

Carbon Emission Forecasting using ARIMA

Anshumaan Phukan¹, Varad Vinayak Godse²

¹ Dept. of Computer Science Engineering, Bennett University, Greater Noida, Uttar Pradesh, India

² Dept. of Computer Science Engineering, Bennett University, Greater Noida, Uttar Pradesh, India

Abstract - Global warming has become a growing concern in recent times. The root cause of the problem directs toward carbon emissions in the form of greenhouse gas. The increasing human activities intervene in the earth's natural carbon-absorbing capacity. It leads to unwanted situations like the melting of ice caps, increasing sea levels, extreme weather conditions, and many others. The contributors to carbon emissions vary across industries ranging from electricity and heat production, transportation, agriculture, forestry, fossil fuel, and many more.

The idea behind our project is to run a prediction, analysis, and forecasting system over datasets related to carbon emissions. We will focus on certain core factors causing carbon emissions. It would include trends over the years, maximum and minimum contributors, etc. The analysis can be a foundation for predicting the future trends of these contributors.

1. INTRODUCTION

1.1 PROBLEM AND MOTIVATION

The distribution of carbon emissions across sectors has different aspects and consequences. It is essential to concentrate on the existing numbers and statistics to understand the scale of the issue.

According to the article from World Resources Institute, agriculture has become the second-largest emitter by releasing 6 billion tons of greenhouse gases. The emissions increased by 8 percent from 1990 to 2010, with a projection of a 15 percent rise till 2030. The sources range from fuel use on farms, fertilizers, manure management, urea, field burning of crop residue.

1.2 BACKGROUND KNOWLEDGE

Transportation has become a large-scale contributor as well. The data from Oxford Martin School account for transportation for around one-fifth of carbon dioxide (CO₂) emissions. A majority of it comes from passenger vehicles like cars, and buses- about 45.1%. The entire transportation sector involving road, air, and rail travel

contributes to 21% of total carbon emissions. The use of gasoline (fossil fuel) engines across vehicles has become the root cause.

Electricity is a widely used resource across industries and daily life. Its production from primary energy sources like coal, uranium, and natural gas contributes to emissions. According to a report from Planete Energy, electricity forms 42.5% of CO₂ emissions. From this the amount, 41 % is produced from coal, 16% from hydropower, 22% from gas, 11% from nuclear power, and 10% percent from oil and renewables. The growing population and technology have triggered an exponential need for electricity. It has caused growing concerns.

The carbon emissions from commercial and residential construction materials have become prominent as well. A report from nature communications sees a rapid emission increase of 750 Mt(22% globally) in 2020. It predicts the range of emissions to be 3.5 to 4.6 Gt in the upcoming 30 years.

The statistical numbers of the contributors are significantly large. The current scenario hints at the growing concerns of the future. The idea behind our effort will be to use the latest technology for developing an analysis and prediction model that provides concrete insights over different contributors.

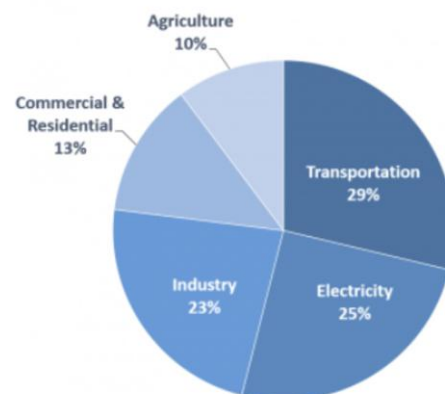


Fig. 1. Top industries responsible for emissions

As seen in the scan to the right, the patient has abnormal tissue in the brain, which can be spotted as a white highlight towards the center of the scan. Unique patterns such as these can be used to detect any malignant in the brain, further helping us classify whether the brain is abnormal.

2. RELATED WORK

CO2 emissions is a big problem all around the planet. There are numerous studies begin conducted to reduce the CO2 emissions. There is an urgent need for a system that can estimate CO2 emissions and allow us to take appropriate actions to minimise the CO2 emissions. IN order to solve this problem machine learning can be used. The process of creating algorithms which can improve through experience is known as machine learning. For example, training a model which could automatically recognise fraud mails. Some models for prediction of CO2 emissions have been created employing machine learning.

