Forecasting Carbon Dioxide Emissions from Industrial Processes in Sudan: A Time Series Approach

Maria H Mohamed[1, 2], Altaiyb Omer Ahmed Mohmmed[1], Mohammedelameen Eissa Qurashi[1], Mubarak H. Elhafian[1]

[1]Sudan University of Science & Technology, Faculty of Science, Department of Statistics

[2]College of Business Administration, University of Hail, Saudi Arabia
Corresponding Author Email: *mariahmaid83[at]gmail.com*

Abstract: ***This study analyzes the long-term behavior of carbon dioxide emissions from Sudan's industrial sector using time series forecasting techniques. Data spanning from 1970 to 2023 were evaluated to identify the most appropriate model for prediction. Preliminary analysis showed that the series was non-linear and non-stationary, but first-order differencing yielded stationarity. Based on model selection criteria, ARIMA (2, 1, 0) was identified as the best fit. Diagnostic checks confirmed the model's validity, with residuals behaving randomly. Forecasts generated from this model offer valuable insights for policymakers, enabling more effective planning and mitigation strategies to reduce industrial carbon emissions.***

Keywords: ARIMA, carbon emissions, Sudan industry, time series forecasting, environmental policy

1. Introduction

Climate change is one of the major global issues that affects humans, animals, and plants alike. This study focused on forecasting the percentage of fossil fuel consumption due to the critical importance of the topic. Climate scientists are deeply concerned with analyzing various phenomena that impact human life, and fossil fuel systems are influenced by several factors, most notably the rate of carbon dioxide emissions from all their sources. In 2017, the African Development Bank reaffirmed its commitment to clean energy and efficiency through its investments in renewable energy. (Ameyaw & Yao. (2018). The majority of environmental studies indicated that development and civilization also have positive roles as well as negative effects on the environment. (Sadorsky (2014).

Sudan is one of the countries that suffer from the problem of carbon dioxide emission because of its significant impact on climate change and temperature changes. (Mohamed, 2022) Sudan is also one of the agricultural countries that depend mainly on agriculture in its gross national product, which is greatly affected by the amounts of rain and carbon dioxide emissions. (Hussein, et. al. (2022). According to the estimates of the International Energy Agency (IEA) for the year (2022), the industry contributes 20-25% of the total carbon dioxide emissions in Sudan, mostly due to the cement industry, as it represents the largest industrial source of carbon dioxide emissions (50-60% of the emissions of the industrial sector and the sugar industry due to the burning of bagasse (sugar cane waste) and the use of fossil fuels. (Eldowma, et al., 2023). Mining (especially gold and oil) and the use of generators and heavy equipment. Vegetable oil and soap. Some factories rely on coal or gas.

This study aims to conduct a time series analysis of carbon dioxide emissions attributable to industrial waste, using longitudinal climate data from 1970 to 2023. The objective is to identify the most statistically appropriate forecasting model by evaluating the stationarity, autocorrelation structure, and residual behavior of the series, ultimately supporting data-driven environmental policy decisions.

Also, this study is significant as it addresses a critical gap in environmental modeling for Sudan, providing data-driven forecasts that support sustainable industrial policy and climate mitigation efforts.

2. Materials and Methods

This study utilized annual time series data on CO_2 emissions from industrial waste in Sudan spanning 1970–2023, sourced from reputable organizations such as the World Bank, IEA, and UNFCCC. To prepare the data for modeling, preprocessing steps included visual inspection, handling missing values through interpolation, and applying a logarithmic transformation when necessary. The ARIMA model was the primary forecasting tool, with model parameters (p, d, q) determined using ACF, PACF plots, and stationarity tested via the Augmented Dickey-Fuller (ADF) test. Model performance was validated using a hold-out approach, and forecast accuracy was assessed through RMSE and MAE metrics to ensure reliability and robustness of the results.

3. Theoretical Aspects

There are four stages in time series analysis: Model Specification, Parameter Estimation, Model Diagnostics, and Forecasting. (Jonathan, & Kung (2008).

Model Specification

The first step in analyzing any time series is the model identification phase, which is usually done through several methods, including plotting the series or testing the stationarity of the series by calculating both the autocorrelation and partial autocorrelation. (Velicer & Fava. (2003).

