Modelling the contribution of CO\(_2\) emissions from fuel used on total CO\(_2\) emissions at power generation in Indonesia

**Ruly Budiono\(^1\), Hafizan Juahir\(^2\), Mustafa Mamat\(^3\), Sukono\(^4*\), Sudradjat Supian\(^4\) and Muhamad Nurzaman\(^1\)**

\(^1\)Department of Biology, Universitas Padjadjaran, Jalan Raya Bandung-Sumedang Km 21, Jatinangor, Sumedang 45363, Indonesia.
\(^2\)East Coast Environmental Research Institute (ESERI), Universiti Sultan Zainal Abidin, Gong Badak, 21300 Kuala Terengganu, Trengganu, Malaysia.
\(^3\)Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, Gong Badak, 21300 Kuala Terengganu, Trengganu, Malaysia.
\(^4\)Department of Mathematics, Universitas Padjadjaran, Jalan Raya Bandung-Sumedang Km 21, Jatinangor, Sumedang 45363, Indonesia

E-mail: sukono@unpad.ac.id

**Abstract.** For electricity production, humans use fossil fuels, such as coal, fuel oil, diesel oil, and gas. The use of these fuels is a major source of greenhouse gas emissions, especially carbon dioxide (CO\(_2\)) gases. In this paper, we have proposed the model of CO\(_2\) emissions from the fuel used to total CO\(_2\), in electricity production in Indonesia. Modelling is done by using multiple linear regression, while the parameter estimation is done by using ordinary least square method (OLS). The data used are CO\(_2\) emissions in million tonnes of greenhouse gas generations for the period of 2000-2015. Based on the results of the analysis, it can be seen that the contribution of CO\(_2\) emissions from the fuel used, to total CO\(_2\) emissions in electricity production significantly follows the multiple linear regression model. The total of CO\(_2\) emission prediction by using estimated model estimator, yields mean absolute error (MAPE) of 0.01026323. These concludes that the prediction data is very close to the actual data.

1. **Introduction**
Fossil fuels such as coal, oil and gas are energy sources, producing carbon dioxide (CO\(_2\)) gases released into the atmosphere as burning residues. The amount of CO\(_2\) emissions is currently 12 times greater than emissions in 1900 because the world burns more fossil fuels [1,2]. Coal is the most carbon-containing fossil fuel. Yet more than a third of the world's electricity is generated from coal and half of global mercury emissions are generated from coal-fired power plants. Electricity sector is important for development [3,4]. But with a high dependence on fossil fuels, this sector accounts for 37% of human-produced CO\(_2\) emissions [5]. It is estimated that there are still about 2 billion people in the world who do not have access to domestic electricity, so the number of demands will increase [6,7]. This means greater CO\(_2\) pollution will be emitted, and the threat of climate change will be more
dangerous. CO₂ emissions may double in the next two decades if there is no policy change handling this issue [8,9].

Senthil et al. [10], in his research stated that power plants have a major role in greenhouse gas emissions. Nearly 21.3% of greenhouse gases emitted by power plants alone. The main source of greenhouse gases is the burning of fossil fuels and deforestation leading to the higher concentrations of carbon dioxide. Harjanto [11], conducted an environmental impact assessment due to the utilization of fossil power plants, by conducting comparative analysis. The results of the study indicate that the use of fossil energy has serious environmental impacts such as: resource depletion, global warming, acid rain, and other derivative impacts such as tidal waves, climate change, ecosystem damage, soaring oil prices, and others will be serious problems in the future. Coi and Abdullah [12], predicted CO₂ emissions using two linear regression-based models. Trends in CO₂ emissions increase along with other economic and variable activities, such as demand and supply in the economy and energy needs.

The linear model is one of the commonly used methods to explain the correlation between CO₂ emissions and related economic variables. However, in certain conditions, the regular linear regression model often have weaknesses in describing a correlation of several variables. To overcome these weaknesses, it is proposed to apply a linear fuzzy regression model to explain the correlation of some variables.

In Indonesia, power plants using fossil fuels include: coal, fuel oil, diesel oil, and gas. Produce CO₂ emissions in million tons of greenhouse gas power plants. In this paper, we modelled the contribution of CO₂ emissions from fuel used, to total CO₂ emissions in power plants in Indonesia. The approaches taken in the research are using linear and non-linear regression model. The objective is to obtain a model that can explain the correlation between the CO₂ emissions variables of the fuel used, with the total CO₂ emission variables at the steam power plant in Indonesia.

