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https://doi.org/10.55737/trt/WR25.167

THE REGIONAL TRIBUNE

Pages: 459 – 472 | Volume: 4 | Issue: 1 (Winter 2025) | ISSN (Online): 3006-8428 | DOI: 10.55737/trt/WR25.167

Forecasting of Pakistan's CO_2 Emission: Using ARIMA Approach

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ABSTRACT: Carbon dioxide (CO_2) is a key driver of global warming and acts as a dominant player in the global warming and climate change phenomenon. Pakistan's economy is heavily dependent on oil, natural gas, and coal and other non-renewable energy sources, which together account for nearly 81% of its total primary energy consumption. Pakistan's CO_2 emissions have risen sharply, reaching 179.80 million tons, making it the second highest emitter in South Asia, despite contributing less than 1% to global emissions. Forecasting CO_2 emissions has become increasingly important in addressing the challenges of climate change, particularly for Pakistan. Accurate forecasting of CO_2 emissions is therefore essential for Environmental sustainability and climate policy formulation. The primary objective of this research study is to forecast the CO_2 emissions of Pakistan. Therefore, the data has been collected for the years from 1950 to 2022 from the Global Carbon Budget. The study used the well-known Auto Regressive Moving Average (ARIMA) model and forecast CO_2 emission of Pakistan for the next 18 years, i.e from 2023 to 2040. With the Box and Jenkins methodology, the ARIMA(6,1,3) model has been selected for forecasting CO_2 emissions in Pakistan. The results indicate a continued increase in Pakistan's CO_2 emission, and is projected to reach 0.30 tons per person by 2040. Hence an average annual increase of 27.2% of CO_2 has been predicted, over the period 2023–2040. Pakistan urgently needs diversified energy, population management, hydro power expansion, and technology for sustainable environmental future.

KEYWORDS: CO_2 Emission, Box-Jenkins Methodology, ARIMA

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Introduction

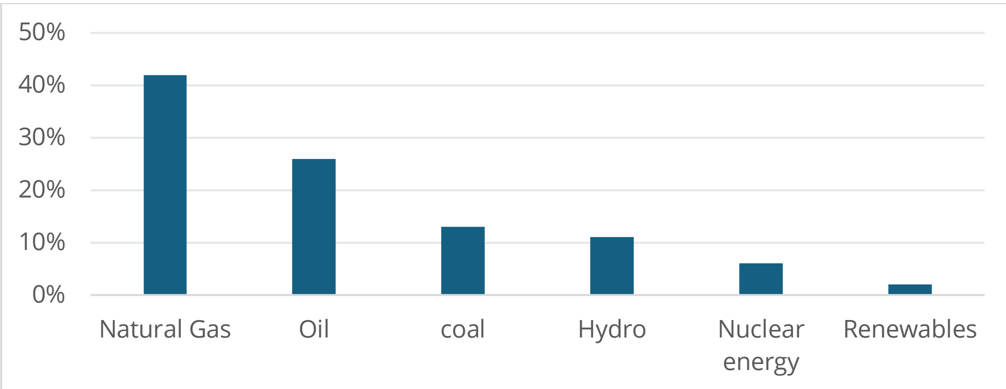
Pakistan heavily relies on oil, natural gas, and coal like nonrenewable energy sources, which together account for nearly 81% of its total primary energy consumption. According to (Energy Institute 2024),The average growth rate of Pakistan's PEC was recorded at 1.4% over the period 2014–2024. And also, the country's total PEC was estimated at 3.20 EJ in 2024. Figure-1 below explains, Pakistan's energy mix during this period comprised approximately 13% coal, 26% oil, 42% natural gas, 11% hydro power, 6% nuclear, and 2% renewable. This trend is projected to persist over the long term, driven by population growth rate, GDP growth, and fast industrialization, which together are expected to increase the national energy demand. With

Cite this Article: Farooq, S., & Khan, R. M. (2025). Forecasting of Pakistan's CO_2 Emission: Using the ARIMA Approach. *The Regional Tribune, 4*(1), 459-472. https://doi.org/10.55737/trt/WR25.167

a total population of more than 255 million, ranked the country as the fifth most populous country throughout the globe (World Population Review, 2024). Pakistan has one of the highest population growth rates in South Asia, with a recent annual rate of 1.66%. This places it as the second highest in the region (World Population Review 2024).

