Analysis of Carbon Dioxide Emissions in Ghana*

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Abstract

The alarming rate of emission of Carbon Dioxide (CO_2) into the atmosphere and its catastrophic effect on the environment, as monitored by many governmental agencies and researchers has become a source of worry for many nations and therefore needs due attention. The total emissions of CO_2 in Ghana was modelled using the Autoregressive Integrated Moving Average (ARIMA) statistical technique. First, a direct Multiple Linear Regression (MLR) was applied on all the sectors contributing to the overall CO_2 emission which caused multicollinearity problems. In order to eliminate multicollinearity problems and better understand the interrelationships among these sectors, Factor Analysis was employed after its appropriateness on the data has been tested. The ARIMA technique was then used to develop a model to forecast the total CO_2 emissions in Ghana. It was concluded that, the Transport sector, the Manufacturing and Construction sector, Electricity and Heat sector were the predominant sectors that significantly contributed to the overall CO_2 emission in the atmosphere. It was recommended that the usage of electric and hydrogen fuelled vehicles will be a suitable alternative to conventional fossil fuel vehicles in the future.

Keywords: Energy, Carbon Dioxide, Multiple Linear Regression Model, Factor Analysis, ARIMA

1 Introduction

The heavy reliance on fossil fuels to generate energy has contributed to a number of environmental and social problems, including depletion of non-renewable resources and the Ozone layer resulting in global warming. In 2000, the CO_2 emitted in Ghana accounted for 44% of the total Greenhouse Gases (GHG) emissions of which the energy sector contributed 41% of the total emissions (Solomon, 2015). According to the International Energy Agency (IEA), in 2008, the burning of fossil fuels for energy accounted for 65% of the global Greenhouse Gases (Anon., 2012). In addition, Topcu and Ulengin (2004) stated that fossil fuel extraction and conversion to usable energy is a cause of acid rain, therefore, expensive air pollution controls are required. Solomon (2015) indicated that climate change is largely irreversible for 1000 years after the emissions stops and has serious adverse effects on the development of the nation. The most affected areas are agriculture, quality of air and settlement around water bodies.

According to the World Bank's report 2011, the main sectors that are responsible for the CO_2 emissions in Ghana include: electricity and heat generation sector, the transport sector, manufacturing industries and construction sector, residential, public and commercial services, and other sectors. In Ghana, road transportation accounts for over 95% of all transport supply. Adu-Kumi (2012) suggested that more than 70% of major roads in Ghana are occupied by vehicles that produce high amount of exhaust emissions, thereby increasing the percentage of CO_2 in the air and decreasing its quality. The negative impacts of the polluted atmosphere on the human health and the environment are very alarming and need urgent attention. It is therefore, imperative to analyse the relationship between various sectors and their corresponding level emissions to the overall CO_2 emission in Ghana. The study will then forecast the total emissions of CO_2 using Autoregressive Integrated Moving (ARIMA) technique to assist policy makers and implementers about the direction to go.

2 Resources and Method Used

2.1 Data Collection

Data was obtained from Environmental Protection Agency (EPA) Head office, Accra and International Energy Agency (IEA). The data set spanning from 1980 to 2011, composed of two parts: CO_2 emissions from the energy sector and CO_2 emissions from other sectors that contribute to emissions in Ghana (all in million metric tons). The models employed were the Multiple Linear Regression (MRL) and ARIMA.

2.2 Multiple Linear Regression Model

The general form of a multiple regression is:

$$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \cdots + \beta_q x_{q,t} + \varepsilon_t \quad (1)$$

where y_t is the variable to be forecast and $x_{1,t}, \ldots, x_{q,t}$ are the q predictor variables. The coefficients $\beta_1, \ldots, \beta_q$ measure the effect of each

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predictor after taking account of the effect of all other predictors in the model. Thus, the coefficients measure the marginal effects of the predictor variables. When forecasting, the general assumption required for the errors ($\varepsilon_1, \ldots, \varepsilon_t$) are as follows:

i. $E(\varepsilon_i) = 0$, for all $i = 1, 2, \ldots, t$. (linearity)

ii. $\operatorname{var}(\varepsilon_i) = \sigma^2$, for all $i = 1, 2, \ldots, t$. (constant variance)

iii. $\operatorname{cov}(\varepsilon_i, \varepsilon_j) = 0$, for all $i \neq j$. (uncorrelated error terms)

iv. $\varepsilon_i \sim N(0,1)$ (error terms be normally distributed)