In 2015 Researcher Chairul Saleh created a model which predicted the CO2 emissions that make use of the Support Vector Machine algorithm in machine learning. Coal combustion and electrical energy were the input parameters for the model, both of which play a major role in CO2 emissions. In order to evaluate and train the model, the data from the Alcohol industry was obtained. In May of 2017, another team of researchers developed a model that described the quantity of CO2 released during the manufacturing of raw milk. Data from various milk manufacturing processes such as dairy processing and packaging waste disposal were provided to the model for predictions of CO2 emissions. According to the findings of the research, 1120 g CO2 is released per litre in manufacturing of raw milk products.

3.SYNOPSIS OF DATA

The trends in carbon emissions depend on certain baseline core factors that cause larger impacts.

The core factors vary as below-

- 1)Coal Sector (CO2 Emissions)
- 2)Natural Gas Sector CO2 Emissions
- 3)Distillate Fuel, Including Kerosene-Type Jet Fuel, Oil Sector CO2 Emissions
- 4)Petroleum Coke Sector CO2 Emissions
- 5)Residual Fuel Oil Sector CO2 Emissions
- 6)Petroleum Sector CO2 Emissions

7)Geothermal Energy Sector CO2 Emissions

8)Non-Biomass Waste Sector CO2 Emissions

9)Total Energy Sector CO2 Emissions

The use of coal across various industries grew to 45 % globally between 2001 and 2010. The burning of coal to generate steams to run turbines for electricity, as a raw material for agricultural fertilizers, as core material for cement production in constructions, as a combustion source in railway and water transport made it a prominent source of carbon emissions.

It is responsible for 46% of global carbon emissions and 72% of total Green House Gas(GHG) emissions.

The emissions from natural gas are comparatively low but account for around half of what is caused by coal. A widescale use for generating electricity(steam generation units), fuel for transport (Compressed Natural Gas- CNG), heat for buildings, household use(refrigerator cooling), agriculture inputs(Pesticides, fertilizers, irrigation- cheaper than electricity) has caused a 43 percent increase since 2005. Although it contributes less compared to coal, it requires significant attention.

Distillate fuels are fractions of petroleum formed as a result of distillation subdues. It includes diesel fuels, jet fuel, and fuel oil(marine fuel, furnace oil, heavy oil). In 2021, the sector emitted 81.92 metric tons of carbon. It causes emissions almost four times that of petroleum. The recent days witnessed limited use of diesel vehicles(not including heavy vehicles) and purer alternatives for jet and marine fuels.

Petroleum coke is a carbon-rich by-product of crude oil refining. Its use in the aluminum industry, graphite electrodes for the steel industry, and fuel for cement kilns has caused growing concerns. It emits more greenhouse gases and air pollutants than raw coal. China initiated the early use, with an 18.9 percent rise between 2010-and 2016. The economic advantages of petroleum coke benefit many industries across the globe.

Petroleum is a widely used resource across industries and daily lives. A largescale application as fuel for vehicles extends to ammonia for fertilizers, heating furnaces, petrochemical industry, and Lubricants. It also produces many harmful by-products. The sector emitted 1.22 million metric tons of carbon dioxide in 2013. In 2020, a 6.3 percent decline in emissions marked the growth rate over the decade.

Geothermal energy uses heat from the earth's core by producing minimal waste products. It emits 38 grams of Carbon dioxide per kilowatt of electricity produced. The minimal emissions from the sector introduce the need to monitor to avoid overexploitation.

Non-biomass sectors like nuclear energy produce zero carbon emissions, but the production processes (extraction and transport of uranium, nuclear waste generation) cause harmful effects.

4. INTRODUCTION

Approach

We plan to achieve our goal by using a combination of machine learning and neural networks to forecast carbon emissions based on meaningful data.