Figure 1

Energy Mix %age Share by Source in Pakistan for 2024

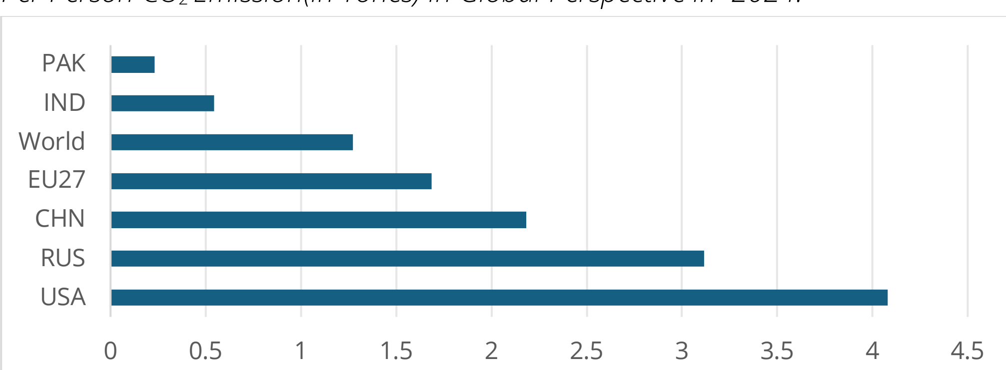


Source: Statistical Review of World Energy (2024)

Greenhouse gases(GHG) accumulation in the atmosphere, with CO_2f rom the combustion of fossil fuel and industrial processes are the key drivers of global warming and climate change. Although Pakistan's contribution to global CO_2 is small in absolute terms, its national emissions and per person footprint are important for policy and planning. Country level estimates indicate Pakistan emitted about 179.80 million tons of CO_2 in 2024, with CO_2 emissions per person was reported as 0.72 tons per person in 2024. According to the latest available statistics the global CO_2 emissions have continued to rise and reached to the level of 38.60 billion tons in 2024 (Global Carbon Budget, 2024). Pakistan is highly vulnerable to climate related risks despite contributing a relatively small share to global emissions(See figure-2). In a recent (Eckstein et al., 2020) report on the global climate risk index 2020, ranked Pakistan as the fifth mostly impacted country, due to climate change, while in another report by (IQAir, 2022) ranked Pakistan as the second generally contaminated country on the basis of air quality index.

Figure 2

Per Person CO_2 Emission(in Tones) in Global Perspective in 2024.



Source: Global Carbon Budget(2024).

The country is already suffering the consequences of climate change, including increased frequency of floods, melting of glaciers ,and extreme weather conditions. The devastating floods of 2022, which displaced millions of persons, and caused economic losses exceeding 30 billion US dollars, highlighted Pakistan's extreme vulnerability to global warming despite its modest historical CO_2 emissions (Ministry of Planning Development & Special Initiatives, 2022). Thus, the need to forecast CO_2 emission, and monitor its future trends has become even more urgent not only for environmental sustainability point of view, but also for economic resilience and policy making. Forecasting CO_2 emissions has become increasingly important in resolving the issues of climate change, particularly for developing economies such as Pakistan. As the country with a rapidly growing population, and expansion in the industrial base, has increased the dependence on fossil fuels, which ultimately rising environmental concerns arising from rising CO_2 emissions. Accurate forecasting of these emissions is therefore essential for sustainable environmental planning, climate policy formulation, and achieving international commitments such as the Paris Agreement(United Nations, 2015).

Among various forecasting approaches, the ARIMA model is widely recognized for its effectiveness in capturing temporal dynamics in environmental and energy-related data. ARIMA models are particularly suitable for CO_2 emission forecasting due to their ability to handle non-stationary time series and generate robust short to medium term forecasts with minimum data requirements. Previous studies have successfully applied ARIMA methods to forecast emissions and energy consumption across diverse economies, demonstrating the model's reliability and methodological simplicity.

This study aims to forecast Pakistan's CO_2 emissions using the ARIMA modeling approach by utilizing historical CO_2 emission data. In this research study, data on Pakistan's CO_2 emission in tons per person from 1950 to 2022 is utilized to Forecast CO_2 emission for the upcoming 18 years, employing a type of uni variate ARIMA(p,d,q) model. The findings are expected to offer significant insights for policymakers, environmental agencies to anticipate future emission levels and develop appropriate mitigation strategies. The structure of the study is as follows: Section-2 discuss in detail the literature review. Then Section-3 of the study Provides detail discussion about the data, and the methodology employed Section-4 includes the application of ARIMA(p,d,q) models for forecasting Pakistan's CO_2 emission in tons per person and a discussion of the findings. Finally, Section 5 offers concluding remarks and some policy suggestions for the future policy framework.

