International Journal of Statistical Sciences *ISSN 1683-5603*
Vol. 16, 2017, pp 33-48

Forecasting Carbon Dioxide Emissions in Bangladesh Using Box Jenkins ARIMA Models

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[Received January 20, 2017; Accepted August 25, 2017]

Abstract

Proper understanding, analyses and forecasts of carbon dioxide (CO_2) emissions is one of the key requirements to face the challenges of global warming, climate change, and clean and healthy environment. Global warming is a major atmospheric issue all over the world and generally caused by greenhouse gas- mainly CO_2 emission in the atmosphere. The study has been developed appropriate statistical models for forecasting CO_2 emissions in Bangladesh. Annual CO_2 emissions data from Gaseous Fuel Consumption (GFC), Liquid Fuel Consumption (LFC), and Solid Fuel Consumption (SFC) in metric tons per capita (kt.) from 1972 to 2013 were collected from World Bank data base. For developing Autoregressive Integrated Moving Average (ARIMA) models, Kwiatkowski Phillips Schmidt Shin (KPSS) test has been applied to detect the unit root property of the study variables. The models take into consideration Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Bias Proportion (BP) metrics. The static forecasting of the ARIMA models show better performance rather than the Holt-Winters Non Seasonal (HWNS) Smoothing and Artificial Neural Networks (ANN) models from 1972-2013. In sample forecasting of ARIMA models are computed from 2011 to 2013 and the Mean Absolute Percent of Error (MAPE) for GFC, LFC and SFC are2.8, 8.4 and 12.9 kt. respectively. The stability of the forecasting process is also checked by Chow forecast test using the actual data. The out sample static forecasting are also made by ARIMA from the year 2014 to 2025 and the forecasted values will be reached 53034.79, 15926.17 and 9579.49 kt. in 2025 from GFC, LFC and SFC respectively which is highly alarming. So, the study results may contribute significant role to make appropriate climate policies of Bangladesh due to CO_2 emission from fuel consumption.

Keywords: Carbon dioxide (CO_2) emissions; Global warming; ARIMA Models; Forecasting.

AMS Classification: 62M10.

1. Introduction

Climate change has been one of the top issues on international political agendas in recent years for global warming. Global warming is one of the most gripping and complicated problems facing the world. It is generally caused by greenhouse gas-mainly CO_2 emission in the atmosphere. The combustion of fuel, a chemical process in which a substance reacts rapidly with oxygen and gives off heat, is at the center of the climate change debate. The fuel can be a solid, liquid, or gas. According to International Energy Statistics (IES), the top CO_2 emission country in the world like China raked 1, USA ranked 2, and India ranked 3, whereas Bangladesh ranked 56 (US Department of Energy, 2016). The top 3 countries at risk for climate change impacts, in order of their vulnerability, are Haiti, Bangladesh and Zimbabwe (Maplecroft Report, 2011). Generally, CO_2 emissions in atmosphere occurred from fuel consumption like gas, liquid and solid fuel particularly coal. Shih and Tsokos developed two non-stationary time series models with trend and seasonal effects to predict future estimates of carbon dioxide emissions for monthly data in the atmosphere using multiplicative ARIMA models and they got minimum RMSE (Shih et al., 2008). Lotfalipour, Falahi and Bastam proposed CO_2 emissions prediction models based on Grey System and ARIMA and compared of these two methods by RMSE, MAE and MAPE metrics, and the results show the more accuracy of Grey system forecasting rather than other methods of prediction (Lotfalipour et al., 2013). Marland, Boden and Andres studied global, regional, and national CO_2 emissions to detect the trend of global warming (Marland et al., 2003). Tudor predicted the evolution of CO_2 emissions in Bahrain with automated forecasting methods-including the exponential smoothing state space model (ETS), the Holt–Winters Model, the BATS/TBATS model, ARIMA, the structural time series model (STS), the naive model, and the ANN model of time series forecasting; and the results show the best performance of ANN rather than other methods of prediction (Tudor, 2016). Kamruzzaman et al. used ARIMA models to forecast the climate variables-daily rainfall and temperature in the western part of Bangladesh effectively and got minimum RMSE (Kamruzzaman et al., 2016). Zafari and Khan proposed Autoregressive Moving Average (ARMA) and Bayesian models in forecasting CO_2 from fossil fuels in China and across the globe and the results validate the accuracy of the models as the ARMA model attains accuracy as high as 99.97% while the Naive Bayesian model reaches an accuracy of 99.8% (Zafari & Khan, 2015). Global-mean near-surface air temperature is already 0.8 degrees Celsius (°C) above preindustrial (1851-79) levels. No climate policy will be sustained for continuing the present level of CO_2 emission in the world (Riahi et al., 2015). As far our knowledge goes no study explicitly forecasting CO_2 emission from GFC, LFC and SFC in Bangladesh using Box Jenkins ARIMA model with comparing to Holt-Winters Non Seasonal (HWNS) Smoothing and Artificial Neural Networks (ANN) methods. So, the present study may be helpful for developing useful statistical models and to forecast CO_2 emissions in Bangladesh.