Hypothesis testing would play a prominent role in our data analysis section. Hypothesis testing is a type of statistical method of drawing conclusions about a probability distribution or population parameter using data from a designated sample. It would be useful for our scenario because it allows us to evaluate 2 mutual exclusive statements, create an assumption and perform statistical analysis to reject or accept the hypothesis. In our use case, tests such as the Chi-Square test, T-Test, and Anova Test will be used. The null hypothesis, abbreviated as H_0 , would be our assumption. If statistical testing rejects our null hypothesis, we will define an alternate hypothesis. As a result, we can clearly deduce the relationships between individual carbon emission variables and total emission levels using these methodologies.

After understanding our data, the necessary feature engineering and selection procedures would be followed to ensure our model can predict carbon emissions with maximum accuracy. Techniques like mutual info index, correlation matrix, and variance threshold would play a huge role in selecting features that affect our prediction the most. Taking too many useful features can also result in a dimensionality curse. Feature extraction techniques like principal component analysis could help us in reducing dimensions by creating eigenvalues and eigenvectors. After acquiring the preprocessed data, numerous statistical models and neural networks will be trained on it. This study will employ models such as linear regression, polynomial regression, locally weighted regression, KNN, naive Bayes, SVM with different kernels, ensemble approaches with different base learners, and ANN. The base machine learning models like regression

The data is from the US Energy Information Administration, and it is a time series data that spans from January 1973 to July 2016. It is a comprehensive collection of carbon emission values spanning several years and involves various energy sectors such as geothermal energy, natural gas, petroleum coke, and so on. With the use of such data throughout constant time intervals, we may run carbon emission forecasting models like ARIMA. It would be useful in cases when vital decisions must be made based on predicted emission values.

will be our introductory approach, which would be followed by the implementation of advanced techniques. If the scatter plot portrays clear subdivisions among our dataset, models like KNN and SVM would be our first priority. Bagging and boosting ensemble techniques like decision tree, AdaBoost, gradient boost, and xgboost will help us combine several base models to produce one optimal predictive model. These techniques are also called as free lunch model as no single model wins. The aim of ensemble models is to build strong learning based on weak learners.

The final model would be the custom neural network with different experimental optimizers, activation functions, and weight initialization techniques. Finally, we will perform a detailed investigation of our findings and discoveries using visualizations and hyperparameter tuning to determine the parameters and model combinations that will provide the best forecast.

5. PROPOSED METHODOLOGY

The dataset consists of time-series data points collected at constant time intervals. The time-dependent or dynamic nature of the problem requires time-series modeling. It is a powerful tool for extracting current data and making future predictions and forecasting.

The overview of the steps for the final output involves the retrieval of the CSV time-series data, transforming or pre-processing of the data for suitable input, visualizing the data, applying different methods for testing whether it is stationary, transforming time-series data to stationary, finding optimal parameters to build SARIMA model, diagnosing, and validating the predictions and forecasting.

RETRIEVAL

The `read_csv` function of pandas extracts the data in the form of a data frame. The `info()` function provides specifications describing 5096 observations with six columns. The data type of four columns is an object, while two have an integer. The current data frame does not

represent a time series. The `read_csv` function needs specialized arguments to bring the data in the form of time series. The arguments go as follows-

- `parse_dates`: Identifies the key for the date-time column. The initial dates come in string format. For example 'YYYYMM'
- `index_col`: Shifts DateTime column into index column.
- `date_parser`: Converts an input string into a DateTime variable.

Further pre-processing involves dropping null rows and null values in the index column using functions like `notNull()` and `dropNa()`. The `coerce` property with setting errors converts columns to float and fills problematic entries with `Null(NaN)`. The `to_numeric` function converts the emission value column from object to numeric.

ANAYLYSIS

TEST STATIONARY

The dataset is analyzed to observe any trends and seasonality. The presence makes it nonstationary data. The removal of nonstationary elements converts the dataset into stationary. The residuals from the process form the base for further analysis.

Stationary Process- A stationary process has a probability distribution that remains unchanged with time. The parameters like mean and variance do not change over time.

The most common violation of stationarity comes from trends in mean. If the cause of non-stationarity is the unit root, then it is not mean-reverting. If it is a deterministic trend, it can transform to stationarity.

The analysis occurs with a single category of Natural gas CO2 emissions. The same steps can repeat for others.