Literature Review

For forecasting CO_2 emission, multiple econometric models have been developed. These models were used for forecasting the accurate estimates of the given time series and thus offering critical insights for policymakers seeking to reform development strategies and mitigate environmental risks (Kumar et al., 2020); and (Sbrana, 2020).

The pioneering work of (Muth, 1960), introduced the concept of rational expectations and the theory of price movements, would be considered as the foundation work for subsequent predictive modeling across various domains, including CO_2 emission forecasting. In recent times, time series approaches especially ARIMA models have been widely used to forecast CO_2 emissions across different sectors and regions. For example,(M et al., 2024) used ARIMA techniques and predicted CO_2 emissions of in India. Moreover, to forecast CO_2

emissions at national level, several studies can be witnessed in the existing literature, for example on Bangladesh (Rehman, 2017), China (Liu, 2023), Pakistan (Kassim & Tawiah, 2023), and Malysia (Yogesswary Segar, 2023) and many others.

Beyond ARIMA, alternative forecasting frameworks such as the Grey Prediction Model (GPM) have also gained much popularity in recent days; (Hsiao, 2011) applied the GPM to forecast CO_2 emissions, energy consumption, and economic growth in Brazil. While similar models can also be witnessed in studies conducted on Pakistan by (Abbas et al., 2023) and China by (Tong et al., 2022), in order to capture CO_2 emission dynamics and foremost to provide guidelines to sustainable development and climate policy planning. Now a days comparative and hybrid forecasting models have also gained great popularity, as they provide more robust and comprehensive forecasting insights (Kumari & Singh, 2022); and (Sbrana, 2020). (Sbrana, 2020) utilized a high dimensional Holt Winters trend model to quickly and accurately forecast CO_2 emission.For instance, several studies have employed multiple models such as ARIMA, the Holt Winters exponential smoothing method, and the artificial neural networks (ANN) to forecast CO_2 emissions in Gulf countries (Kumar et al., 2024).

As the primary objective of this study to forecast CO_2 emission in Pakistan context with ARIMA models. Therefore, we want to focus our discussion only on ARIMA models and its application for forecasting the CO_2 emission. The time series forecasting models often presume that time series under consideration must be stationary; meaning that the mean value and standard deviation be remain constant over the desired period of time (Chen et al., 2011). In other words, we can say that the time series be free from seasonality component. Numerous statistical models have been devised for predicting time series data set. Among these, the ARIMA model, developed by Box and Jenkins [(Anderson et al., 1978); (Huong, 2023); (Huong et al., 2020)], is the predominant one. A dominant feature of ARIMA model is, that it entertained a non-stationary time series, as it can transform non-stationary series into stationary ones by the difference process, which is crucial for achieving stationarity. Results obtained by ARIMA are not only accurate for the short to medium period but also can be easily interpreted. Every component of the model like, the Auto regressive (AR), the Integrated (I), and the Moving Average (MA) represents a distinguished, feature of the time series, and of all it provides information about the trend behaviour of the series. The dominant feature of ARIMA models is its robustness in a variety of real world applications. The ARIMA model is validated first through the application of the residual analysis and other statistical checks. ARIMA models are easy to use, as these models only needs the lagged values of the time series and does not require any further inputs, unlike regression or machine learning models. ARIMA has been applied extensively in multiple studies, and thereby successfully applied in many industries (Hopali & Çakmak, 2020).

ARIMA has been utilized in various fields to develop forecasting models, such as forecasting CO_2 emissions and fuel consumption in Turkey, as demonstrated by ((Ediger & Akar, 2007). To forecast CO_2 emission in Bangladesh (Rahman and Hasan, 2017) utilized the data from 1972 t0 2015 and made a forecast of CO_2 emission with the use of ARIMA(0,2,1) structure of the ARIMA model. The study utilized several criteria for determining the appropriate ARIMA structures. With the application of ARIMA (0, 2, 1) model, they were succeeded to accurately forecast values of CO_2 emission in Bangladesh for the year 2016, 2017 and 2018 were obtained, as 83.95 Metric Tons (MT),89.91 MT and 96.29 MT respectively.

