure in the economy over a period of 1 year (Kasperowicz, 2015). Indonesia is the fourth most populous country in the world. Based on data published by the Indonesian Central Bureau of Statistics 2017 entitled "Statistik Indonesia 2017" (Statistical Yearbook of Indonesia 2017), the population in Indonesia was 258,704,900 in 2016. This figure is 8.5% higher or 20,186,200 more people compared to 2015 which amounted to 238,518,800 inhabitants. This is cause for worry in an environmental sense, as a country's economic growth is directly proportional to the decline in environmental function and quality, including the increased emissions of carbon dioxide (CO_2).

CO_2 emissions are substances, energy or other components resulting from an activity in the form of CO_2 gas. Studies often sample CO_2 emissions to illustrate the level of pollution (Ru et al., 2012). For example, to increase economic growth means that people must perform economic activities and consume energy which causes air pollution. The higher a country's value of GDP and population density, the higher a citizen's purchase power. Similarly, the higher the activity and energy consumption, the higher the CO_2 emissions produced. According to Alam (2014), global warming due to climate change is a critical global problem wherein CO_2 is considered a significant contributor to the problem.

Therefore, it is essential to analyse the effect of GDP and the population density on CO_2 emissions in Indonesia.

Many researchers have conducted studies on the relationship between GDP and CO_2 emissions. Among others, Alam (2014) researched changes in economic structure and CO_2 emissions trends with GDP per capita of Bangladesh. His study is based on the Environmental Kuznets Curve hypothesis, using World Bank data throughout 1972-2010. The results show faster structural shifts from the agricultural sector to the non-agricultural sector, and the emergence of the service sector as a dominant part of the economy, resulting in a rapidly increasing trend of CO_2 emissions.

Bozkurt and Akan (2014) researched economic growth, CO_2 emissions, and energy consumption relations in Turkey using a cointegration test based on GDP data, CO_2 emissions, and energy consumption for the 1960-2010 period. The results showed that CO_2 emissions negatively affect GDP growth, while energy consumption has a positive effect on CO_2 emissions. Similar research has also been conducted by Farhani and Rejeb (2012), Sharif et al. (2014), Kemal and Hizarci (2017), Magazino (2016), Salahuddin et al. (2018), Al mamun et al. (2014) and Tiwari (2011) among others.

To analyse a problem requires a model and a hypothesis that something will happen in uncertain conditions called parameters. In research on the influence of input variables on an output variable, one parameter could be the production function of the Cobb-Douglas model. According to Reynes (2017), to date, the Cobb-Douglas model production function is the most commonly used analysis of growth and productivity. Estimation of aggregate production function parameters is critical in growth analysis, technological change, productivity, and labour. Samsami (2013) conducted a study on the application of Ant Colony Optimisation (ACO) to predict CO_2 emissions in Iran based on socio-economic indicators. Forms of linear and non-linear equations were developed to predict CO_2 emissions using ACO. The results provide useful insights into energy systems and CO_2 emission control modelling. Based on the above reviews, the authors are interested in researching the effect of GDP and the population density on CO_2 emissions in Indonesia. The analysis was performed using the Cobb-Douglas model production function, and parameter estimation were performed using the ACO algorithm. The purpose of this study is to obtain a model that can be used to predict CO_2 emissions as influenced by the GDP and population density in Indonesia.

2. MATERIALS AND METHODS

2.1. Materials

This study used secondary data, namely GDP Indonesia, the Indonesian population, and CO_2 emissions in Indonesia for the period from 1967 to 2014. The data are obtained from the official website of the World Bank. In this study, we used the Cobb-Douglas model and ACO algorithm. Data processing was carried out using Microsoft Excel 2013 and MATLAB R2015a software.

