

# A Study on Sector-Wise Carbon Dioxide Emission Prediction Using Arima Model

**D. Helen\*, V. R. Elangovan, V. Nisha, J. Devagnanam, M. Ganesh Raja**

<sup>1\*</sup> Assistant Professor, Department of Computer Applications, Faculty of Science and Humanities,  
SRM Institute of Science and Technology, Kattankulathur, Chennai-603203, India.  
Email:helensaran15@gmail.com

<sup>2</sup> Assistant Professor, Department of Computer Applications, Faculty of Science and Humanities,  
SRM Institute of Science and Technology, Kattankulathur, Chennai-603203, India Email  
elangovv1@srmist.edu.in

<sup>3</sup> Assistant Professor, Department of Computer Applications, Faculty of Science and Humanities,  
SRM Institute of Science and Technology, Kattankulathur, Chennai-603203, India. Email:  
nishav@srmist.edu.in

<sup>4</sup> Assistant Professor, Department of Computer Applications, Faculty of Science and Humanities,  
SRM Institute of Science and Technology, Kattankulathur, Chennai-603203, India. Email:  
devagnaj@srmist.edu.in

<sup>5</sup> Assistant Professor, Department of Computer Science, Dhanraj Baid Jain College, Chennai 600097,  
Email :Ganeshraja888@gmail.com

Article Received: 15 Feb 2025,      Revised: 10 April 2025,      Accepted:08 May 2025

## ABSTRACT

Timely prediction of Carbon Dioxide (CO<sub>2</sub>) emissions is significant for climate change mitigation and sustainable environmental planning. The study uses ARIMA model for forecasting the sectorial CO<sub>2</sub> emissions. Long-term CO<sub>2</sub> emissions were examined for the six different sectors: power, industry, transport, residential, domestic and international aviation industry based on historical CO<sub>2</sub> emissions dataset. The Augmented Dickey-Fuller test is performed to assess the stationarity of the time series dataset, and Autoregressive Integrated Moving Average (ARIMA) model is selected for CO<sub>2</sub> emission prediction. Several ARIMA (p, d, q) formations were examined for each sector, and the best suitable parameter are recognised and the model is evaluated based on various performance metrics including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The results shows the emission trends across various sectors and offers reliable statistical substance for forecasting future emissions. This study supports data-driven decision-making for environmental policy makers and contributes to the broader discourse on climate resilience and sustainable development.

**Keywords:** carbon dioxide (CO<sub>2</sub>) emissions, ARIMA, Augmented Dickey-Fuller , climate resilience

## 1. INTRODUCTION

Climate change is one of the world's top issues, and Carbon Dioxide (CO<sub>2</sub>) emission is one of the major reason for global warming and environmental damage (Rabajczyk & Rabajczyk, 2021). Humans causes CO<sub>2</sub> emissions by various activities such as the combustion of fossil fuels for industrial growth, energy consumption, transport, and residential energy consumption (Lyngfelt, 2001). Accurate assessment of CO<sub>2</sub> emissions is critical for policy makers and

environmental organizations to formulate effective plans, evaluate mitigation policies, and ensure compliance with international climate treaties (Aresta, 2010). Time series prediction techniques, Autoregressive Integrated Moving Average (ARIMA) method are effective for modelling and predicting environmental data patterns over time. ARIMA models do account for the linear dependencies and trends in time series data, so it is suitable to forecast emissions data for different sectors.