Similarly in another study conducted by (Iftikhar et al., 2024) on forecasting of CO_2 emission in Pakistan, utilized a hybrid combination of time series and regression models. With a statistical test like mean errors and graphical analysis, used accuracy checks, the study evaluated the proposed hybrid forecasting model. From the accuracy checks, the study concluded that the proposed hybrid combination forecasting technique is highly accurate and efficient in forecasting CO_2 emissions. In the result section the study concluded the per person CO_2 emissions in Pakistan will reach to the level of 1.130 MT by 2030. On the basis of the results the study advised the government to reduce population growth rate, encourage tree plantation especially in much densely populated areas, adopt clean technology, and provision of research funds in renewable energy technologies. In a more concise words, the government is required to regulate electricity from zero carbon sources in Pakistan.

And also (Malik et al., 2020) conducted a study to forecast CO_2 emissions for Pakistan, where they they predicted CO_2 emissions in Pakistan till 2030, with the use of different scenarios developed by them. They developed China Pakistan Economic Corridor (CPEC) scenario, where they used CO_2 emissions from the CPEC energy projects only. The study found that forecast value of CO_2 emissions are bound to increase under the CPEC scenarios. And thereby the study conclude that the country would fail to meet the pledge made at UN Climate Change Conference held in 2015 at Paris.

In a latest research study, (Tawiah et al., 2023) conducted to forecast the CO_2 emission in Pakistan with both linear and nonlinear time series models. They were used the root mean square error (RMSE) and the mean absolute error (MAE) criteria as performance checks, in order to assess and select the best model among these linear and nonlinear time series models. They prefer to use the nonlinear machine learning models, because of having the lowest RMSE and MAE values compared to other models. They witnessed, that CO_2 emissions in Pakistan will reach to 1.05 MT per person by the end of 2028. From the findings of their respective study, they were concluded some policy suggestion. They were suggested that innovative based policies should be introduced to control the increasing trend of the CO_2 emission further in the country. For achieving this target, they were strongly advocated of pricing of CO_2 emissions by companies per ton and also stressed upon need of the generation of electric power from hydro power projects, and from other renewable sources with zero CO_2 emissions.

Most recently, Qader et al. (2021) examined the factors, like industrial, residential and commercial building structures that are responsible for raising CO_2 emissions in the selected nine selected Asian countries from 1972 to 2014. In addition to ARIMA model, they were also use the simple exponential smoothing (SES) models to forecast CO_2 emissions in the selected nine Asian economies. The study explored the relationship between all the selected factors and CO_2 emissions with the help of multiple linear regression. In the findings section, the study was concluded that the residential and commercial and the transport sectors were confirmed as the primary factors of CO_2 emission in China. Moreover, heat and electricity were confirmed as the primary drivers of growing CO_2 emissions in Pakistan, Sri Lanka, Bangladesh, India, and Iran respectively. Furthermore, the selected factors of their respective finding no significant impact on CO_2 emissions in Singapore and Nepal as well. The study was concluded with some policy recommendations, that would be of great significance, not only for researchers, but politicians and policy makers also in the effective policy making regarding the environmental sustainability.

Although a substantial research study has explored CO_2 emission forecasting using various statistical, econometric, and machine learning techniques, but several important research gaps are still remain. While ARIMA, Grey models, ANN, and hybrid approaches have been widely applied in countries including China, India, Malaysia, and Gulf states, empirical applications for Pakistan are still scarce, fragmented, and often outdated. Considering these gaps, there is a clear need for an updated, rigorous, and context specific forecasting study that applies robust time series techniques to Pakistan's CO_2 emissions. This study aims to contribute to the existing literature by the stepwise application of ARIMA modeling using the most recent available data on CO_2 emission in tons per person.

Data and Methodology

This research study utilizes annual CO_2 emission tons per person data in Pakistan covering the period from 1950 to 2022. Data is downloaded from the Global Carbon Budget (Global Carbon Budget, 2023). With the help of E-Views 9, statistical software we build a class of ARIMA models. The Box and Jenkins(B-J) methodology was developed by two statisticians: George Box and Gwilym Jenkins in 1970. It is a systematic approach of time series modeling and forecasting. It is widely applied in economics, environment, energy, finance and several other fields, for predicting future values of a time series (Y_t) of a dependent variable based on its past behaviour (Y_{t-1}) (Newbold, 1975). Although the methodology primarily focusing ARIMA models, yet it is also applicable to simpler ARMA processes when the given data series is stationary. The study follows the (Box and Jenkins, 1978), that involves four steps- procedure, to identification, estimation, diagnostic checking, and forecasting of a time given series (Y_t), (i.e CO_2 emission in our case).