Stationarity Test
In the analysis process, it is essential to ensure the stability and stationarity of the series as an important step that must be confirmed; their absence makes the model inefficient in the prediction process. (Pourahmadi, 2001).
Dickey–Fuller test for a unit root: (Paparoditis & Politis, 2018).

$$H_0: \rho = 0$$
$$H_1: \rho \neq 0$$
$$t = \frac{\rho}{S.E\ (\rho)}$$

If the null hypothesis is accepted, that means the series is not stationary.

Parameter Estimation

ARIMA Models
Time series analysis models generally include three main models: Autoregressive models (AR (P)), Moving Average models (MA (q)), and mixed models or Autoregressive-Moving Average models (ARMA (p, q)). Now we will study these models along with some of their characteristics. (Chiang, et. al (2024).

Autoregressive models AR (p):

And which is generally known as follows.

$$\varphi_p(B)z_t = \delta + a_t \ (1)$$
$$Z_t = \delta + \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + \ldots + \varphi_p Z_{t-p} + a_t, a_t \sim N\ (0, \sigma^2)\ (2)$$

Moving Average Models MA (q):
And which is generally known as follows (Rossum. (2019).

$$z_t = \delta + \left(1 - \theta_q B\right) a_t \ (3)$$
$$z_t = \delta - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-q} + a_t, a_t \sim N(0, \sigma^2)\ (4)$$

Autoregressive-Moving Average Models (ARMA (p, q)):
These models are considered the general case where autoregressive models and moving average models are theoretically considered special cases of autoregressive-moving average models. However, practically, each model has its own formulation and characteristics. It is written in the form (Düker, et. al (2025) :

$$z_t - \varphi_1 z_{t-1} - \varphi_2 z_{t-2} - \cdots - \varphi_p z_{t-p} = \delta + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q}\ (5)$$
$$z_t - \varphi_1 B z_t - \varphi_2 B^2 z_t - \cdots - \varphi_p B^p z_t = \delta + a_t - \theta_1 B a_t - \theta_2 B^2 a_t - \cdots - \theta_q B^q a_t$$
$$\left(1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p\right) z_t = \delta + \left(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q\right) a_t$$
$$\varphi_p(B) z_t = \delta + \theta_q(B) a_t\ (6)$$

Where $\varphi_p(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$ is an Autoregressive Operator

And $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ Moving Average Operator .

Model Criteria Selection
Additionally, criteria are used to compare models and determine their rank based on these criteria (Rahman). et. al (2017). Analysis and prediction of rainfall trends over Bangladesh using Mann–Kendall, Spearman's rho tests, and ARIMA model. Meteorology and Atmospheric Physics.

Akaike Information Criterion (AIC)
The form of this standard is (Akaike, 2011).

$$AIC = nLn\ SSR + 2k \ldots\ldots\ldots\ldots (7)$$

Where:
SSR: Sum of squares of the residuals
n: sample size

$$k = p + d + q$$

Model Diagnostics
After estimating the model, it is necessary to test the model's validity to represent the time series data. There are several methods for both time and frequency trends:

- Checking and testing the model's accuracy in the time trend: The model's coefficients must be statistically significant, i. e., significantly different from zero. The student's t-test is used for this. If they are not significant, one of the AR or MA tests must be excluded. (Smith. (1985)
- Residual analysis: The following tests are used for this: After identifying an initial model and estimating its parameters, we perform some diagnostics on the residuals or application errors to determine how much the model matches the observed series. The residuals are assumed to be white noise estimators, which we assume are normally distributed with a zero mean and variance σ^2. (Mauricio, 2008).

Forecasting
The forecasting phase is considered one of the most important stages in the analysis of time series models, and it is the primary goal of the model estimation process. After identifying the model in the first stage, which is the diagnostic stage, and then estimating the model parameters in the second stage, and verifying and testing the model in the third stage, we move to the fourth stage, which is the most important stage: the forecasting stage, where the behavior of the phenomenon being studied in the future is determined. When forecasting using time series models, the error value at the time when the value of the phenomenon is being forecasted is assigned a value of zero. (Xue & Hua, 2016).

