Journal of Applied and Natural Science
17(2), 821 - 829 (2025)
ISSN : 0974-9411 (Print), 2231-5209 (Online)
journals.ansfoundation.org

Research Article

Mathematical modelling and projecting CO_2 by Autoregressive integrated moving average (ARIMA) and Simple exponential smoothing (SES) model for Bangladesh,Bhutan,Nepal and Pakistan

Mohammed Nizam Uddin
Department of Applied Mathematics, Noakhali Science and Technology University, Noakhali, Bangladesh
Mumtahin Taharima
Department of Applied Mathematics, Noakhali Science and Technology University, Noakhali, Bangladesh
Chowdhury Khaled Mahmud
Department of Applied Mathematics, Noakhali Science and Technology University, Noakhali, Bangladesh
Sofi Mahmud Parvez*
Department of Electrical and Electronic Engineering, Southeast University, Dhaka, Bangladesh.
A.N.M. Rezaul Karim
Department of Computer Science & Engineering, International Islamic University Chittagong, Bangladesh

*Corresponding author. E-mail: sofi.mahmud@seu.edu.bd

Article Info
https://doi.org/10.31018/jans.v17i2.6351
Received: October 29, 2024
Revised: May 29, 2025
Accepted: June 06, 2025

How to Cite
Uddin, M. N. *et al.* (2025). Mathematical modelling and projecting CO_2 by Autoregressive integrated moving average (ARIMA) and Simple exponential smoothing (SES) model for Bangladesh,Bhutan,Nepal and Pakistan. *Journal of Applied and Natural Science*, 17(2), 821 - 829. https://doi.org/10.31018/jans.v17i2.6351

Abstract
The impact of climate change has been a vital problem where CO_2 emission is one of the greatest contributors to global warming, and it has a negative effect on the environment.The core objective of this study was to understand, analyse and forecast the future CO_2 emission in Bangladesh, Bhutan, Nepal, and Pakistan using the Autoregressive Integrated Moving Average (ARIMA) and Simple Exponential Smoothing (SES) models. Annual CO_2 emission data produced from various carbon fuels and industries from 1946 to 2021 for Bangladesh, 1970 to 2021 for Bhutan, 1950 to 2021 for Nepal and from 1946 to 2021 for Pakistan were collected from the World Data Bank database and other sources. The study used this data to predict the CO_2 emission for the next 27 years, from 2024 to 2050. The ARIMA and SES models with the highest accuracy for Bangladesh, Bhutan, Nepal and Pakistan were determined by possessing the lowest value of Akaike's Information Criterion (AIC) with a graphical representation of ACF and PACF plots. Based on this method, ARIMA (0,1,1), ARIMA (0,1,0), ARIMA (1,1,1), ARIMA (0,1,0) were assumed to be the most perfect technique for predicting the CO_2 emission in Bangladesh, Bhutan, Nepal, and Pakistan. These models were used to draw numerical pictures of future CO_2 emission. Projected carbon dioxide emission values in Bangladesh, Bhutan, Nepal and Pakistan will increase, indicating major climate change and global warming. Different policies and strategies should be developed to tackle this situation.

Keywords: Carbon dioxide emission, Simple Exponential Smoothing (SES) Model, Autoregressive Integrated Moving Average (ARIMA) model

INTRODUCTION

One of the most important issues of the present moment is climate change. The persistent increase in carbon dioxide emissions significantly contributes to global warming. This trend represents one of the largest and arguably most complex challenges to the environment, society, and economy in the current century (Shirmohammadi *et al.*, 2018). As a consequence, human health is impacted by carbon emissions in both direct and indirect ways (Dong et al., 2021). High levels of carbon emissions directly affect respiratory health, leading to symptoms such as shortness of breath, headaches, dizziness, weakness, and confusion. Indirectly, carbon emissions contribute to worldwide concerns like climate change, global warming, and acid rain (Turgut et al., 2021) Furthermore, the transportation sector is a significant source of pollutants such as $PM_{2.5}$, PM_{10}, SO_2, and N_2O, posing environmental and health concerns (Magazzino et al., 2020) .In 2022, global emissions of CO_2 from the combustion of fossil fuels and cement manufacturing reached 36.1 ± 0.3 $GtCO_2$. This marked an increase from the levels observed in 2019, 2020, and 2021, with growth rates of 2.0%, 7.9%, and 1.5%, discretely. The 2022 growth rate of 1.5% (0.9 –2.6%) estimated by Carbon Monitor data aligns with projections from other sources such as the Global Carbon Project (GCP) (Friedlingstein, 2022) and the International Energy Agency (IEA), which anticipated growth rates of around 1.0 ± 0.9% and less than 1.0%, respectively, based on energy consumption (Defying Expectations, CO_2 Emissions from Global Fossil Fuel Combustion are Set to Grow in 2022 by Only a Fraction of Last Year's Big Increase, 2022). The remaining carbon budget from 2020 is estimated by the 2021 IPCC report to have a 67% chance of keeping warming to 1.5°C and 2°C at 400 $GtCO_2$ and 1,150 $GtCO_2$, respectively, or an 83% chance of keeping it to 300 $GtCO_2$ and 900 $GtCO_2$ (Masson-Delmotte, 2021).