Stage 1: Identification

The identification stage involves determining, whether the time series is suffered from the unit root problem, or not and also to decide on the initial model structure. Since ARMA/ARIMA models assume stationary series, i.e. the mean and variance of the time series under consideration remains constant over time. It is also to be noted that if a time series is nonstationary, then by the transformations (e.g., differencing, or log transformation) the series can be made as stationary one. It is important to note that ARMA model is used when (Y_t) time series is stationary at level i.e. I(0). However, in case of non-stationary series, we have to use the ARIMA Model. For checking the unit root process of the given time series, we will utilize the Augmented Dickey Fuller (ADF) unit root test. After the unit root test, we then plot a corellogram, for the identification of the appropriate values of both the Auto correlation Function (ACF) and Partial Auto correlation Function (PACF) respectively. Both these plots will enable us to select the most appropriate values of order (p,d.q) for ARMIA model. As we are interested in the ARIMA (p,d,q) model only, we therefore focus our discussion towards the ARIMA (p,d,q) approach only.

Stage 2: Estimation

After selection of appropriate ARIMA (p,d,q) model, the model parameters will then be estimated by the method of Maximum Likelihood Estimation (MLE) or by the Least Squares procedure. The use of the appropriate ARIMA (p,d,q) structure will provide the desired parameters values with the least forecast errors. Fitness of the model is typically judged by some criteria, like Akaike Information Criterion(AIC), Shwartz Information Criterion (SIC), and Bayesian Information Criterion (BIC) respectively.

Stage 3: Diagnostic Checking

After the estimation stage , the model adequacy is then tested by residual analysis and some other statistical tests. The residual analysis will guide us whether the residuals resemble the white noise error term (i.e., ε_t are normally distributed with zero mean, and constant variance). The test also provides the information that whether the resulting residuals are free/suffer from auto correlation problem. In the diagnostic checking stage the Ljung–Box Q-test also performed, to check for auto correlation in residuals. In addition, normality test of the residuals is also performed. If the diagnostics section reveal adequacy, then the desired ARIMA (p,d,q) model, be used for forecasting purpose.

Stage 4: Forecasting

In the final stage the selected ARIMA (p,d,q) model is utilized for the prediction of the future values of the desired time series (Y_t). It is notable, that Short-term forecasts are typically more accurate than the long term ones. In addition, forecast intervals are constructed to provide confidence bounds for forecasting the (Y_t) series.

The Auto-Regressive Integrated Moving Average (ARIMA) Model

ARMA is a fundamental and widely used statistical model in time series analysis and applied to stationary time series data sets. By definition, an ARMA model has a finite and time invariant mean and covariance. In a more technical way, An ARMA is a covariance stationary model. For an ARMA model to be stationary, then the characteristic roots of the differencing equation, must lie inside with in the unit root circle. Furthermore, the process has to be started infinitely far in the past. The ARMA model is an extension of two key models: i,e the (AR) model and the (MA) models. Both are combined to capture the auto correlation structure and the stochastic error dynamics of a given time series(Y_t). A data set consisting of at least 50 observations is the desired range for (Y_t) series in ARMA models (Chatfield 2005).

The AR part expresses the time series (Y_t) current value as the linear function of its own lagged values (Y_{t-1}).

Mathematically, an AR process of order p can be mathematically expressed as:

$$Y_t = C_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots\ldots + \alpha_p Y_{t-p} + \varepsilon_t \qquad 1$$

In equation-1, Yt denotes, the time series he current value, and Yt−1, ...,+ Yt−p representing the past/lagged values from lag-1 up to lag-p respectively. C0 is a constant, while α1⋯αp are representing AR coefficients, and a white noise error term is represented by ϵt.

The MA part is expressing the (Yt) as, a function of the lagged error terms (shocks or disturbances). Hence, an MA(q) process of qth order can be mathematically expressed as:

$$Y_t = \mu + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \ldots\ldots + \beta_p \varepsilon_{t-p} + \varepsilon_t \qquad 2$$

In equation-2, μ representing the mean of the series, β1⋯+βp representing MA coefficients, and ϵt denotes the white noise error term.