The autoregressive moving average model of order ARMA (p, q) can be written in the form

$$\boldsymbol{z_t - \mu = \sum_{j=0}^{\infty} \psi_j a_{t-j}}, \quad \boldsymbol{a_t \sim N(0, \sigma^2)}, \ \boldsymbol{\psi_0 = 1}, \ \boldsymbol{\sum_{j=0}^{\infty} \psi_j^2} < \infty\ (8)$$

$$z_t - \mu = a_t + \psi_1 a_{t-1} + \psi_2 a_{t-2} + \psi_3 a_{t-3} + \cdots = \sum_{j=0}^{\infty} \psi_j a_{t-j}, \quad \psi_0 = 1\ (9)$$

For the observed time series$\{z_1, z_2, \cdots, z_{n-1}, z_n\}$, the predictions $z_n(\ell)$, $\ell \geq 1$ for future values $z_{n+\ell}$, $\ell \geq 1$ can be expressed in the form

$$z_n(\ell) = \xi_0 a_n + \xi_1 a_{n-1} + \xi_2 a_{n-2} + \cdots,\ \ell \geq 1 \quad (10)$$

Future values$z_{n+\ell}$, $\ell \geq 1$ It is written according to the model as follows.

$$z_{n+\ell} - \mu = a_{n+\ell} + \psi_1 a_{n+\ell-1} + \cdots + \psi_{\ell-1} a_{n+1} + \psi_\ell a_n + \psi_{\ell+1} a_{n-1} + \cdots,\ \ell \geq 1 \quad (11)$$

4. Results and Discussion

In this study, secondary sources of data related to the World Bank were relied on through the official website of the Bank, where data were obtained for Sudan for variables concerned with climate change and the impact of carbon dioxide emissions emitted from industry during the period (1970-2023)

To reach results and build a model characterized by being able to predict the phenomenon of fossil fuel consumption, which depends in its composition mainly on carbon dioxide gas and to apply all these models using ready-made programs such as EViews13, Stata17 and SPSS VER (27), and then the results were extracted and placed in tables and shapes so that they are easy to understand and read.

Table 1: Descriptive Statistics

Mean	Std. Error of Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis	Minimum	Maximum
0.463107	0.071466	0.525167	1.424	0.325	0.576	0.639	0.104	1.8875

Table 1 shows that the mean carbon dioxide emissions from industrial sources was 0.463107 million tons, with a standard deviation of 0.5251665. The skewness coefficient is positive (1.424), indicating that the data is right-skewed. The kurtosis coefficient is positive (0.576), suggesting that the distribution has a sharper peak than a normal distribution. The minimum emission rate recorded was 0.1040 million tons, while the maximum emission rate was 1.8875 million tons.

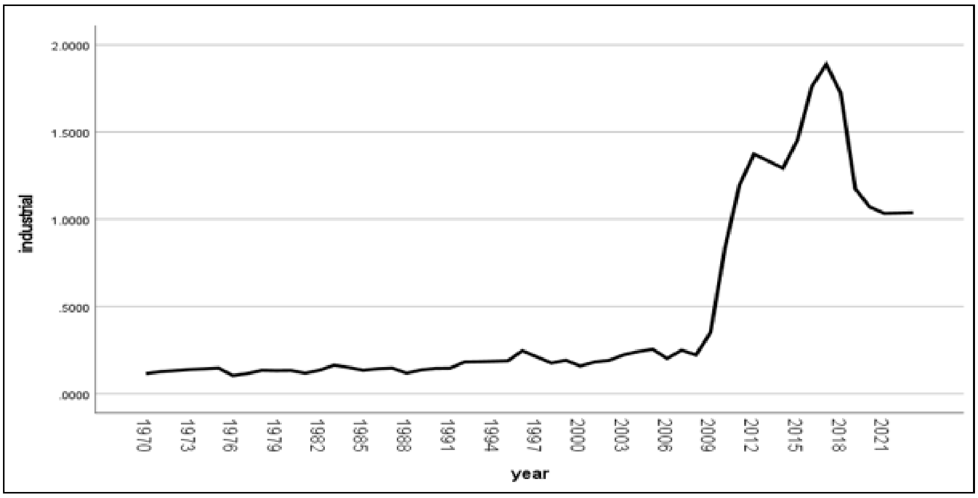


Figure 1: Percentage of carbon dioxide emissions from industrial processes

Figure 1 illustrates that the time series exhibits a non-linear pattern with an exponential trend, indicating that the variable is non-stationary. To formally test for stationarity, a unit root test was employed. Specifically, the Augmented Dickey-Fuller (ADF) test was used to evaluate the statistical properties of the series, determine its order of integration, and identify the necessary level of differencing to achieve stationarity.

