Carbon Emission Prediction and Forecast Using Multiple Linear Regression In West African Developing Countries

Abstract:

250 words

Keywords: Linear regression, Carbon emission, Climate change, Green Energy, Machine learning

Introduction:

500 words

Paper Contribution:

Literature review:

Albeit a critical piece of the world's goal currently is transitioning to cleaner form of energy and bringing about a decrease in CO2 emissions. Carbon emission has always been one of the biggest environmental threats facing the world, (Wang and Jia, 2022) did mention that huge challenges has developed from environmental damages caused by C02 emissions emanating from fossil energy, coal and oil-based energy consumption. The world is largely dependent on fossil fuel for energy consumption but this contribute largely to carbon emission. Extracted crude oil will typically oxidize completely over longer time periods, so increased crude oil throughput is synonymous with increased CO2 emissions of up to 323 Mton in 2020, corresponding to ~1% of the total global CO2 emissions from fossil fuels (Krantz *et al.*, 2022). The United Nations Framework Convention on Climate Change (UNFCCC) established an international environmental treaty to combat "dangerous human interference with the climate system", in part by stabilizing greenhouse gas concentrations in the atmosphere. Africa accounts for the smallest share of global greenhouse gas emissions, at just 3.8%, in contrast to 23% in China, 19% in the US, and 13% in the European Union (CDP, 2020). Despite accounting for the littlest share of greenhouse gas emissions, Africa is still quite vulnerable to climate change, the continent is the most vulnerable to the impacts of climate change. Already experiencing temperature increases of above 0.7°C over much of the continent, and with predictions that temperatures will rise further, Africa is facing a wide range of impacts, including increased drought and floods (UNCCC, 2006). A quality forecast of the annual carbon emission is one of the keys to accessing and managing climate risks and working towards a resilient future where CO2 emissions can be mitigated, though, other than the historical emissions, the models employed in different studies will also affect emission projections (Wang *et al.*, 2019).

To date, there have been a number of studies regarding CO2 emissions, its projections and ways to curb it. Striving to complete the carbon emissions reduction targets of "13th Five-Year" and realize low carbon development, (Yin *et al.*, 2017) predicted CO2 emissions based on an analysis of combustion process while (Hosseini *et al.*, 2019) applied multiple regression (MR) models to be able to forecast Iran’s CO2 emissions using on the historical data derived from World Bank Open Data.

Carbon emissions have a direct negative impact on environment, the industrial and transportation sectors does also really contributes to CO2 emission. (Raza and Hasan, 2022) applied the Quantile Regression model over a 38 years range between 1980 to 2018 to determine variables used at estimating the scenario analysis of the carbon emissions forecasting from 2019 to 2040 on the basis of the current level of CO2 emissions resulting from technological advancement in the manufacturing and industrial sectors in Bangladesh. (Belbute and Pereira, 2020) did provide reference forecasts for CO2 emissions from burning fuel fossil and cement production in Portugal based on an ARFIMA model approach and using yearly data from 1950 to 2017 with their reference projections suggesting a pattern of decarbonisation that will cause the reduction of 3.3 Mt until 2030 and 5.1 Mt between 2030 and 2050. Energy consumption also does influence carbon emissions so is economic growth and technological advancement. The relationship of energy consumption, economic growth and carbon dioxide (CO2) emission was investigated in the context of the Environmental Kuznets Curve by (Ardakani and Seyedaliakbar, 2019). (Saeed Meo and Karim, 2022)Used the quantile on quantile regression (QQR), to examine the dependence structure between different quantiles of green finance and CO2 emissions. (Cai *et al.*, 2021) developed an integrated CO2 emission pathway model (Chinese Academy of Environmental Planning Carbon Pathways 1.2 model), a pathway model that coupled the top–down and bottom–up methods and conducted optimization analysis under social fairness and optimal cost conditions with results providing a clear CO2 emission pathway and offer insights for implementing fine management of CO2 emissions at the national, regional, sectoral, and spatial gridded levels. (Yu *et al.*, 2019) came about a predictive control of CO2 emissions via modelling the correlations between CO2 emissions from a grate boiler and fuel nature structure. (Lovcha, Perez-Laborda and Sikora, 2022) developed a model that can be used as a monitoring tool for carbon price dynamics. This model links the energy sector (oil, natural gas, coal, electricity prices, and the share of fossil fuels in electricity generation), economic activity, and the carbon price. It was represented empirically through a Structural Vector Auto regression and frequency-domain analysis was used to distinguish the effects of changes in fundamental factors from shocks to market microstructure.