2.2. Cobb-Douglas Model

The Cobb-Douglas model is used to estimate a production function (Douglas, 1928; Reynes 2017; Soukhovolsky and Ivanova 2018). These equation involving two or more variables, a dependent variable, and independent variables. The production function of the Cobb-Douglas model with multiplicative error terms is given as the following equation:

$$Q_t = \beta_0 K^{\beta_1} L^{\beta_2} e^{\varepsilon_t} \tag{1}$$

Where in this study, Q_t is output as CO_2 emissions; K_t is the input as the GDP; L_t is the input as the population density: β_0, β_1, and β_2 are the Cobb-Douglas model parameters, and ε_t is the exponential of the residual. The elasticity of production E is the percentage change in output, divided by the percentage of input changes. Production elasticity is the ratio of the relative change of output produced to the relative changes in the number of inputs that effect. The output elasticity of the GDP E_K is measured using the following equation:

$$E_K = \frac{\%\Delta Q}{\%\Delta K} = \beta_1 \tag{2}$$

The output elasticity of GDP can also be measured using coefficient parameters β_1 of the production function of the Cobb-Douglas model. The output elasticity of the population density E_L is measured using the equation:

$$E_L = \frac{\%\Delta Q}{\%\Delta L} = \beta_2 \tag{3}$$

The output elasticity of the population can also be measured using coefficient parameters β_2 of the production function of the Cobb-Douglas model. The sum of the elasticity of production $\sum_{i=1}^{2}\beta_i$ explains the size of a venture scale or called a return to scale. There are three characteristics of the return to scale as follows:

- If $\sum_{i=1}^{2}\beta_i = 1$, then the function shows a scale with a constant return (constant return to scale), meaning that an increase in proportional output will follow the increase in the input.
- If $\sum_{i=1}^{2}\beta_i < 1$, then the function shows the scale with decreasing return (decreasing return to scale), meaning the percentage increase output is smaller than the percentage of input addition.
- If $\sum_{i=1}^{2}\beta_i > 1$, then the function shows the scale with the increase (increasing return to scale), meaning the percentage of output addition is higher than the percentage of input addition.

In equation (1), if the left and right segments are taken as a natural logarithm, the following linear equations are obtained:

$$\log Q_t = \log\beta_0 + \beta_1 \log K + \beta_2 \log L + \varepsilon_t \tag{4a}$$

If $Y_t = \log Q_t$; $\alpha_0 = \log\beta_0$ and $X_{1t} = \log K_t$; and $X_{2t} = \log L_t$, then the last equation can be expressed as:

$$Y_t = \alpha_0 + \beta_1 X_{1t} + \beta_2 X_{1t} + \varepsilon_t \tag{4b}$$

Thus, the estimator obtained from the regression equation (5) is:

$$\hat{Y}_t = \alpha_0 + \beta_1 X_{1t} + \beta_2 X_{2t} \tag{5}$$

Equation (5) is linear in the parameters α_0, β_1 and β_2 as well as residuals ε_t. Thus, it is shaped as a linear regression model. Constant α_0 is an intercept, and β_1, β_1 are a parameter of elasticity of production. For parameter estimation, an optimisation equation can be formed from equation (5) as follows:

Minimisation

$$\sum \varepsilon_t^2 = \sum (Y_t - \hat{Y}_t)^2 = \sum (Y_t - \alpha_0 - \beta_1 X_{1t} - \beta_2 X_{2t})^2 \tag{6}$$

Equation (7) is used to estimate the value of α_0, β_1 and β_2 which can minimise the sum of squares of residuals $\sum \varepsilon_t^2$. The process of minimising the sum of square residual in this study was performed using the ACO algorithm.

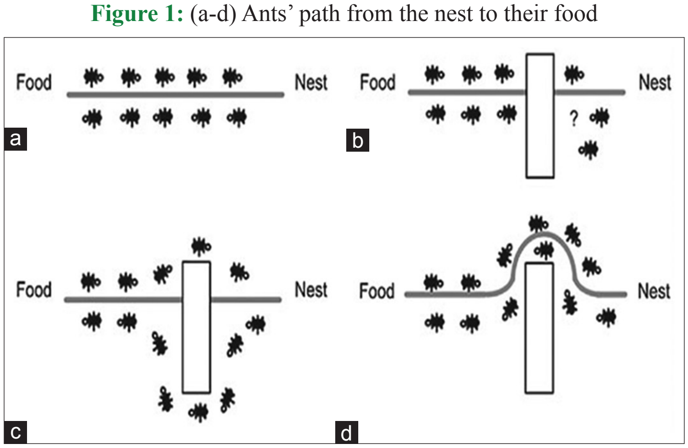
2.3. ACO Algorithm

According to Samsami (2013), Deif and Gadallah (2017), and Bouarafa et al. (2018), ACO is derived from ant treatment, known as the ant system. Naturally, ant colonies can find the shortest route from the nest to the source of food and back again. As the ants walk, they leave information called pheromone where it passes and marks the route. Pheromones are used to communicate between ants while constructing routes. The path of ants from the nest to their food is illustrated in Figure 1 using the ACO algorithm.

