九州大学学術情報リポジトリ
Kyushu University Institutional Repository

Nexus Between CO_2 Emission, Economic Development and Energy Consumption in Bangladesh

Rahman, Jamilur
Department of Electrical and Electronic Engineering, Chittagong University of Engineering and Technology (CUET)

Gaylan Ibna Wahid
Department of Electrical and Electronic Engineering, Chittagong University of Engineering and Technology (CUET)

Ahmed, Sharif
Department of Marine Engineering, Marine Fisheries Academy

F. M. Nizazul Islam
Department of Marine Engineering, Marine Fisheries Academy

他

https://doi.org/10.5109/7157953

出版情報：Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 9, pp.86-92, 2023-10-19. 九州大学大学院総合理工学府
バージョン：
権利関係：Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International

KYUSHU UNIVERSITY

Nexus Between CO_2 Emission, Economic Development and Energy Consumption in Bangladesh

Jamilur Rahman[1], Gaylan Ibna Wahid[1], Sharif Ahmed[2], F. M. Nizazul Islam[2], Bidyut Baran Saha[3], Sampad Ghosh[1*]

[1]Department of Electrical and Electronic Engineering, Chittagong University of Engineering and Technology (CUET), Chattogram, Bangladesh
[2]Department of Marine Engineering, Marine Fisheries Academy, Chattogram, Bangladesh
[3]International Institute for Carbon-Neutral Energy Research, Kyushu University, Fukuoka, Japan
*Corresponding author email: sampad@cuet.ac.bd

Abstract: *Energy shortages are global concerns. This issue can be addressed and correlated with economic growth and environmental degradation. This study employs annual available time series data to model the nexus among electricity generation (derived from oil, gas, and coal sources), consumption of fossil fuel energy, gross domestic product (GDP) per capita, and carbon dioxide (CO_2) emission (from solid fossil fuel) in Bangladesh. The statistical Autoregressive Distributed Lag (ARDL) test reveals the long and short-run equilibrium relationship between variables. It is found that electricity production and GDP per capita have a significant and positive impact on CO_2 emissions, i.e., economic activity and energy consumption has a substantial influence on the release of CO_2 into the atmosphere. Besides, static and dynamic forecasting techniques are incorporated to anticipate future values based on past data. It is observed that static forecasting is superior to dynamic forecasting.*

Keywords: ARDL model; CO_2 emission; Economic growth; Energy consumption; Static forecast

1. INTRODUCTION

Global primary energy consumption is increasing with the pace of population growth and rapid urbanization. Following similar trends in the global scenario, Bangladesh has also increased its energy consumption in recent years. Despite this, Bangladesh's energy consumption is still quite low on a per-person basis, in fact, one of the lowest in the world [1]. Noteworthy to mention that energy consumption is closely related to economic development. Sustainable economic development demands sustained economic growth [2] and energy consumption [3]. Energy consumption in general refers to the use of energy to power activities that involve industrial production, transportation, and household usage [4]. Conversely, economic growth is commonly evaluated based on the Gross Domestic Product (GDP) and pertains to a rise in the worth of commodities and amenities generated within a nation during a certain duration. It is said that GDP per capita affects energy consumption significantly.

There is always worldwide tension regarding the consumption of energy and economic development and their potential impact on the environment. In recent years, many types of research have been conducted intending to find an accurate solution to ensure adequate energy for all and to grow awareness of the environmental effect on the policymaker. It is already proven that the burning of primary fuels, i.e., fossil fuels, is the main culprit to an increase of carbon dioxide (CO_2) emissions globally. It is widely believed that CO_2 is one of the key factors that contribute to global warming because it creates more than 60% of greenhouse gas (GHG) [5]. The climate agreements in Kyoto and Paris demonstrate the efforts that countries are making to limit emissions of greenhouse gases. Usually, developed and developing countries consume the most energy and consequently emit the most greenhouse gases. These countries have committed to lowering their greenhouse gas emissions by forty percent by the year 2030, compared to the levels seen in 1990. However, there is a possibility that energy reduction may lower productivity [6]. In addition, ensuring access to inexpensive, sustainable, and contemporary energy is one of the aims of the United Nations' sustainable development goal. Hence, it is essential to investigate how energy consumption, economic expansion, and CO_2 emissions are related to one another.