2. Methodology
The methodology of this section consist of: several regression models, parameter estimation methods, goodness of fit tests, and forecasting.

2.1 Several regression models
In this section the discussion of the regression model includes: linear regression, quadratic regression, cubic regression, and multiple linear regression in general.

- Simple linear regression model
A simple linear regression equation model can be actually expressed as follows [13]:

\[ Y = b_0 + b_1X + e \]  \hspace{1cm} (1)

where \( Y \) is dependent variable (regression), \( X \) is independent variable (regressor), \( b_0 \) is intercept parameter (constant), \( b_1 \) is coefficient parameter (slope), and \( e \) is residual. Equation (1) can be estimated by the following equation:

\[ \hat{Y} = b_0 + b_1X, \]

so this equation is called a simple regression estimator.

- Quadratic regression model
The model of quadratic regression equation can actually be expressed as follows [6]:

\[ Y = b_0 + b_1X + b_2X^2 + e \]  \hspace{1cm} (2)

where \( Y \) is dependent variable (regression), \( X \) independent variable (regressor), \( b_0 \) is intercept parameters (constants), \( b_1 \) and \( b_2 \) are coefficient parameters (slopes), and \( e \) is residual. If you replace \( X_1 = X \) and \( X_2 = X^2 \), then equation (2) can be expressed as follows [13]:

\[ Y = b_0 + b_1X_1 + b_2X_2 + e \]  \hspace{1cm} (3)
Equation (3) is a multiple linear regression equation with two independent variables $X_1$ and $X_2$. The multiple linear regression equation (3) has the following estimator equation:

$$\hat{Y} = b_0 + b_1 X_1 + b_2 X_2.$$ 

- **Cubic regression model**
  The cubic regression equation model can be expressed as follows:
  $$Y = b_0 + b_1 X + b_2 X^2 + b_3 X^3 + e$$  
  (4)

where $Y$ is dependent variable (regression), $X$ is independent variable (regressor), $b_0$ is intercept parameter (constant), $b_1$, $b_2$, and $b_3$ are coefficient parameters (slopes), and $e$ is residual. If $X_1 = X$, $X_2 = X^2$ and $X_3 = X^3$, then (4) can be expressed as follows:

$$Y = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + e$$  
(5)

Equation (5) is a multiple linear regression equation with two independent variables $X_1$, $X_2$ and $X_3$. The multiple linear regression equation (5) has the following estimator equation:

$$\hat{Y} = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3.$$  

- **Multiple linear regression model in general**
  The model of multiple linear regression equation can generally be expressed as follows [14, 15]:

$$Y = b_0 + b_1 X_1 + b_2 X_2 + \ldots + b_k X_k + e$$  
(6)

where $Y$ is dependent variable (regression), $X_1$, $X_2$ and $X_3$ are independent variables (regressors), $b_0$ is intercept parameter (constant), $b_1$, $b_2$, ..., $b_k$ are coefficient parameters (slopes), and $e$ is residual. The multiple linear regression equation (6) has the estimator equation which is expressed as follows:

$$\hat{Y} = b_0 + b_1 X_1 + b_2 X_2 + \ldots + b_k X_k$$  
(7)

### 2.2 Method of parameter estimation

In this section we discuss the method of estimating these multiple regression parameters in general. Using the matrix equation approach, multiple linear regression equations (7) can be expressed as follows [14, 16]:

$$Y = XB + e$$  
(8)

where:

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}, \quad X = \begin{bmatrix} 1 & X_{12} & X_{13} & \cdots & X_{1k} \\ 1 & X_{22} & X_{23} & \cdots & X_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{n2} & X_{n3} & \cdots & X_{nk} \end{bmatrix}, \quad B = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}, \quad e = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix},$$

where $Y$ matrix of $(n \times 1)$, $X$ matrix of $(n \times k)$, $B$ matrix of $(k \times 1)$, and $e$ matrix of $(k \times 1)$. To get the parameter estimator value of matrix $B$, the sum of squared residuals must be minimized, namely:

$$\text{Minimization } \Sigma e_i^2 = e^T e = (Y - XB)^T (Y - XB)$$  
(9)

where $e^T = (Y - XB)^T$ transpose of $e$. Because $B^T X^T Y$ is a scalar, hence the same as the transpose, i.e. $Y^T XB$. For the minimizing process, from equation (9) is obtained as follows:

$$\frac{\partial \Sigma e_i^2}{\partial B} = -2X^T Y + 2X^T XB = 0$$  
(10)