Wijaya draws attention to the global disparity in the effects of climate change, highlighting how developing countries are more vulnerable since they have fewer resources available for adaptation and mitigation (Wijaya and A S, 2014). Bangladesh's energy consumption and CO_2 emissions are expected to rise by 6.7% per year, surpassing both GDP and energy consumption increases (Sarkar et al., 2018). The best models for projecting CO_2 emissions were ARIMA models, which predicted extremely alarming values of 53,034.79 kt (GFC), 15,926.17 kt (LFC), and 9,579.49 kt (SFC) by 2025 (Hossain *et al*., 2017). According to Parvez, the most accurate model for estimating Bangladesh's CO□ emissions is ARIMA (1, 2, 1), which projects a total of 171.33 billion tons by 2045 (Parvez *et al*., 2023).According to Fatima's analysis of CO□ emissions in Asian countries from 1971 to 2014, all but Singapore saw increasing trends, and Asia accounted for 49–50% of the world's industrial CO_2 output (Fatima, et al., 2019). Sawant focused on finding the best time series model for short term forecasting of carbon dioxide emission in the various industrial sectors in the US, which would aid the policymakers in implementing new policies and taking action on the various sectors (Sawant *et al*., 2022). In order to reach Kyoto Protocol commitments, Dritsaki *et al*. (2014) projected EU-28 CO_2 emissions using the ARIMA and ARCH models, estimating a 33.8% decrease by 2020 and a 40% reduction by 1990 levels. According to (Sharma & Nigam, 2020), ARIMA is the best model for predicting COVID-19 cases in limited areas of India; its accuracy was 97.38% for ARIMA (5,2,5) and 99.86% for ARIMA (5,2,3). According to (Jevrejeva et al., 2018), persistently increasing greenhouse gas emissions may cause sea level rise, and by 2100, flood-related damages might cost society $14 trillion yearly. According to (Bonga et al., 2019) , ARIMA (2,2,0) is the most accurate model for projecting India's CO_2 emissions, which are expected to reach 3.89 million kilotons by 2025. Chipo *et al*., 2019)found ARIMA (1,2,1) to be the best model for forecasting China's CO_2 emissions, predicting they will surpass 10 million kilotons by 2024. According to Chigora *et al*. (2019), who forecasted Zimbabwe's CO_2 emissions from 1964 to 2014 using the ARIMA(10,1,0) model, emissions will reach approximately 15,000 kilotons by 2024 .With an accuracy of 99.97% for ARMA and 99.8% for the Naive Bayesian model (Zafari and Khan, 2015)showed that both models can accurately forecast CO_2 emissions from coal.

Predicting CO_2 emissions requires using time-series forecasting techniques like ARIMA and SES. In order to provide insights into future patterns, the present study uses historical data to project emissions in Bangladesh, Bhutan, Nepal, Afghanistan, and Pakistan using these models. The study intends to help climate science and aid in climate change solutions by improving knowledge of emission patterns, thereby fostering a sustainable future. Therefore, using the past CO_2 emissions pathways and providing a reliable prediction of future CO_2 emissions are necessary for a better, sustainable future.

MATERIALS AND METHODS

Data sources

The study considered annual periodic data of CO_2 emissions in Bangladesh, Bhutan, Pakistan and Nepal from 1946 to 2021.Annual secondary data were collected from World Bank (https://data.worldbank.org/indicator/EN.ATM.CO2E.PC) and the world data (https://ourworldindata.org/search?q=CO2) and also from Bangladesh Meteorological Department (https://www.bmd.gov.bd/), Department of Hydrology and meteorology, Nepal (https://www.dhm.gov.np/request-data), National Center for Hydrology and Meteorology, Bhutan(https://www.nchm.gov.bt/), Pakistan Meteorological Department (https://www.pmd.gov.pk/en/); and the ARIMA and Simple Exponential Smoothing Model were applied to generate forecasts of carbon dioxide releases for the next 50 years. In this study, an annual periodic data set of CO_2 emissions of four Asian countries were used from 1946 to 2021. The countries were Bangladesh, Bhutan, Pakistan and Nepal. The reason behind choosing these countries was because of the availability of data. As geometrically, these countries are nearby, and the weather is similar in these countries. That is why the process of collecting and analysing data was uncomplicated.

Auto Regressive Integrated Moving Average (ARIMA) Model

A statistical analysis model called autoregressive integrated moving average (ARIMA) makes use of time series data (Parvez, 2023).The data set was used to forecast environmental, financial, energy data and future trends. Box-Jenkins ARIMA are used to forecast (Chipo *et al*., 2019) A time series model forecast the future value of the series based on past value data of the series and an uncorrelated random variable (ϵ_t) is called Autoregressive (AR) model.

$$A_t = K + \theta_1 A_{t-1} + \theta_2 A_{t-2} + \cdots + \theta_m A_{t-m} + \epsilon_t$$

$$A_t = K + \sum_{i=1}^{m} \theta_i A_{t-1} + \epsilon_t \quad \dots\dots\dots\dots\dots\dots\dots (1)$$

Where the equation (1),

AR (m) method= A_t

Order = m

Obstruct parameter = K

Autoregressive parameter = θ_i

Random variables without correlation with mean and variance = ϵ_t

Alternately , a moving average is a statistic that captures the average changes in a data series overtime.

$$A_t = L + \varphi_1 \epsilon_{t-1} + \varphi_2 \epsilon_{t-2} + \cdots + \varphi_n \epsilon_{t-n} + \epsilon_t$$

$$A_t = L + \sum_{j=1}^{n} \varphi_j \epsilon_{t-j} + \epsilon_t \dots\dots\dots\dots\dots\dots\dots\dots (2)$$

Where the equation (2),

Constant = L

Unknown parameter (MA coefficients) = $\varphi_j \geq 0$

White noise disturbance term= ϵ_t

In the AR(p) model, the partial autocorrelation coefficient stops at the p order, but the autocorrelation coefficient drops in a geometric progression or oscillation as the delay order grows. The autocorrelation coefficient for MA(q) models is truncated at order q.As the delay order increases, the partial autocorrelation coefficient decreases geometrically or oscillating. The autocorrelation coefficient for the ARMA(p,q) model goes to zero after the q order and drops geometrically or oscillates as the delay order grows. As the delay order grows, the partial autocorrelation coefficient declines geometrically or oscillatorily and tends to zero after p order (Ning *et al*., 2021).