The `group-by` function creates data frames with columns corresponding to the categories and having emission values. The index column has date-time entries.

GRAPH METHOD

The `plot` method from `Matplotlib` generates a graph. It has emission values on the y-axis and `DateTime`(in years) data on the x-axis. The structure and trends of the plot can help to observe stationarity.

DICKY-FULLER TEST

The test considers a null hypothesis. In this case, the null hypothesis is- that the time series is nonstationary. A Test statistic gets compared with critical values at different confidence values. If the critical value exceeds the Statistic, the null hypothesis gets rejected. The time series is stationary.

The opposite case accepts the null hypothesis keeping the time-series data non-stationary.

The `Adler` function from python takes the data and lag parameters. A lag describes the delay time between two sets of observations. Methods like Akaike Information Criterion(AIC) determine the optimal number of lags. The auto lag parameters set the number of lags to minimize the AIC.

The test provides a p-value which gets compared to the user-provided cutoff.

It also gives a test statistic that compares critical values at different confidence levels.

CONVERSION TO STATIONARY

The technique focuses on taking the mean of a set of consecutive values.

We target a yearly trend that requires an average of 12 consecutive values or months. The value in each entry in the column is the mean of the previous 12 values. The first 11 values remain null as they do not have a sufficient number of values prior(12). The original data gets subtracted from the new data of the moving average. It gets tested through the dicky fuller test that tells whether the conversion to stationarity is successful.

The technique uses the rolling method from python.

Adding seasonal terms to an ARIMA model results in a model called SARIMA. This model is characterized by 3 terms:

P: order of the auto regressive term

Q: order of moving average term

D: number of differencing required to convert non stationary time series data to stationary.

When a seasonal ARIMA model needs to be fitted, our goal should be to determine the parameters that are responsible for optimizing the metric of interest. While implementing

seasonal ARIMA, we considered two possible scenarios. First one being a stationary time series data with no dependence. In this case, residuals were modeled as white noise. The second case would involve a time series data with noticeable dependence among values. We specifically needed to implement statistical model like ARIMA in the second scenario.

For forecasting stationary time series data, the ARIMA model, which is a linear function akin to linear regression, is commonly utilized.

For finding optimal parameters, we implemented two major techniques: Plotting of ACF and PACF curve. Autocorrelation Function and Partial Autocorrelation Function are both responsible for measuring correlation between ts (time series) with a lagged version of itself. But in the case of PACF, elimination of variations are already explained beforehand by intervening comparisons. As a result, these two graphs will be used to determine the model's tuning parameters (p and q).

Second method involves Grid Search for optimizing parameters. This method was included as it a more systematic approach compared to the previous one. It is an iterative technique of exploring all possible combination of parameters of our forecasting model. Seasonal ARIMA model will be fitted all combinations. After exploration, parameters that yield the best performance will be opted. A function called SARIMAX() was used in our case to perform hyperparameter optimization.

6.RESULTS

STATIONARITY

The result of the first adder fuller test yielded a greater value of -1.827631 for Test Static compared to the critical values at different confidence levels. The initial critical value was set at 0.01. The confidence levels were set at 95, 90%, 99%. It means 5%(-2.867303), 10%(-2.569840) and 1% (-3.443418)of the critical value.

```
In [90]: TestStationaryAdfuller(mte)
(-1.827630925557218, 0.36683253565669094, 14, 508, {'1%': -3.44328828958775, '5%': -2.8672462791357867, '10%': -2.569809231353463}, 3113.7276283046313)
Test Statistic          -1.827631
p-value                 0.366833
#Lags Used              14.000000
Number of Observations Used  508.000000
Critical Value (1%)     -3.443288
Critical Value (5%)     -2.867246
Critical Value (10%)    -2.569809
dtype: float64
Weak evidence against null hypothesis, time series has a unit root, indicating it is non-stationary
```