From equation (10), it can be obtained parameter estimator:

$$B = (X^T X)^{-1} X^T Y$$  
(11)
where $(X^T X)^{-1}$ is the inverse of $(X^T X)$. This approach can be used when $(X^T X)$ has an inverse, but if there is multicollinearity, the inverse matrix calculation becomes doubtful.

2.3 Goodness of fit test

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

- Individual significance test

Individual significance tests are intended to test each parameter $\beta_i (i = 0, 1, 2, \ldots, k)$, where $\beta_i \in \{b_0, b_1, b_2, \ldots, b_k\}$ is element of equation (4), in affecting the dependent variable. To test the parameters $\beta_i$, the hypothesis is $H_0: \beta_i = 0$ and $H_1: \beta_i \neq 0$. Testing is done using statistic $t_{stat}$, with the equation:

$$t_{stat} = \frac{\hat{\beta}_i}{SE(\hat{\beta}_i)}$$

(12)

where $SE(\hat{\beta}_i)$ is the standard error of parameter $\beta_i$. Reject the hypothesis $H_0$ if $|t_{stat}| > t_{(n-2, \alpha)}$, or $Pr[t_{stat}] < \alpha$, where $t_{(n-2, \alpha)}$ is the critical value of the $t$ distribution with a level of significance $100(1-\alpha)\%$ and $n$ the number of data [17].

- Simultaneous significance test

The simultaneous significance test is intended to test parameters $\beta_i (i = 0, 1, 2, \ldots, n)$, where $\beta_i \in \{b_0, b_1, b_2, \ldots, b_k\}$ is element of equation (4), in affecting the dependent variable. The hypothesis is $H_0: b_0 = b_1 = b_2 = \ldots = b_k = 0$ and $H_1: \exists b_0 \neq b_1 \neq b_2 \neq \ldots \neq b_k \neq 0$. Testing is done using statistic $F$, with the equation:

$$F_{stat} = \frac{MS_{Reg}}{MS_{Error}}$$

(13)

where $MS_{Reg}$ mean square due to regression, and $MS_{Error}$ mean square due to residual variation. Reject the hypothesis $H_0$ if $F_{stat} > F_{(1, n-2, \alpha)}$, or $Pr[F_{stat}] < \alpha$, where $F_{(1, n-2, \alpha)}$ is the critical value of the $F$ distribution with a level of significance $100(1-\alpha)\%$, and $n$ the number of data [17].

- Residual normality test

The normality test is intended to determine that the residual data is spreading normally. Normal testing can be performed using Kolmogorov-Smirnov (KS) statistics. The hypothesis is $H_0$: data is normally distributed, and $H_1$: data is not normally distributed. Testing is done by determining residual standard deviation by using equation:

$$Se_i = \sqrt{\frac{\sum_{i=1}^{n}(e_i - \bar{e})^2}{n-1}}$$

(14)

Transform value $e_i$ become $z_i$ with equations $z_i = (e_i - \bar{e})/Se_i$. Determination of probability value $P(z_i)$ is performed using standard normal distribution tables. While the probability $S(z_i)$ is determined using the equation $S(z_i) = randl(z_i)/n$. Furthermore, the value of absolute difference is calculated using $|S(z_i) - P(z_i)|$. The Kolmogorov-Smirnov Statistics $KS_{stat}$ is determined using the equation:

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

(15)
to determine the critical value of statistics $KS_{(a,n-1)}$, at a significant level $\alpha = 0.05$. The testing criteria is rejected $H_0$ if $KS_{stat} > KS_{(a,n-1)}$ [17].