According to Samsami (2013), Deif and Gadallah (2017), and Bouarafa et al. (2018), the ant algorithm functions as follows: (i) First, the ants move randomly. (ii) When ants find different paths, such as an intersection, they begin to determine the direction of the path at random. (iii) Some ants walk up, and others choose to walk down.

- When they have found their food, they return to the colony while marking it with pheromone traces.
- Since the path taken down the path is shorter, the lower ant arrives first, assuming the velocity of all the ants is the same.
- The pheromone left by the ants on the shorter path of the aroma is stronger, compared to the pheromone on the longer path.

Figure 1: (a-d) Ants' path from the nest to their food



- The other ants are more interested in following the lower path, because of the stronger pheromone scent.

Also, according to Samsami (2013), Deif and Gadallah (2017), and Bouarafa et al. (2018), the ant algorithm requires several variables and steps to determine the shortest distance.

Step 1:

a. The parameters required in the ant algorithm are as follows:
   - The intensity of ant traces between places τ_{ij} and changes $\Delta\tau_{ij}$.

   Intensity τ_{ij} must be initialised before starting the cycle. Change $\Delta\tau_{ij}$ initialised after one cycle. Change $\Delta\tau_{ij}$ used to specify τ_{ij} for the next cycle.
   - Ant cycle constant Q.

   Ant cycle constant Q is a constant used in the equation to determine $\Delta\tau_{ij}$. The value Q determined by the user.
   - An ant trace intensity control constant α.

   The traceability control constant is used in the probability of the place visited and served as the ant trace intensity controller. Value α is determined by the user.
   - Time visibility controller β.

   Time visibility controller β is used in the probability of the visited place and serves as a visibility controller. The value β is determined by the user.
   - Visibility between places η_{ij}.

   Visibility between places η_{ij} used in the probability of places visited. Value η_{ij} is the result of $1/d_{ij}$ (the distance of the place).
   - Lots of Ants m.

   Lots of Ants m are many ants that cycle in the ant algorithm. The value m is determined by the user.
   - The ant trap evaporation constant ρ.

   The ant trap evaporation constant ρ is used to determine τ_{ij} for the next cycle. Value ρ is determined by the user.
   - Maximum number of cycles $NC_{max.}$

   The maximum number of cycles NC_{max} is the maximum number of cycles that will take place. The cycle will stop according to the value of NC_{max} which has been determined by the user.
   - Charging the coordinates of the place.

b. Initialise first place of each ant.

After initialisation of τ_{ij} done, then m the ant is placed at a random starting point. For parameter values, α should be rated $\leq 0 \leq \alpha \leq 1$ to avoid unlimited pheromone accumulation. Since the amount of pheromone left behind is unlikely to get stronger, it gets weaker. For parameter values, β should not be given a value of 0, because if given a value of 0 then the results achieved are not optimum. Not optimum refers to a condition where the length of the journey achieved is not the shortest distance.

Step 2:

Inputting the data of the starting point into the taboo list. The initialisation result of the first place of each ant in step 1 should be loaded as the first element of the taboo list. The result of this step is the data input of the taboo of each ant with the index of a certain place.

Step 3:

Arranging the route of each ant visit to every destination. Ant colonies that have been distributed to a number or destinations begin to travel from their place of origin to a destination. From the second place, each ant colony continues its journey, choosing one of the places not on the taboo list as the next destination. Ant colony trips continue continuously until all the places are visited one by one. If s specifies the index of the order of visits, the place of origin is expressed as $tabu_k(s)$, and other places are declared as $\{N{-}tabu_k(s)\}$. To determine the destination, the probability equations of places to visit are as follows:

$$P_{ij}^{k}(s)=\begin{cases}\dfrac{[\tau_{ij}(s)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum\limits_{k'\in\{N-taboo_k(s)\}}[\tau_{ij}(s)]^{\alpha}[\eta_{ij}]^{\beta}};\text{if } j\in\{N-taboo_k(s)\}.\\ 0;\ \text{for other } j.\end{cases}$$

Where i is the index of the place of origin, and j as the destination index's.