The ARMA model, first presented by Box and Jenkins in 1976, is the total of an Autoregressive and Moving Average process. Equation represents an ARMA model mathematically,

$$A_t^* = k + \sum_{i=1}^{m} \theta_i A_{t-i} + \sum_{j=1}^{m} \varphi_j \epsilon_{t-j} + \epsilon_t \dots\dots\dots\dots (3)$$

The ARMA(p,q) program class extension significantly increases its empirical value.An autoregressive composite moving average serves as the descriptor for non -stationary time series. The seasonal ARIMA model is represented by ARIMA(p,d,q).An autoregressive composite moving average serves as the descriptor for non -stationary time series. The seasonal ARIMA model is represented by ARIMA (p, d, q) (Fatima, et al., 2019)

Here,

p =the number of periodic autoregressive mechanisms,

q =the number of periodic moving average positions, and

d =the number of seasons, the variance required to introduce stability.

This d number is an integration process and requires differentiation to fix the task.

An autoregressive integrated moving average, or ARIMA (p, d, q), is the process name for the integration process. Forecasting, diagnostic testing, and estimate are all part of the ARIMA modelling process. Box and Jenkins describe the steps involved in developing an ARIMA model.

Model detection; Model parameter assessment; Problem-solving testing (Parvez, 2023) (Rahman and Hasan, 2017)

The data used in this study consisted of an annual time series of CO_2 emissions in Bangladesh, Pakistan, Nepal, and Bhutan, meaning there is non-periodic inequality in the data. Therefore, only non-periodic ARIMA (p, d, q) are applicable. To compare the various parametric fusions of the ARIMA (p,d,q) and SES families, various selection criteria such as Akaike's Information Criterion (AIC), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Maximum Absolute Standard Error (MASE), Bayesian Information Criterion (BIC), and Mean Absolute Error (MAE) are used. The selection is based on finding the combination with the lowest value for each criterion (Parvez, 2023).

Simple Exponential Smoothing Model

The time series technique, the Simple Exponential Smoothing Model (SES), is used with univariate data to forecast corporate, financial, and economic data.This data has no trend and no seasonal pattern. SES provides the optimal forecast, which is the weighted linear sum of delays or recent observations.

Simple Exponential Smoothing Model is mathematically written as,

$$S_{t+1} = \lambda y_t + (1-\lambda)S_t$$

Also written as follows,

$$S_{t+1} - S_t = \lambda(y_t - S_t)$$

$$S_{t+1} = \lambda\epsilon_t + S_t \dots\dots\dots\dots (4)$$

here,

y_t = Time series under consideration

λ = Smoothing parameter (weighted) which lies between $0 < \lambda < 1$

ϵ_t = Error

S_t = Predicted values at time t

S_{t+1} = Predicted values at time t+1 (Parvez, 2023)

By employing the recursive technique, the overall structure of equation (4),

$$S_{t+1} = \lambda \sum_{i=0}^{t-1} (1-\lambda)\, y_{t-i} + (1-\lambda)\, y_t \dots\dots\dots\dots (5)$$

The weights in equation (5) fall exponentially to zero, known as "exponential smoothing." Since the decay is slow for small values of λ, the decay rate can be regulated by selecting a suitable value for λ (Fatima *et al*., 2019)

The data used consisted of a yearly time series of CO_2 emissions in Bangladesh, Pakistan, Nepal, and Bhutan, which means there is non-periodic variation in the data. Therefore, only non-periodic SES methods are applicable. To compare the various parametric combinations of the ARIMA(p,d,q) and SES families, various selection criteria such as Akaike's Information Criterion (AIC), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Maximum Absolute Standard Error (MASE), Bayesian Information Criterion (BIC), and Mean Absolute Error (MAE) are used. The selection is based on finding the combination with the lowest value for each criterion (Parvez *et al*., 2023).

RESULTS

With a 95% forecast confidence level, the forecasting findings utilizing the ARIMA and Simple Exponential Smoothing (SES) models showed a concerning rise in CO□ emissions throughout Bangladesh, Pakistan, Nepal, and Bhutan between 2024 and 2050.This is shown in Fig. 1. Figures 2 to 5 show the partial autocorrelation function with a significance limit of 0.05 for Bangladesh, Bhutan, Pakistan and Nepal, respectively. Figure 6 to Figure 9 shows the partial autocorrelation with a residuals significance limit of 0.05 Bangladesh, Pakistan, Nepal and Bhutan, respectively. Tables 1 and 2 show the ARIMA and Simple exponential model summary and the statistics, respectively. Table 3 shows the forecasting accuracy of Bangladesh, Bhutan, Nepal and Pakistan. Then we see the forecasting of CO_2 emission of Bangladesh, Bhutan, Nepal and Pakistan from 2024 to 2050.

