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Research article

Decomposition analysis of electricity generation on carbon dioxide emissions in Ghana

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A R T I C L E I N F O

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A B S T R A C T

This study analyses the factors driving CO_2 emissions from electricity generation in Ghana from 1990 to 2020. Employing Logarithmic Mean Divisia Index (LMDI) and Autoregressive Distributed Lag (ARDL) techniques, the research decomposes electricity generation into different factors and assesses their impact on CO_2 emissions, considering both short and long-run effects. The LMDI analysis reveals that the total CO_2 emissions from electricity generation amount to 3.33%, with all factors contributing positively in each subperiod. Notably, fossil fuel intensity, production, and transformation factors exhibit substantial contributions of about 1.16%, 0.49%, and 0.48%, respectively. Contrastingly, the ARDL results highlight that only electricity intensity and production factors significantly increase CO_2 emissions by about 0.20% and 0.09% (0.38% and 0.10%) in the short-run (long-run), while other factors contribute to a reduction in electricity generation emissions. Overall, we conclude that electricity intensity and production factors are the primary drivers of CO_2 emissions from electricity generation in Ghana. Nevertheless, effective measures to address all decomposition factors is crucial for effective mitigation of electricity generation CO_2 emissions.

1. Introduction

The escalating global warming crisis has brought about a deep concern on the level of climate change worldwide. Reliance on fossil fuel for energy production is unquestionably the source of this crisis. Economies cannot function very efficiently without energy. Energy is one of the fundamental forces that drives economies and is required for society's successful functioning, such as lighting, heating, and transportation. Access to energy is critical for social and economic development [1]. Because of the benefits of energy use for human development, the seventh target of the Sustainable Development Goals (SDGs) was created to improve universal access to affordable, dependable, and modern energy services [2]. The most used kind of energy in Ghana is electricity, which was produced mostly by hydropower in the 1960s and supplemented by thermal power generation in the 1980s due to the harsh and drought-prone

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weather changes that oscillated production.

At the forefront of CO_2 emissions, the energy sector stands out, contributing a staggering 80% of the global total. Within this sector, electricity generation holds the largest share, accounting for 42% of emissions [3]. Transportation and industry follow closely behind, contributing 25% and 18%, respectively [4,5]. The predominant use of coal, oil, petroleum products, and natural gas play a greater role in explaining climate change. Therefore, countries have made frantic efforts under these global agreements to create policy frameworks that are expected to mitigate these worrying climate changes, and Ghana is not an exception [6]. This has led to significant empirical studies on how electricity production and generation mitigate this problem in both developed and developing countries with the literature on the former economies dominating the discussion [7–15].

Electricity generation tends to increase as a result of increasing demands for it when the country's population grows, which consequently leads to high CO_2 emissions. According to the International Energy Association (IEA) [16], electricity generation and heat production account for nearly half of global CO_2 emissions. Owusu and Asumadu-Sarkodie [1] also stated that in Ghana, there has been a consistent exponential increase in population coupled with the dominance of fossil-fuel based power generation, resulting in greenhouse emissions over the last decade. Simultaneously, Ghana's electricity sector has been plagued by recurring blackouts, prompting government to employ diesel generators in residential and industrial settings. These diesel-powered generators pose more severe environmental drawbacks [17]. Ghana's Environmental Protection Agency (EPA) underscores the significant contribution of electricity generation and to greenhouse gas (GHG) emissions, causing detrimental environmental impacts. Ghana's government also failed to achieve its 2020 target of incorporating 10% renewable energy. Renewable energy goals can be realized through the implementation of clean technology for power generation. Fig. 1 (see Section 4) shows that electricity generation and CO_2 emissions over the years have exhibited a positive association in Ghana. This is an indication that electricity generation has a possible influence on CO_2 emissions in Ghana.

According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), "continued emissions of greenhouse gases will cause further warming and long-term changes in all components of the climate system, increasing the likelihood of severe, pervasive, and irreversible impacts for people and ecosystems." Given this, the goal of the twenty-first Conference of the Parties (COP26) was to highlight the potential and imminent irreversible dangers of climate change to human society and the planet as a whole, Ghana's condition is not immune to the global challenges of climatic change caused by rising CO_2 emissions and their negative impact on its people and ecology.

Furthermore, this study is driven by recent concerning events that impact Ghana's efforts to achieve carbon neutrality. Horizontal and vertical environmental cooperation is flexible and reliable in Ghana, but they are ineffective, per the 2021 Climate Action Tracker (CAT) governance assessment for the country. Even though research claims that the government of Ghana has the necessary mechanisms in place to mobilize and manage climate money, so far it has been unable to secure sufficient funds for climate action [18]. The various studies also note that Ghana lacks a comprehensive plan to reduce carbon emissions over time. Its low-carbon economy strategy only applies to the period leading up to 2030 and does not go into effect until then. In addition, the administration has not shown any signs that it plans to create any new climate-related laws beyond the Green Energy Act, which creates the outline for the generation of green energy. While the authorities have tried to educate the public about global warming, the CAT report shows that only about 20% of people are aware of the problem and its detrimental effects. From the CAT assessment, it can be inferred that Ghana's efforts to reduce GHG emissions and strengthen its ability to withstand and adapt to climate change have been less successful than those of other developing nations. So, it is important to do this research to help the country's motivation to fight the bad impact of climate change on the current global environment. As a result, investigating the drivers of electricity energy generation on CO_2 emissions becomes critical.

Unraveling the driving forces behind CO_2 emissions and comprehending the interplay between electricity generation and CO_2 emissions is crucial to mitigate environmental concerns and attain sustainable development objectives. This study stems from the desire to address these critical questions: Which driving factor exerts a more pronounced influence on CO_2 emissions in Ghana? And how does the form of electricity generation impact CO_2 emissions in Ghana? This research endeavor to pursues three primary objectives: (1) to conduct a decomposition analysis of CO_2 emissions arising from electricity generation fueled by primary fossil fuels in Ghana over the 1990–2020 period; (2) to gain a deeper understanding of the decoupling dynamics between CO_2 emissions from electricity generation and economic growth in Ghana; and (3) to provide valuable insights to policymakers formulating strategies pertaining to global warming, climate change, and sustainable development. This is critical because, first, identifying the paths of CO_2 pollution and electricity generation over the study period allows future prediction and policy direction to mitigate emissions. Second, by decomposing electricity generation into different factors and examining their contributions to pollution in Ghana, policy makers may identify the relevant causes and propose effective policies to mitigate these pollution. Ghana is considered in this study because it is not only stable small-opened economy, but it is endowed with relatively large reserves of fossil fuel for exports. Thus, the country's contribution to carbon dioxide emissions cannot be ignored. More so availability of data is another factor. Thus, the innovation of this paper which is an empirical one is the decomposition of electricity generation on CO_2 emissions using the Logarithmic Mean Divisia Index (LMDI) and Autoregressive Distributed Lag Model (ARDL) which is virtually nonexistent in studies on Ghana.

The ensuing sections of the paper embark on a comprehensive exploration of the research's foundations, including a discussion of the theories presented in Section 2; a detailed explanation of the methodology applied to test the hypothesis in Section 3; the presentation of the research findings and their implications in Section 4; and the formulation of policy recommendations in Section 5, the final component.

2. Literature review

The mounting pressure of environmental problems on social and economic advancement is a stark reality in today's world. Serving as the foundation of these challenges is CO_2 emissions, the primary contributor to GHG emissions. To effectively address this pressing matter, numerous scientists have extensively employed decomposition and decoupling analyses to analyze the factors influencing CO_2 emission patterns and examine the relationship between CO_2 emissions and economic growth [19–22].