Step 4:

a. Calculation of the route length of each ant or L_k of each ant is done after all ants complete one cycle. The calculation is based on $tabu_k(s)$ each with the following equation:

$$L_k=d_{taboo_k(n),taboo_k(1)}+\sum_{s=1}^{n-1}d_{taboo_k(s),taboo_k(s+1)}$$

Where d_{ij} is the distance between place i to place j and calculated based on the equation:

$$d_{ij}=\sqrt{(x_i-x_j)^2(y_i-y_j)^2}$$

b. Shortest distance search

After the L_K is calculated for each ant, it will get the minimum price of the closed route length of each cycle, or $L_{min}NC$ and the minimum price of the overall closed line length is L_{min}.

c. Calculation of price changes in the intensity of ant footprints between places Δt_{ij}

An ant colony leaves footprints on the path between the places it passes. The existence of evaporation and differences in the number of ants that passes causes the possibility of changes in the price of ant footprints intensity between places. The equation of the change is:

$$\Delta\tau_{ij}=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}$$

Where m is the number of ants; and t_{ij} is the path length of each ant. Where $\varnothing\tau_{ij}^{k}$ is the price change of the ant footprint intensity between places which is calculated for each ant using equation (12):

$$\Delta\tau_{ij}^{k}=\begin{cases}\dfrac{Q}{L_k};\text{for } (i,j)\in \text{ place of origin and destination in taboo}_k\\ 0;\ \text{for other } (i,j)\end{cases}$$

Where Q is the ant cycle constant; and L_K is close length tour (lct).

Step 5:

a. Calculation of the price of the ant footprint intensity between places for the next cycle. The intensity of the ant footprints between places on all tracks is likely to change as there is evaporation, as well as the difference in the number of ants that pass through. For the next cycle, the ants passing through the trajectory of the intensity price have changed. The equation calculates the price of the ant footprint intensity between places for the next cycle:

$$\tau_{ij}=(1-\rho)\times\tau_{ij}+\Delta\tau_{ij}$$

b. Reset the price of the ant footprint intensity changes between places. For subsequent cycles, the change in the intensity value of ant traces between places needs to be reset to have a value equal to zero.

Step 6:

Dismiss the taboo list and repeat Step 2 if needed. The taboo list needs to be emptied to be filled again with a new place order in the next cycle. If the maximum number of cycles has not been reached, the algorithm is repeated from the taboo input step, with the price of the ant footprint intensity parameter between the updated places.

2.4. Model Significance Test

In this section, we discuss the significance test of the model, with the aim of finding the viability of the model resulting from the estimation process. The model significance test includes the partial parameter significance test, the test of the significance of the parameters, and the assumption of residual normality test. Also, this study measured the strength of the relationships between independent and dependent variables, along with the accuracy of forecasting (prediction).

1. Partial significance test: This partial significance test examines the significance of each coefficient parameter θ_i (i=1,2,3), where $\theta_i \epsilon \{\alpha_0, \beta_1$ and $\beta_2\}$ of equation (2), in affecting the dependent variable. For the parameter test θ_i, the hypothesis used is $H_0{:}\theta_i{=}0$ and $H_1{:}\theta_i{\neq}0$ H_1: Testing is done using statistic t, where the equation is:

$$t_{Statistic}=\frac{\theta_i}{SE(\theta_i)}$$

Where $SE(\theta_i)$ is the standard error of the parameter θ_i?

Reject the hypothesis H_0 when $|\,t_{Statistic}\Big|>t_{(n-2,\frac{1}{2}c)}\Big|$, or $\Pr[t_{Statistic}]<c$

where $t_{(n-2,\frac{1}{2}c)}$ the critical value of the distribution t at a level of significance 100(1−c)%, and n the number of data (Sukono et al., 2016).