Table 2: Dickey-Fuller stationarity test

Dickey–Fuller test	Level		
	intercept	intercept and trend	without
t	-0.921372	-3.652228	-0.185395
sig	0.7735	0.0357	0.6145
decision	insignificant	significant	insignificant
stationarity	non stationary	stationary	non stationary

Table 2 presents the results of the Augmented Dickey–Fuller (ADF) test used to assess the stationarity of the time series representing the percentage of carbon dioxide emissions from industrial processes. The test was conducted under three conditions: with an intercept, with a trend and intercept, and without either. The findings indicate that the series is stationary when tested with an intercept and with both trend and intercept, but not stationary under the model without any deterministic components.

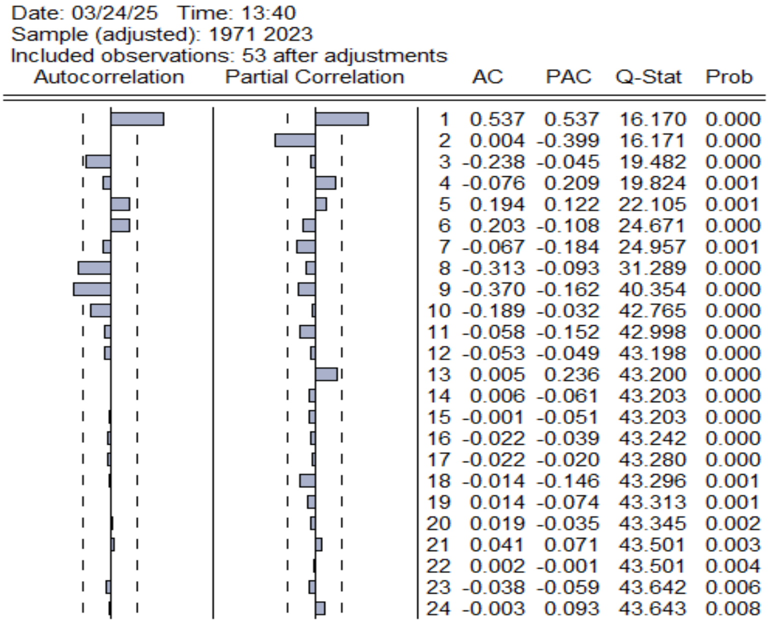
Overall, the series is considered non-stationary, as it must demonstrate stationarity under all model specifications. As a result, the first difference of the series was taken, and the ADF test was repeated to determine whether the series becomes stationary at the first level of differencing.

Table 3: Dickey–Fuller test after the First Difference

Dickey–Fuller test	First Difference		
	intercept	intercept and trend	without
t	-5.087159	-5.087159	-5.087159
sig	0.0000	0.0000	0.0000
decision	significant	significant	significant
stationarity	stationary	stationary	stationary

After taking the first difference, all the results for the series were stationary, and for all the intercept, trend, and intercept without.

After we have confirmed that the series is stationary, the next step is to test the autocorrelation and partial autocorrelation of the series to determine the rank of the model Autocorrelation – Partial Autocorrelation Test



	AC	PAC	Q-Stat	Prob
1	0.537	0.537	16.170	0.000
2	0.004	-0.399	16.171	0.000
3	-0.238	-0.045	19.482	0.000
4	-0.076	0.209	19.824	0.001
5	0.194	0.122	22.105	0.001
6	0.203	-0.108	24.671	0.000
7	-0.067	-0.184	24.957	0.001
8	-0.313	-0.093	31.289	0.000
9	-0.370	-0.162	40.354	0.000
10	-0.189	-0.032	42.765	0.000
11	-0.058	-0.152	42.998	0.000
12	-0.053	-0.049	43.198	0.000
13	0.005	0.236	43.200	0.000
14	0.006	-0.061	43.203	0.000
15	-0.001	-0.051	43.203	0.000
16	-0.022	-0.039	43.242	0.000
17	-0.022	-0.020	43.280	0.000
18	-0.014	-0.146	43.296	0.001
19	0.014	-0.074	43.313	0.001
20	0.019	-0.035	43.345	0.002
21	0.041	0.071	43.501	0.003
22	0.002	-0.001	43.501	0.004
23	-0.038	-0.059	43.642	0.006
24	-0.003	0.093	43.643	0.008

Figure 2: The Autocorrelation and Partial Autocorrelation after the first difference

Figure 2 assists in verifying the stationarity of the series, identifying the order of the model, and detecting any trends. The autocorrelation values remain within acceptable limits (less than one), while the partial autocorrelation values may reach up to 2. Therefore, it is proposed to test ARIMA models with varying orders (0, 1, and 2) alternately, resulting in a total of eight possible model combinations. The best-fitting model will be selected based on commonly used model selection criteria.