2.3 Factor Model

The factor model can be thought of as a series of multiple regressions, predicting each of the observable variables X_i from the values of the unobservable common factors f_i :

$$\begin{aligned} X_1 &= \mu_1 + l_{11} f_1 + l_{12} f_2 + \cdots + l_{1m} f_m + \in_1 \\ X_2 &= \mu_1 + l_{21} f_1 + l_{22} f_2 + \cdots + l_{2m} f_m + \in_2 \\ &\vdots \\ X_p &= \mu_p + l_{p1} f_1 + l_{p2} f_2 + \cdots + l_{pm} f_m + \in_p \end{aligned} \quad (2)$$

The variable means μ_1 through μ_p can be regarded as the intercept terms for the multiple regression models. The regression coefficients l_{ij} (the partial slopes) for all of these multiple regressions are called factor loadings, where l_{ij} is the loading of the i^{th} variable on the j^{th} factor. And finally, the errors $\in_i$ are called the specific factors for variable i.

In summary, each of the response variables X is to be predicted as a linear function of the unobserved common factors $f_1, f_2, \cdots, f_m$. Thus, the explanatory variables are $f_1, f_2, \cdots, f_m$. Therefore, it is assumed that m unobserved factors control the variation among our data. Generally, Equation (2) can be expressed in a matrix notation as shown in Equation (4).

$$\mathrm{X} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_p \end{pmatrix} + \begin{pmatrix} l_{11} & l_{12} & \cdots & l_{1m} \\ l_{21} & l_{22} & \cdots & l_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ l_{p1} & l_{p2} & \cdots & l_{pm} \end{pmatrix} \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_m \end{pmatrix} + \begin{pmatrix} \in_1 \\ \in_2 \\ \vdots \\ \in_p \end{pmatrix} \quad (3)$$

$$\mathrm{X} = \mu + \mathrm{Lf} + \in \quad (4)$$

In general, it is expected that $m < p$.

2.3 ARIMA Model

An ARIMA (p, d, q) model is a combination of Autoregressive (AR) model which shows that there is a relationship between present and past values, a random value and a Moving Average (MA) model which shows that the present value has something to do with the past residuals. The ARIMA process is given as:

$$\phi(B)\Delta^d Y_t = \theta(B) e_t \quad (5)$$

where

Y_t is the total CO_2 emission at time t

Δ^d is the integrated term

$\phi(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$ is the autoregressive (AR) and $\theta(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$ is the moving average (MA) characteristic operators

e_t is the error term.

The estimation of the model consists of four steps, namely: identification, estimation of parameters, diagnostic checking and finally forecasting.

3 Results and Discussion

3.1 Descriptive Statistics

From the data collected, the average emissions of CO_2 from the various sectors such as transportation, electricity and heat, manufacturing industries and construction, residential and public and commercial services, and other sectors in Ghana were: 0.81, 2.48, 0.73, 0.20 and 0.45 million metric tons respectively as shown in Table 1.

Table 1 Descriptive Statistics of Data

Variable	Mean	Standard Deviation	Min	Max
Total CO_2 Emission (TCO)	4.47	2.10	1.91	9.25
Sector				
Transport (TRN)	0.81	0.95	0.03	3.10
Electricity and Heat (ECH)	2.48	1.20	0.98	5.46
Manufacturing and Construction (MNC)	0.73	0.35	0.26	1.57
Residential, Public and Commercial (RPC)	0.20	0.10	0.07	0.52
Other (OTH)	0.45	0.13	0.22	0.86

3.2 Multiple Regression Model

Multiple regression analysis is employed in this study to determine the relationships among the various sectors as well as the contribution each sector makes to the annual Total CO_2 (TCO) emitted into the atmosphere. Using TCO emitted as the dependent variable; TRN, ECH, MNC, RPC and OTH denoting the emission of CO_2 emitted from the various sectors considered.

Table 2 presents the results of the multiple regression analysis conducted to the determine the relations as well as the individual contribution each sector makes to the total emission of CO_2. As observed, the p-value from the F-test of the model (<0.0001), shows that the model is statistically significant. The adjusted R-squared indicates that about 94.77% of the variability of total CO_2 emission is accounted for by the model.

However, the regression model had two major deficiencies: *i.e.* about 67% (4 out of 6) of the parameter are not significant (p-value>0.05). Also, the Variance Inflation Factors (VIF) values of some of the parameters were greater than 10, which is an indication of high level of multicollinearity in the multiple regression model involving all the variables. According to Hair *et al*., (2013), these deficiencies could lead to the poor estimation of model parameters, affect the relative contribution of each parameter to the total CO_2 emissions (TCO).