This study is centred on projecting CO2 emissions using linear regression and with this results we can work on a pathway towards achieving zero emissions and a greener environment in Africa.

Data:

Carbon emission not only create environmental damage but does threaten the global ecosystems also and from this knowledge, we did select nine West African countries (Benin, Ghana, Guinea, Burkina Faso, Ivory Coast, Mali, Niger, Nigeria and Senegal) considering the uniformity and consistency in their rate of CO2 emission compared to other west African countries with quite low values and their GDP (gross domestic product) based on an analysed relationship between GDP and CO2 emission. (Ameyaw and Yao, 2018) revealed that there exist a unidirectional causality running from GDP to CO2 emission. To every increase in per capita GDP, there is an increase in the level of CO2 emission (Snöbohm, 2018).

Data Source – https://ourworldindata.org

Block diagram of proposed methodology

Year

Population

Annual CO2 Emission

GDP Per Capita

Fossil Fuel (% of electricity)

Carbon Intensity

Annual CO2 Emissions Per Unit Energy

**Target**

CO2 emissions per unit energy

**Forecast the variables using**

Linear Regression

Multivariate Analysis

**Create a forecasting function for each predictors**

**Create Correlation Matrix**

**Select the output with the best index**

**Develop Regression Model**

Multiple Regression Model

**Forecasted CO2 Emission**

(2021 – 2050)