Table 4: ARIMA Proposed Models for Industry Emission Variable

Model	Model Evaluation Criteria				
	AIC	BIC	MAPE	RMSE	R^2
ARIMA (0, 1, 1)	0.3976	-4.377	14.106	0.108	0.958
ARIMA (0, 1, 2)	0.5813	-4.366	14.916	0.105	0.962
ARIMA (1, 1, 0)	-1.0798	-4.319	13.513	0.111	0.956
ARIMA (2, 1, 0)	**0.0388**	**-4.391**	**15.217**	**0.103**	**0.962**
ARIMA (1, 1, 1)	-1.4489	-4.329	14.577	0.107	0.960
ARIMA (1, 1, 2)	-1.0442	- 4.235	15.567	0.107	0.961
ARIMA (2, 1, 1)	-1.0655	-4.297	15.174	0.104	0.963
ARIMA (2, 1, 2)	0.0823	-4.331	15.612	0.099	0.967

Table 4 presents the criteria used to determine the best-fitting model. The process begins by verifying the statistical significance of the model itself, followed by confirming the significance of its estimated parameters. Only after these conditions are met can the most suitable model be selected. From Table 4, we observe that all the models ARIMA (1, 1, 0), ARIMA (0, 1, 2), ARIMA (2, 1, 0), and ARIMA (1, 1, 2) are statistically insignificant. Among these, a comparison reveals that the ARIMA (2, 1, 0) model performs best based on the selection criteria.

Once the optimal model is chosen and its parameters are confirmed, the next steps involve model estimation, validation, and finally, forecasting.

After all possible models were identified and we made sure of the significant models with significant parameters, the best model was chosen, depending on the methods of differentiation known according to the criteria in the above table, model was built using the time series data, resulting in the following specification.

Table 5: ARIMA Model Parameters

ARIMA Model Parameters						
			Estimate	SE	t	Sig.
No Transformation	AR	Lag 1	.745	.129	5.782	.000
		Lag 2	-.378	.129	-2.932	.005
	Difference		1			

Table 5 presents the parameters of the best-fitting model, identified as ARIMA (2, 1, 0). The results indicate that both autoregressive (AR) terms are statistically significant, as their corresponding p-values are less than 0.05. This significance suggests that the past values of the differenced series have a meaningful influence on the current value. The inclusion of two AR terms implies that the current level of carbon dioxide emissions from industrial waste is strongly influenced by the two preceding periods. The statistical significance of these parameters supports the reliability of the model in capturing the underlying structure of the time series and in generating accurate forecasts.

After selecting the best model, it is essential to verify that all statistical assumptions are satisfied. This involves examining the residuals through plots of residuals versus actual values, autocorrelation and partial autocorrelation functions of the residuals, and evaluating the Q-statistic to ensure randomness and model adequacy.