Hence, an application of a direct multiple linear regression produced inaccurate interpretations (spurious). In order to solve the multicollinearity problem, Factor Analysis is employed to help identify logical combinations of the sectors and better understand the interrelationships among them.

3.3 Factor Analysis

Preliminary inspection of the correlation matrix in Table 3 reveals that most the correlations among the various sectors (correlations with TCO excluded) are significant at the 0.05 level (9 out of 10, *i.e*. 90%). Also, the Bartlett's test showed that the correlations, when taken collectively, are significant at the 0.0001 level. Moreover, the overall Measure of Sampling Adequacy (MSA) value is above the acceptable range (0.74>0.5). Collectively, these tests suggested that dataset is appropriate for Factor Analysis (on both an overall basis and for each variable).

Table 3 Pearson Correlation among Variables

Pearson Correlation Coefficients, N = 32
Prob > |r| under H0: Rho=0

	TCO	ECH	TRN	MNC	OTH	RPC
TCO	1.00000	0.88457 <.0001	0.97296 <.0001	0.96745 <.0001	0.50919 0.0029	0.60798 0.0002
ECH	0.88457 <.0001	1.00000	0.89476 <.0001	0.90219 <.0001	0.38594 0.0291	0.55903 0.0009
TRN	0.97296 <.0001	0.89476 <.0001	1.00000	0.98155 <.0001	0.54901 0.0011	0.70668 <.0001
MNC	0.96745 <.0001	0.90219 <.0001	0.98155 <.0001	1.00000	0.47693 0.0058	0.68725 <.0001
OTH	0.50919 0.0029	0.38594 0.0291	0.54901 0.0011	0.47693 0.0058	1.00000	0.29285 0.1038
RPC	0.60798 0.0002	0.55903 0.0009	0.70668 <.0001	0.68725 <.0001	0.29285 0.1038	1.00000

Table 4 contains the eigenvalues and proportion of variance explained regarding the five possible factors. Using the latent root criterion of retaining factors with eigenvalues greater than 1.0, one factor is retained which accounts for about 92.15% of the variance of the five sectors, deemed sufficient in terms of total variance explained. Hence, one factor is retained.

Table 4 Eigenvalues of the Reduced Correlation Matrix

Factor	Eigenvalue	Proportion	Cumulative
1	3.51	0.92	0.92
2	0.25	0.07	0.99
3	0.12	0.03	1.02
4	-0.01	0.00	1.02
5	-0.06	-0.02	1.00

Table 2 Summary of Model

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|	VIF
Intercept	0.9505	0.3506	2.7120	0.0119	0.00
TRN	1.5366	0.4266	3.6020	0.0014	34.1776
ECH	-0.1023	0.2050	-0.4990	0.6222	5.3336
MNC	1.5944	1.3006	1.2260	0.2317	27.4115
RPC	-2.6829	0.9077	-2.9560	0.0067	1.8635
OTH	-0.8485	1.0507	-0.8080	0.4270	1.8188

F-Value=109.80, P-Value=<0.0001, R^2(adjusted)=0.9477

The retained factor pattern in Table 5 is examined to ascertain the size of each sector's communality. The size of the communality is a useful index for assessing how much variance in a particular sector is accounted for by the factor solution. This is a measure for how well the model performs for that particular sector (Hair *et al*., 2013).

From Table 5, it is indicated that the Transport sector (TRN) accounts for the highest communality (1.00), which implies that the Transport sector contributes the highest to CO_2 emission. This confirms the findings of Costa and Tian (2015) indicating the Transport sector as one of the principal sources of CO_2 emissions. This is followed by the Manufacturing and Construction sector (MNC), Electricity and Heat sector (ECH), Residential, Public and Commercial sector (RPC) and the Other sector (OTH) with communalities 0.97, 0.79,0.48, 0.26 respectively. This could be attributed to the numerous number of old age vehicles, poor maintenance culture as well as the poorly regulated emissions from manufacturing factories/industries in Ghana.

Table 5 Factor Pattern

Sector	Factor1	Communality
ECH	0.89	0.79
TRN	1.00	1.00
MNC	0.99	0.97
OTH	0.51	0.26
RPC	0.69	0.48

3.4 ARIMA Model

The purpose for employing ARIMA modelling technique in this section is to model the annual total emission of CO_2 in the atmosphere. Fig. 1 shows that the total annual CO_2 emissions from all the sectors exhibit a rough upward trend with no hint of seasonal variations.