The moving average method results in test static(-5.985419e+00) lesser than critical values 10%(-2.569840), 1% (-3.443418) and 5%(-2.867303)

```
: TestStationaryAdfuller(mte_moving_avg_diff)
(-5.98541893268373, 1.797036297199716e-07, 14, 497, {'1%': -3.4435761493506294, '5%': -2.867372960189225, '10%': -2.5698767442886696}, 2960.293244266059)
Test Statistic          -5.985419e+00
p-value                 1.797036e-07
#Lags Used              1.400000e+01
Number of Observations Used  4.970000e+02
Critical Value (1%)     -3.443576e+00
Critical Value (5%)     -2.867373e+00
Critical Value (10%)    -2.569877e+00
dtype: float64
Strong evidence against the null hypothesis, reject the null hypothesis
. Data has no unit root, hence it is stationary
```

EVALUATION

For performing evaluation, we first plotted the **Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)** curve for our seasonal ARIMA model. As finding the optimal parameters manually graphs is time consuming, we opted for grid search method. Using this method, we explored each and every possible combination of parameters possible. When analyzing and comparing statistical models with various parameters, each can be rated against the others based on how well they fit the data or their ability to properly forecast future data points. A statistical value called AIC was used for the scenario. For this example, we are taking emission values only for Coal Electric Power Sector. The Akaike Information Criterion value measures how well a model fits our training data. It is calculated using the number of independent variables, and the maximum likelihood estimate of the model. AIC values are only useful in comparison scenarios. A lower score of AIC indicates our model is performing well. After performing hyperparameter tuning through grid search, the SARIMAX

(1, 1, 1)x(0, 1, 1, 12) yielded the lowest AIC score of 2003.553. Hence, we considered these conditions for our proposed model. Next step we went for in-depth analysis of the model with the above-mentioned parameters.

```

=====
SARIMAX Results
=====
Dep. Variable:    Coal Electric Power Sector CO2 Emissions    No. Observations:    523
Model:           SARIMAX(1, 1, 1)x(0, 1, 1, 12)             Log Likelihood       -1470.285
Date:            Tue, 26 Apr 2022                            AIC                  2948.569
Time:            20:14:58                                    BIC                  2965.396
Sample:         01-31-1973                                    HQIC                 2955.174
                - 07-31-2016
Covariance Type: opg
=====
                coef    std err          z      P>|z|    [0.025    0.975]
-----
ar.L1            0.6117    0.049    12.610    0.000    0.517    0.707
ma.L1           -0.8883    0.027   -32.509    0.000   -0.942   -0.835
ma.S.L12        -0.7584    0.028   -26.667    0.000   -0.814   -0.703
sigma2          21.7666    1.166    18.660    0.000   19.480   24.053
=====
Ljung-Box (L1) (Q):    0.07  Jarque-Bera (JB):    29.14
Prob(Q):              0.79  Prob(JB):             0.00
Heteroskedasticity (H): 2.69  Skew:                 -0.32
Prob(H) (two-sided):  0.00  Kurtosis:             4.00
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
    
```

Fig: State-space model result for Coal Electric Power Sector

The next analysis would plot the residual errors for our seasonal ARIMA model.

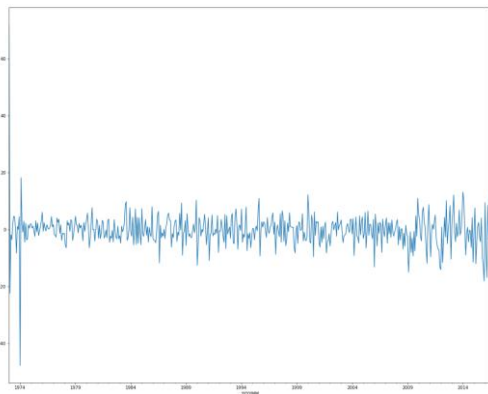


Fig: Residual errors for SARIMA for coal power generation

The residual error distribution is depicted in the diagram. It shows that the prediction is a little skewed.