The whole world, including Bangladesh, is looking for a better outcome that involves increased energy consumption and economic growth with minimum CO_2 emissions. Numerous domestic and global agreements have been sanctioned and numerous initiatives are currently underway. A Memorandum of Understanding (MoU) was signed between Bangladesh and Nepal on cooperation in the field of the power sector on 10 August 2018 [7]. This collaboration focused on lessening energy usage and carbon discharges. According to the Bangladesh-India agreement on cooperation in the power sector (2010), India and Bangladesh inked a deal in July 2010 for the transmission of 250 megawatts of electricity from India to Bangladesh. In August 2010, India's National Thermal Power Corporation (NTPC) and Bangladesh Power Development Board (BPDB) entered into an additional accord to establish a collaborative enterprise aimed at initiating a 1320-megawatts power project in Bangladesh [8]. The objective of this pact was to find a sustainable energy alternative and reduce greenhouse gas emissions. To maintain the same pace for healthy collaboration in the energy sector with neighboring countries, South Asian Association for Regional Cooperation (SAARC) Agreement on Energy Cooperation was signed in 2014 [9]. This accord aimed to encourage collaboration among SAARC nations in the energy sector, encompassing renewable energy, electricity production, transmission, and distribution. There exist certain deals which necessitate the cooperation of multiple nations in their entirety, for instance, the Bangladesh-Bhutan-India-Nepal (BBIN) Motor Vehicles Agreement (2015). The purpose of this accord was to enhance the efficiency of transportation channels and decrease travel durations, ultimately resulting in a reduction of CO_2 emissions.

Above all, many scientific research studies explicated the interconnection between the national economy, CO_2 emission, and energy production, which is crucial to understand their impact on the environment. Several decades back, Alam et al. [10] pointed out the devastating impact of CO_2 emission that helped in elucidating and refining the pattern of development and progress in low-income nations like Bangladesh. They presented an empirical equation showing the relationship between the quality of life and electrical energy consumption and found a linear relationship.

The authors of a separate study [11] conducted an analysis utilizing the Autoregressive Distributed Lag (ARDL) bounds testing approach to investigate the impact of financial trends, economic growth, and energy consumption on CO_2 emissions within the confines of China. The findings indicated that CO_2 emissions are mostly influenced by income, energy use, and trade openness. A pooled mean group (PMG) panel ARDL approach was used in the study by Mensah et al. [12] to evaluate the connection between economic development, fossil fuel energy consumption, CO_2 emissions, and oil price in Africa. According to the study, there is a long-term connection between economic development, the use of fossil fuels for energy, CO_2 emissions, and oil prices in Africa. The study conducted by Apergis et al. [13] employed the Autoregressive Distributed Lag (ARDL) methodology to examine the relationship between carbon dioxide (CO_2) emissions and the utilization of renewable and non-renewable energy sources in Uzbekistan. The research results suggested a sustained correlation between carbon dioxide emissions and the nation's consumption of both renewable and nonrenewable energy resources. Besides, Non-linear Autoregressive Distributed Lag (NARDL) method was incorporated to look into the asymmetries between technical advancement, carbon dioxide emissions, and renewable energy in industrialized economies [14]. According to the research [15], the industrial sectors of European Union (EU) nations had a considerable long-term association between energy efficiency and sustainable growth.

Marathe et al. [16] reported the presence of unidirectional causality between gross domestic product (GDP) and electricity consumption. The authors examined the unidirectional relationship between energy consumption and economic growth, both in the short and long term [17]. A bi-directional long-term causality was illustrated between electricity consumption and economic growth. Nonetheless, a causal relationship was not identified in the short run. Subsequently, it was determined that a persistent correlation exists among economic growth, energy consumption, and CO_2 emission in the long run [18]. In 2019, Pandey et al. found a co-integration relationship between economic growth and CO_2 emission, which meant the presence of a long-run equilibrium towards the system converges over time [19]. In addition, a study on the emission cost of a renewable energy system was conducted in 2020 [20]. It was reported that after the removal of emission costs, the effect on the energy system didn't improve greatly. In that study, they estimated that about 94% of the total electricity will be produced by renewable energy sources in 2050. They also mentioned some present energy policies that create some major issues namely high electricity costs, energy insecurity, rapid increase in the emission of greenhouse gases, and others.