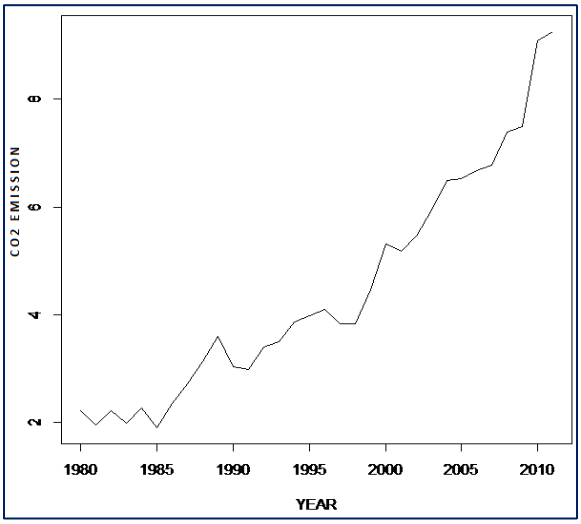

Fig. 1 Sequence Plot of total CO2 Emissions in Ghana

3.4.1 Analysis of Autocorrelations and Partial Autocorrelations

The ACF plot in Fig. 2 shows a slow decline from its highest value at lag 1 (slow decay), which is typical of a nonstationary time series. This is also confirmed by the p-value (0.99>0.05) from Augmented Dickey-Fuller (ADF) test of stationary (order 0) in Table 6. Thus, the series became stationary after second order differencing as shown in Table 6. Hence, the ARIMA model will be of the form (p, 2, q).

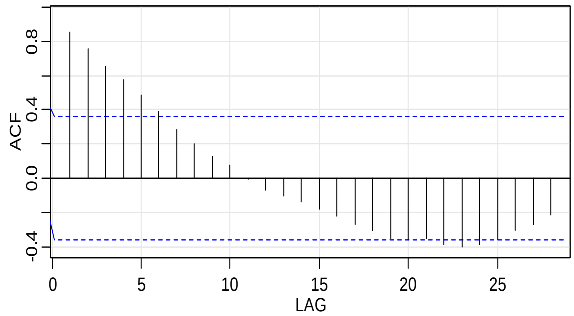

Fig. 2 ACF Plot of the Original Series

Table 6 Summary of Stationarity Test on Series

Test	**Differencing (P-Value)**		
	Order 0	**Order 1**	**Order 2**
ADF	0.99	0.104	0.043

3.4.2 Model Identification

In selecting the 'best' ARIMA model for the Total CO_2 emission (TCO), nine competing models were fitted and the result shown in Table 7. The 'best' model is the model with the minimum information criteria, thus, the 'best' model is ARIMA (0,2,1) or IMA (2,1).

Table 7 Competing ARIMA models and Information Criteria

Model (p, d=2, q)	**AIC**	**AICc**	**BIC**
(0,2,0)	49.21	49.36	50.57
(1,2,0)	43.26	43.72	46.00
(0,2,1)	37.78	38.24	40.51
(1,2,1)	39.39	40.35	43.49
(2,2,0)	44.55	45.51	48.65
(2,2,1)	41.38	43.05	46.85
(0,2,2)	39.36	40.32	43.46
(1,2,2)	39.50	41.17	44.97
(2,2,2)	4150	44.11	48.34

3.4.3 Parameter Estimation of ARIMA (0,2,1)

At this point, the study proceeds to estimate the parameters as shown in Table 8Table and investigate whether the residuals of the selected

ARIMA models are normally distributed and uncorrelated between successive residuals.

3.4.4 Diagnostic Checking of ARIMA (0,2,1)

For model diagnostic checking, the p-values from the Box-Pierce test (>0.05) in Table 8Table indicates that the residuals of the model are uncorrelated. Also, the Shapiro-Wilk test (p-value >0.05), indicates that the residuals are normally distributed. This is also confirmed by the diagnostic plots in Fig. 3. Collectively, these tests suggest that the model fits very well.

Table 8 Parameter Estimates of ARIMA (0,2,1)