Decomposition analysis (DA) has emerged as a valuable tool for scrutinizing the underlying forces driving carbon emissions and industry-related emissions [19,20,23]. DA can also be coupled with economic growth and energy structure scenarios to forecast the future impact of these driving forces [24]. A prominent area of application has been carbon emissions from the electricity sector, with numerous studies published in recent times [23,25–29]. Their results suggest that improvements in steam efficiency in power plants have played a crucial role in reducing carbon intensity.

2.1. Decomposition analysis focusing on Ghana

Given the potency that energy (both consumption and production) can have on climate change through its effect on CO_2 emissions, a large body of literature in both developed and developing countries has focused on the effect of energy consumption and production (or generation) on CO_2 emissions. For example, in Ghana, Asumadu-Sarkodie and Owusu [30] used ARDL to analyze how electricity consumption and production in Ghana influence CO_2 emissions. The study found energy production from combustible renewables and waste and electric power consumption to induce higher CO_2 emissions whereas electricity production from hydroelectric sources reduces emissions levels in Ghana. Similarly, Kwakwa and Alhassan [31] empirically revealed that combustible renewables and waste and electricity production from hydro are associated with a reduction in CO_2 emissions. However, they found that fossil fuel consumption and the production of electricity from fossil fuels are among the key factors driving CO_2 emissions. In fact, other studies in Ghana [32–34] have also indicated that energy consumption in Ghana causes CO_2 emissions, consistent with the studies by Asumadu-Sarkodie and Owusu [30] and Kwakwa and Alhassan [31]. More recently, Nyasapoh et al. [15] examined CO_2 emissions from fossil fuel power plants in Ghana applying quantitative modelling and simulation techniques. The study revealed that the inclusion of technologies for the conversion of energy, such as renewable and nuclear energy, is important to limit CO_2 emissions in the energy sector. This is an indication that renewable energies have the potential to contribute to a sustainable environment in Ghana.

Although reviewed studies in Ghana have shown the connection between energy consumption or production and CO_2 emissions, these studies failed to capture the analysis of the breakdown (decomposition) of electricity generation on CO_2 emissions in Ghana. The decomposition analysis of electricity generation on CO_2 emissions helps to specifically assess which form of electricity generation contribute to CO_2 in Ghana and thus, must be targeted in terms of policy formulation for a sustainable environment. Though Asumadu-Sarkodie and Owusu [30] and Kwakwa and Alhassan [31] employed electricity production from fossil fuels and hydro, they used aggregated data of electricity production, which fails to identify the drivers of electricity generation. Therefore, the present study filled these gaps in the literature on energy-CO_2 emissions in Ghana by offering a decomposition analysis of electricity generation on CO_2 emissions using recent LMDI techniques, which deviate from previous studies in Ghana and therefore provide a contribution.

2.2. Decomposition analysis beyond Ghana

Regarding other studies beyond Ghana, several studies have shown that energy consumption and production have the capacity to either improve (or deplete) the environment by limiting (increasing) CO_2 emissions. Starting with Malaysia, Gul et al. [35] used the maximum entropy bootstrap method to show the existence of unidirectional causality from energy consumption to CO_2 emissions. Such causality analysis has been supported by Mohiuddin et al. [36] and Shahbaz et al. [37]. In the case of Mohiuddin et al. [36], the study revealed that energy consumption and electricity energy production from oil, coal and natural gas induces CO_2 emissions in Pakistan. Furthermore, using the ARDL approach, Anwar and Alexander [38], Cetin et al. [39] and Bekun et al. [40] have postulated that energy consumption significantly depletes the environment by increasing CO_2 emissions in Vietnam, Turkey and South Africa, respectively. Contrary to the ARDL method, Awodumi and Adewuji [41] employed the nonlinear ARDL (NARDL) technique in five oil producing economies in Africa and found that nonrenewable energy consumption (petroleum and natural gas) reduces CO_2 emissions in Nigeria and Gabon, while its effect in Angola was mixed (positive and negative). The study also shows that nonrenewable energy consumption has no impact on CO_2 emissions in Egypt and Algeria.

Although there are virtually no studies on the analysis of the decomposition of electricity generation on CO_2 emissions in Ghana, studies in other countries have shown the relevance of the analysis of the decomposition of energy or electricity generation on CO_2 emissions. For example, studies in China [42–46] have used the LMDI for decomposition analysis of China aggregate electricity intensity (CAEI), electricity generation and thermal electricity generation, respectively. Specifically, Yongxiu et al. [42] shows that the intensity effect has a role in declining CAEI during 1995–1999. However, since 2000 both the intensity and structure effects have contributed to an increase in CAEI. Zhang et al. [43] also indicated that coal product is the main fuel type in thermal power generation and accounted more than 90% of CO_2 emissions in China. Furthermore, Zhou et al. [44] found that China's intensity effect and the energy mix effect positively contribute to the reduction of CO_2 emissions. Also, Yan et al. [45] noticed that regional energy efficiency and changes in regional energy structure reduce CO_2 emissions resulting from thermal electricity generation. However, Wang et al. [46] observed that utilization efficiency effect and thermal power proportion effect have the largest share in the aggregate carbon intensity of China. On the contrary, Yan et al. [47] used index decomposition analysis (IDA) via generalized divisia index model (GDIM) to investigate the driving factors on China's CO_2 emission changes in thermal electricity generation. The study showed that among the factors contributing to CO_2 emission, economic activity is the highest whiles the least is energy use. Furthermore, the study indicated that the change in carbon intensity exerts the highest negative effects (−17.7%), followed by technology (−11.3%) on CO_2, and the effect of energy efficiency has the least effect on CO_2 emissions.

In Korea, Kim and Kim [48] examined the analysis of GHG emissions decomposition in Korea's electricity generation sector. Using the same LMDI factor decomposition method, the study decomposed the emission into five factors and argued that the production effect, electricity generation structure, fossil-fuel mix, and the electricity generation efficiency have contributed to increased GHG emissions at different levels. However, the emission factor effect has a decreasing GHG emissions effect. Similarly, Oryani et al. [49] evaluate the impact of renewable electricity generation mix on economic growth and CO_2 emissions in Iran. The study indicated that the share of renewable electricity in the energy combination is not at a desirable level to decrease CO_2 emissions. Furthermore, Alcántara et al. [50] investigated the elements that contribute to CO_2 emissions from energy generation in Spain. Empirical data revealed that fossil intensity, electricity intensity, and production effects contributed to CO_2 emissions during 1999–2005, while carbonization and fossil intensity effects were the main factors in the reduction of CO_2 emissions from 2006 to 2010.

2.3. Gaps in literature

From the empirical review, while a number of studies have focused on the analysis of energy generation decomposition, Ghanaian studies have failed to consider such an analysis. While its relevance is widely recognized, gaps in the literature warrant further research. Existing studies have primarily focused on single-year or short-term analyses, limiting insights into long-term trends and the impact of policy interventions. A more comprehensive study spanning a longer timeframe, considering subsectors like thermal and renewable energy generation, would provide deeper insights into specific drivers of emissions and policy effectiveness. Specifically, analysis of the decomposition of electricity generation on CO_2 emissions is virtually nonexistent in Ghana. Therefore, the present study contributes to knowledge in that direction. We do so, by studying the trends in total electricity generation and CO_2 emissions in Ghana. Further, we deconstruct electricity generation into several components through the LMDI method and investigate the effect of those factors on CO_2 emissions. Furthermore, the study offers the short and long run effects of the deconstructed power generating components on CO_2 emissions. Additionally, more detailed analyses of the relationship between economic growth and electricity consumption patterns, and direct comparisons of Ghana's emissions trends with other countries, are needed to guide policy formulation and inform international cooperation. By addressing these gaps, a comprehensive study on DA in Ghana would provide crucial insights for policymakers and stakeholders to effectively reduce carbon emissions and pursue sustainable development.