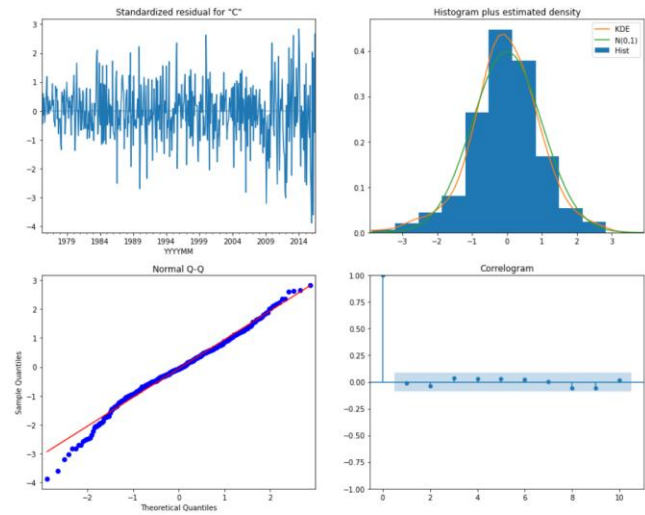


Fig: Diagnostic Plot

The red KDE line in the top right plot closely resembles the N(0,1) line. This indicates the residual residuals are normally distributed. However, we can observe some deviations in the straight line, indicating the normal distribution is not perfect for the distribution of errors in the forecast, but it is defiantly acceptable. The qq-plot at the bottom left again indicated our residuals are normally distributed.

After we obtained our model for time series forecasting, we started comparing the predicted and real values of the data. We got the values and accompanying confidence intervals for time series forecasts using the get prediction() and conf_int() properties.

	lower Natural Gas Electric Power Sector CO2 Emissions	upper Natural Gas Electric Power Sector CO2 Emissions
2013-01-31	30.203834	37.257324
2013-02-28	29.088380	36.141870
2013-03-31	28.958984	36.012474
2013-04-30	30.708073	37.761563
2013-05-31	32.104079	39.157569

Fig: One step ahead forecast

The table above portrays one-step forecasts at each point using the entire historical data until the current point.

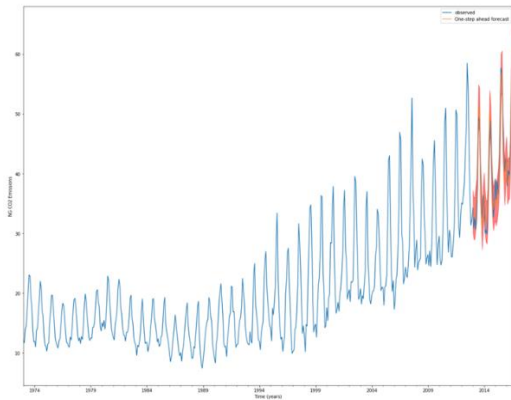


Fig: Real vs Forecasted values of CO2 emissions for coal power generation

Overall, our forecasts closely match the true numbers, indicating a similar pattern of behavior.

The model we built gave us an MSE score of 14.39 and an

RMSE score of 3.7936, which is fairly low. The model's purpose was to achieve high-quality predictive power through dynamic forecasting.

FORECASTING

The `get_forecast` method undertakes the total number of steps to forecast. The `conf_init()` method provides confidence intervals. A confidence interval has a set of values within which the parameter can lie.

The data from the above function is used to draw the plots to display the forecast for different categories.

The highlighted area in green color represents the other possible variations in the forecasted values. The forecasting model performs better when it is less.

The natural gas forecast shows an upward trend for the next ten years. The green area remains shorter as a result of a good prediction.

The coal forecast shows a downward trend highlighting the decreased use of coal in the future. The shorter green area corresponds to a good prediction.

The distillate fuel category witnesses a slightly decreasing but almost constant trend. The larger green area suggests more variations in the forecasted line.

The petroleum category witnesses a slightly decreasing trend.

It consists of variations in the forecasted line.

The total energy plot combining every sector shows a downward trend with negligible variations.

7.CONCLUSION

The categories like natural gas and coal are used widely and have led to environmental consequences. The growing trend in natural gas is alarming, but a decreasing trend in coal highlights an improved scenario.

Other categories like petroleum and distillate have constant growth.