2. Simultaneously parameter test: This simultaneous significance test examines the significance of the coefficient parameters simultaneously θ_i (i=1,2,3), where $\theta_i\epsilon$ $\{\alpha_0\beta_1\beta_1\}$ of equation (2), in affecting the dependent variable. The hypothesis used is H_0: $\theta_1{=}\theta_2{=}\theta_3{=}0$ and H_1: $\ni\theta_1{\neq}\theta_2{=}\theta_3{\neq}0$. Testing has done using statistic F, where the equation is:

$$F_{Statistic}=\frac{\mathrm{MS_{Reg}}}{s^2}$$

Where MSReg is the mean square due to regression, and s^2 mean square due to residual variation.

Reject the hypothesis H_0 when $F_{Statistic}>F(1,n-2,1-c)$, or $\Pr[F_{Statistic}]<c$, where $t_{(df,\frac{1}{2}c)}$ the critical value of the distribution F at the level of significance 100 (1−c) %, and n the number of data (Sukono et al., 2016).

3. Residual normality test: According to Jäntschi and Bolboaca (2018), the cumulative distribution function (CDF) F_0 follows the empirical distribution function F_n. Given the ordered sample data $X_1{\le}X_2{\le}\ldots{\le}X_n$, it is assumed that H_0: CDF

following distribution $F_0(x)$, and H_1: CDF not following distribution $F_0(x)$.

The Aderson-Darling (AD) test is a normality test performed using the equation:

$$AD_{Statistic} = \sum_{t=1}^{n} \frac{1-2t}{n} \{\log(F_0[z_{(t)}]) + \log(1 - F_0[z_{(n+1-t)}]\} - n \quad (16)$$

Where F_0 is the normal distribution assumed by the parameter estimator (μ, σ^2); $z(t)$ is the sample sequence value to t; n is the sample size; log is the natural logarithm (base e); and t=1, 2,…,n. The null hypothesis H_0 is rejected if the value of $AD_{Statistic} > AD_{Critical}$, with $AD_{Critical}$=0.752/(1+0.75/n+2.25/n^2.

4. The coefficient of Determination: Coefficient of determination r^2 is used to determine the strength of the relationship between independent variables with the dependent variable in a regression model. The value of the coefficient of determination r^2 can be determined using the equation:

$$r^2 = \frac{\sum_{t=1}^{n} (\hat{Y}_t - \bar{Y})^2}{\sum_{t=1}^{n} (Y_t - \bar{Y})^2}$$

Where the value r^2 ranged $0 \leq r^2 \leq 1$. If r^2 is close to zero, then it explains that the relationship between the independent variable and the dependent variable is weak. If r^2 is close to one, then it indicates that the relationship between independent variables and dependent variables is strong (Sukono et al., 2016).

5. Precision Forecast Size: According to Karmaker (2017) and Khair et al. (2017), accuracy is vital in forecasting and measures the suitability between existing data and forecasting data. Certain calculations are commonly used to determine total forecast errors, one of which is Mean Absolute Deviation (MAD). MAD statistics measure the accuracy of the prediction by averaging the alleged error (the absolute value of each error). MAD statistics are the size of the overall forecasting error for a model. The formula for calculating MAD is as follows:

$$MAD = \frac{\sum_{t=1}^{n} | Y_t - \hat{Y}_t |}{n}$$

Where Y_t is the actual data in the period t, $\hat{Y}_t$ the value of forecasting in the period t, and n is the number of data points.

3. RESULTS AND DISCUSSION

This section discusses the result and provides detailed statistical data, estimates the model parameters, tests the significance of the model estimator, determines the Cobb-Douglas model estimator, and forecasts CO_2 emissions for the 2015-2017 period.

3.1. Descriptive Statistics Data

Descriptive statistics are structured to provide an overview of the quantitative data used in this study. Let us say Q_t is the CO_2 emissions; K_t is the GDP, and Lt is the population density. The descriptive statistical data of this research is presented in Table 1. The graph of GDP data is illustrated in Figure 2, the population density in Figure 3, and the graph of CO_2 emission data in Figure 4.