A time series analysis from 1971 to 2010 was used in the study by Alam et al. [21] to examine the connection between energy use, carbon emissions, and economic growth in Bangladesh. They employed the Autoregressive Distributed Lag (ARDL) Bounds Testing method to test for co-integration while determining the direction of causality between the variables using the Granger causality test. They found a long-run equilibrium link between the variables as well as a one-way causation connecting energy use and carbon emissions to economic growth. In other words, Bangladesh's economic development was significantly impacted by energy use and carbon emissions. However, the study [21] only used macroeconomic data, which might not fully reflect the underlying correlations between the variables at the micro-level.

The primary objective of this study is to investigate the correlation between fossil fuel energy consumption, economic advancement, and electricity generation with regard to CO_2 emissions in both the short term and long term. This work is further extended to forecast future CO_2 emissions, which will let us plan for future energy consumption. The Autoregressive Distributive Lag (ARDL) bound testing technique is used in this research paper for co-integration. For balancing environmental quality and economic growth, this study will help in providing a new forethought for the policymakers to design key policy decisions. The following subsections will describe the step-by-step analysis procedures followed by the results and discussion and conclusions section.

2. METHODOLOGY

2.1 Variable Selection and Data Collection

To establish the long-run and short-run relationship, we selected multiple variables. These variables include CO_2 emission from fossil fuel consumption (% of total), GDP per capita (current value of USD), fossil fuel energy consumption (% of total), and electricity generation from oil, gas, and coal sources (% of total) in Bangladesh. We use the following basic model [22] for our further analysis, as shown in equation (1).

$$CO_{2t} = f\,(EPOGC_t, FFEC_t, GDP_t) \qquad (1)$$

Here, EPOGC, FFEC, GDP, and t represent Electricity Production from Oil, Gas, and Coal sources (% of total), Fossil Fuel Energy Consumption (% of total), Gross Domestic Products (USD), and the time dimension (year), respectively. In this work, we used the time series data that are available between 1960 and 2021 and subsequently collected it from the world development indicator [23].

2.2 Unit Root Test

The first step for approaching the ARDL model is checking for the chosen variables' stationary conditions. A variable is said to be stationary when its mean, variance, and co-variance do not change over a certain range of time. However, in real-time applications, the variables can't be stationary over a period of time, and such variables are known as unit root variables. In this research, we perform the unit root test using the Augmented Dickey-Fuller (ADF) method [24].

2.3 Autoregressive Distributive Lag (ARDL) Model

Co-integration can be used to model the time series data and maintain their long-run information, which can be obtained by several tests. In this paper, we apply the ARDL bound test method and identify the co-integration among the selected variables. This method is used because it is anticipated to be very useful when the variables are stationary at level zero or the first difference. Equation (2) is used for the ARDL bound test.

$$\begin{aligned}\Delta CO_{2t} = \beta_0 + \textstyle\sum_{i=1}^{q1}\beta_{1i}\,\Delta CO_{2t-1} + \sum_{i=1}^{q2}\beta_{2i}\,\Delta EPOGC_{t-1} + \sum_{i=1}^{q3}\beta_{3i}\,\Delta FFEC_{t-1} \\ + \textstyle\sum_{i=1}^{q4}\beta_{4i}\,\Delta GDP_{t-1} + \delta_0 CO_{2t-1} + \delta_1 EPOGC_{t-i} + \delta_2 FFEC_{t-i} + \delta_3 GDP_{t-i} + \mu_t\end{aligned} \quad (2)$$