2. Materials and Methodology

2.1 Data Source

The study uses the yearly CO_2 emissions data about GFC, LFC and SFC in Bangladesh from 1972 to 2013. The source of data is in the World Bank data base accessed on 25 July 2016. (Data base link at: http://data.worldbank.org/indicator/EN.ATM.CO2E.PC?location=BD).

2.2 Box Jenkins ARIMA Model

Box and Jenkins (1976) theorized the ARIMA model. It has been formulized in the following way. Differencing is often needed to make a time series stationary, supposing Y_t be a time series variable and considering the model:

$$Y_t - Y_{t-1} = C + \varepsilon_t$$

Where, ε_t is a white noise disturbance term. Then, Y_t is said to be generated by an integrated process of order one and it is denoted as I(*1*).

In compact way, the model can be written as: $\nabla Y_t = C + \varepsilon_t$ Where, $\nabla = 1 - B$

Similarly, an integrated process of order *d* is denoted by *I(d)* and it can be written as: $\nabla^d Y_t = C + \varepsilon_t$

The theoretical ACF of an integrated process decays slowly (Barlett, 1946). From the above discussion, it is clear that an ARIMA process is nothing but the combination of the three processes- auto regression (AR) process, moving average (MA) process, and integrated process. The general ARIMA process of order *p, d*, and *q* is denoted by ARIMA (*p, d, q*) and it can be written in a compact way as follows: $\varphi(B)\nabla^d Y_t = C + \theta(B)\varepsilon_t$ (1)

$\nabla^d = (1-d)^d$ (The *d* order differencing operator)

$\varphi(B) = (1 - \varphi_1 B - \varphi_2 B^2 - \varphi_3 B^3 - \cdots - \varphi_p B^p)$ (The *p* order AR operator)

$\theta(B) = (1 - \theta_1 B - \theta_2 B^2 - \theta_3 B^3 - \cdots - \theta_p B^p)$ (The *q* order MA operator)

Where, ε_t = random shocks, *C* is the constant, and Y_t is any time series.

When difference is not necessary to achieve stationary, d = 0 and the model reduced to ARMA.

2.3 ARIMA Forecasting

This is a very difficult question to choose the best algorithm. Since, real data do not follow any model. Box Jenkins ARIMA modeling strategy for Carbon dioxide emissions forecast is shown in Figure 1. Statistical Software- Eviews 4.1 has been used to construct ARIMA models, necessary statistical test and forecasting evaluation as well. We used the following forecasting algorithm-

i) Detect the trend of CO_2 emission using time series plot
ii) Check the stationary of CO_2 emission data using KPSS (Kwiatkowski et al., 1992)
iii) R^2, RMSE, MAE, AIC, SIC and BP have been used for appropriate model selection (Sakamoto et al., 1986 and Schwarz, 1978)
iv) Check residual normality, autocorrelation and serial autocorrelation using Jarque Bera, Durbin Watson and Breusch Godfrey serial correlation LM test, respectively
v) Chow forecast test is used to check the stability for CO_2 emission of proposed model
vi) Finally, static forecast using the proposed model

2.4 HWNS Forecasting

The model was first suggested in the early 1960s and relates three exponential smoothing formulae to the series, respectively to the mean, trend, and each seasonal sub-series (Chatfield, 1978). Here, we apply the Holt–Winters Non Seasonal (HWNS) smoothing automated forecasting algorithm provided through the software Eviews 4.1.