Both AR and MA terms are combined in the ARMA(p,q) model, and therefore, providing a more comprehensive representation of the given time series behavior. The general form of an ARMA(p, q) model can be mathematically expressed as:

$$Y_t = C_0 + \Sigma_{i=1}^{p} \alpha_i Y_{t-i} + \epsilon_t + \Sigma_{j=1}^{q} \beta_j \epsilon_{t-j} \qquad 3$$

Here in equation-3, the order of the AR component is represented by p, while here q representing the MA components order. And the white noise process with zero mean and constant variance is represented by the notation of $\epsilon_{t.}$

Subsequently, the uni-variate ARMIA(p,d,q) model, can be expressed as:

$$\Delta\, CO2_t = C_0 + \Sigma_{i=1}^{p} \alpha_i CO2_{t-i} + \epsilon_t + \Sigma_{j=1}^{q} \theta_j \epsilon_{t-j} \qquad 4$$

where, ΔCO_{2t} is the CO_2 emission per capita with with 1st difference, while α and θ are parameters that are unknown. Ɛt representing the white noise error term.

Results and Discussion

In the model identification phase, the Augmented Dickey-Fuller (ADF) unit root test is used both with and without incorporating a time trend variable to determine the unit root process of a given time series (i.e CO_{2t}). The presence of a unit root suggests that the given time series is non-stationary, and the utilization of non-stationary series could produce spurious results. The results of the ADF unit root test are shown in below Table-1, that shows that at level the CO_{2t} series is not stationary but becomes stationary only at 1st difference. As a result, the CO_{2t} series is utilized as the dependent variable in the uni variate ARIMA (p,d,q) model. Since the CO_{2t} series has been confirmed as I(1), thereby we are bound to forecast the CO_{2t} series by ARIMA model (Rao et al. 1972).

Table 1

Results of the ADF Unit Root Test

Variables and Time period		At-level	At-first difference
CO_2 (1950-2022)	wc	- 0.833	-8.117*
	wct	-2.920	-8.033*

Source: Based on author's own computation obtained by using EViews-9 software. Notes: *, shows level of significance at 1%.

The optimal order of the model parameters, as well as the most suitable ARIMA (p,d,q) models, would be determined by using like (AIC) and (SIC) model selection criteria respectively. Table-2 below provides, the results of the six estimated tentative ARIMA (p,q,d) models for Pakistan's CO_{2t}. Among these 6 ARIMA models, ARIMA (6,1,3) model emerges as the best fit as it exhibits the greater number of significant coefficients, has highest adjusted R^2 value, and also having the lowest volatility as well as the lowest values of both (AIC) and(SIC) respectively. Hence, Pakistan's CO_{2t} is predicted with the using of the ARMA(6,1,3) model.

Table 2

Results of the Six Tentative ARIMA Models for Pakistan CO_2 Series

Model	No of significant Coefficients	Significance of the ARMA Components	Adjusted R^2	Volatility (SIGMASQ)	(AIC)	(SIC)
ARIMA (1,1,1)	2	AR(1)* MA(1)	0.070	0.0000718	-6.561	-6.435
ARIMA (2,1,2)	1	AR(2) MA(2)	0.030	0.0000795	-6.491	-6.364

Model	No of significant Coefficients	Significance of the ARMA Components	Adjusted R^2	Volatility (SIGMASQ)	(AIC)	(SIC)
ARIMA (3,1,3)	2	AR(2) MA(2)*	0.148	0.0000657	-6.661373	-6.535
ARIMA (3,1,6)	3	AR(3)* MA(6)*	0.176	0.0000636	-6.690	-6.564
ARIMA (6,1,3)	3	AR(6)* MA(3)*	0.178	0.0000634	-6.695	-6.569
ARIMA (6,1,6)	1	AR(6) MA(6)	0.113	0.0000684	-6.613	-6.487

Source: Based on author's computation obtained by using EViews-9 software. Note:*, Shows significance at 1%.

After identification of appropriate ARIMA structure (ARIMA 6,1,3 in our case), we next conduct some diagnostic tests in order to confirm that either the selected ARIMA(6,1,3) model qualifies these tests or not. For this purpose, we perform some diagnostic checks in order to check ARMA(6,1,3) model validity for forecasting. In the diagnostic checking stage, we perform Ljung–Box Q-test to check for auto correlation in residuals. The Table-3 last column given below, provides the Q- test statistic, probability values. As the table shows, the Q-statistic value up to 32 lags is 18.60, and the probability of obtaining such a Q value is practically not zero but 0.948. It is evident that the residuals are free of auto correlation. Hence, residuals are following the white noise process, which means that the model is valid. Hence, the desired ARMA(6,1,3) model can be used for forecasting.