3.2. Estimating the Model Parameters

In this section, the parameters of the linear regression model (5) are calculated using the ACO algorithm. In this estimate, the objective function is the minimisation of the sum of residual squares in equation (6). The model parameter estimation steps using the ACO algorithm is done with the help of Matlab R2015. The result of parameter estimation using the ACO algorithm gives the parameter estimator values of $\hat{\alpha}_0 = -30.967$, $\hat{\beta}_1$ = 0.19552 and $\hat{\beta}_2 = 1.558$. Substitute values are α_0, β_1, and β_2 in equation (5) to obtain the multiple linear regression equation:

$$Y_t = -30.967 + 0.19552 X_{1t} + 1.558 X_{2t} + \varepsilon_t$$

3.3. Testing the Model Estimator Significance

First, examine the partial effect of the parameters α_0, β_1, and β_2. For parameter estimator of α_0, assume H_0: $\hat{\alpha}_0 = 0$ and H_1: $\hat{\alpha}_0 \neq 0$. The result of the calculation using equation (11) gives $t_{Statistic} = -10.80$, while at a significant level c = 0.05 with degrees of freedom df = 51-2=49 the critical value is t(49;0.05) = −2.0105. So, it shows that $|t_{Statistic}| > |t_{(49;0.05)}|$ thus the hypothesis, H_0 is rejected which means parameter $\hat{\alpha}_0 = -30.967$ is significant. Using the same method, testing is done for parameter estimators $\hat{}$ = 0.19552 and $\hat{\beta}_2$ = 1.558. The test results conclude that parameter estimators $\hat{\beta}_1$ = 0.19552 and $\hat{}$ = 1.558 are significant. Second, we tested the simultaneous effect and significance value of parameter estimators α_0, β_1 and β_2. The hypothesis used is $H_0 : \hat{\alpha}_0 = \hat{\beta}_1 = \hat{\beta}_2 = 0$, and $H_1 : \exists \hat{\alpha}_0 \neq \beta_1 \neq \hat{\beta}_2 \neq 0$. The result of calculation using equation (12) gives the value $F_{Statistic}$ = 1114.50, while at the level of significance c = 0.05 the critical value is $F_{(1;49;0.95)}$ = 4.02 which shows that $F_{Statistic} > F(1;49;0.95)$. Thus hypothesis H_0 is rejected which means parameters $\hat{\alpha}_0 = -30.967$, $\hat{\beta}_1 = 0.19552$, and $\hat{\beta}_2 = 1.558$ significantly affects the dependent variable.

Third, test the assumption of residual normality ε_t. H_0: ε_t normally distributed with zero mean and certain variance, and H_1:ε_t not normally distributed with mean zero and variance one. The calculation using equation (16) yields a value of $AD_{Statistic} = 0.2222$, while the critical value $AD_{Critical}$ = 0.74047. It shows that $AD_{Statistic} < AD_{Critical}$ thus the hypothesis H_0 accepted, which means ε_t is normally distributed. The estimation result also generated that mean $\hat{\mu}$ = 0.005426 " 0 and variance $\hat{\sigma}^2$ = 0.014568. Therefore, we conclude that $\varepsilon_t \sim$ N (0, 0.014568).

Table 1: Descriptive statistics data

Statistic	Q_t	K_t	L_t
	Unit	Unit	Person
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
SD	0.57736700	1011.15700	446,693,252