2.5 ANN Forecasting

Artificial neural networks are forecasting approaches that permit complex nonlinear relationships between the response variable and its predictors. A detailed explanation of the procedure can be found in Hyndaman and Athanasopolus (2013) and is therefore not repeated here. We employ the automated neural networks using STATISTICA 8 software to our CO_2 emission time series. Through this automatic procedure, univariate time series are forecasted by Radial Basis Function (RBF) and Multi-Layer Perceptron (MLP) networks with hidden layers and lagged inputs (Azadeh et al., 2008).

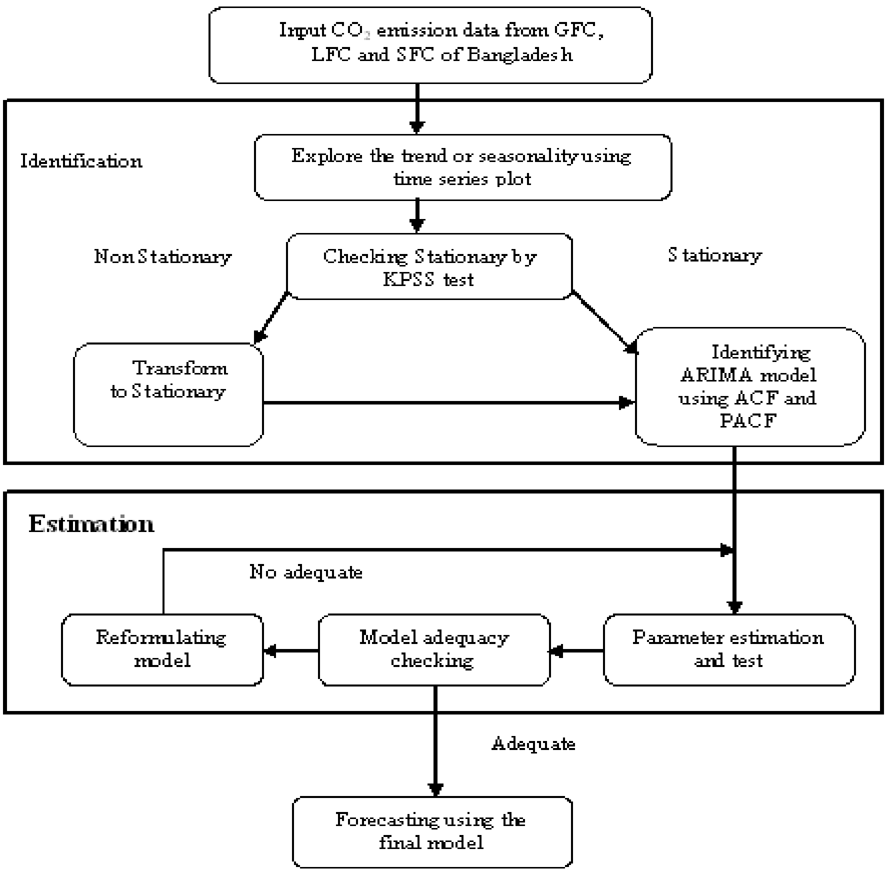

Figure 1: Carbon dioxide emissions forecasting strategy using Box Jenkins ARIMA models

3. Results and Discussions

At first, the CO_2 emissions from GFC, LFC and SFC in Bangladesh have been explored and analyzed using visual inspection. The time series plot shows that the CO_2 emission from GFC, LFC and SFC have rightly upward trend over time but no seasonality present in the series (Figure 2) (Granger et al., 1978). To check the stationary condition of CO_2 emission from GFC, LFC and SFC, KPSS test is used. KPSS tests suggest that GFC and SFC are stationary after non-seasonal differencing of order two and LFC is stationary after non-seasonal differencing of order one (See Table 1).