3. Empirical methodology

In this section, we discuss the methods employed for decomposition analysis and the estimation of both short and long-term impacts of the decomposition factors influencing CO_2 emissions. Initially, we utilize the LMDI to decompose electricity generation factors. This helps us discern the significant contributors to CO_2 emissions. Subsequently, we employ the ARDL model to evaluate the short and long-term effects of the identified decomposition factors. To ensure the appropriateness of the ARDL model, we conduct preliminary tests such as unit root and cointegration tests.

Several methods have been proposed in the empirical literature for decomposing the change in a variable, such as an environmental pressure indicator into multiple components in order to determine the influence of various factors in an identity. The STIRPAT model, LMDI decomposition, Tapio elasticity approach, and structural decomposition analysis (SDI) are some of these methodologies [50]. This study uses the LMDI to break down electricity generation into separate components. We choose the LMDI over the other decomposition strategies due to its advantages. For example, LMDI allows for the quantification of the impact of the various electricity generation factors on CO_2 emissions. It also allows for the identification of the main driving forces behind changes in CO_2 emissions from electricity generation. Most researchers examining the connection between environmental concerns and economic growth employ the LMDI decomposition approach [42,50]. Furthermore, the LMDI technique breaks down power generation into multiple components and evaluates the numerous elements that contribute to or drive CO_2 emissions in a given economy. Ang [51] compares and contrasts the various decomposition methods, highlighting their benefits and drawbacks and found that the LMDI approach has the best features because of its strong theoretical underpinning, adaptability, and ease of use and interpretation compared to the others. The fact that the method guarantees flawless decomposition and thus eliminates the problem of unallocated residues in the decomposition stands out among its benefits. Again, the ARDL method was employed for the long- and short run analysis.

3.1. LMDI decomposition specification

This study follows the Kaya [52] identity to express CO_2 emissions [in kilotonnes (Kt)] resulting from the use of fossil fuels in electricity generation (CO_2E) based on different explanatory factors, as shown in equation (1).

$$CO_2E = \frac{CO_2E}{FEI} \times \frac{FEI}{FEG} \times \frac{FEG}{TEG} \times \frac{TEG}{GDP} \times GDP \tag{1}$$

where $FEI, FEG, TEG, and\ GDP$ denotes fossil fuel energy input used in electricity production (measured in Kt of oil equivalent, ktoe), electricity generation from fossil fuel origins (Ktoe), total electricity generation (Kt) and gross domestic products (measured in constant prices), respectively. Therefore, following Alcántara et al. [50], the right-hand side of equation (1), $\frac{CO_2E}{FEI}, \frac{FEI}{FEG}, \frac{FEG}{TEG}, \frac{TEG}{GDP}$, and GDP denote the carbonization factor (c), transformation factor (e), fossil intensity factor (s), electricity intensity factor (w), and production factor (y), respectively. CO_2 emissions from electricity generation are classified into five (5) explanatory elements as shown in Equation (1). This signifies the driving forces of CO_2 emissions, according to Alcántara et al. [50] extension of Kaya's [52] identification. Table 1 shows the description of these variables.

Equation (1) is then expressed in identity given in equation (2). For simplicity, we denote $CO_2E = C, \frac{CO_2E}{FEI} = c, \frac{FEI}{FEG} = e, \frac{FEG}{TEG} = s, \frac{TEG}{GDP} = w$, and $GDP = y$.

$$C \equiv c_t \times e_t \times s_t \times w_t \times y_t \tag{2}$$

However, accounting for changes in CO_2 emission over time from equation (2) gives equation (3).

$$C_t - C_{t-1} = c_t \times e_t \times s_t \times w_t \times y_t - c_{t-1} \times e_{t-1} \times s_{t-1} \times w_{t-1} \times y_{t-1} \tag{3}$$

LMDI is defined by Ang [53] as a change in CO_2 emissions from the base year to the target year. The LMDI technique of total CO_2 emissions can be stated using the additive approach as follows from equations (4)–(9).

$$\Delta C_{TOT} = C^t - C^0 = \Delta C_{c-effect} + \Delta C_{e-effect} + \Delta C_{s-effect} + \Delta C_{w-effect} + \Delta C_{y-effect} \tag{4}$$

where

$$\Delta C_{c-effect} = \sum_i \frac{C_i^t - C_i^0}{ln\ C_i^t - ln\ C_i^0} \times \ln\left(\frac{c - effect^t}{c - effect^0}\right) \tag{5}$$

$$\Delta C_{e-effect} = \sum_i \frac{C_i^t - C_i^0}{ln\ C_i^t - ln\ C_i^0} \times \ln\left(\frac{e - effect^t}{e - effect^0}\right) \tag{6}$$

$$\Delta C_{s-effect} = \sum_i \frac{C_i^t - C_i^0}{ln\ C_i^t - ln\ C_i^0} \times \ln\left(\frac{s - effect^t}{s - effect^0}\right) \tag{7}$$

$$\Delta C_{w-effect} = \sum_i \frac{C_i^t - C_i^0}{ln\ C_i^t - ln\ C_i^0} \times \ln\left(\frac{w - effect^t}{w - effect^0}\right) \tag{8}$$

$$\Delta C_{y-effect} = \sum_i \frac{C_i^t - C_i^0}{ln\ C_i^t - ln\ C_i^0} \times \ln\left(\frac{y - effect^t}{y - effect^0}\right) \tag{9}$$

where ΔC_{TOT} represents the total change of CO_2 emission from electricity generation in a given period been decomposed into five (5) factors such as change in carbonization index ($\Delta C_{c-effect}$), change in transformation effect ($\Delta C_{e-effect}$), change in fossil intensity of electricity effect ($\Delta C_{s-effect}$), change in electricity intensity of GDP effect ($\Delta C_{w-effect}$) and change in economic activity effect ($\Delta C_{y-effect}$).

3.2. Model specification

Following the decomposition factors of the LMDI, we specified a linear model of CO_2 emissions from electricity generation as a function of the decomposition factors (c-effect, e-effect, s-effect, w-effect, and y-effect). This helps to determine the long-and short-run impacts of the decomposition factors. Therefore, we specify the functional model in equation (10).

$$C = f(c - effect, e - effect, s - effect, w - effect, y - effect) \tag{10}$$

where C is carbon dioxide emissions from electricity generation, while c-effect, e-effect, s-effect, w-effect, and y-effect represent the carbonization index effect, transformation effect, fossil fuel intensity effect, electricity intensity effect, and economic activity effect, respectively.

Table 1
Decomposition factors.