At last, Table 5, which displays the anticipated CO□ emissions every three years, displays the expected data for these nations. According to the ARIMA model, Bangladesh's output will increase by 1,090,516,171 metric tons over a 26-year period, from 120,555,188.7 metric tons in 2024 to 1,211,071,360 metric tons in 2050. This notable expansion demonstrates how Bangladesh's growing industrialization and energy use are driving up carbon emissions. Additionally, the forecasts for Pakistan showed a consistent increase in CO_2 emissions. Emissions from Pakistan are expected to increase by 181,262,292.8 metric tons (SES) and 181,241,096 metric tons (ARIMA). The accuracy of these forecasting techniques is supported by the small variation between the two models, which points to con-

Table 1. Arima and Simple exponential model summary

ARIMA & SES Model summary				
	Bangladesh	**Bhutan**	**Nepal**	**Pakistan**
AR Order (p)	0	0	1	0
I Order (d)	1	1	1	1
MA Order (q)	1	0	1	0
SAR Order (P)	0	0	0	0
SI Order (D)	0	0	0	0
SMA Order (Q)	0	0	0	0
Seasonal Frequency	1	1	1	1
Include Constant	1	1	1	1
No. of Predictors	0	0	0	0
Model Selection Criterion	AIC	AIC	AIC	AIC

Table 2. Arima and Simple exponential model statistics

ARIMA & SES Model Statistics				
	Bangladesh	**Bhutan**	**Nepal**	**Pakistan**
Observations	76	72	72	76
DF	73	50	68	74
StDev	0.191894751	81.58221434	0.174798859	498.3314632
Variance	0.036823596	6655.657696	0.030554641	248334.2473
Log-Likelihood	18.36667071	-296.3480403	23.14829603	-571.7652983
AICc	-30.39531324	596.9460806	-37.69053146	1147.697263
AIC	-30.73334141	596.6960806	-38.29659206	1147.530597
BIC	-23.78087707	600.5597319	-29.24587255	1152.165573

Table 3. Forecasting Accuracy of Bangladesh, Bhutan, Nepal, Pakistan

Forecast Accuracy				
Metric	**Bangladesh**	**Bhutan**	**Nepal**	**Pakistan**
N	75	51	71	75
RMSE	1805753.768	48100.18056	547793.9372	4982041.371
MAE	957837.8407	32897.40704	272832.7151	2804777.795
MAPE	6.735336344	24.2135588	13.09328828	6.5916032
MASE	0.743798405	0.823265706	0.816277422	0.775803961

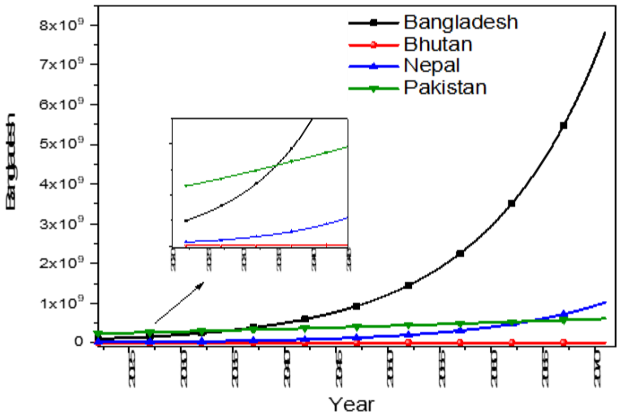

Fig. 1. *Forecasting chart 95.0% prediction intervals*

sistency in the forecasts.Emissions from Nepal are expected to rise by 170,758,399.5 metric tons (SES) and 151,606,626.1 metric tons (ARIMA). Although it is less than that of Bangladesh and Pakistan, this increased trend shows how Nepal's expanding industrial activity and energy demand are affecting the country. With emissions rising by 1,916,063.965 metric tons (ARIMA) and 1,917,752.606 metric tons (SES), Bhutan exhibits the least amount of increase. Bhutan has the lowest emissions, but they are still predicted to increase, highlighting how pervasive carbon emissions are throughout South Asia. These estimates demonstrate how CO_2 emissions are rising in the four nations. According to the data, Bangladesh contributes the most CO□ emissions out of the four countries, followed by Pakistan, Nepal, and Bhutan. The ongoing increase in emissions across all countries indicates an increasing difficulty in controlling carbon footprints, which may greatly impact regional efforts to mitigate climate change and maintain environmental sustainability.

DISCUSSION

The results are in line with the worldwide trend of rising CO□ emissions when contrasted with other research, such as those by Chipo *et al*. (2019) and Hossain *et al*. (2017), who also forecasted emissions in various locations- in China from 2015 to 2024 and in Bangladesh from the year 2014 to 2025 respectively using ARIMA models. The results of the ARIMA and SES models utilized in this study are nearly similar; however, they highlight their precision and show how reliable they are for long-term forecasting in this setting.