- Coefficient of determination

According to Koen and Holloway [15], the coefficient of determination $R^2$ is to measure how much the diversity of independent variables impacts the dependent variable, based on the level of strength of the relationship. So the coefficient of determination is the ability of independent variables $X_i(i = 1,2,\ldots,k)$ in affecting the dependent variable $Y$. Coefficient of determination $R^2$ is determined using the equation:

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$  \hspace{1cm} (16)

The value of the coefficient of determination is between 0 and 1. A small determinant value close to 0 means that the variation of the free variable is very weak, and a value close to 1 means the variation of the free variable gives all the information required in predicting the dependent variable.

2.4 Forecasting

Forecasting (prediction) is done by the complexity and uncertainty faced by the model maker, therefore, it takes a great degree of accuracy. There are many methods that can be used to measure the accuracy of a forecasting model, in this research we applied Mean Absolute Percentage Error (MAPE). MAPE is determined using the equation:

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right|\right) \times 100\%$$  \hspace{1cm} (17)

The smaller the MAPE value, the smaller the value of error, which means the greater the accuracy [17].

3. Result and Analysis

The discussion of the results and analysis includes: the data analyzed, the modeling of total CO$_2$ emissions, and modeling the contribution of CO$_2$ emissions from the fuel.

3.1 Data analyzed

In this study the CO$_2$ emissions data is in Million Tons of greenhouse gases emitted by power plants in Indonesia. It Represent secondary data obtained from the Ministry of Energy and Mineral Resources of the Republic of Indonesia from 2000 to 2015. The data can be shown as the amount of CO$_2$ emissions in power plants. The graph is given in Figure 1.

![Figure 1. CO$_2$ emission data from electricity power plant in Indonesia](image)
Taking into account on Figure 1, it appears that the total CO$_2$ emissions emitted by power plants from year to year, tend to increase with a high trend. The largest contribution of total CO$_2$ emissions is derived from the coal fuel-based power plant. The next contribution is from diesel fuel, gas, fuel oil and diesel oil, each of which fluctuates with a relatively constant trend. Furthermore, based on the data in this research is modeling the trend of total CO$_2$ emission from year to year by using time series regression equation. As for the analysis of the contribution of CO$_2$ emission emissions from each of the fuels used, to the total emission of CO$_2$ emissions in power plants, is done by using multiple linear regression equation.

### 3.2 Modeling the total CO$_2$ emission

In this section a total CO$_2$ emission emitted from the power plant is modelled. The data used in this modeling is the total CO$_2$ emissions from power plants in the period of 2000 to 2015. Modeling is done by using the time series regression equation. The estimation were performed using the Ordinary Least Square (OLS) method approach referring to equations (9) and (11). Model estimation is done by using Minitab 16 software. Based on exploration using Minitab 16 software, the best estimation result is given in Table 1.

### Table 1. Estimation results of total CO$_2$ emission radiance models

| Predictor | Coef | SE | t | P |
|-----------|------|----|---|---|
| Intercept | 87.521 | 1.424 | 61.45 | 0.000 |
| Years Code | 4.4448 | 0.4554 | 9.76 | 0.000 |
| Years Code$^2$ | 0.04018 | 0.04390 | 9.70 | 0.000 |
| Years Code$^3$ | 0.009729 | 4.76 | 0.000 |

\[ S = 2.63416 \text{ E-Sq} = 99.24 \text{ R-Sq(Adj)} = 99.46 \]

| Analytic of Variance |
|----------------------|
| Source | DF | SS | MS | \( Y \) | \( F \) |
| Regression | 3 | 1077996.8 | 359326.2 | 472.22 | 0.000 |
| Residual Error | 12 | 15856.3 | 13.2 |
| Total | 15 | 109356.3 |

Based on Table 1, and also referring to equation (4), it indicates that the total emission of CO$_2$ emissions can be expressed as equations:

\[ Y = 87.521 + 4.4448X + 0.46018X^2 + 0.046301X^3 + e \quad (18) \]

where \( Y \) is total CO$_2$ emissions, \( X = \{-8, -7, -6, -5, -4, -3, -2, -1, 1, 2, 3, 4, 5, 6, 7, 8\} \) is the year code, and \( e \) is residual. Furthermore, the goodness of fit of the equation (18) needs to be tested. First, the individual significance test is applied on the parameter estimator \( b_0 = 87.521, b_1 = 4.4448, b_2 = 0.46018, \) and \( b_3 = 0.046301 \). The test is performed by referring to the equation (12), using a significance level \( \alpha = 0.05 \). Based on the test results presented in Table 1, it shows that parameter estimator \( b_0, b_1, b_2 \) and \( b_3 \), respectively significantly affect the variable \( Y \) (CO$_2$ emissions). Second, the simultaneous significance test of the parameter estimators \( b_0, b_1, b_2 \) and \( b_3 \). Testing is done by referring to equation (13), also by using the level of significance \( \alpha = 0.05 \). Based on the test results presented in Table 1, it shows that parameter estimator \( b_0, b_1, b_2 \) and \( b_3 \), simultaneously significant effect on the variable \( Y \) (CO$_2$ emissions).