The patterns and trends forecasted by the model prove essential as it helps to understand the future. The global aim of achieving net carbon emission to zero by 2050 needs continuous analysis and predictions over the current scenarios. The current emission trend might seem constant or decreasing, but the situation will deteriorate because the present emissions have effects in the far future. Hypothetically, if we reduce the net emissions to zero at once, the impact of recent emissions will trigger the problem again.

The use of technology to analyze datasets for generating insights plays a significant role. The various machine learning techniques extended by python libraries help run efficient and useful predictions and forecasts.

We focussed on the techniques to generate a forecasting analysis that is useful to environmentalists, researchers, and others working towards the cause.

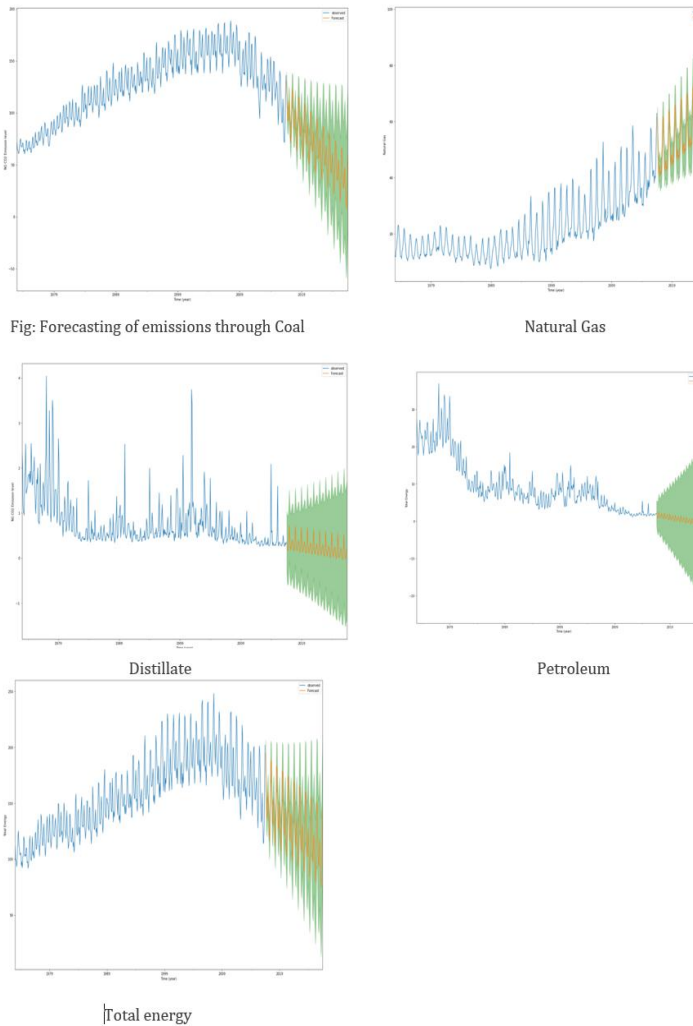


Fig: Forecasting of emissions through Coal

Natural Gas

Distillate

Petroleum

Total energy

- <https://www.machinelearningplus.com/time-series/augmented-dickey-fuller-test/>
- <https://machinelearningmastery.com/moving-average-smoothing-for-time-series-forecasting-python/>
- <https://neptune.ai/blog/select-model-for-time-series-prediction-task>
- <https://towardsdatascience.com/identifying-ar-and-ma-terms-using-acf-and-pacf-plots-in-time-series-forecasting-ccb9fd073db8?gi=e940575f86f8>
- <https://www.yourdatateacher.com/2021/05/19/hyperparameter-tuning-grid-search-and-random-search/>
- <https://robert-alvarez.github.io/2018-06-04-diagnostic-plots/>
- https://pandas.pydata.org/docs/reference/api/pandas.read_csv.html

REFERENCES

- <https://www.wri.org/insights/4-charts-explain-greenhouse-gas-emissions-countries-and-sectors>
- <http://www.annualreviews.org/doi/abs/10.1146/annurev-environ-032310-112100>
- <https://www.planete-energies.com/en/medias/close/electricity-generation-and-related-co2-emissions>
- <https://machinelearningmastery.com/arima-for-time-series-forecasting-with-python/>