Variables	Construction	Series	Measurement
c-effect	CO_2E/FEI	Carbonization factor	Fossil fuel energy used in electricity generation (Emissions per unit of fossil fuel energy used in electricity generation).
e-effect	FEI/FEG	Transformation factor	The inverse expression of the efficiency in the conversion of inputs of fossil fuel into electricity.
s-effect	FEG/TEG	Fossil fuel intensity factor	Share of the electricity of fossil origin in the total electricity generated in the system.
w-effect	TEG/GDP	Electricity intensity factor	The electricity intensity of economic activity (Efficiency factor in the use of electrical power by economic agents).
y-effect	GDP	Production factor	Production obtained by the economic system which is a proxy of "scale". The variations in GDP would determine the path that emissions (production) would follow (Sun, 1999)

Source: Alcántara et al. (2022)

Equation (10) then is specified in the empirical estimation model as shown in equation (11).

$$ln\ C_t = \beta_0 + \beta_1\ ln\ (c - effect)_t + \beta_2(e - effect)_t + \beta_3(s - effect)_t + \beta_4\ ln\ (w - effect)_t + \beta_5\ ln\ (y - effect)_t + \varepsilon_t \quad (11)$$

where $\beta_1 \ldots\ldots\ldots \beta_5$ are parameters to be estimated. All variables are defined in the preceding equations.

3.3. ARDL model and cointegration test

The autoregressive distributive lag (ARDL) model developed by Pesaran and Shin [54] was utilized to estimate the empirical model of equation (11). This technique was adopted because of its capability to handle small sample size (as in this study) data. Moreover, it does not require variable pretesting [30], thus avoiding uncertainty. Thus, the estimator is suitable and applicable regardless of been stationary at the levels or first-difference or mixed. The ARDL cointegration approach can estimate both the short-and long-run equilibrium connection between the dependent and independent variables. Following the aforementioned benefits of the ARDL, the used of ARDL to ascertain the long-and short-run effects in this study is appropriate. Therefore, the ARDL specification of equation (11) is expressed in equation (12).

$$\begin{aligned} lnC_t = {} & \beta_0 + \beta_1 lnC_{t-1} + \beta_2\ ln\ (c - effect)_{t-1} + \beta_3(e - effect)_{t-1} + \beta_4(s - effect)_{t-1} + \beta_5\ ln\ (w - effect)_{t-1} + \beta_6\ \ln\ (y - effect)_{t-1} \\ & + \sum_{i=1}^{p} \delta_i \Delta lnC_{t-i} + \sum_{t=1}^{p} \gamma_i \Delta \ln(c - effect)_{t-i} + \sum_{t=1}^{p} \theta_i \Delta(e - effect)_{t-i} + \sum_{t=1}^{p} \tau_i \Delta(s - effect)_{t-i} + \sum_{t=1}^{p} \varphi_i \Delta \ln(w - effect)_{t-i} \\ & + \sum_{t=1}^{p} \sigma_i \Delta \ln(y - effect)_{t-i} + \varepsilon_t \end{aligned} \quad (12)$$

where $\beta_1 \ldots\ldots\ldots \beta_6$ are the long run coefficients whereas as $\delta_i, \gamma_i, \theta_i, \tau_i, \varphi_i$ and σ_i are the short parameters. The p, Δ, and ε_t denote lag order, first-difference operator, and the error term, respectively. All other variables are defined in the previous equations.

Although stationarity testing is not a necessity for the ARDL since ARDL is applicable whether series are stationary at levels or first-difference. However, absence of stationarity of the series could lead to bias and inconsistent results [55]. As a result, we used the augmented Dickey-Fuller (ADF) and Phillips-Perron (P–P) unit root tests for the stationarity properties of the variables. In both tests, rejection of the null hypothesis indicates that the variables exhibit stationarity. After the stationarity properties, we follow Pesaran et al. [56] to employ the F-test of joint significance of the series in equation (1) for cointegration or long-run relationship among the variables. The F-test holds the null hypothesis of no long-run relationship whereas the alternate claims presence of long-run relationship among the variables. The F-test is compared to the two critical values [lower, $I(0)$ and upper, $I(1)$ bounds] provided by Pesaran et al. [56]. Given the F-test and the critical values, the study claims cointegration among the variables if the F-statistic is greater than the upper bounds. It is worth noting that the optimal lag selection was based on the Schwartz Bayesian Criterion (SBC) since it gives a parsimonious model.

Moreover, the ARDL model offers various advantages in comparison to alternative methodologies: The ARDL approach is more dependable for small samples than other cointegration methodologies such as Johansen and Juselius's cointegration methodology. The ARDL model enables the concurrent estimation of short- and long-run effects, which is advantageous as it offers a comprehensive understanding of the relationships between variables [57]. The ARDL cointegration methodology stands out from other methods as it does not necessitate pretests for unit roots[2]. This streamlines the process of modelling. Furthermore, the ARDL cointegration technique is highly resilient when working with variables that have varying levels of integration, such as I(0), I(1), or a combination of both. It is also robust when there is just one long-term link between the underlying variables, even in cases of small sample sizes [58–60].

Nevertheless, we diagnosed the ARDL model to ensure efficient and unbiased results. In doing so, we utilized the Breusch-Pagan-Godfrey test and the Breusch-Godfrey LM test for heteroscedasticity and autocorrelation problems. Furthermore, the Jarque-Bera test was used for normality of the series. In these tests, failure to reject the null hypothesis indicates absence of these deficiencies. Again, cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) plots were used for the stability of the model.

3.4. Data source

The data for the analysis spans from 1990 to 2020 and was sourced from two primary outlets: the World Bank's World Development Indicator (WDI) [61] and Ghana's Energy Statistics [62]. The time series data covers the period from 1990 to 2020, allowing for a comprehensive examination of trends and patterns in various variables related to electricity production and CO_2 emissions. The WDI provided key variables such as electricity production, electricity generation from fossil fuels, total electricity generation, CO_2 emissions, and GDP, with each variable measured in distinct units as per Alcántara et al. [50]. Specifically, fossil fuel energy input used in electricity production was measured by fossil fuel kilotonnes of oil equivalent, electricity generation measured from fossil fuel origins in kilotonnes of oil equivalent, total electricity generation measured by total electricity generation in kilotonnes, CO_2 emissions measured in Kt, and GDP measured in US dollars constant prices. The data obtained from WDI was specifically used for the decomposition analysis of electricity generation. This analytical approach involves breaking down the total electricity generation into its constituent components to understand the contribution of each factor over time using the LMDI and ARDL. Information on the trend in total electricity generation sources, including crude oil, natural gas, petroleum, biomass, and hydro, was sourced from the Ghana Energy Statistics report [62]. This data is crucial for understanding the evolution of the energy mix in Ghana over the specified period.

4. Results and discussions

The study starts the discussions with the trend analysis (specifically, the trends of CO_2 emissions and electricity generation, electric intensity and degree of electrification of energy, and energy mix of electricity generation). The decomposition results from the LMDI are then analyzed and finally discussed the long-and-short-run results.

4.1. CO_2 emission and electricity generation trends

Fig. 1 shows the trends of Ghana's carbon emissions and electricity generation from 1990 to 2020. Total electricity generation increased continuously from 1990 to 2002 but fluctuated between 2002 and 2006. Again, total electricity generation increased dramatically from 2008 to 2012, decreased abruptly from 2012 to 2016, and increased sharply from 2016 to 2020. Although there exist fluctuations in electricity generation in Ghana, it is, however, obvious that electricity generation has been increasing over time. This is an indication that electricity generation is among the primary sources of energy in Ghana.