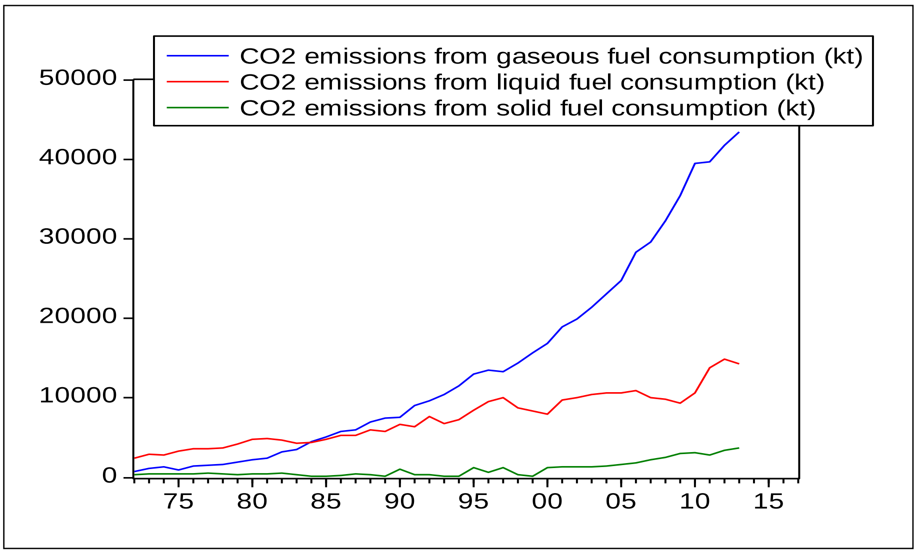

Figure 2: Time series plot of CO_2 emission from GFC, LFC and SFC

To select the best ARIMA models- AIC, SIC, and R^2 value are used (Table 2). Finally, ARIMA(12, 2, 12), ARIMA (8, 1, 3) and ARIMA (5, 1, 5) models have been selected for CO_2 emission from GFC, LFC and SFC, respectively due to lowest value of AIC and SIC; and highest value of R^2. The actual, fitted and residual plots of CO_2 emission for selected ARIMA model from GFC, LFC and SFC are shown by Figure 3, Figure 4 and Figure 5, respectively.

Table 1: Stationary test of CO_2 emission from GFC, LFC and SFC

Variable	Deterministic terms	KPSS test Statistics value	Asymptotic critical values at 5%	Results
GFC	Constant	0.7529	0.4630	Non Stationary
GFC	Constant and linear trend	0.2049	0.1460	Non Stationary
ΔGFC	Constant	0.6527	0.4630	Non Stationary
Δ(ΔGFC)	Constant	0.2599	0.4630	Stationary
LFC	Constant	0.8236	0.4630	Non Stationary
LFC	Constant and linear trend	0.0694	0.1460	Stationary
ΔLFC	Constant	0.3698	0.4630	Stationary
SFC	Constant	0.6322	0.4630	Non Stationary
SFC	Constant and linear trend	0.2053	0.1460	Non Stationary
ΔSFC	Constant	0.4901	0.1460	Non Stationary
Δ(ΔSFC)	Constant	0.0691	0.4630	Stationary

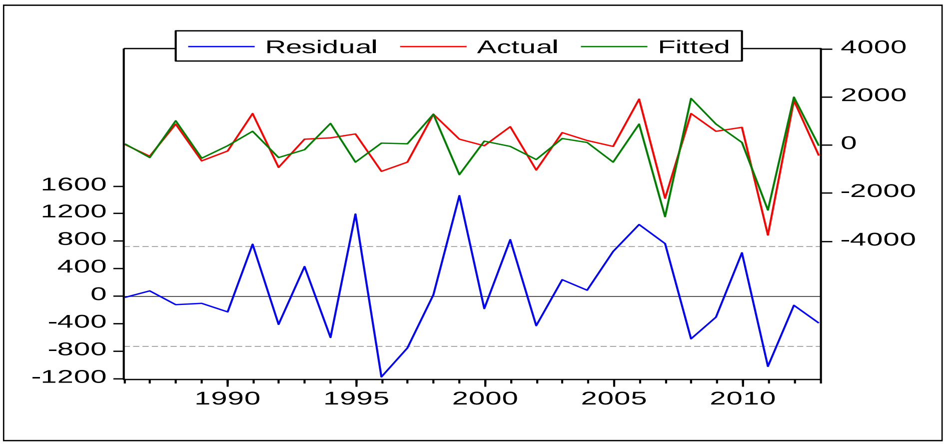

Figure 3: Actual, fitted and residual plot of CO_2 emission for selected model from GFC