## 2. LITERATURE REVIEW

The study proposed ARIMA model to predict CO<sub>2</sub> emissions in India from 1990 to 2023. By using the Box–Jenkins method, it assures accurate predictions by retrieving data stationarity through the Augmented Dickey–Fuller test and choose the models based on the Akaike Information Criterion (AIC). The findings demonstrate the ARIMA model effectiveness in predicting CO<sub>2</sub> emissions which provides valuable information to assist in decision making process (Hrithik et al., 2024). The research paper implemented ARIMA method to estimate carbon dioxide (CO<sub>2</sub>) emissions in India from 1980 to 2021. The study shows that ARIMA model effectively capture the trend and seasonality of emissions. This indicates the increase in carbon emissions in spite of reduction efforts that has important influence for renewable energy production (Sharma et al., 2024). The paper propose Autoregressive Integrated Moving Average (ARIMA) techniques for estimating CO<sub>2</sub> emission. The paper proposed Discrete Wavelet Transform (DWT-ARIMA) for CO<sub>2</sub> emission prediction. And the proposed Discrete Wavelet Transform (DWT-ARIMA) was compared with the traditional ARIMA model. The results shows that the Discrete Wavelet-ARIMA model forecast CO<sub>2</sub> emission more accurately and provide valuable insights for decision-makers in environmental protection efforts. The research study uses ARIMA approach to examine and predict CO<sub>2</sub> emissions in aluminum industry from 2005 to 2030. The ARIMA model access for meticulous assessments of emission patterns, revealing an anticipated reduction in CO<sub>2</sub> emissions within the aluminum sector. The result aims to offer guidance for sustainable policy measures and contribute to minimize the environmental impacts associated with aluminum production, solving the challenges related to climate change (Hasanov et al., 2024). The study uses the Box-Jenkins ARIMA model to predict carbon dioxide (CO<sub>2</sub>) emissions in Morocco from 1928 to 2020. It defines that the time series data was stationary, apply ARIMA model and finds the best fit for the data. The study estimated a continuous growth in CO<sub>2</sub> emissions in the period between 2021 and 2040, emphasising the efficiency of ARIMA in long-term emissions forecasting (Jamii et al., 2021). The paper proposed ARIMA model to forecast regional carbon emissions by accessing time series data related to population, economy, and energy consumption. This statistical approach identifies the trends in carbon emissions over time, assisting the preparation of effective carbon reduce strategies. By incorporating ARIMA with the Kaya model, the research shows a novel predictive framework which assists in understanding the CO<sub>2</sub> emissions in specific regions (Wang et al., 2023).

## 3. RESEARCH METHODOLOGY:

### 3.1 Dataset :

This dataset provides the detailed information about CO<sub>2</sub> emissions across various countries, emphasizing particular sectors and temporal trends. The dataset contains 1,35,408 entries and 6 features, encompassing information about combination of country, sector, and CO<sub>2</sub> emission values, organized by date and timestamp. The features are Date, Country, Sector, Value, Timestamp, Year.

### **3.2 Data Pre-processing:**

In order to achieve time series analysis the Unix timestamp converted into date time format which allows to perform time series analysis. The resampling method is applied to obtain the aggregate the co2 emission data based on the month. The conversion is important to analyse the patterns, trends and seasonal affects over the time.

### **3.3 ARIMA Model:**

ARIMA model is one of the optimal tools widely uses statistical mechanism for predicting future value based on the historical dataset within time series data (Luceño & Peña, 2008). The ARIMA model using three key elements: Autoregression (AR), it denoted by  $p$ . It narrates the dependency of current value to its previous values through a regression equation. Differencing, it is denoted by  $d$ . It performs the differencing to change the non-stationary into stationary in time series data to make it stationary, one by differencing consecutive observations. Moving Average (MA), it represented by  $q$ . It defines the dependency among current observation and previous residual errors. The proposed paper, utilized the Autoregressive Integrated Moving Average (ARIMA) model for forecasting the CO<sub>2</sub> emission value based on time-series dataset.

### **ARIMA Model Implementation**

#### **Algorithm:**

- 1.1 Load the Dataset CO<sub>2</sub> emission dataset
2. Resample the Data to a Monthly Frequency, Consolidate the data by summing the total emissions for every month
3. Check Stationarity of the Data, perform the Augmented Dickey-Fuller (ADF) test for stationarity
4. Plotting ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) used to inspect appropriate  $p$  and  $q$  values.
5. Building the ARIMA Model, define the ARIMA model using the determined order ( $p, d, q$ )
6. Fit the ARIMA model to the training data
7. Forecasting CO<sub>2</sub> emissions for the test dataset using the fitted ARIMA model.

### **RESULT ANALYSIS:**

The CO<sub>2</sub> emissions in India, categorized by various sectors - power sector, industry sector, Transport, Domestic Aviation, and International Aviation, are used to trend the four

years of time series dataset to forecast CO<sub>2</sub> emissions. The Augmented Dickey-Fuller (ADF) test specifies that the series is stationary. And the p-value is 0.0096, which is less than 0.05, that represents that the null hypothesis is non-stationary can be rejected at the 5% significance level. After confirming that the series is stationary, ARIMA(p,d,q) model different combination of parameter model is analysed for carbon dioxide emission. The results of ARIMA(p,d,q) different combinations are (0,2, 1), (0, 2, 1), ( 2,1,0), (0,1,2), (0, 1, 0), (1,1,0) is analysed for various sectors. Table:1 summarises the best fitted model for different sector.