Table 3

The (ACF) and(PACF) Graphs of the Residual

Sample: 1950 2022
Included observations: 72
Q-statistic probabilities adjusted for 2 ARMA terms

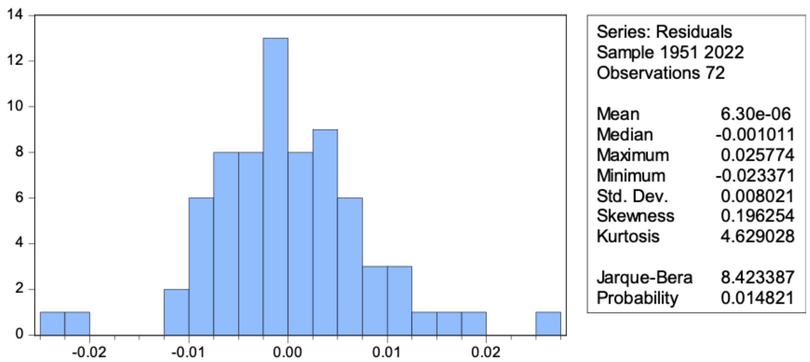
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.101	-0.101	0.7590	
		2	0.024	0.014	0.8032	
		3	-0.021	-0.017	0.8374	0.360
		4	0.073	0.070	1.2578	0.533
		5	-0.048	-0.034	1.4398	0.696
		6	-0.011	-0.022	1.4496	0.836
		7	-0.112	-0.114	2.4799	0.780
		8	-0.014	-0.042	2.4962	0.869
		9	0.018	0.021	2.5221	0.925
		10	0.099	0.106	3.3647	0.909
		11	0.056	0.094	3.6370	0.934
		12	0.012	0.021	3.6506	0.962
		13	-0.035	-0.047	3.7635	0.976
		14	0.071	0.034	4.2208	0.979
		15	-0.149	-0.153	6.3020	0.934
		16	-0.142	-0.176	8.2233	0.877
		17	0.090	0.104	9.0063	0.877
		18	-0.190	-0.165	12.577	0.703
		19	0.004	-0.007	12.579	0.764
		20	-0.050	-0.051	12.836	0.801
		21	0.003	-0.057	12.837	0.847
		22	-0.007	-0.023	12.843	0.884
		23	0.036	-0.017	12.987	0.909
		24	-0.084	-0.081	13.767	0.910
		25	0.063	0.054	14.222	0.920
		26	-0.131	-0.105	16.222	0.880
		27	0.082	0.072	17.012	0.881
		28	-0.027	0.008	17.100	0.906
		29	-0.045	-0.050	17.351	0.922
		30	-0.049	-0.017	17.649	0.935
		31	0.041	-0.071	17.866	0.947
		32	-0.074	-0.054	18.601	0.948

Source: Based on author's own computation obtained by using EViews-9 software

Moreover, to check the normality of the residuals we also perform the normality test. We use the Jarque Berra test of normality. We test our null hypothesis i.e Ho: Residuals are normally distributed at 5 % level of significance. Figure 2 below reveals the normality test results. From the result it is evident that the Jarque-Berra Probability value is equal to 0.015, that is less than 0.05 level of significance, thus the null hypothesis cannot be rejected. From the result it can be concluded that residuals are distributed normally and having a bell shaped distribution.

Figure 3

Residuals Normality test

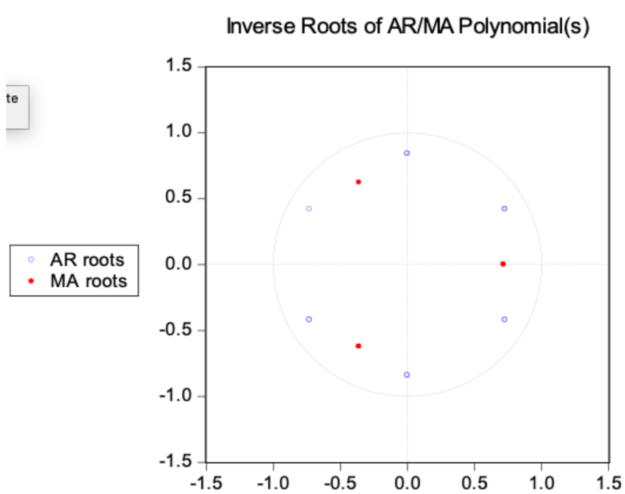


Source: Based on author's own computation and obtained by using EViews-9 software

In the below figure 4 we also provide the location of the AR root and MA roots. The inside location of these roots in a unit root circle, are considered as essential conditions for a model to be valid and produce meaningful forecasts. Figure-3 show that that,the AR(roots) lies inside within the unit circle, indicating that the selected ARIMA(6,1,3) is stationary. Furthermore, the MA (roots) also lies inside indicating that our selected ARIMA(6,1,3) model is invertible also. Hence, it is evident from all these diagnostic checks that the desired ARIMA(6,1,3) model can be used for forecasting purpose.