Variable	Parameter
MA1	-0.8667
Standard Error	0.1049

Box-Pierce=0.7261, P-value=0.3942,
Shapiro-Wilk=0.9529, P-value=0.1870

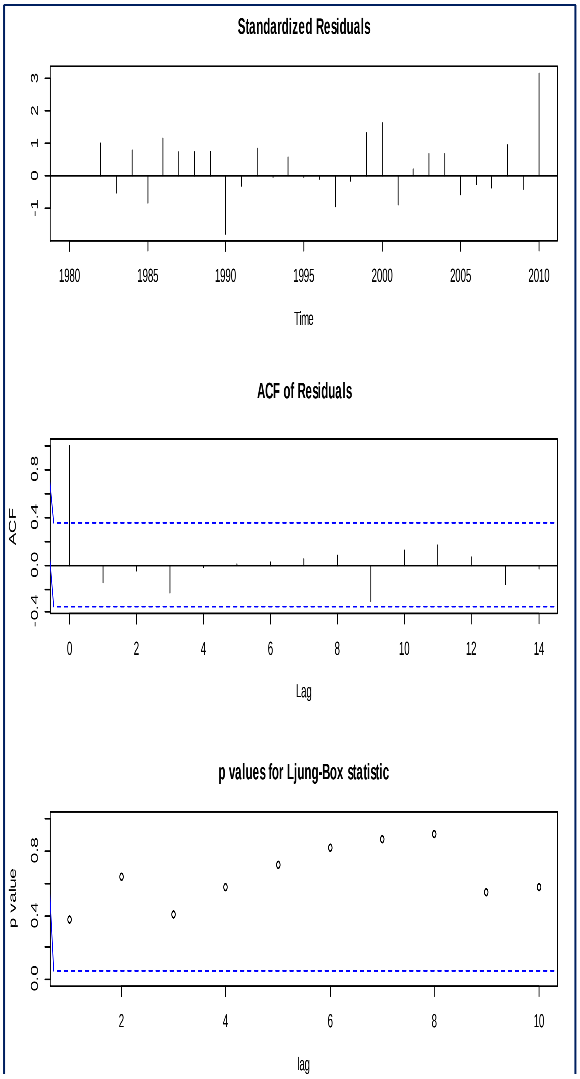

Fig. 3 Diagnostic plot of residuals

Since the model fits well, the ARIMA (0,2,1) model for forecasting the total CO_2 emission in Ghana at any time *t* is given by Equation (5).

$$Y_t = 2Y_{t-1} - Y_{t-2} + 0.8667e_{t-1} + e_t \quad (5)$$

The fitted model indicates that current total CO_2 emission is a linear combination of the previous total CO_2 emissions and the forecast error.

3.4.5 Forecasting

Using the fitted ARIMA (0,2,1) model from Equation (5), Fig. 4 shows the corresponded forecasted trend of total CO_2 emissions in Ghana.

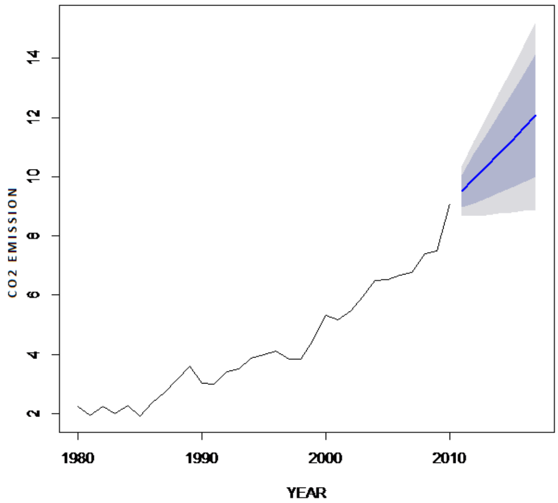

Fig. 4 Forecast for Total CO2 Emissions in Ghana

The forecast plot in Fig. 4 shows that the total CO_2 emissions in Ghana had been increasing since 1980 and will continue to increase into the future if proper measures are not taken. Table 9 presents the forecast values (in million metric tons) as well as the corresponding confidence intervals.

Table 9 Observed and Forecasted Values

Year	Observed	Predicted	Lo (80)	Hi (80)
2011	9.25	9.50	8.95	10.06
2012		9.93	9.10	10.77
2013		10.36	9.27	11.45
2014		10.79	9.45	12.12
2015		11.21	9.63	12.79
2016		11.64	9.81	13.47
2017		12.07	9.99	14.14

MAPE (%)=2.70

4 Conclusion

The study sought to analyse the relationship between various sectors and their corresponding contribution to the total emissions of CO_2 in Ghana. The conclusion drawn from the analysis indicated that the Transport sector was the major contributor, followed by the Manufacturing and Construction sector, Electricity and Heat sector, Residential, Public and Commercial sector and the Other sector. Also, an ARIMA (0,2,1) model for forecasting the annual total CO_2 emission in Ghana has been developed. It is expected CO_2 will continue to increase and that in 2017, the emissions level would reach 12 million metric tons if proper measures are not taken.

In order to curb high carbon dioxide emission from the transport sector, it is recommended that the use of electric, Liquified Petroleum Gas (LPG) and hydrogen fuelled vehicles as an alternative to conventional fossil fuel vehicles in the future.

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