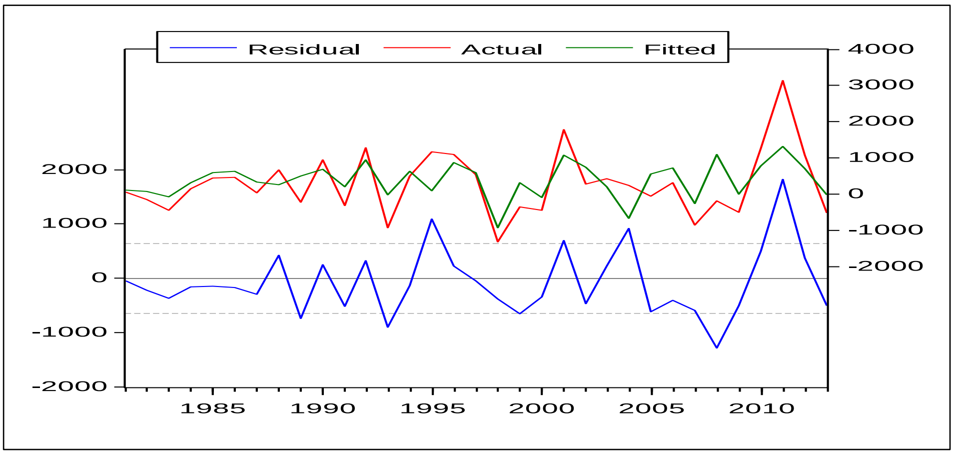

Figure 4: Actual, fitted and residual plot of CO_2 emission for selected model from LFC

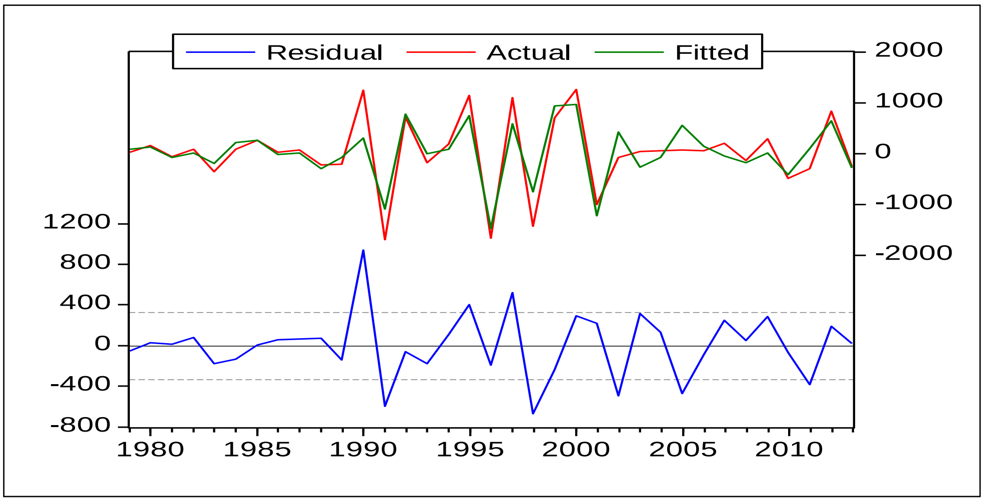

Figure 5: Actual, fitted and residual plot of CO_2 emission for selected model from SFC

The actual, fitted and residual plots of CO_2 emission for selected ARIMA model from GFC, LFC and SFC suggest that GFC and SFC's models are better fitted than LFC's model. Residual normality, autocorrelation and serial correlation test for CO_2 emission of selected ARIMA model from GFC, LFC and SFC is shown in Table 3. This table suggests that the estimated residual for selected models of

GFC and SFC may be normal, and the estimated residual for selected models of LFC may not be normal; Durbin-Watson value of the estimated residuals is approximately equivalent to 2 for selected models of GFC, LFC and SFC. Therefore, the residuals of the estimated models may not be auto correlated. Breusch Godfrey serial correlation LM test suggests that the estimated residual for selected models of LFC and SFC may be free from serial correlation and the estimated residual for selected models of GFC may be serially correlated. Due to sort of constraints, our selected models are better than others ARIMA models in comparison metrics (See Table 2). To check the superiority of ARIMA models over other methods of forecasting in recent literature, univariate HWNS Smoothing and ANN performance are compared with the selected ARIMA models.