Figure 2: Graph of gross domestic product

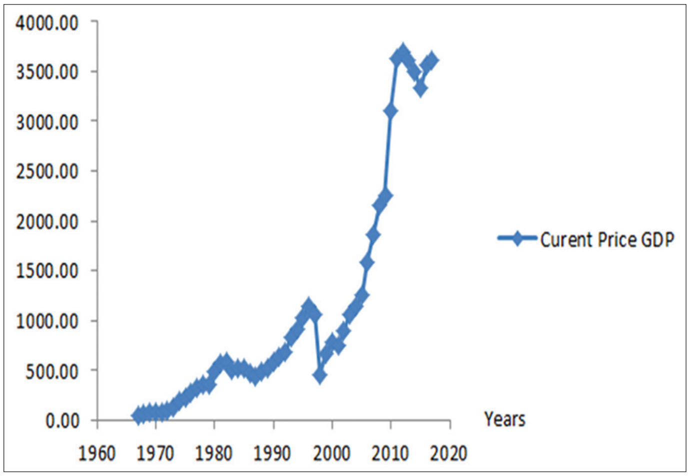


Figure 3: Graph of population density

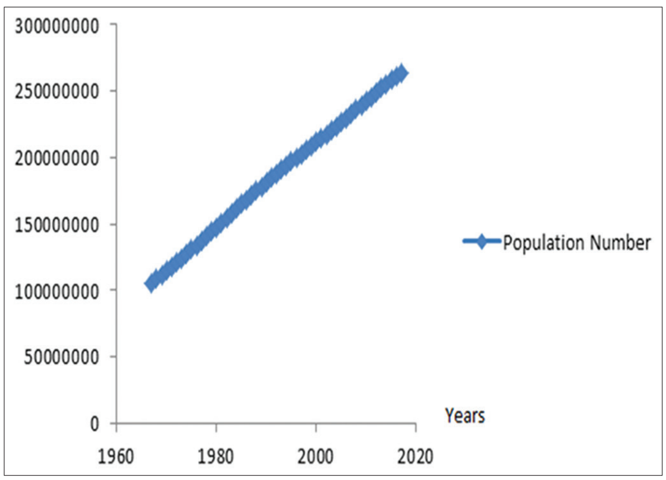


Figure 4: CO_2 Emissions in Indonesia

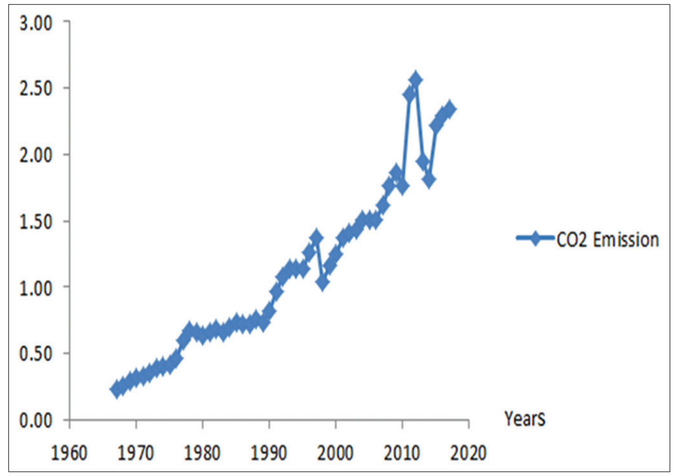
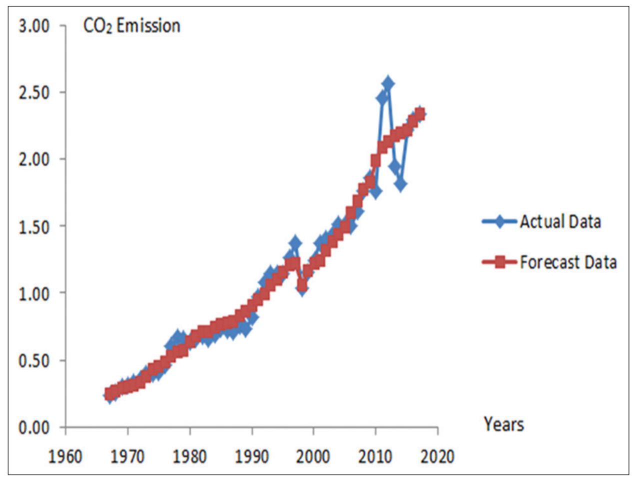


Figure 5: Graph of forecast and actual CO_2 emission data in Indonesia



This section also measured the strength of the relationship between independent and dependent variables. The strength of this relationship is measured by determining the deterministic coefficient value using equation (17). The calculation yields the value of the deterministic coefficient $r^2 = 98.0\%$, showing that the relationship between the independent and dependent variable is very strong.