Similarly, carbon emissions demonstrated patterns or tendencies to electricity generation trends; however, carbon emission trends are lower or lie below total electricity trends. This suggests that overall electricity generation was seen to be higher than total carbon emissions throughout the study period. The similar trends of electricity generation and CO_2 emissions gives indication that electricity generation is linked to CO_2 emissions. We noticed a rapid increase in CO_2 from 2000 to 2020 compared to 1990–1999. This supports Twerefou et al. [12], arguing that CO_2 emissions in Ghana increased from 12.2 to 23.9 metric tonnes (Mt) between 2000 and 2010. This, however, confirms that CO_2 levels are rising and remain a key concern in Ghana.

Overall, the figure demonstrates that electricity generation has a positive association with carbon emissions over the 1990–2020 research period. This trend of Ghana somehow supports the IEA arguments that 1.55 billion to 1.71 billion Mt of CO_2 is associated to 4.01 trillion kilowatt-hours (kWh) of electric power from all energy sources. This corresponds to around 0.85 pounds of CO_2 emissions per kWh [16]. This confirms the fact that electricity generation and CO_2 exhibit a positive relationship over the study period.

4.2. GDP electric intensity and degree of electrification of energy

The trends in electricity intensity and electrification are depicted in Fig. 2. Following the pattern, electricity intensity decreased from 1990 to 2014 before significantly increasing from 2014 to 2020. The amount of electricity consumed to create a particular level of production or activity is called electrical intensity. Overall, the use of electricity has increased in recent years, meaning that a larger proportion of the population now uses electricity for the majority of their activities.

Again, from 1990 to 2001, the degree of electrification increased gradually, then dropped from 2001 to 2004, before continuously increasing from 2004 to 2020. This suggests that on average, electrification has increased with time, confirming the rising trend for total power generation in Fig. 1. The electrification level is the proportion of accessible electrical power to total power. Notably, from 2015 to 2020, the degree of electrification and electricity intensity had a positive association, whereas from 1990 to 2009, they had an inverse relationship on average. If the demand for electricity rises, as expected, generation will have to expand to meet the rising demand or usage of electricity. According to Owusu and Asumadu-Sarkodie [1], Ghana's population has grown rapidly over the years, and as a result, the amount of electric power accessible has increased as well, as seen in Figs. 1 and 2.

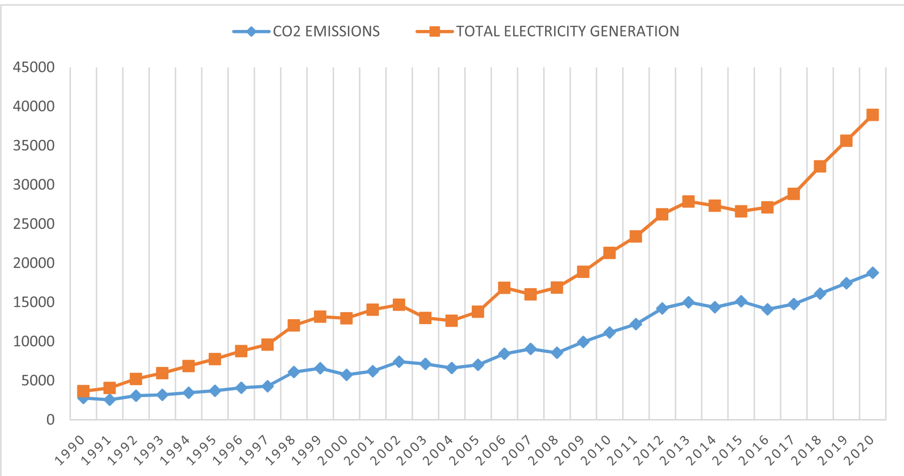

Fig. 1. Trends of CO_2 emissions and electricity generation.

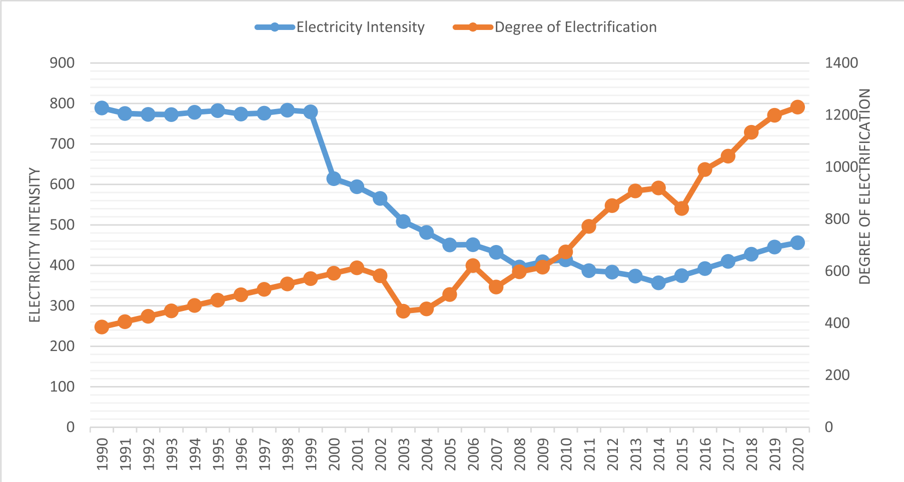

Fig. 2. Electric intensity and degree of electrification of energy.

4.3. Energy mix of electricity generation

Fig. 3 depicts the mix of energy sources used for power generation throughout the time study period. Natural gas's contribution to power generation has gradually increased over the study period, whereas biomass's contribution to electricity generation has decreased over the study period. A steam production unit is the most common way to generate electricity from natural gas. To generate steam, a boiler or a network of boilers is used. The combustion of natural gas in boilers produces steam, which powers a turbine. Natural gas is used to generate electricity in steam turbines and gas turbines, which emit CO_2 throughout the process.

Furthermore, biomass fuels are all non-fossil, carbon-based (biogenic) energy sources. All other non-biogenic wastes are classified as waste fuels. Direct combustion is used to create the majority of biomass electricity. Biomass is burned in a boiler to produce high-pressure steam. This steam spins turbine blades as it rushes over them. The rotation of the turbine drives a generator, which provides energy. All of these processes release CO_2 into the atmosphere over time. Due to dependency on subsidies, pollution problems, and other challenges, utility-scale biomass has been on the decline. Biomass has a bleak future as a fuel, and it pales in comparison to other possibilities [16]. Like natural gas, the role of crude oil in electricity generation has been increasing, but it fluctuates over time. Fig. 3 also shows that throughout the study period, electricity generation from hydro increases but oscillates. In contrast to hydro, the contribution of petroleum to energy generation declines but oscillates from 2004 to 2019. In general view, while the contribution of crude oil, hydro and natural gas to electricity generation has increased, the proportion of biomass and petroleum to electricity

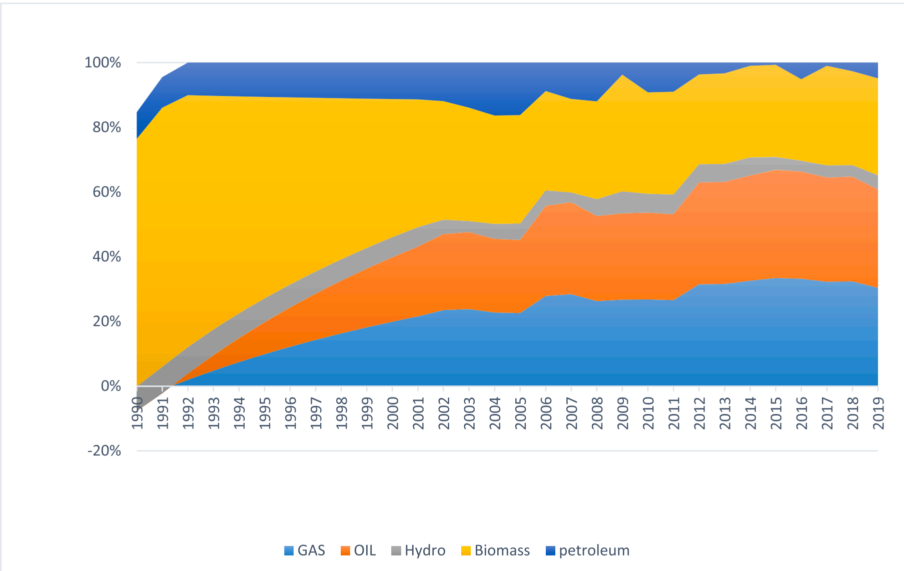

Fig. 3. Energy mix of electricity generation.

generation has decreased.