In the above equation, Δ and μ_t represent the first difference and the residual term, respectively. β and δ are the co-efficient terms, while i is the integer term. In ARDL analysis, we have to consider two hypotheses. First, we test the null hypothesis H_0: $\delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$. So, the alternative hypothesis is H_a: $\delta_0 \neq \delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq 0$, which represents the long-run association among the variables. Then, the F-test value is to be checked from the ARDL bound test and evaluated co-integration. When the simulated F-test value exceeds the upper limit, the null hypothesis is rejected. Alternately, the hypothesis is considered un-decidable when the F-value is within the upper and lower limits. The null hypothesis of no co-integration is accepted when the F-test value is less than the lower limit. We estimate the error correction model in the short run using equation (3).

$$\begin{aligned}\Delta CO_{2t} = \beta_0 + \textstyle\sum_{i=1}^{q1}\beta_{1i}\,\Delta CO_{2t-1} + \sum_{i=1}^{q2}\beta_{2i}\,\Delta EPOGC_{t-1} + \sum_{i=1}^{q3}\beta_{3i}\Delta FFEC_{t-1} + \sum_{i=1}^{q4}\beta_{4i} \\ \Delta GDP_{t-1} + \eta_1 ECT_{t-1} + \mu_t\end{aligned} \quad (3)$$

Where the speed of adjustment is indicated by η_1. ECT_{t-1} represents the lagged Error Correction Term, and this should be negative and significant [8].

2.4 Data Forecasting

Data forecasting techniques are utilized to predict a future value based on the available previous data. We employ static and dynamic forecasting techniques and then compare the results. In the static forecast method, the actual values of the independent variables are employed in making the forecast. In dynamic forecasting, the previous forecasted value of the dependent variables is used to compute the next forecast. The basic equation for estimating the static and dynamic forecast is given in equations (4) and (5), respectively.

$$CO_{2t} = \beta_0 + \beta_1 EPOGC_t + \beta_2 FFEC_t + \beta_3 GDP_t + \mu_t \quad (4)$$

$$CO_{2t} = \beta_0 + \beta_1 EPOGC_t + \beta_2 FFEC_t + \beta_3 GDP_t + \beta_4 CO_{2t-1} + \mu_t \quad (5)$$

Where the β terms are co-efficient, which comes from the simulation. The term CO_{2t-1}, the lag of the dependent variable CO_2, is called the dynamic term. In the absence of a dynamic term, the dynamic model approach is invalid.

3. RESULTS AND DISCUSSION

Before starting with the ARDL model, it is compulsory to investigate the stationary conditions of the variables, i.e., whether they are stationary at level zero or first difference [8]. For this purpose, a unit root test is utilized. Table 1 displays the probability values (p-values) for the level and first difference, only with intercept and trend and intercept. According to the results of the unit root test, it has been determined that the CO_2 emissions resulting from solid fuel consumption exhibit stationarity at the zero level. In contrast, the generation of electricity (derived from oil, gas, and coal sources), the consumption of energy from fossil fuels, and the gross domestic product per capita exhibit stationarity upon undergoing first-order differencing. Hence, the Autoregressive Distributed Lag (ARDL) model is capable of determining short-term and long-term associations.

Table 1. Unit Root Test by Augmented Dickey-Fuller (ADF) method

Level		
Variables	Intercept	Trend & Intercept
CO_2 Emission	0.0026	0.0151
Electricity Production	0.6888	0.0391
Fossil Fuel Consumption	0.7694	0.1263
GDP per Capita	1.0000	1.0000
First Difference		
Variables	Intercept	Trend & Intercept
CO_2 Emission	0.0000	0.0000
Electricity Production	0.0000	0.0032
Fossil Fuel Consumption	0.0000	0.0001
GDP per Capita	0.2584	0.0007

Table 2 interprets the outcomes of lag length selection criteria for co-integration. The optimal lag length is selected by the Akaike Information Criterion (AIC), which is found to be lag-1. Hence, this lag length is used in our model. On the other hand, Table 3 shows the result of the bound test for co-integration. To understand the relationship of co-integration, we have to check the F-statistics. As mentioned earlier, the F-stats value more than the upper bound indicates the existence of co-integration and the F-stats value less than the lower bound indicates the non-existence of co-integration. The result is considered inconclusive when the F-stats is between the value of the upper and lower bound. The F-stats for F(CO_2) is 7.49, which is greater than the upper bound at 5% significance, implying that the variables have co-integration among them. Next, we changed the dependent variable to EPOGC. The F-stats, in this case, is 14.71. Since this value is also greater than the upper bound, there exists a co-integration. Later on, we incorporated fossil fuel energy consumption as a dependent variable, and the F-statistics value is 0.48. The result is inferior to the lower bound at 5% significance, indicating no co-integration. Finally, GDP per capita is considered a dependent variable in the bound test. The coefficient value is 10.12, which is superior to the upper limit indicating the existence of co-integration and a relation in the long run between the variables at 5% significance.