Block diagram of proposed methodology – Block diagram of proposed methodology –

Methodology

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Predicted Future CO2 Emission** | | | | | | | | |
| **Benin** | **Ghana** | **Guinea** | **Burkina Faso** | **Ivory Coast** | **Mali** | **Niger** | **Nigeria** | **Senegal** |
| 7947499.45 | 4808504.13 | 18684081 | 3866771.87 | 11398041.5 | 4117242.58 | 2353197.87 | 142355419.6 | 12588037.4 |
| 8357734.22 | 5119727.04 | 19526163.7 | 4101420.81 | 11773056.9 | 4323097.51 | 2482108.03 | 145897099.6 | 13271215.2 |
| 8778706.81 | 5442118.04 | 20391307.6 | 4352644.88 | 12158690.1 | 4534255.6 | 2615473.26 | 149438779.5 | 13978772.7 |
| 9210417.2 | 5775677.12 | 21279512.7 | 4621159.88 | 12554941 | 4750716.85 | 2753293.57 | 152980459.5 | 14710710.1 |
| 9652865.42 | 6120404.3 | 22190778.8 | 4907681.59 | 12961809.5 | 4972481.26 | 2895568.96 | 156522139.5 | 15467027.3 |
| 10106051.4 | 6476299.56 | 23125106.2 | 5212925.8 | 13379295.8 | 5199548.82 | 3042299.43 | 160063819.4 | 16247724.3 |
| 10569975.3 | 6843362.92 | 24082494.6 | 5537608.3 | 13807399.8 | 5431919.54 | 3193484.97 | 163605499.4 | 17052801.1 |
| 11044636.9 | 7221594.36 | 25062944.2 | 5882444.87 | 14246121.4 | 5669593.42 | 3349125.59 | 167147179.4 | 17882257.6 |
| 11530036.4 | 7610993.9 | 26066454.9 | 6248151.3 | 14695460.8 | 5912570.45 | 3509221.29 | 170688859.3 | 18736094 |
| 12026173.7 | 8011561.52 | 27093026.8 | 6635443.39 | 15155417.9 | 6160850.64 | 3673772.07 | 174230539.3 | 19614310.2 |
| 12533048.8 | 8423297.23 | 28142659.8 | 7045036.91 | 15625992.6 | 6414433.99 | 3842777.92 | 177772219.3 | 20516906.2 |
| 13050661.7 | 8846201.04 | 29215353.9 | 7477647.65 | 16107185.1 | 6673320.49 | 4016238.86 | 181313899.3 | 21443882 |
| 13579012.4 | 9280272.93 | 30311109.2 | 7933991.41 | 16598995.3 | 6937510.15 | 4194154.87 | 184855579.2 | 22395237.6 |
| 14118101 | 9725512.91 | 31429925.7 | 8414783.96 | 17101423.1 | 7207002.97 | 4376525.95 | 188397259.2 | 23370973 |
| 14667927.3 | 10181921 | 32571803.2 | 8920741.1 | 17614468.7 | 7481798.95 | 4563352.12 | 191938939.2 | 24371088.2 |
| 15228491.5 | 10649497.1 | 33736741.9 | 9452578.62 | 18138131.9 | 7761898.08 | 4754633.36 | 195480619.1 | 25395583.2 |
| 15799793.5 | 11128241.4 | 34924741.8 | 10011012.3 | 18672412.9 | 8047300.37 | 4950369.68 | 199022299.1 | 26444458 |
| 16381833.3 | 11618153.7 | 36135802.8 | 10596757.9 | 19217311.6 | 8338005.82 | 5150561.08 | 202563979.1 | 27517712.6 |
| 16974610.9 | 12119234.2 | 37369924.9 | 11210531.3 | 19772827.9 | 8634014.43 | 5355207.56 | 206105659 | 28615347 |
| 17578126.3 | 12631482.7 | 38627108.1 | 11853048.2 | 20338962 | 8935326.19 | 5564309.11 | 209647339 | 29737361.2 |
| 18192379.5 | 13154899.3 | 39907352.5 | 12525024.4 | 20915713.7 | 9241941.11 | 5777865.74 | 213189019 | 30883755.2 |
| 18817370.6 | 13689484 | 41210658.1 | 13227175.7 | 21503083.2 | 9553859.18 | 5995877.45 | 216730699 | 32054529 |
| 19453099.5 | 14235236.8 | 42537024.8 | 13960217.8 | 22101070.4 | 9871080.42 | 6218344.24 | 220272378.9 | 33249682.6 |
| 20099566.1 | 14792157.7 | 43886452.6 | 14724866.7 | 22709675.2 | 10193604.8 | 6445266.1 | 223814058.9 | 34469216 |
| 20756770.6 | 15360246.6 | 45258941.6 | 15521838 | 23328897.8 | 10521432.4 | 6676643.04 | 227355738.9 | 35713129.2 |
| 21424712.9 | 15939503.7 | 46654491.7 | 16351847.6 | 23958738 | 10854563.1 | 6912475.06 | 230897418.8 | 36981422.2 |
| 22103393.1 | 16529928.9 | 48073102.9 | 17215611.2 | 24599196 | 11192996.9 | 7152762.16 | 234439098.8 | 38274095 |
| 22792811 | 17131522.1 | 49514775.3 | 18113844.6 | 25250271.6 | 11536733.9 | 7397504.33 | 237980778.8 | 39591147.6 |
| 23492966.7 | 17744283.4 | 50979508.8 | 19047263.6 | 25911965 | 11885774.1 | 7646701.59 | 241522458.8 | 40932580.1 |
| 24203860.3 | 18368212.8 | 52467303.5 | 20016584 | 26584276 | 12240117.4 | 7900353.91 | 245064138.7 | 42298392.3 |

Table: predicted values

Table: Independent Variables Not Considered For CO2 Forecast

Analysis and Discussions

Abbreviations

RMSE – Root Mean Square Error

FF – Fossil Fuel

GDP – Gross Domestic Product

Conclusion and recommendation

References

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