Effective climate change mitigation techniques are desperately needed, as seen by the steady increase in emissions in Bangladesh, Pakistan, Nepal, and Bhutan. The study's conclusions are important because they support global trends found in earlier studies (Jevrejeva *et al*., 2018; Dritsaki *et al*., 2014), highlighting the serious environmental effects of rising CO□ levels. Out of all the nations examined, Bangladesh is the biggest

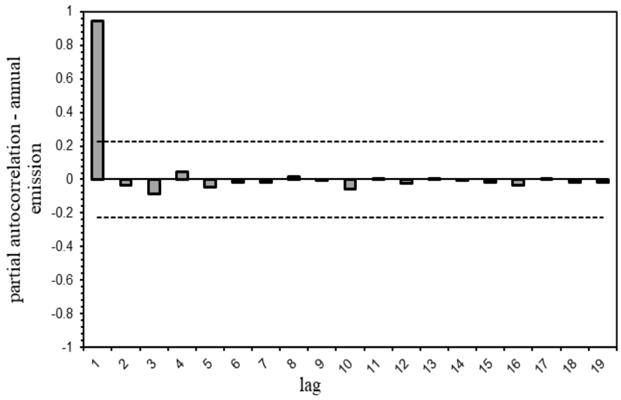

Fig. 2. *Partial Autocorrelation Function (PACF) Plot significance limit alpha=0.05 of Bangladesh*

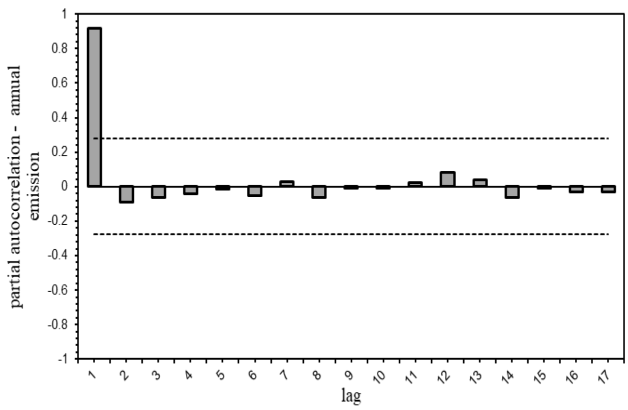

Fig. 3. *Partial Autocorrelation Function (PACF) Plot significance limit alpha=0.05 of Bhutan*

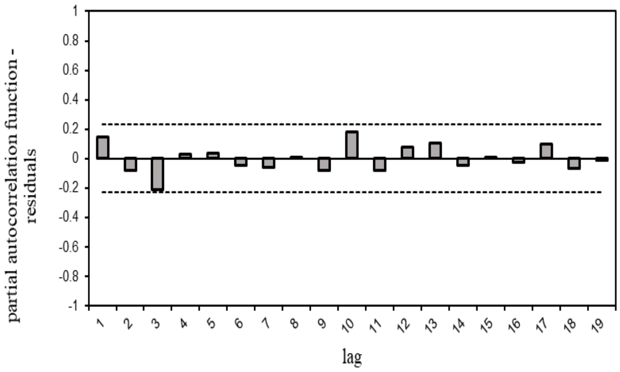

Fig. 4. *Partial Autocorrelation Function (PACF) Plot significance limit alpha=0.05 of Pakistan*

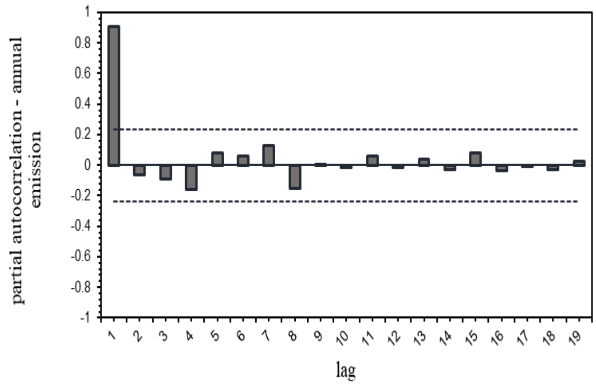

Fig. 5. *Partial Autocorrelation Function (PACF) Plot significance limit alpha=0.05 of Nepal*

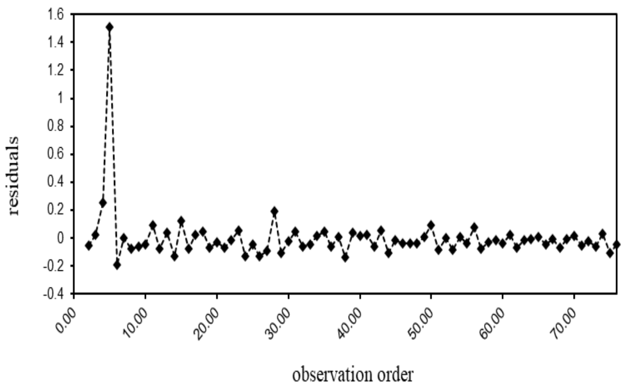

Fig. 6. *Partial Autocorrelation Function (PACF) plot – residuals significance limit alpha = 0.05 of Bangladesh*

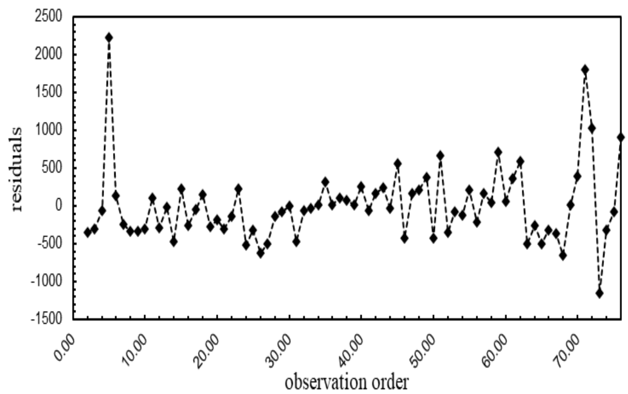

Fig. 7. *Partial Autocorrelation unction (PACF) plot – residuals significance limit alpha = 0.05 of Pakistan*

emitter, followed by Pakistan, Nepal, and Bhutan. According to earlier studies, elevated CO_2 levels are directly linked to worsening air pollution and the consequences of climate change, including rising temperatures (Fatima *et al.,* 2019).