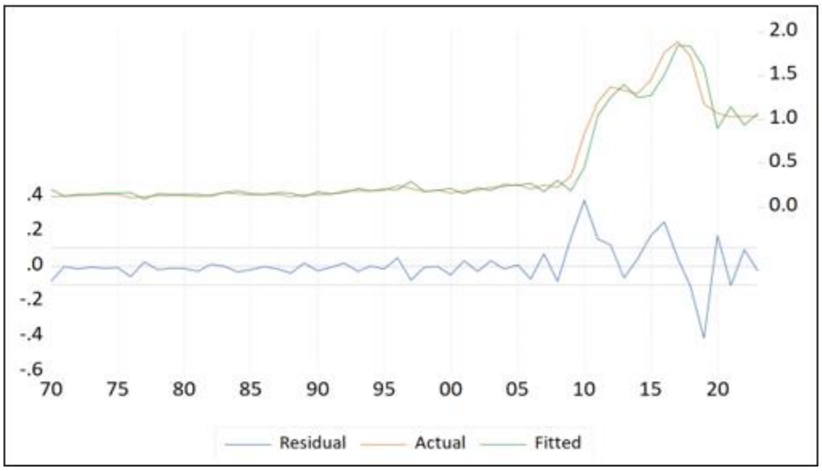


Figure 3: Draw the residues with actual values

Figure 3 shows the chart of the residuals alongside actual values

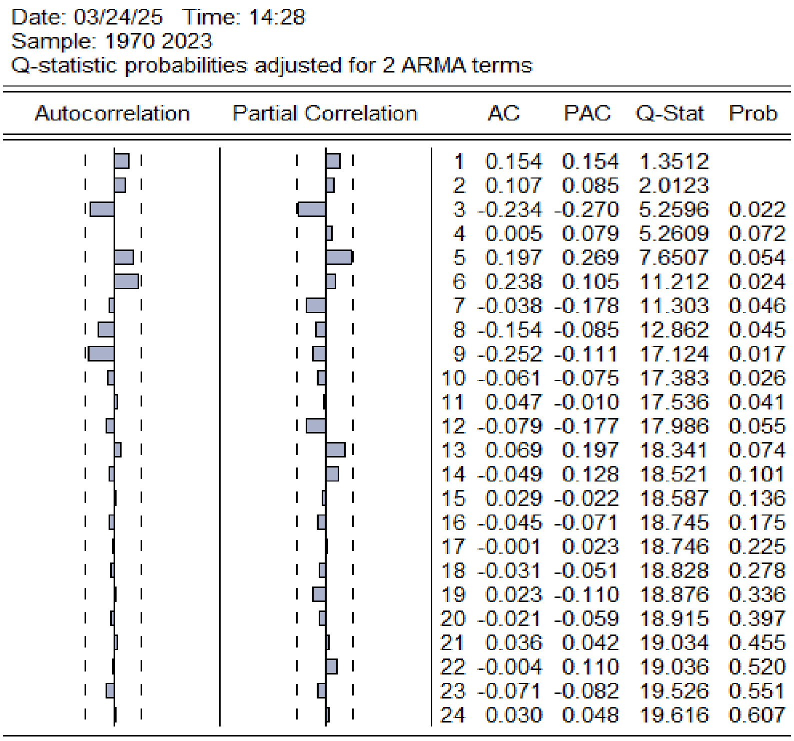
Test the randomness of the residual

After the residual series has been plotted and matched with the actual values, we must test the randomness of the residuals of the chain by testing Q-Stat, and then draw the autocorrelation and partial autocorrelation of the residuals and make sure that all of them fall within the limits

Table 6: Residual Test

Model Statistics						
Model	Number of Predictors	Model Fit Statistics	Ljung-Box Q (18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
industrial-Model_1	0	.394	12.454	16	.712	0

Table 6 shows the residual randomness test, which is used to ensure that the model has exhausted all patterns in the data, leaving no unexplained temporal relationships. One of the tests employed to examine the randomness of residuals is the Ljung-Box test under the hypothesis of random residuals (no autocorrelation). Table 6 shows that the residuals in this model are random (Ljung-Box=12.454, sig=0.712).



Date: 03/24/25 Time: 14:28
Sample: 1970 2023
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.154	0.154	1.3512	
		2	0.107	0.085	2.0123	
		3	-0.234	-0.270	5.2596	0.022
		4	0.005	0.079	5.2609	0.072
		5	0.197	0.269	7.6507	0.054
		6	0.238	0.105	11.212	0.024
		7	-0.038	-0.178	11.303	0.046
		8	-0.154	-0.085	12.862	0.045
		9	-0.252	-0.111	17.124	0.017
		10	-0.061	-0.075	17.383	0.026
		11	0.047	-0.010	17.536	0.041
		12	-0.079	-0.177	17.986	0.055
		13	0.069	0.197	18.341	0.074
		14	-0.049	0.128	18.521	0.101
		15	0.029	-0.022	18.587	0.136
		16	-0.045	-0.071	18.745	0.175
		17	-0.001	0.023	18.746	0.225
		18	-0.031	-0.051	18.828	0.278
		19	0.023	-0.110	18.876	0.336
		20	-0.021	-0.059	18.915	0.397
		21	0.036	0.042	19.034	0.455
		22	-0.004	0.110	19.036	0.520
		23	-0.071	-0.082	19.526	0.551
		24	0.030	0.048	19.616	0.607

Figure 4: The Autocorrelation and Partial Autocorrelation for the residuals

From Figure 4, we observe that the residuals of the series are stationary and that the values of autocorrelation and partial autocorrelation fall within the acceptable limits, indicating that the chosen model can be relied upon for the prediction process.