| Sector                 | Order     | RMSE    | MAE    | MAPE   | AIC      | BIC      |
|------------------------|-----------|---------|--------|--------|----------|----------|
| Power                  | (0, 2, 1) | 11.4041 | 9.9961 | 8.7194 | 297.8594 | 301.2372 |
| Industry               | (0, 2, 1) | 3.24888 | 2.5897 | 3.8837 | 284.6140 | 287.9917 |
| Transport              | (2, 1, 0) | 0.9515  | 0.7846 | 3.1620 | 223.5855 | 228.7263 |
| Residential            | (0, 1, 2) | 12.4660 | 9.1313 | 6.4566 | 313.2982 | 318.4389 |
| Domestic Aviation      | (0, 1, 0) | 0.0291  | 0.0245 | 4.2158 | 68.1107  | 66.3972  |
| International Aviation | (1, 1, 0) | 0.07817 | 0.0684 | 6.7481 | 60.7340  | 67.3069  |

**Table :1 Performance of Evaluation Metrics**

Based on the comparative analysis of various ARIMA model configurations with standard model selection measures such as RMSE, MAE, MAPE, AIC, and BIC, it is selected the most suitable model for forecasting carbon dioxide (CO<sub>2</sub>) emissions across various sectors. In the Power and Industry sectors, the ARIMA(0, 2, 1) model generated the lowest AIC and BIC values, shows the accurate fit for capture the emission patterns. In the Transport sector, ARIMA(2, 1, 0) configurations with the lowest prediction errors (RMSE = 0.9515, MAPE = 3.16%). In the Residential sector, ARIMA (0, 1, 2), shows irregular patterns in residential emissions. For the Domestic Aviation and International Aviation sectors, such as ARIMA(0, 1, 0) and ARIMA(1, 1, 0) respectively delivered the best predictions, with lower RMSE and AIC values, shows the accurate predictive performance. In summary, sector-wise selection of optimal ARIMA models assures accurate and reliable results, enables targeted policy interventions for emission deduction in each domain. Table: 2 shows CO<sub>2</sub> emission forecasting for next five years with Lower Emission Limit(LEL) and Upper Emission Limit(UEL) .

|  |  |
|--|--|
|  |  |
|--|--|

|   |          |          |           |  |            |            |            |
|---|----------|----------|-----------|--|------------|------------|------------|
| Sector: Domestic Aviation<br>Forecast for the next 5 years: |          |          |           | Sector: Ground Transport<br>Forecast for the next 5 years: |            |            |            |
|   | Forecast | LEL      | UEL       |  | Forecast   | LEL        | UEL        |
| Year  |          |          |           | Year   |            |            |            |
| 2023  | 4.027631 | 1.581840 | 6.473421  | 2023   | 174.675151 | 103.026008 | 246.324294 |
| 2024  | 6.904510 | 1.028731 | 14.837750 | 2024   | 299.240932 | 85.086587  | 513.395277 |
| 2025  | 6.994510 | 4.066648 | 17.875667 | 2025   | 319.239700 | 77.919131  | 590.560268 |
| 2026  | 7.804510 | 6.416647 | 20.225667 | 2026   | 368.239700 | 52.426325  | 650.905724 |
| 2027  | 8.904510 | 8.407301 | 22.216321 | 2027   | 489.239700 | 103.767492 | 702.246891 |
| 2028  | 9.876879 | 4.032822 | 39.786580 | 2028   | 524.683208 | 56.928374  | 806.294791 |

|  |             |             |             |  |           |           |           |
|--|-------------|-------------|-------------|--|-----------|-----------|-----------|
| sector: Industry<br>Forecast for the next 5 years: |             |             |             | sector: International Aviation<br>Forecast for the next 5 years: |           |           |           |
|  | Forecast    | LEL         | UEL         |  | Forecast  | LEL       | UEL       |
| Year   |             |             |             | Year   |           |           |           |
| 2023   | 471.275747  | 273.391951  | 669.159543  | 2023   | 7.263476  | 3.562105  | 10.964847 |
| 2024   | 813.897302  | 290.903803  | 1506.890800 | 2024   | 12.465648 | 1.108104  | 26.039401 |
| 2025   | 821.471223  | 319.092703  | 1862.035149 | 2025   | 24.465659 | 6.717283  | 31.648601 |
| 2026   | 829.045144  | 527.947405  | 2186.037694 | 2026   | 32.465659 | 10.995502 | 35.926820 |
| 2027   | 836.619066  | 824.025774  | 2497.263906 | 2027   | 36.465659 | 14.600090 | 39.531409 |
| 2028   | 1052.826636 | 1029.013175 | 1130.666447 | 2028   | 65.194025 | 7.040265  | 77.428314 |