The ARIMA and SES models included in this work have demonstrated superior predictive accuracy compared to other forecasting techniques, such as Exponential Smoothing and ANN, making them appropriate instruments for climate prediction in these areas. Specifically, the ARIMA model has been shown to be useful for forecasting CO_2 emissions in several research. Ahammad Hossain (2017) researched sample static forecasting using ARIMA in Bangladesh from 2014 to 2025. The predicted values from GFC, LFC, and SFC in 2025 were 53034.79, 15926.17, and 9579.49 kt. Correspondingly, this is really concerning. Using the ARIMA(1,2,1) model, which proved superior to other forecasting methods like Holt-Winters and Artificial Neural Networks (ANN), Nyoni and Chipo evaluated the chance of an increase in CO_2 emissions in China from 2015 to 2024.(Hossain *et al.,* 2017); (Chipo *et al*., 2019),

Table 4. Forecasting table of Bangladesh, Bhutan, Nepal, Pakistan

Bangladesh						
ARIMA				**SES**		
Period	**Forecast**	**Lower 95.0% PI**	**Upper 95.0% PI**	**Forecast**	**Lower 95.0% PI**	**Upper 95.0% PI**
2024	120555188.7	56636076.18	256613001.7	120555188.7	56636076.18	256613001.7
2028	171924300.1	52219654.99	566031410.4	171924300.1	52219654.99	566031410.4
2032	245182022.4	54361457.44	1105824364	245182022.4	54361457.44	1105824364
2036	349655191.6	59805021.08	2044289105	349655191.6	59805021.08	2044289105
2040	498644851.1	68037084.37	3654575880	498644851.1	68037084.37	3654575880
2044	711119678.7	79214817.97	6383795486	711119678.7	79214817.97	6383795486
2048	1014130992	93831083.95	10960777869	1014130992	93831083.95	10960777869
2050	1211071360	102656884.5	14287340268	1211071360	102656884.5	14287340268
Bhutan						
ARIMA				**SES**		
Period	**Forecast**	**Lower 95.0% PI**	**Upper 95.0% PI**	**Forecast**	**Lower 95.0% PI**	**Upper 95.0% PI**
2024	1697131.804	3.07868E+12	3.08783E+12	1697264.144	1348959.599	2085524.775
2028	1945343.197	7.18677E+12	7.20173E+12	1945668.635	1389869.149	2594732.734
2032	2210488.291	1.12953E+13	1.13153E+13	2211031.079	1479140.798	3089537.14
2036	2492567.087	1.54039E+13	1.54287E+13	2493351.476	1594662.888	3592049.67
2040	2791579.584	1.95125E+13	1.9542E+13	2792629.827	1729578.824	4109126.935
2044	3107525.782	2.36211E+13	2.36554E+13	3108866.131	1880887.751	4643769.807
2048	3440405.681	2.77297E+13	2.77688E+13	3442060.389	2047050.027	5197517.946
2050	3613195.769	2.9784E+13	2.98255E+13	3615016.75	2135415.25	5481842.416
Nepal						
ARIMA				**SES**		
Period	**Forecast**	**Lower 95.0% PI**	**Upper 95.0% PI**	**Forecast**	**Lower 95.0% PI**	**Upper 95.0% PI**
2024	18474378.51	11373840.41	30007688.61	18724841.05	10523599.61	33317466.01
2028	26095960.91	15209357.91	44775011.54	26733573.25	11380635.49	62798245.28
2032	36737650.52	21229566.32	63574306.93	38167690.55	13202352.94	110341892
2036	51661637.08	29784574	89607618.55	54492251.67	15849647.39	187348363
2040	72621776.36	41820724.97	126107866.5	77798930.19	19438611.3	311373762.5
2044	102073651.1	58730894.8	177402886.2	111074021.6	24199535.52	509821284.1
2048	143464146	82482573.25	249531026.6	158581078.7	30466647.9	825425842.7
2049	156206720.7	89791942.17	271745314.9	173344906.7	32319186.19	929740510.8
2050	170081004.6	97749110.52	295936689	189483240.5	34302179.71	1046694372
Pakistan						
ARIMA				**SES**		
Period	**Forecast**	**Lower 95.0% PI**	**Upper 95.0% PI**	**Forecast**	**Lower 95.0% PI**	**Upper 95.0% PI**
2024	247238260.3	2.9622E+12	3.07144E+12	247238679.8	221004394.1	274943950.8
2028	271898325	6.95145E+12	7.12644E+12	271901346.3	230407365	316828869.1
2032	297730455.4	1.09463E+13	1.11758E+13	297736318.3	243741561.2	357128742.8
2036	324734651.6	1.49432E+13	1.52232E+13	324743595.8	259270303.5	397580251.9
2040	352910913.6	1.89411E+13	1.92695E+13	352923178.8	276434369.1	438742619.6
2044	382259241.4	2.29394E+13	2.33155E+13	382275067.2	294978519.2	480871085.6
2048	412779634.9	2.69379E+13	2.73613E+13	412799261.1	314765224.8	524103179.2
2050	428479356.3	2.89371E+13	2.93842E+13	428500972.6	325097624.8	546159997.8