Table 2: Selection of best fitted ARIMA model of CO_2 emission

Variable	Model	Coefficient (Prob.)					AIC	SIC	R^2 value
GFC	ARIMA (1, 2, 0)	AR(1) -0.5407 (0.0003)					16.4024	16.4451	0.2904
	ARIMA (0, 2, 1)	Constant 1040.4520 (0.0000)	MA(1) 0.3025 (0.0551)				16.5538	16.6374	0.1349
	ARIMA (12, 2, 12)	**AR(1) -0.6376 (0.0005)**	**AR(2) -0.4555 (0.0050)**	**AR(10) 0.3148 (0.0112)**	**AR(12) 0.8686 (0.000)**	**MA(12) -1.659 (0.000)**	**16.1642**	**16.4021**	**0.6880**
LFC	ARIMA (1, 1, 0)	Constant 1040.4520 (0.0586)	AR(1) 0.1156 (0.4833)				16.2691	16.3536	0.0130
	ARIMA (0, 1, 1)	Constant 287.7601 (0.0457)	MA(1) 0.1256 (0.4415)				16.2421	16.3257	0.0148
	ARIMA (8, 1, 3)	**Constant 280.9305 (0.0000)**	**AR (8) -0.4093 (0.0925)**	**MA (3) -0.8571 (0.000)**			**15.8748**	**16.0108**	**0.4844**
SFC	ARIMA (1, 2, 0)	Constant 80.8692	AR(1) -0.3295				14.8134	14.8979	0.1076

Variable	Model	Coefficient (Prob.)					AIC	SIC	R^2 value
		(0.0885)	(0.0388)						
	ARIMA (0, 2, 1)	Constant 79.2415 (0.0349)	MA(1) -0.3999 (0.0119)				14.7606	14.8442	0.1302
	ARIMA (5, 1, 5)	**Constant** **14.2941** **(0.0347)**	**AR (5)** **0.4959** **(0.0061)**	**MA(1)** **-1.2068** **(0.000)**	**MA (5)** **0.2603** **(0.0017)**		**14.5541**	**14.7319**	**0.7987**

Note. Models are estimated by removing highly insignificant lags orders of ARIMA

Table 3: Test of residual normality, autocorrelation and serial correlation of selected ARIMA models

Variable	Jarque Bera (Prob.)	Durbin Watson	Breusch Godfrey LM test (Prob.)
GFC	0.7438 (0.6894)	1.8	1.1695 (0.3299)
LFC	6.7906 (0.0335)	2.1	0.7578 (0.4780)
SFC	2.3839 (0.3036)	2.1	4.4380 (0.0208)

The forecasting evaluations of better performed HWNS methods and ANN methods are shown in Table 4 and Table 5, respectively.

Table 4: Forecasting evaluation for CO_2 emission with HWNS method from 1972-2013

Variable	**Parameters**		**RMSE**
	Alpha	**Beta**	
GFC	0.840	0.340	745.738
LFC	1.000	0.000	776.246
SFC	0.120	0.790	327.332

Note. Cycles: 5

Table 5: Forecasting evaluation for CO_2 emission with ANN method from 1972-2013

Variable	Net. Name	Training Alg.	Hidden Act.	Output Act.	Training Perf.	Test Perf.	Training error	Test error
GFC	RBF 1-11-1	RBFT	Gaussian	Identity	0.9988	0.9837	0.00012	0.00003
LFC	MLP 1-4-1	BFGS 31	Tanh	Logistic	0.9671	0.9609	0.00244	0.00071
SFC	MLP 1-8-1	BFGS 10	Identity	Identity	0.9984	0.9832	0.00016	0.00003

Note. RBF- Radial Basis Function, MLP-Multi-layer Perceptron networks; individual ANN model is chosen using Training Performance, Test Performance, Training Error and Test Error metrics.