Based on the model presented in Table 5, the percentage of carbon dioxide emissions from the industrial sector in Sudan was predicted for a period of 10 years, starting from 2024 to 2033, as shown in Table 7 and Figure 5.

Table 7: The Percentage of carbon dioxide emissions emitted from an industrial sector in Sudan was predicted for the period (2024-2033)

Model	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
Forecast	1.0386	1.0384	1.0379	1.0377	1.0376	1.0377	1.0378	1.0378	1.0378	1.0378
UCL	1.2459	1.4553	1.6147	1.7215	1.7972	1.8599	1.9190	1.9769	2.0329	2.0862
LCL	.8313	.6215	.4612	.3538	.2780	.2155	.1566	.0988	.0427	-.0106

Table 6 shows the predictive values of the percentage of carbon dioxide emissions emitted from an industrial sector in Sudan for the period (2024-2033). Where the table shows a slight upward trend in the percentage of carbon dioxide emissions from Sudan's industrial sector

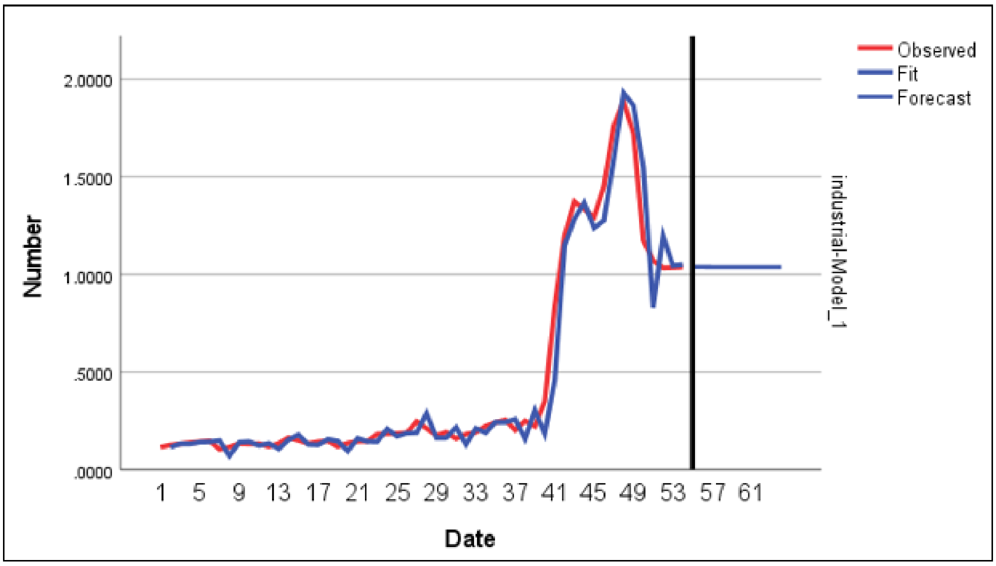


Figure 5: The curve of observed and forecast values

Figure 5 shows a curve comparing the actual value with the estimated and predicted values for the percentage of carbon dioxide emissions emitted from an industrial sector in sudan.

5. Conclusion

This study examined the time series behavior of carbon dioxide emissions from industrial waste. Initial analysis showed the series was non-stationary and nonlinear. The Augmented Dickey-Fuller (ADF) test confirmed the original series was non-stationary, making it unsuitable for direct forecasting. After applying first differencing, the series became stationary, validating differencing. As an effective method to stabilize the data and improve forecasting accuracy, the analysis concluded that the ARIMA (2, 1, 0) model was the most suitable for modeling the time series, based on standard differencing techniques. Diagnostic checks confirmed the model's validity, with the Ljung-Box test indicating randomness in the residuals (Ljung-Box = 12.454, p-value = 0.712), and both the autocorrelation and partial autocorrelation functions falling within acceptable confidence limits.

These results confirm that the chosen model effectively represents the data's underlying structure and is reliable for forecasting. Forecasts indicate minimal variation in industrial carbon dioxide emissions over time, suggesting a manageable trend. This stability presents an opportunity for policymakers and stakeholders to develop targeted strategies and adopt alternative practices to further mitigate environmental impact.

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