Table 2. Lag Length Selection for Co-Integration

Lag	Akaike Information Criterion (AIC)
0	29.97
1	22.87*
2	23.05
3	22.99

**Significance at 5% level*

Table 3. Bound Test for Co-Integration

Dependent Variable	F-statistics	Comment
F(CO_2)	7.49	Co-integration
F(EPOGC)	14.71	Co-integration
F(FFEC)	0.48	No co-integration
F(GDP)	10.12	Co-integration
Significance	Level Zero, (I0)	Level One, (I1)
1%	4.29	5.61
2.5%	3.69	4.89
5%	3.23	4.35
10%	2.72	3.77

Table 4 exhibits the result of the Serial Correlation test and Heteroskedasticity test. The former test shows that the data is free from serial correlation since the probability value of Chi-square is 0.62, which exceeds the 5% data. Besides, the probability of the Chi-square value is 0.77 in the latter test. This implies that no Heteroskedasticity error is found.

Table 4. Serial Correlation and Heteroskedasticity Test

	Prob. Chi-Square
Serial Correlation Test	0.62
Heteroskedasticity Test	0.77

The long-run co-efficient is depicted in Table 5. Here, CO_2 is considered to be the dependent variable, and the others, such as Electricity Production from Oil, Gas, and Coal sources (EPOGC), Fossil Fuel Energy Consumption (FFEC), Gross Domestic Products (GDP), are selected as independent variables because we want to know their effects on CO_2. The coefficient of EPOGC is 0.26, which is a positive value and has a significant impact on CO_2. It also means that if there is a rise of one unit in EPOGC, there will be an increase of 0.26 or ~26% in CO_2. This positive value indicates that electricity production in Bangladesh is intensely involved with CO_2 emissions. In the long run, this effect is consistent and further emphasizes the minimization of carbon emissions. Similarly, the increase in GDP also signifies a positive and significant increase of 1.3% in CO_2 emission. On the contrary, a negative and significant impact can be observed with FFEC on CO_2 emission. This also implies that to reduce the emission of carbon in the long run, we have to consider taking necessary steps to increase the FFEC in moderation.

Table 6 shows the results for the short-run co-efficient. Here, ECT(−1) represents the lag value of the Error Correction Term. The value of its coefficient is less than zero and significant. Therefore, the model will adjust toward the long-run value monotonically. The short-run coefficients imply a similar result to the long-run coefficients.

Table 5. Long Run ARDL Results

Variable	Coefficient
β_0	−4.479747
EPOGC	0.259518
FFEC	−0.356298
GDP	0.013050

Table 6. Short Run ARDL Results

Variable	Coefficient
β_0	−0.643
D(CO_2(−1))	−0.168
D(EPOGC)	0.154

D(EPOGC(−1))	−0.095
D(FFEC)	0.093
D(FFEC(−1))	−0.031
D(GDP)	0.013
D(GDP(−1))	0.0001
ECT(−1)	−0.433
$CO_2(-1)$	0.389

Since our model does not have any serial correlation and Heteroskedasticity issues, we are now ready for the model forecasting. As stated earlier, we use two methods for forecasting: static and dynamic forecasting. Here, CO_2 and the remaining (EPOGC, FFEC, and GDP) is considered the dependent and independent variable, respectively. Since our data series is between 1960 and 2021, data from 1960 to 2000 is used to estimate the regression line, while data between 2000 and 2021 is used for forecasting. Table 7 includes the coefficients of static and dynamic forecasting.