The forecasting performance of ARIMA, HWNS and ANN models in Root Mean Square Error (RMSE) metrics for CO_2 emission from 1972-2013 is shown in Table 6. The RMSE of ARIMA model is minimum than HWNS and ANN models. Thus, these proposed ARIMA models for GFC, LFC and SFC show better performance over HWNS and ANN models in sample forecasting from 1972-2013. Therefore, these selected ARIMA models are the proposed models for forecasting carbon dioxide (CO_2) emission from GFC, LFC and SFC, respectively.

Table 6: Comparison of forecasting performance for CO_2 emission from 1972-2013

Variable	RMSE		
	ARIMA	**HWNS**	**ANN**
GFC	**654.973**	745.738	657.796
LFC	**618.653**	776.246	830.371
SFC	**312.257**	327.332	761.269

There is the potential for structural instability across the whole data range with proposed ARIMA models. It is important to test every observation for a structural break. Chow forecast test is used to check the null hypothesis of structural stability. Date (2000) is used as break point for Chow forecast test over the range from 1972 to 2013 with the proposed ARIMA models. We may accept the null hypothesis of structural stability for GFC and SFC except LFC with certain probability value (See Table 7). We conclude that there is a structural break in this model.

Table 7: Stability test for CO_2 emission of proposed model

Variable	Chow forecast test stat (Forecast from 2000 to 2013)	Prob.
GFC	1.3715	0.3225
LFC	2.7251	0.0288
SFC	0.6902	0.7554

The forecasting evaluation for CO_2 emission of the proposed ARIMA models from GFC, LFC and SFC in RMSE, MAE and BP metrics from 1972 to 2013 are shown in Table 8.

Table 8: Forecasting evaluation for CO_2 emission of proposed model

Variable	RMSE	MAE	BP
GFC	654.9728	523.6588	0.0079
LFC	618.6530	495.9309	0.0183
SFC	312.2573	227.9869	0.0001

To check the justification of appropriate forecasts with proposed ARIMA models, the actual and forecast CO_2 emission values of GFC, LFC and SFC are compared in sample period from 2001-2013 and observed that the actual and forecast values are nearly identical (See Table 9).

Table 9: In sample forecasting CO_2 emission with proposed model from 2001 to 2013

Year	Actual GFC (kt.)	Forecast GFC (kt.)	Actual LFC (kt.)	Forecast LFC (kt.)	Actual SFC (kt.)	Forecast SFC (kt.)
2001	18918.05	18093.80	9710.220	9018.620	1110.99	1331.12
2002	19904.48	20334.41	9981.570	10450.61	1826.48	1331.12
2003	21407.95	21173.17	10403.28	10182.33	1053.63	1367.79
2004	23109.43	23028.66	10648.97	9737.350	1318.87	1452.13
2005	24744.92	24096.89	10586.63	11207.44	2080.97	1606.15
2006	28279.90	27242.60	10905.66	11314.77	1901.18	1811.50
2007	29603.69	28839.75	10047.58	10644.08	1965.13	2211.20
2008	32251.27	32877.70	9853.230	11142.92	2421.12	2471.56

Year	Actual GFC (kt.)	Forecast GFC (kt.)	Actual LFC (kt.)	Forecast LFC (kt.)	Actual SFC (kt.)	Forecast SFC (kt.)
2009	35470.89	35776.46	9350.850	9854.490	2736.59	3017.94
2010	39431.25	38803.74	10619.63	10128.14	3142.93	3076.61
2011	39658.61	40677.42	13747.58	11929.49	3224.64	2838.26
2012	41748.80	41882.02	14825.68	14455.79	3233.85	3424.98
2013	43413.61	43806.35	14304.97	14807.09	3732.27	3751.34

From Table 9, Mean Absolute Percent of Error (MAPE) for GFC, LFC and SFC is 2.8, 8.4 and 12.9 kt. respectively. Finally, the out sample static forecasts CO_2 emission values and bar diagram from GFC, LFC and SFC are made using proposed ARIMA models for the period 2014 to 2025 in Table 10 and Figure 6 after checking every sort of possible stabilities.