3.4. Establishing a Cobb-Douglas Model Estimator

After testing the significance, it shows that the regression model given in equation (19) is well suited to model the effect of GDP and the population density on CO_2 emissions in Indonesia. In equation (6), the model estimator is used for forecasting and obtained the equation:

$$\hat{Y}_t = -30.967 + 0.19552 X_{1t} + 1.558 X_{2t}\text{, or}$$

$$\log \hat{Q}_t = \log e^{-30.967} + 0.19552 \log K_t + 1.558 \log L_t\text{, or}$$

$$\hat{Q}_t = e^{-30.967} K_t^{0.19552} L_t^{1.558}$$

Equation (20) is a production function of the Cobb-Douglas model estimator, which describes the effect of GDP K_t and population density L_t on CO_2 emissions in Indonesia Q_t.

3.5. CO_2 Emissions Forecast for 2015-2017

Using equation (20), CO_2 emissions in Indonesia generated in 2015-2017 are predicted by including the increased in each variable from 2015 to 2017. The results of these predictions are shown in Figure 5.

The forecast accuracy is measured using equation (15). The calculation obtained the value of MAD = 6.67%. Thus, the error of the CO_2 emission model influenced by GDP and population density using MAD is relatively small, indicating that the model estimator is very good.

3.6. Discussion

Taking into account the graph of the GDP data in Figure 2, it appears that the value of the GDP in Indonesia has increased year on year. Although there is a decrease in 2000, there is a very sharp rise after the year 2000. The year 2010 recorded a slight decrease, but the trend rose immediately afterwards. It shows that the GDP in Indonesia is increasing steadily. Similarly, the population density data in Figure 3 is a straight line with a rising trend. It illustrates that the population density in Indonesia also increased year on year.

As a consequence of the increase in the value of GDP and population density, there is a sharp rise in CO_2 emissions in Indonesia. Even the year 2010 experienced an increase in CO_2 emissions, although there is a slight decline in the rate of increase. In general, CO_2 emissions in Indonesia from year to year have increased. Many studies CO_2 emissions from exhaust gases to illustrate the degree of pollution. High CO_2 emissions can be caused by high energy consumption and deforestation. The higher the income of a country, the higher the community's ability to pay for energy consumption. Similarly, the higher the increase in population, the higher the rate of deforestation exploited for economic purposes. Figures 2-4 indicate increased CO_2 emissions in Indonesia accompanied by increases in GDP and population density.

The estimation of the effect of GDP and population density on CO_2 emissions is expressed as a production function of the Cobb-Douglas model of equation (20). Taking into account the Cobb-Douglas model estimator in equation (20), the elasticity of output as the GDP can be measured using the estimator coefficient parameter $\hat{\beta}_1 = 0.19552$ while the output elasticity as the population density can be measured using the estimator coefficient parameter $\hat{\beta}_2$ = 1.558. It indicates that population density is more elastic compared to GDP. That is, the increase in CO_2 emissions in Indonesia is influenced more by the population density compared to the GDP growth rates. Similarly, the sum of parameters is $\hat{\beta}_1 + \hat{\beta}_2 = 1.75352$ or $\hat{\beta}_1 + \hat{\beta}_2 > 1$, so that the production function of the Cobb-Douglas model of equation (20) has the characteristics of increasing return to scale. That is, an increase in GDP and population density will lead to an increase in CO_2 emissions with an elasticity of 1.75352. It should be a concern for the Indonesian people and recognise the roles played by economic growth and population density on CO_2 emissions and air pollution in Indonesia.

4. CONCLUSION

In this paper, we have analysed the effect of GDP and population density on CO_2 emissions in Indonesia. Based on the results, we conclude that GDP and population density significantly affect CO_2 emissions in Indonesia. The effect of GDP and population density on CO_2 emissions can be modelled as a production function of the Cobb-Douglas model. The estimator of the production function of the Cobb-Douglas model has the characteristics of increasing return to scale. It means that any increase in input in the form of GDP and population density will lead to a rise in output in the form of CO_2 emissions in Indonesia.

Forecasting (prediction) of CO_2 emissions using the Cobb-Douglas model estimators gives a MAD error rate of 6.67%. The error rate is small meaning that the estimated Cobb-Douglas model estimator is considered a suitable tool to measure the relationship between GDP and population density and CO_2 emissions.

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