Table 7. Static and Dynamic Forecast

Variable	Coefficient
β_0	−4.909
EPOGC	0.189
FFEC	−0.344
GDP	0.021

Fig. 1 depicts static forecasting where the solid line is the actual forecasted value of CO_2, and the dotted lines are for the significant errors. Here, the Theil inequality constant is used for analyzing the forecasted model. The obtained value for the Theil inequality coefficient is 0.27, which is in the range between 0 and 1. So, the forecasted model is close to reality. Dynamic forecasting is shown in Fig. 2, where the blue line indicates the actual forecasted value of CO_2. The Theil inequality coefficient in dynamic forecasting is 0.34. Again, this value is laid between 0 and 1, indicating the forecasted model has superior performance.

Comparing Fig. 1 and Fig. 2, we may observe that the Theil inequality coefficient value is much closer to 0 in static forecasting than the dynamic forecasting. So, static forecasting is much more accurate than dynamic forecasting. The same result can be seen in Fig. 3, which shows this comparison between static and dynamic forecasting with respect to the actual value. Here, the black line represents the original curve, the blue line is the static forecast and the green line depicts the dynamic forecast. We can observe from the figure that the blue line is much closer to the original curve. Therefore, the accuracy of static forecasting is more precise than dynamic forecasting as shown by the Theil Inequality co-efficient. Also, we can see an upward trend in the CO_2 emission from the figure which is alarming for the country, Bangladesh. The research outcomes can help policymakers deal with upcoming threats and cope with future trends.

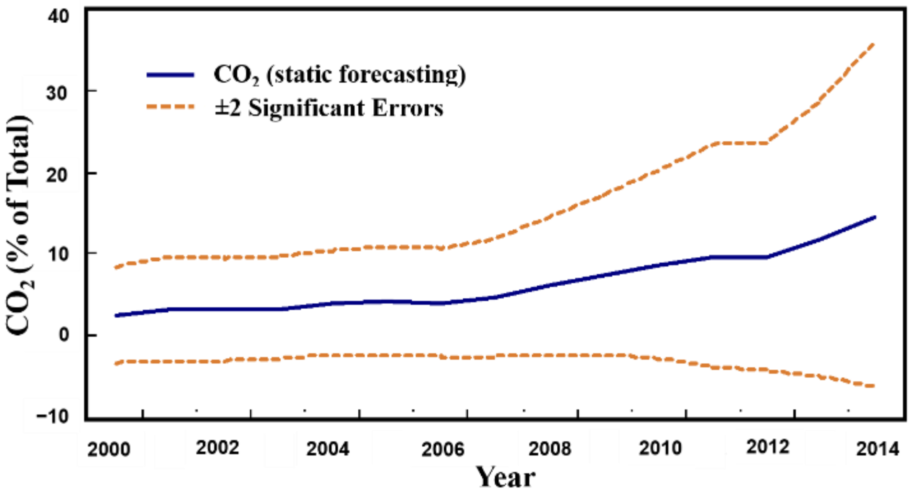

Fig. 1. Static forecasting.

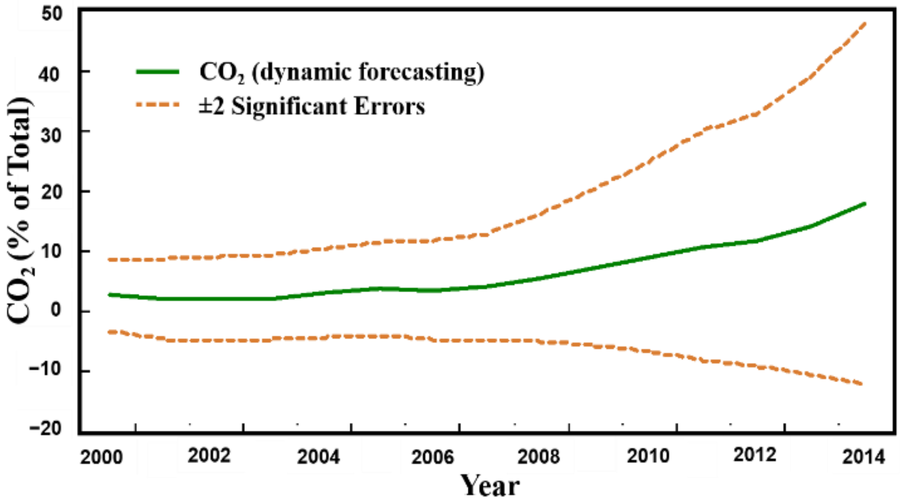

Fig. 2. Dynamic forecasting.