Intuitively, the increased contribution of natural gas, hydro and crude oil to power generation may be related to the positive impact of electricity generation on CO_2 emissions in Table 2 during the research period. Ghana has a total installed electricity capacity of 3.8 gigawatt (GW) and generated around 13,000 gigawatt-hours (GWh) of electricity in 2016, according to national energy data. Three hydropower units account for approximately 42 percent of installed generation capacity, and the remaining 58 percent are accounted for by oil and natural gas power plants. Solar and biogas also contribute 22.6 megawatt to the total electricity capacity [62].

4.4. Annual electricity decomposition results in Ghana (LMDI)

From 1990 to 2020, the study decomposed electricity into several factors as discussed previously to determine which variables contribute to CO_2 emissions in Ghana. The findings of the decomposition are shown in Table 2. From Table 2, the total average contribution (1990–2020) of power generation to CO_2 emissions is 3.33 percent, culminating in an average emission of 138250.65 Kt from 1990 to 2020. In particular, 1.61 percent of the contribution comes from the fossil fuel intensity factor (s-effect), 0.49 percent from the production factor (y-effect), 0.48 percent from the transformation factor (e-effect), 0.43 percent from the carbonation factor (c-effect), and 0.32 percent from the electricity intensity factor (w-effect).

Individually, these causes have prevailed in contributing to CO_2 emissions in Ghana in different periods. From 1990 to 1996, the transformation factor was the largest contributor to CO_2 emissions in Ghana, accounting for 24.77 percent, followed by the electricity intensity factor at 8.53 percent, the production factor at 8.45 percent, the carbonation factor at 7.95 percent, and the intensity factor at 0.51 percent. This is linked to the biomass electricity source shown in Fig. 3 for generating electricity, which was the primary source of electricity at the time. Carbonization was found to contribute more to CO_2 emission by emitting 24.33 percent between 1997 and 2002, while the intensity factor contributed the least to CO_2 emission by emitting 8.58 percent. This could be due to the increased contribution of crude oil and natural gas, as well as the decrease in biomass energy sources in Fig. 3. From 2003 to 2008, we observed the largest contributor of CO_2 emission was the production factor, which emitted 11.01 percent CO_2, while the least contributor was the intensity factor, which contributed 1.29 percent to CO_2 emission. As expected, using primitive ways to generate electricity has the potential to increase CO_2 emissions over the research period. Another factor contributing to the higher CO_2 emissions during the production process could be a lack of advanced technology.

Furthermore, between 2009 and 2014, the intensity factor and the transformation factor contributed 81.35 percent and 33.92 percent of CO_2 emissions, respectively, making them the biggest and lowest contributors to CO_2 emissions. Electricity generated with fossil fuels is more carbon intensive since the process of generation produces CO_2 emissions. Fossil fuel inputs, such as natural gas, crude oil, and hydro were the primary contributors to electricity generation between 2009 and 2014, causing the intensity factor to dominate in CO_2 emissions. In contrast to 2009–2014, the recent (2015–2020) component contributing the most to CO_2 emissions was the electricity intensity of economic activity, which emitted 30.75 percent, and the least contributor was the intensity factor, which emitted 8.28 percent. It can be stated that numerous variables have contributed considerably to the emission of CO_2 in Ghana over the studied period. Although the contributions of various factors fluctuate, the overall contributions of the various factors to CO_2 emission can be determined to be positive. The increasing contribution of natural gas, hydro and crude oil to electricity generation may be linked to the positive contribution of electricity generation to CO_2 emissions. Fig. 1 also shows a positive trend in the relationship between electricity generation and CO_2 emissions.

4.5. Decomposition short and long run results (ARDL)

After decomposition analysis, we used the ARDL model to ascertain the long- and short-run effects of the various factors of electricity generation on CO_2 emissions. We start by first examining the stationarity of the series, followed by the cointegration test results, and finally we discuss the long-and short-run results as well as its diagnostic tests.

4.5.1. Stationarity test results

Using the Augmented Dickey-Fuller (ADF) and Philips-Perron (P–P) methods, we tested the series stationarity, and the results are reported in Table 3. We observed a mixed stationarity of the variables in both tests. While some are stationary at the levels, others are stationary at the first difference. Particularly, the ADF indicates that except for E-effect and S-effect, all other variables are stationary at the first difference. In contrast, the P–P shows that all variables are stationary at the levels except for CO_2 emissions. Since the ARDL

Table 2
Annual Electricity decomposition results in Ghana (figures in percentages).

Year	c-effect	e-effect	s-effect	w-effect	y-effect	Total
1990–1996	0.0795	0.2477	0.0051	0.0853	0.0845	0.5020
1997–2002	0.2433	0.1598	0.0858	0.2016	0.1959	0.8864
2003–2008	0.0709	0.0726	0.0129	0.0451	0.1101	0.3117
2009–2014	0.3468	0.3392	0.8135	0.3606	0.3672	2.2273
2015–2020	0.2594	0.1807	0.0828	0.3075	0.2422	1.0726
Overall decomposition effect						
1990–2020	0.0043	0.0048	0.0161	0.0032	0.0049	0.0333

Note: Decomposition in 5-year subperiods.

Table 3
Unit root test results.

Variable(s)	ADF		P–P	
	$I(0)$	$I(1)$	$I(0)$	$I(1)$
lnC	−1.433	−5.483***	−0.840	−5.726***
lnc-effect	−1.074	−3.345**	−2.866**	−10.322***
e-effect	−4.321***	−6.697***	−5.484***	−8.702***
s-effect	−3.708***	−5.930***	−5.162***	−8.868***
lnw-effect	−1.048	−2.894**	−2.606*	−8.923***
lny-effect	−1.046	−3.745***	−2.784*	−12.756***

Note: $I(0)$ and $I(1)$ denote levels and first difference, respectively. *, **, *** denote the significant level at 10%, 5%, and 1%, respectively.

model is suitable and applicable to mixed stationarity variables, we proceeded to adopt it in this study.

4.5.2. Cointegration test results

Following the stationarity of the series, we tested the existence of a long-run relationship between CO_2 emissions and the decomposition factors using the bounds test for cointegration. The results are shown in Table 4, and we noticed the presence of cointegration among the variables. Thus, there is a long-run relationship between CO_2 emissions and decomposition factors. This is because the F-test of 17.00 exceeds the upper bound [$I(1)$] at all significant levels. Given this, we conclude that the series are cointegrated. Therefore, the study proceeds with the long- and short-run estimates.

4.5.3. Long-and short-run analysis (ARDL)

We present in Tables 5 and 6 the long-and short-run results of the decomposition factors of electricity generation on CO_2 emissions in Ghana, respectively. We begin with the long-run analysis and thereafter discuss the short-run results.