Figure 4

The Structure of ARMA

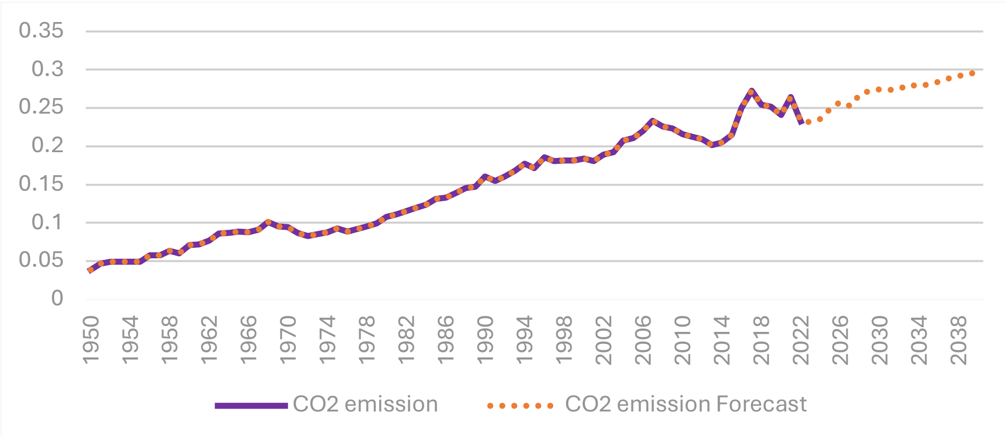


Source: Based on author's computation, obtained by using EViews-9 software

With the use of ARMIA(6,1,3) model, we are forecasting Pakistan's CO_{2t} for the years 2023 to 2040. Based on Figure-4 and Table-4, reveals an increasing trend in the CO_{2t} has been observed for Pakistan. The results indicates that the CO_{2t} time series, is expected to rise more by the end of 2040. The CO_{2t} is projected to reach at 0.298 tons per person level, which signifies an average increase of 27.2% increase from its 2022 value of 0.232 tons per person.

Figure 5

Actual and Forecasted values of CO_2 *emission per person (in tons) of Pakistan*



Source: Based on author's computation using EView-9 software

Table 4

CO_2 Emission Forecast (CO_2F) for Pakistan (in Tons)

Year	CO_2F	Year	CO_2F
2023	0.231	2032	0.275
2024	0.236	2033	0.280
2025	0.250	2034	0.279
2026	0.257	2035	0.281
2027	0.253	2036	0.284
2028	0.268	2037	0.289
2029	0.272	2038	0.292
2030	0.275	2039	0.294
2031	0.274	2040	0.298

Source: Based on author's computation using EView-9 software

Conclusion and Policy Recommendations

In this research study, the ARIMA (6,1,3) model for CO_2 emission has been selected for forecasting future values because it yields the greater significant coefficients in numbers, the highest value of the adjusted R^2, and also it provides the least volatility value. The model also provides the lowest values of both(AIC) and (SIC) criteria respectively. The results indicates that Pakistan's CO_2 emission is showing a continuous increase at an annual average rate of 27.2 % in the next 18 i.e. from 2023-2040.

The projected 27.2% increase in Pakistan's CO_2 emission from 2023 to 2040 necessitates immediate policy actions. As the energy mix remains heavily dependent on fossil fuels, contributing significantly to CO_2 emissions in Pakistan. Therefore an accelerated transition towards renewable energy would be required reduce the CO_2 emission level in Pakistan. This includes promoting investment in renewable energy projects. Besides these Pakistan also required to properly manage and check its population growth rate. Moreover Pakistan is required to promote innovative production process to control the value of CO_2 emission further increase. Overall, a proactive, evidence based environmentally friendly strategy is essential to control the projected increase in CO_2 emission in Pakistan, and to ensure environmental sustainability for the future generations of Pakistan.

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