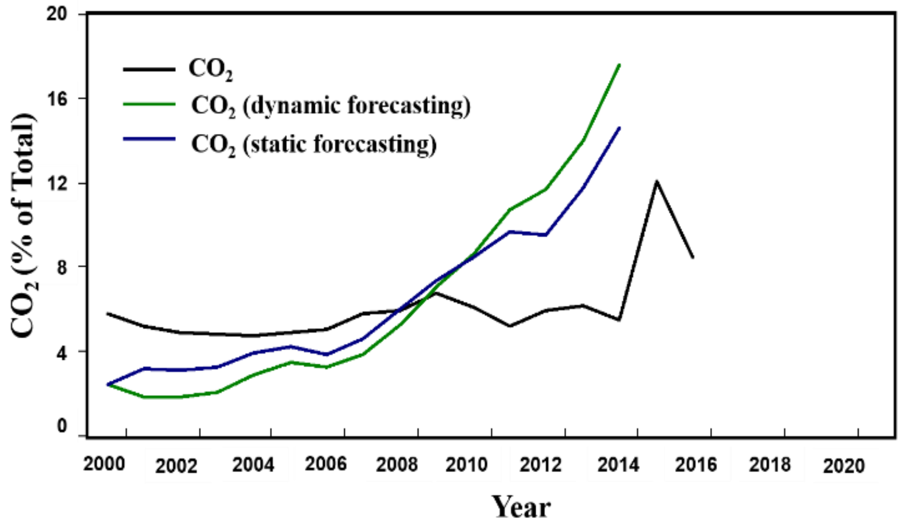

Fig. 3. Comparison between static and dynamic forecasting with actual value.

4. CONCLUSIONS

This research study examines the nexus among electricity production from oil, gas, and coal sources (EPOGC), fossil fuel energy consumption (FFEC), GDP per capita, and CO_2 emission from solid fossil fuels. Time series analyses are employed to run statistical tests on the selected available data range. As a prerequisite for running long-run and short-run tests, the unit root test is performed using Augmented Dickey-Fuller (ADF) test. The ADF results indicated that all the time series are stationary at the level and first difference. After that, the Autoregressive Distributive Lag (ARDL) bound test approach is utilized to validate the relationship among the variables to confirm the long and short-run relationship. FFEC does not co-integrate with other variables in the short or long term. However, the long and short-run relationship of CO_2 emission from solid fossil fuel is demonstrated. We exhibited and compared static and dynamic forecasting and found static forecasting outperformed dynamic forecasting. This research work demonstrates a positive and significant effect of EPOGC, GDP per capita, on CO_2 emission from solid fossil fuels. Thus, economic growth and energy consumption significantly affect CO_2 emissions in Bangladesh. So, some kind of restriction should be thought of to keep the amount of carbon dioxide released to a minimum in the environment for the good health of the world.

5. REFERENCES

[1] J.M.A. Munim, M.M. Hakim, M. Abdullah-Al-Mamun, Analysis of energy consumption and indicators of energy use in Bangladesh, Econ. Chang. Restruct. 43-4 (2010) 275–302.

[2] F.N. Rahman, H. Farzaneh, Low Emission Scenarios Analysis in the Urban Transportation in Dhaka, In Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 8 (2022) 215–220.

[3] S. Hosan, S.C. Karmaker, M.M. Rahman, M.A. Uddin, B.B. Saha, Digitalization, Energy Intensity and Economic Growth: A Panel Study on South Asian Economies, In Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 7 (2021) 19–25.

[4] M.G. Kibria, I. Jahan, J. Mawa, Asymmetric effect of financial development and energy consumption on environmental degradation in South Asia? New evidence from non-linear ARDL analysis, SN Bus. Econ. 1-4 (2021) 1–8.