Table 5. CO_2 emissions by Countries (1950-2020)

Period	Bangladesh	Nepal	Pakistan	Bhutan
1950	993068	25648	5354962	
1955	1379291	43968	7437157	
1960	2211905	80608	11926437	
1965	3121306	179536	16829590	
1970	3803195	227168	20504408	3664
1975	4856723	351714	23187848	3664
1980	7597219	541295	31931550	21984
1985	10189161	676018	46813544	62288
1990	14081596	721436	67827370	128240
1995	21041714	2308915	83614360	236263
2000	26524610	3037431	105419770	382875
2005	37676584	2986772	134692300	378475
2010	53991556	4824304	153908660	464723
2015	73157550	6904657	166410770	965039
2020	90825304	13944494	210383920	1499693

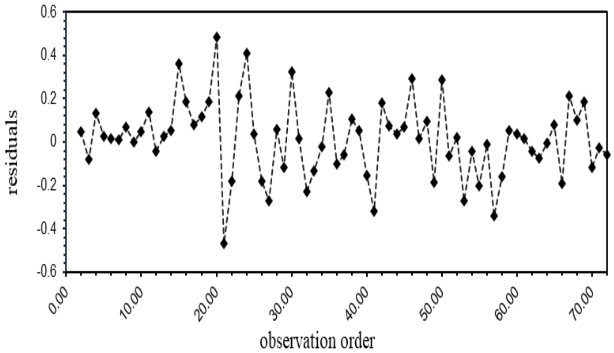

Fig. 8. *Partial Autocorrelation Function (PACF) plot – residuals significance limit alpha = 0.05 of Nepal*

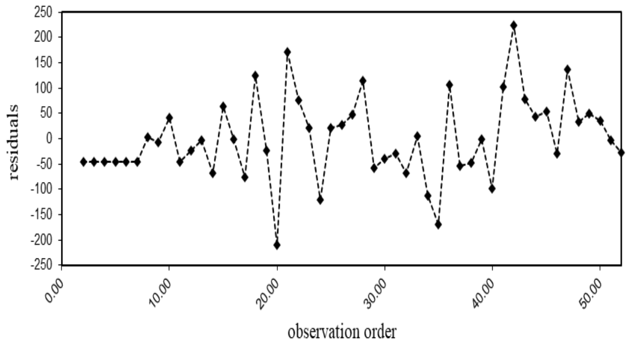

Fig. 9. *Partial Autocorrelation Function (PACF) plot – residuals significance limit alpha = 0.05 of Bhutan*

In summary, this work highlights the urgent need to address CO_2 emissions in rapidly developing South Asian countries by validating the accuracy of the ARIMA and SES models for climate change forecasting. The models exhibit strong predictive capabilities, as reflected by the low RMSE, MAE, and MASE values across Bangladesh (RMSE: 1805753.77, MAE: 957837.84, MASE: 0.74), Bhutan (RMSE: 48100.18, MAE: 32897.41, MASE: 0.82), Nepal (RMSE: 547793.94, MAE: 272832.72, MASE: 0.82), and Pakistan (RMSE: 4982041.37, MAE: 2804777.80, MASE: 0.78). These accuracy metrics demonstrate superior model performance compared to prior studies, which often lacked comprehensive validation across multiple countries. The precise long-term forecasts generated by these models offer valuable insights into future CO_2 emission trends, aiding the region's data-driven policy-making and sustainable development initiatives.

Conclusion

The study study used ARIMA and Simple Exponential Smoothing (SES) models to correctly anticipate carbon dioxide (CO□) emissions in Bangladesh, Bhutan, Nepal, and Pakistan. The results showed that CO_2 emissions were steadily increasing in all four countries, with Bangladesh expected to see the largest increase, followed by Pakistan, Nepal, and Bhutan. The SES model offered a more straightforward but efficient method for datasets with steady trends, whereas the ARIMA model showed greater adaptability for managing non-stationary data. Both models demonstrated as dependable instruments for encapsulating the fundamental patterns and fluctuations in CO_2 emissions, providing insightful information to environmental planners and policymakers. The use of ARIMA and SES models to predict CO_2 emissions in South Asian nations—a region that has been neglected in climate change studies— makes this work interesting. This study adds to the expanding body of research on mitigating the effects of climate change. It lays the groundwork for further studies in this field by offering comprehensive forecasts for the next 27 years (2024–2050). It is recommended that future research include other variables like population dynamics, economic growth, and energy consumption patterns to improve the accuracy of emission estimates further. This would facilitate the creation of focused mitigation measures and offer a more comprehensive understanding of the variables influencing CO_2 emissions. This study emphasized how urgently proactive steps are needed to address growing emissions and lessen the effects of climate change in the area.