Third, the assumption of residual normality test of \( e \), intended to ensure that residual \( e \) has normal distribution. Testing is done by referring to equation (15), also by using the level of significance \( \alpha = \)
Based on the results of testing using Minitab 16 software, it shows that residual $e \sim N(-0.002851, 0.0006293)$. Fourth, the determination coefficient test is intended to reduce the strength of the relationship between the independent variable and the dependent variable. Determination of coefficient value of determination is done by referring to equation (16). Based on the test results presented in Table 1, it is found that the value of determination $R^2= 99.2\%$. This shows that the independent variable and the dependent variable is very strong.

After a goodness of fit test and all test results are significant, thereby obtaining the model estimator of total CO$_2$ emissions (18), can be expressed as equations:

$$Y = 87.521 + 4.4448X + 0.46018X^2 + 0.046301X^3$$  \hspace{1cm} (19)

After a goodness of fit test and all test results are significant, furthermore, the model estimator in equation (19) can be used for forecasting. First, forecasting based on data in sample result is shown as total prediction graph in Figure 2.

Concerning Figure 2, it appears that the total prediction graph (forecast) is almost coincides with the actual data, and forecasting based on the sampled data in gives the measured error rate using MAPE of 2.6126384%. This means that the model estimator has an accuracy of 97.38736%. Second, forecasting based on sampled data out are performed by adding code year from data in sample. In this case, the number 9 is determined for 2016, 10 for 2017 and 11 for 2018. Based on the year code of the data out sample, using the model estimator (19), it obtained the forecast result of total CO$_2$ emission from the power plant in 198.55, 224.29, and 253.72.

3.3 **Modeling the contribution of CO$_2$ emissions from fuel used**

In this section modeling the contribution of CO$_2$ emissions from materials used to total CO$_2$ emissions at power plants. The data used in this model is the emission of CO$_2$ emissions from the materials used and the total CO$_2$ emissions from power plants in the period of 2000 to 2015. Modeling is done by using multiple linear regression equations. Estimation were performed using the Ordinary Least Square (OLS) method approach referring to equations (9) and (11). The model estimation is done by using Minitab 16 software and the estimation results are given in Table 2.

Based on Table 2, and referring to equation (6), it indicates that the emission of CO$_2$ from the fuel used for total CO$_2$ emissions can be expressed as equations:

$$Y = -0.00281 + 1.00065X_1 + 1.00243X_2 + 0.998266X_3 + 1.01520X_4 + 0.998331X_5 + \varepsilon$$  \hspace{1cm} (20)

Where $Y$ is total CO$_2$ emissions, $X_1$ is coal, $X_2$ fuel oil, $X_3$ diesel fuel, $X_4$ diesel oil, $X_5$ gas, and $\varepsilon$ is residual. Furthermore, equation (19) needs to be tested of its goodness of fit. First, the individual significance test is performed on the parameter estimator $\hat{\beta}_0 = -0.00281$, $\hat{\beta}_1 = 1.00065$, $\hat{\beta}_2 = 1.00243$, $\hat{\beta}_3 = 0.998266$, $\hat{\beta}_4 = 1.01520$ and $\hat{\beta}_5 = 0.0998331$. The test is performed by referring to equation (12),
using a significance level $\alpha = 0.05$. Based on the test results presented in Table 2, it shows that parameter estimator $\beta_0$ is not significant. While $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$ and $\beta_5$, respectively significantly affect the variable $Y$ (CO$_2$ emissions). Second, the simultaneous significance test of the parameter estimators $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$ and $\beta_5$. Testing is done by referring to equation (13), also by using the level of significance $\alpha = 0.05$. Based on the test results presented in Table 2, it shows that parameter estimator $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$ and $\beta_5$, simultaneously significant effect on the variable $Y$ (CO$_2$ emissions).