Table 10: Out sample static forecasting CO2 emission with proposed model for 2014 to 2025

Year	Forecast GFC (Kt.)	Forecast LFC (Kt.)	Forecast SFC (Kt.)
2014	44375.27	12993.28	4277.00
2015	46017.83	13498.55	4597.83
2016	48182.45	14267.41	4703.15
2017	47875.61	14804.88	5170.81
2018	49252.42	14732.70	4139.33
2019	47673.53	14033.12	3668.24
2020	49634.52	14037.01	3605.04
2021	50513.77	14587.10	3984.39
2022	50658.89	15427.15	5141.67
2023	50078.67	15628.67	6013.04
2024	51913.11	15731.15	7504.09
2025	53034.79	15926.17	9579.49

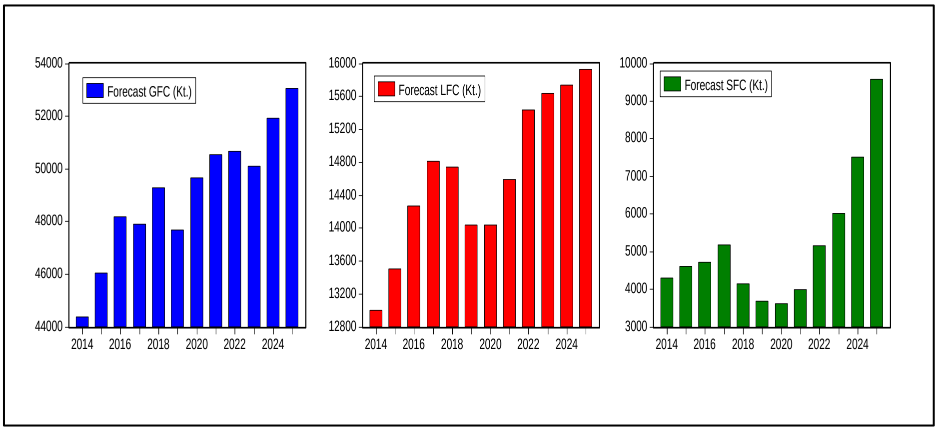

Figure 6: Bar diagram for out sample static forecasting CO_2 emission from 2014-2025

The forecasted values of Table 10 are used to detect the decade wise percent level of increasing CO_2 emission from the consumption of fuels- the emission for GFC may be increased 85.96% kt. in 2015 than 2005, 15.24% kt. in 2025 than 2015; emission for LFC may be increased 20.44% kt. in 2015 than 2005, 17.98% kt. in 2025 than 2015; and emission for SFC may be increased 186.26% kt. in 2015 than 2005, 108.34% kt. in 2025 than 2015. The data in the bar diagrams (Figure 6) show that the consumptions of the fuels are increasing gradually in Bangladesh. Between 2016 and 2024, the country will consume comparatively less solid fuel than that of gaseous and liquid fuels. In 2014, the consumption of gaseous fuel was slightly over 44000 kt. which rose to about 48000 kt. in 2016 and it will shot up 54000 kt. by 2025. Meanwhile, the country will consume about 16000 kt. liquid fuels by 2025, which was only about 12800 kt. in 2014 and 14800 kt. in 2016. In the case of solid fuel consumption, there will be dramatic rise in the country in the year 2022 to 2025. In 2016, the amount of solid fuel consumption is only about 5000 kt. which will be doubled to 10000 kt. by 2025. So, it is evident that the increase of fuel consumption will lead to higher amount of CO_2 emission in the country.

4. Conclusions

The study provided an appropriate model for forecasting CO_2 emissions based on fuel and energy consumption attributes. Findings of the study have established that ARIMA (12, 2, 12), ARIMA (8, 1, 3) and ARIMA (5, 1, 5) are the best fitted models for forecasting CO_2 emission from GFC, LFC and SFC rather than the other methods of forecasting- HWNS and ANN models. Hence, the results of the study may useful for researchers, stakeholders as well as Bangladesh government to take appropriate actions for introducing sustainable climate policy. Moreover, accurate forecast of CO_2 emission from GFC, LFC and SFC in own territory will help the country policy makers to bargain for climate fund with the international community.

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