The long-run results in Table 5 show that the C-effect (carbonization factor) has an insignificant negative relationship with CO_2 emissions. This outcome, although insignificant implies that carbonization factor to electricity generation in the long run will reduce CO_2 emissions. This further suggests that if synthetic fossil fuels are utilized in electricity generation, then, the impact of electricity generation via the carbonization factor will reduce CO_2 emissions and, therefore, improve the environment. This result is consistent with Alcántara et al. [50] whose study argue that the carbonization factor is one of the dominant factors in reducing emissions in Spain. However, the results of this study seem to suggest that carbonization factor does not matter for the study period in Ghana. The study also reveals that E-effect (transformation factor) and S-effect (fossil fuel intensity) both contribute to the reduction of CO_2 emissions in the long run at a 10% and 5% significance level, respectively. Although the coefficients are marginal, the signs point to the fact that these factors are capable of reducing electricity generation effect on CO_2 emissions. The outcome of E-effect could be explained that higher efficiency (in terms of technology) in transforming fossil fuel inputs to electricity with modern power plants compared to traditional coal power plant will result in the reduction of CO_2 emissions. While Kim and Kim [48] find contradictory results for the E-effect in Korea, Alcántara et al. [50] observed that the E-effect reduces CO_2 emissions in Spain. Similarly, the outcome of the S-effect suggests that it impedes CO_2 emissions as demonstrated by statistically significant negative coefficient at 5% level. While we have observed the S-effect to reduce CO_2 emissions in Ghana, Kim and Kim [48] find a stimulating effect of this variable on emission in Korea.

Furthermore, the long-run results reveal that both the W-effect (electricity intensity factor) and the Y-effect (production factor) contribute positively to CO_2 emissions in Ghana. However, we found W-effect to be insignificant. In fact, the coefficients indicate that 1% increases in the W-effect and the Y-effect will result in a 0.38% and 0.97% increase in CO_2 emissions in Ghana, respectively. The production effect could be attributed to the fact that many economic activities in Ghana depends on electricity generation, and this tends to increase the electricity energy consumption and hence higher emissions. This supports the empirical findings that electricity production results in CO_2 emissions [16]. The Y-effect accords with findings by Kim and Kim [48], Li et al. [63], Kim et al. [26], Mai et al. [64], and Alcántara et al. [50] that production effect is the largest contributor of CO_2 emissions.

Focusing on the short-run results in Table 6, we observed that the results were not different from those obtained from the long-run in terms of its impact (signs). However, the short-run results indicate that all factors are significant. Specifically, the results reveal that in the short run, carbonization, transformation, and fossil fuel intensity factors contribute significantly to reducing CO_2 emissions, which is not different from what we observed in the long run estimates. On the contrary, as observed in the long run, both electricity intensity and production factors induce CO_2 emissions. Specifically, we found that 1% increases in both electricity intensity and production factors leads to about 0.19% and 0.09% increase in CO_2 emissions, respectively. Our argument for the long run effects of

Table 4
Cointegration test results.

F-test statistic	Significance level	$I(0)$	$I(1)$
	1%	3.9	5.419
17.00	5%	2.804	4.013
	10%	2.331	3.417

Note: Null hypothesis of no cointegration is tested against the alternate of cointegration relationship.

Table 5
Long run estimates.

Variable(s)	Coefficient	Standard error	P-value
lnc-effect	−0.3407	0.7588	0.6722
e-effect	−0.0001*	0.00005	0.0737
s-effect	−0.00001**	0.000004	0.0156
lnw-effect	0.3794	0.4350	0.4230
lny-effect	0.9742*	0.4230	0.0690
Constant	2.8840***	0.3422	0.0004

Table 6
Short run estimates.

Variable(s)	Coefficient	Standard error	P-value
Δ lnc-effect	−0.2217*	0.0877	0.0527
Δ*e*-effect	−0.00001*	0.000005	0.0682
Δ*s*-effect	−0.000002**	0.000001	0.0266
Δ lnw-effect	0.1919**	0.0714	0.0433
Δ lny-effect	0.0865*	0.0420	0.0947
ECM(-1)	−0.1822***	0.0349	0.0034
R-square	0.9997		
Adj. R-square	0.9991		
DW-statistic	2.8666		
F-statistic	1626.291***		
Prob. (F-statistic)	0.0000		

production factor in CO_2 emissions may be responsible for the short run outcome. This means that in both the short-run and the long-run, an alternative safer and environmentally friendly energy production technology and use have not been adopted. On the contrary, it is clear that, whiles electricity intensity is statistically significant in the short-run this cannot be observed in the long-run. We argue that in the short-run, economic agents are unable to adjust to efficiency factor in the use of electrical power. Thus, its statistically significant positive contribution to CO_2 emissions. However, the long-run permits the economic agent to adjust leading to CO_2 emissions insensitive to the variable.

As expected, the error correction term (ECM) of the model, which indicates the speed of adjustment at which equilibrium will be restored in the long run given an unexpected shock in the short run, was found to be negative and significant. This suggests that in the long run there will be convergence given any unexpected shock in the short run. Specifically, it implies that disequilibrium in the short run will be restored at a speed of 18% annually. Comparing the ARDL results to the LMDI results, we noticed that regardless of the heterogenous (by periods) analysis or the homogenous (entire period) analysis, both W-effect and Y-effect contribute to emissions positively. Regarding the C-effect, E-effect, and S-effect, the homogenous (entire period) analysis suggests that they reduced emissions in both the short and long run. However, if we accounted for the heterogenous (by periods) analysis using the LMDI, we found they impact positively to CO_2 emissions. Suggesting that the decomposition impact of C-effect, E-effect, and S-effect on CO_2 emissions is essential to be examined overtime.

4.5.4. Diagnostic test results

Finally, we diagnosed the efficiency and accuracy of the results by testing for serial correlation, heteroskedasticity, series normality and the stability of the model.

The results from Table 7 show absence of both serial correlation and heteroskedasticity. Furthermore, the Jarque-Bera test shows that the series were normally distributed, allowing inferences or predictions to be made. The results provide the above conclusions because the p-values of these tests fail to reject the null hypotheses. Regarding the stability of the model, the CUSUM and CUSUMSQ (see Figure A1 in the Appendix) indicate that the model is stable as the model is within the 95% confidence intervals.

Table 7
Diagnostic tests results.

Diagnostic test(s)	Test statistic(s)	P-value(s)
Serial correlation	0.3286	0.7430
Heteroskedasticity	0.7207	0.6985
Normality	0.6770	0.7129
CUSUM	Stable	
CUSUMSQ	Stable	

5. Conclusion and implications

The study examines the drivers of electricity generation and CO_2 emission in Ghana with data spanning 1990–2020 using LMDI and ARDL models. The study focused on examining the trends of CO_2 emission and total electricity generation, the mix of energy sources used for electricity generation and the short and long run effect of the decomposition factors of electricity generation on CO_2 emissions. The trends show that total electricity generation and CO_2 emission both increase overtime indicating a positive relationship between them. The study decomposed electricity generation into five factors, including carbonization factor, transformation factor, intensity factor, electricity intensity of economic activity, and production factor. Conclusions from the results (LMDI) show that all the factors had a positive impact on CO_2 emission over the study period. The empirical findings from the ARDL confirmed that the electricity intensity of economic activity and the production factor had a positive impact on CO_2 emissions in both the long- and short-run, while the carbonization factor, the transformation factor, and the fossil fuel intensity factors reduce CO_2 emissions in both the long- and short-run. From the LMDI results we established that electricity generation and CO_2 had positive relationship and this relationship is driven by the carbonization factor, transformation factor, intensity factor, electricity intensity of economic activity, and production factor. We also conclude based on the LMDI and ARDL results that the electricity intensity of economic activity and the production factors are the predominant contribution to CO_2 emissions in Ghana.