[5] S. Sarker, A. Khan, R. Mahmood, FDI, Economic Growth, Energy Consumption & Environmental Nexus in Bangladesh, Ann. Dunarea Jos Univ. Fascicle I Econ. Appl. Informatics. 22 (2016) 33–44.
[6] Łukasz Topolewski, Relationship between Energy Consumption and Economic Growth in European Countries: Evidence from Dynamic Panel Data Analysis, Energies. 14 (2021) 3565.
[7] Energy Cooperation: https://bd.nepalembassy.gov.np/energy-cooperation/ (accessed 22.03.2023).
[8] India-Bangladesh Joint: https://www.orfonline.org/research/india-bangladesh-joint-communique-2010-a-review/ (accessed 22.03.2023).
[9] SAARC Framework Agreement for Energy: https://policy.asiapacificenergy.org/node/377 (accessed 22.03.2023).
[10] M. S. Alam, K. K. Islam, A. M. Z. Huq, Simulation of rural household fuel consumption in Bangladesh, Energy. 24-8 (1999) 743–752.
[11] A. Jalil, M. Feridun, The impact of growth, energy and financial development on the environment in China: A co-integration analysis, Energy Econ. 33-2 (2011) 284–291.
[12] I. A. Mensah, M. Sun, C. Gao, A.Y.O. Sasu, D. Zhu, B.C. Ampimah, A. Quarcoo, Analysis on the nexus of economic growth, fossil fuel energy consumption, CO_2 emissions and oil price in Africa based on a PMG panel ARDL approach, J. Clean. Prod. 228 (2019) 161–174.
[13] N. Apergis, B. Kuziboev, I. Abdullaev, A. Rajabov, Investigating the association among CO_2 emissions, renewable and non-renewable energy consumption in Uzbekistan: an ARDL approach, Environ. Sci. Pollut. Res. (2023) 39666–39679.
[14] N. Saqib, Asymmetric linkages between renewable energy, technological innovation, and carbon-dioxide emission in developed economies: non-linear ARDL analysis, Environ. Sci. Pollut. Res. 29-40 (2022) 60744–60758.
[15] A.C. Marques, J.A. Fuinhas, C. Tomás, Energy efficiency and sustainable growth in industrial sectors in European Union countries: A nonlinear ARDL approach, J. Clean. Prod. 239 (2019).
[16] P. Mozumder, A. Marathe, Causality relationship between electricity consumption and GDP in Bangladesh, Energy Policy. 35-1 (2007) 395–402.
[17] M. Jahangir Alam, I. Ara Begum, J. Buysse, G. Van Huylenbroeck, Energy consumption, carbon emissions and economic growth nexus in Bangladesh: Cointegration and dynamic causality analysis, Energy Policy. 45 (2012) 217–225.
[18] A. Ali, S. Khatoon, M. Ather, N. Akhtar, Modeling Energy Consumption, Carbon Emission and Economic Growth: Empirical Analysis for Pakistan, Int. J. Energy Econ. Policy. 5-2 (2015) 624–630.
[19] K.K. Pandey, H. Rastogi, Effect of energy consumption & economic growth on environmental degradation in India: A time series modelling, Energy Procedia. 158 (2019) 4232–4237.
[20] A. Gulagi, M. Ram, A.A. Solomon, M. Khan, C. Breyer, Current energy policies and possible transition scenarios adopting renewable energy: A case study for Bangladesh, Renew. Energy. 155 (2020) 899–920.
[21] M.J. Alam, I.A. Begum, J. Buysse, G.V. Huylenbroeck, Energy consumption, carbon emissions and economic growth nexus in Bangladesh: Co-integration and dynamic causality analysis, Energy Policy. 45 (2012) 217–225.
[22] G. Zhang, M. Nuruzzaman, B. Su, Nexus between household energy consumption and economic growth in Bangladesh (1975–2018), Energy Policy. 156 (2021) 112420.
[23] World Bank 2021 data: https://www.worldbank.org/en/home (accessed 08.11.2022).
[24] M.K. Khan, M.I. Khan, M. Rehan, The relationship between energy consumption, economic growth and carbon dioxide emissions in Pakistan, Financ. Innov. 6-1 (2020) 1–13.