|   |             |            |             |   |            |            |            |
|---|-------------|------------|-------------|---|------------|------------|------------|
| Sector: Power<br>Forecast for the next 5 years: |             |            |             | Sector: Residential<br>Forecast for the next 5 years: |            |            |            |
|   | Forecast    | LEL        | UEL         |   | Forecast   | LEL        | UEL        |
| Year  |             |            |             | Year  |            |            |            |
| 2023  | 963.054914  | 719.564539 | 1206.545288 | 2023  | 120.716645 | 54.413371  | 295.846662 |
| 2024  | 1718.494096 | 865.755152 | 2571.233040 | 2024  | 203.226913 | 96.257199  | 512.711026 |
| 2025  | 1803.811338 | 523.325272 | 3084.297403 | 2025  | 253.226913 | 106.257363 | 532.711190 |
| 2026  | 1889.128579 | 219.180586 | 3559.076572 | 2026  | 308.226913 | 168.257527 | 617.711354 |
| 2027  | 1974.445820 | 169.275622 | 4018.167262 | 2027  | 325.226913 | 208.257691 | 782.711518 |
| 2028  | 2047.866194 | 111.896648 | 4807.629036 | 2028  | 484.677881 | 344.274086 | 813.629848 |

Table: 2 Forecasting CO<sub>2</sub> Emission for Next Five Years

## CONCLUSION:

This research study applied ARIMA model which uses the statistical method for predicting carbon dioxide emissions, across different sectors such as industry, transport, power, residential, and aviation. The CO<sub>2</sub> emission dataset is pre-processed and stationarity is checked using Augmented Dickey-Fuller (ADF) test, ACF and PACF plots defines the appropriate ARIMA parameters. By selecting optimal ARIMA (p,d,q), the model is trained to predict the future CO<sub>2</sub> emission. The five-year forecast provides valuable insights into future emission patterns, which are important for policy makers and environmental planners to achieve sustainable development goals.

## REFERENCES

- [1] Rabajczyk, A., & Rabajczyk, G. (n.d.). *Managing CO<sub>2</sub> Emission in the Energy Sector and Climate Policy*. , T VOL. 58 ISSUE 2, 2021, PP. 6–21, 2021, <https://doi.org/10.12845/sft.58.2.2021.1>
- [2] Lyngfelt, A. (2001). *An Introduction to CO<sub>2</sub> Capture and Storage*. ,[Http://www.entek.chalmers.se/~anly/symp/01lyngfelt.pdf](http://www.entek.chalmers.se/~anly/symp/01lyngfelt.pdf)
- [3] Aresta, M. (2010). *Carbon Dioxide: Utilization Options to Reduce its Accumulation in the Atmosphere* (pp. 1–13). John Wiley & Sons, Ltd. <https://doi.org/10.1002/9783527629916.CH1>

- [4] Hrithik, P. M., Rehman, M. Z., Dar, A. A., & Wangmo, T. (2024). Forecasting CO2 Emissions in India: A Time Series Analysis Using ARIMA. *Processes*, 12(12), 2699. <https://doi.org/10.3390/pr12122699>
- [5] Sharma, S., Mittal, A., Bansal, M., Joshi, B. P., & Rayal, A. (2024). *Forecasting of Carbon Emissions in India Using (ARIMA) Time Series Predicting Approach* (pp. 799–811). Springer Science Business Media. [https://doi.org/10.1007/978-981-99-6749-0\\_53](https://doi.org/10.1007/978-981-99-6749-0_53)
- [6] Hasanov, R., Safarov, J., & Safarli, A. (2024). Analyzing and forecasting co2 emissions in the aluminum sector using arima model. *Agora International Journal of Economical Sciences*, 18(1), 55–64. <https://doi.org/10.15837/aijes.v18i1.6710>
- [7] *Forecasting of CO2 Emissions in Algeria Using Discrete Wavelet Transform –Based Autoregressive Integrated Moving Average Models.* (2023). <https://doi.org/10.21203/rs.3.rs-2632684>
- [8] Jamii, M., Oumidou, N., & Maaroufi, M. (n.d.). *Using the Box-Jenkins ARIMA Approach for Long-term Forecasting of CO2 Emissions in Morocco.*, Volume 1, 496-501, 2021, <https://doi.org/10.5220/0010737600003101>
- [9] Wang, L., Tong, X., Jia, X., Im, S.-K., & Wang, Y. (2023). *Prediction of Regional Carbon Emissions Based on ARIMA Model and Kaya Model.* 2560–2564. <https://doi.org/10.1109/iccc59590.2023.10507588>
- [10] Luceño, A., & Peña, D. (2008). *Autoregressive Integrated Moving Average (ARIMA) Modeling.* <https://doi.org/10.1002/9780470061572.EQR276>