Table 2. Estimation result of CO$_2$ emission contribution model of the fuel used to total CO$_2$ emissions

| Predictor | DF | DF | Value | F | P |
|-----------|----|----|-------|---|---|
| Constant  | 1  | 1  | 0.00221  | 0.01009 | 0.00100 |
| Coal      | 1  | 1  | 1.00064  | 0.00036 | 1.79448  | 0.000 |
| Fuel oil  | 1  | 1  | 1.00145  | 0.00029 | 3.42435  | 0.000 |
| Diesel fuel | 1  | 1  | 0.999256  | 0.000141 | 0.59729  | 0.000 |
| Diesel oil | 1  | 1  | 1.00200  | 0.00020 | 0.93110  | 0.000 |
| Gas       | 1  | 1  | 0.999231  | 0.000944 | 0.50620  | 0.000 |

$S = 0.003975809$, $R^2 = 100.0\%$, $R^2(adj) = 100.0\%$

Third, the assumption of residual normality test of $\varepsilon$, intended to ensure that residual $\varepsilon$ has normal distribution. Testing is done by referring to equation (15), also by using the level of significance $\alpha = 0.05$. Based on the results of testing using Minitab 16 software, it shows that the residual $\varepsilon \sim N(0.000035, 10.5625)$. Fourth, the determination coefficient test is intended to reduce the strength of the relationship between the independent variable and the dependent variable. Determination of coefficient value of determination is done by referring to equation (16). Based on the test results presented in Table 2, it is found that the value of determination $R^2 = 100.0\%$. This shows that the relationship between the independent variable and the dependent variable is very strong.

Having passed the goodness of fit test and all test results are significant, thereby obtaining the model estimator from the emission of CO$_2$ emitted from the fuel used for total CO$_2$ emissions (18), can be expressed as equation:

$$\hat{Y} = -0.00281 + 1.00065 X_1 + 1.00243 X_2 + 0.998266 X_3 + 1.01520 X_4 + 0.998331 X_5 \quad (21)$$

Furthermore, the model estimator in equation (21) can be used for forecasting. First, forecasting based on data in sample result is shown as total prediction graph in Figure 3.

**Figure 3.** Graph of prediction and actual data of total CO$_2$ emissions.
Considering Figure 2, it appears that the total prediction (forecast) graph is in tandem with the actual data, and forecasting based on the sampled data-in gives the measured error rate using MAPE of 0.008566%. This means that the model estimator has an accuracy of 99.99143%. Second, forecasting based on sampled data-out has been conducted by estimating CO$_2$ emission rates from fuel used in future generating power plants. For example in certain years, CO$_2$ emissions are estimated from the fuel used in succession are: coal 133.52, fuel oil 3.22, diesel fuel 30.75, diesel oil 0.02, and gas 27.50. Using the model estimator (21), the forecast result predict the total CO$_2$ emissions from the power plant amounted to 195.01 million tons.

4. Conclusion
In this paper we have conducted a modelling of CO$_2$ emission in power plants in Indonesia, using time series regression equations and multiple linear regressions. Based on the analysis and result, it can be concluded that the total emission of CO$_2$ emission from year to year follows the cubic regression model that has a high trend, with the deterministic coefficient value of 99.2%. Estimator of the cubic regression model generated has an insurance rate for forecasting of 97.38736%. Using the estimated cubic regression model estimator, it can be predicted that by 2016, 2017, and 2018 the total emissions of CO$_2$ from power plants will reach 198.55, 224.29, and 253.72. Meanwhile, the contribution of CO$_2$ emission from the fuel used to total CO$_2$ emissions in the power plant can be modelled by using multiple linear regression equation, with a deterministic coefficient value of 100%. The multiple linear regression model estimation generated has an insurance rate for forecasting of 99.99143%. If in a given year CO$_2$ emissions from fuel used are estimated consecutively: coal 133.52, fuel oil 3.22, diesel fuel 30.75, diesel oil 0.02, and gas 27.50, the power plant in Indonesia will emit total CO$_2$ emissions of 195.01 million tons. Therefore, the result of CO$_2$ emission model from this power plant is expected to be taken into consideration in the effort of decreasing CO$_2$ emission in air.

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