Conflict of interest

The authors declare that they have no conflict of interest

REFERENCES

1. Bonga, Nyoni, T., & G., W. (2019). Prediction of ٱء Emissions in India using ARIMA Models. *Dynamic Research Journals (drj) , 4*(2), 1-10.
2. Chigora, D. F., Thabani, N., & Mutambara, D. E. (2019). Forecasting 2 Emission for Zimbabwe's Tourism Destination vibrancy: A Univariate Approach using Box- Jenkins ARIMA Model. *African Journal of Hospitality, Tourism and Leisure, 8*(2), 1-15.
3. CHIPO, Thabani, N., & Mutongi. (2019). Modeling and forecasting carbon dioxide emissions in China using Autoregressive Integrated Moving Average (ARIMA) models. *Munich Personal RePEc Archive*, 1-13.
4. Defying Expectations, CO2 Emissions from Global Fossil Fuel Combustion are Set to Grow in 2022 by Only a Fraction of Last Year's Big Increase. (2022). International Energy Agency.
5. Dong, H., Xue, M., Xiao, Y., & Liu, Y. (2021). Do carbon emissions impact the health of residents? Considering China's industrialization and urbanization. *Science of the Total Environment, 758*, 143688. DOI:10.1016/j.scitotenv.2020.143688
6. Dritsaki, Chaido, & Dritsaki, M. (2014). Causal relationship between energy consumption, economic growth and CO2 emissions: A dynamic panel data approach. *4.2*(125-136).
7. Dritsaki, M., & Dritsaki, C. (2020). Forecasting European Union CO2 Emissions Using Autoregressive Integrated Moving Average-autoregressive Conditional Heteroscedasticity Models. *International Journal of Energy Economics and Policy , 10*(4), 411-423. DOI: https://doi.org/10.32479/ijeep.9186
8. Fatima, Samreen, Ali, & Saad, S. (2019). Forecasting Carbon Dioxide Emission of Asian Countries Using ARIMA and Simple. *Int. J. Econ. Environ. Geol*, 65. DOI:10.46660/ojs.v10i1.219
9. Friedlingstein. (2022). Global Carbon Budget 2022. *Earth System Science Data, 14*, 4811–4900. DOI:10.5194/essd-14-4811-2022
10. Hossain, A., Islam, M. A., Kamruzzaman, M., Khalek, M. A., & Ali, M. A. (2017). Forecasting Carbon Dioxide Emissions in Bangladesh Using Box Jenkins ARIMA Models. *International Journal of Statistical Sciences, 16*, 33-48.
11. Jevrejeva, S., Jackson, L. P., Grinsted, A., Lincke, D., & Marzeion, B. (2018). Flood damage costs under the sea level rise with warming of 1.5 ◦C and 2 ◦C. *Environmental Research Letters, 13*(7), 1-12. DOI:10.1088/1748-9326/aacc76
12. Magazzino, C., Mele, M., & Schneider, N. (2020). The relationship between air pollution and COVID-19-related deaths: An application to three French cities. *Applied Energy, 279*, 115835. DOI:10.1016/j.apenergy.2020.115835
13. Masson-Delmotte. (2021). *IPCC Climate Change 2021: The Physical Science Basis.* Cambridge Univ. Press.
14. Ning, L., Pei, L., & L, F. (2021). Forecast of China's Carbon Emissions Based on ARIMA Method. *Discrete Dynamics in Nature and Society*, 2-12. DOI:10.1155/2021/1441942
15. Parvez, S. M. (2023). Analyzing Bangladesh's Present Patterns in Population Growth and. *International Journal of Scientific Research in* , 41-48.
16. Parvez, S. M., Uddin, M. N., & Karim, A. N. (2023). Projection of Carbon Dioxide Discharge by applying ARIMA Model in Bangladesh. *Journal of Computer Science & Computational Mathematics*, 118-121. DOI:10.20967/jcscm.2023.04.003
17. Rahman, A., & Hasan, M. M. (2017). Modeling and Forecasting of Carbon Dioxide. *Open Journal of Statistics*, 560-566. DOI:10.4236/ojs.2017.74038
18. Sarkar, M. S., Sadeka, S., Sikdar, M. M., & Badiuzzaman. (2018). ENERGY CONSUMPTION AND CO2EMISSION IN BANGLADESH:TRENDS AND POLICY IMPLICATIONS. *Asia Pacific Journal of Energy and Environment, 5* (1), 41-48. DOI:10.18034/apjee.v5i1.249
19. Sawant, Manoj, & Vineet. (2022). Forecasting Carbon Dioxide Emission from Energy Consumption within the Industrial Sector in U.S. *NORMA eResearch platform*, 1-22.
20. Sharma, V. K., & Nigam, U. (2020). Modeling and Forecasting of COVID19 Growth Curve in India. *Transactions of the Indian National Academy of Engineering, 5*, 697–710. DOI:10.1007/s41403-020-00165-z
21. Shirmohammadi, Soltanieh, Romeo, & L.M. (2018). Thermoeconomic analysis and optimization of post-combustion CO2 recovery unit utilizing absorption refrigeration system for a natural-gas-fired power plant. *Environmental Progress & Sustainable Energy, 37*(3), 1075–1084. DOI:10.1002/ep.12866
22. Turgut, M., Eliiyi, U., Turgut, O., Öner, E., & Eliiyi, D. (2021). Artificial intelligence approaches to estimate the transport energy demand in Turkey. *Arabian Journal for Science and Engineering, 46*, 2443–2476. DOI:10.1007/s13369-020-05108-y
23. Wijaya and A S. (2014). Climate Change, Global Warming and Global Inequity in Developed and Developing Countries (Analytical Perspective, Issue, Problem and Solution). *IOP Conf. Series: Earth and Environmental Science*. DOI:10.1088/1755-1315/19/1/012008
24. Zafari, & Khan. (2015). Accuracy of ARMA and Bayesian Models in Forecasting Carbon Dioxide Emission from Fossil Fuels in China and Across the Globe. *Journal of Environment, 4*, 36-40.