5.1. Policy implication

- ➢ The results from LMDI indicate that all factors (carbonization factor, transformation factor, intensity factor, electricity intensity of economic activity, and production factor) from electricity generation over the study period contribute positively to CO_2 emissions in Ghana. Therefore, to effectively reduce carbon pollution from electricity generation, decisions must be made while considering the elements that influence lowering CO_2 emissions in this sector. It is imperative to take proactive steps to accelerate the transition to renewable energy sources and increase their share in the energy mix. To achieve this, Ghana should prioritize the integration and expansion of renewable energy sources, such as solar, wind, hydro, and biomass. This can be accomplished through the implementation of supportive policies, providing incentives, and making significant investments in renewable energy infrastructure.
- ➢ However, it is crucial to acknowledge that the adoption of renewable energy sources presents systemic challenges, particularly related to the power infrastructure and electric load. To increase the amount of renewable energy that the power grid can absorb, measures must be taken to improve peak shaving. Direct methods include encouraging privately operated power plants to participate in maximum load shaving, supporting the installation of grid storage stations, and transitioning thermal power plants to more environmentally friendly alternatives. Furthermore, since the transformation factor and intensity factor positively impact CO_2 emissions, implementing energy efficiency and conservation measures is essential. The government and stakeholders should encourage industries and households to adopt energy-efficient technologies, conduct energy audits, and launch awareness campaigns to promote responsible energy consumption. By combining efforts to promote renewable energy integration and implement energy efficiency measures, Ghana can effectively address the challenge of increasing electricity generation while reducing CO_2 emissions, thus contributing to a more sustainable and environmentally friendly energy sector.
- ➢ To address the issue of rising CO_2 emissions driven by electricity-intensive economic activities and production factors, it is crucial to shift away from carbon-intensive industries. Promoting the growth of low-carbon sectors like technology, services, and sustainable agriculture is essential. This can be achieved by investing in research and development of clean energy technologies and sustainable practices, ultimately reducing carbon emissions from electricity generation and overall economic processes. Collaborative efforts between academia, the private sector, and government are key to driving innovation in the energy sector. Local governments play a vital role by implementing demand-side measures such as tax incentives and subsidies, encouraging businesses and individuals to embrace energy conservation. Introducing carbon pricing mechanisms and taxes can effectively internalize the external costs associated with CO_2 emissions. This approach motivates businesses and individuals to adopt cleaner practices and energy sources, curbing their carbon footprint. Additionally, policies should prioritize the adoption of renewable energy and energy-efficient products by government agencies and institutions. This stimulates market demand for cleaner technologies, contributing to a reduction in CO_2 emissions. By implementing these strategies, a robust supply chain for clean energy utilization can be established.

5.2. Limitation and future studies

It is being observed that, this study employed both LMDI and ADRL methods for its analysis, which have limitations such as.

1. The LMDI approach is excessively comprehensive and fails to accurately depict energy efficiency.
2. The analysis solely considers the first and final years, which hinders the ability to track yearly variations during the study period, particularly in cases of significant volatility in the indicators or their underlying factors.
3. The majority of studies employing LMDI fail to accurately capture the intricate characteristics of the physical energy system due to its utilization of a top-down decomposition method that relies on macro-level elements of influence.

Nevertheless, these limitations do not invalidate the results of this study. Therefore, other techniques such as Quantile regression, threshold technique etc. can be employed for future studies. Again, the entire sub-Sahara Africa countries data can be analysis.

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Additional information

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CRediT authorship contribution statement

Eric Fosu Oteng-Abayie: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Foster Awindolla Asaki:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Emmanuel Duodu:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Sulemana Mahawiya:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Bright Akwasi Gyamfi:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

APPENDIX

Table A1
Decomposition of the variation of CO_2 emissions from electricity generation by explanatory effects (kt).

YEAR	c-effect	e-effect	s-effect	w-effect	y-effect	Total
1990–1991	−0.011	−0.002	−0.014	−0.024	−0.014	−0.065
1991–1992	0.033	0.014	0.010	0.046	0.029	0.132
1992–1993	0.006	0.004	0.002	0.008	0.007	0.027
1993–1994	0.016	0.011	0.004	0.018	0.018	0.066
1994–1995	0.014	0.019	0.002	0.015	0.018	0.068
1995–1996	0.022	0.201	0.000	0.022	0.027	0.273
1996–1997	0.011	0.001	0.044	0.013	0.012	0.082
1997–1998	0.133	0.095	0.022	0.118	0.105	0.472
1998–1999	0.028	0.026	0.006	0.033	0.028	0.120
1999–2000	−0.040	−0.047	−0.011	−0.053	−0.055	−0.206
2000–2001	0.027	0.025	0.006	0.027	0.032	0.118
2001–2002	0.084	0.060	0.018	0.063	0.075	0.300
2002–2003	−0.021	−0.012	−0.005	−0.013	−0.019	−0.070
2003–2004	−0.026	−0.028	−0.007	−0.032	−0.030	−0.124
2004–2005	0.021	0.024	0.005	0.027	0.024	0.101
2005–2006	0.077	0.091	0.015	0.066	0.130	0.379
2006–2007	0.043	0.029	0.010	0.031	0.037	0.150
2007–2008	−0.023	−0.031	−0.006	−0.033	−0.032	−0.125
2008–2009	0.086	0.078	0.017	0.090	0.081	0.353
2009–2010	0.067	0.001	0.757	0.079	0.073	0.978
2010–2011	0.058	0.026	0.032	0.066	0.067	0.249
2011–2012	0.128	0.201	0.014	0.125	0.122	0.590
2012–2013	0.041	0.052	0.009	0.038	0.064	0.204
2013–2014	−0.034	−0.019	−0.017	−0.038	−0.040	−0.147
2014–2015	0.045	0.018	0.027	0.043	0.043	0.176
2015–2016	−0.046	−0.039	−0.021	−0.072	−0.060	−0.239
2016–2017	0.038	0.026	0.012	0.045	0.039	0.160
2017–2018	0.073	0.058	0.022	0.096	0.076	0.325
2018–2019	0.076	0.058	0.021	0.095	0.075	0.325
2019–2020	0.074	0.061	0.021	0.101	0.070	0.326
1990–2020	0.0043	0.0048	0.0161	0.0032	0.0049	0.0333

Note: Decomposition in 1-year subperiods.

Table A2
Decomposition of the variation of CO_2 emissions from electricity generation by explanatory effects (kt).

YEAR	c-effect	e-effect	s-effect	w-effect	y-effect	Total
1990–1996	1414.884	4958.437	338.161	1149.044	1721.765	9582.291
1997–2002	4331.226	3197.971	5711.838	2717.240	3992.476	19950.751
2003–2008	1262.968	1453.408	857.824	607.892	2244.201	6426.294
2009–2014	6173.692	6788.324	54161.372	4859.838	7482.612	79465.839
2015–2020	4618.430	3617.280	5511.391	4144.065	4934.306	22825.472
1990–2020	17801.200	20015.420	66580.586	13478.079	20375.362	138250.65

Note: Decomposition in 5-year subperiods.

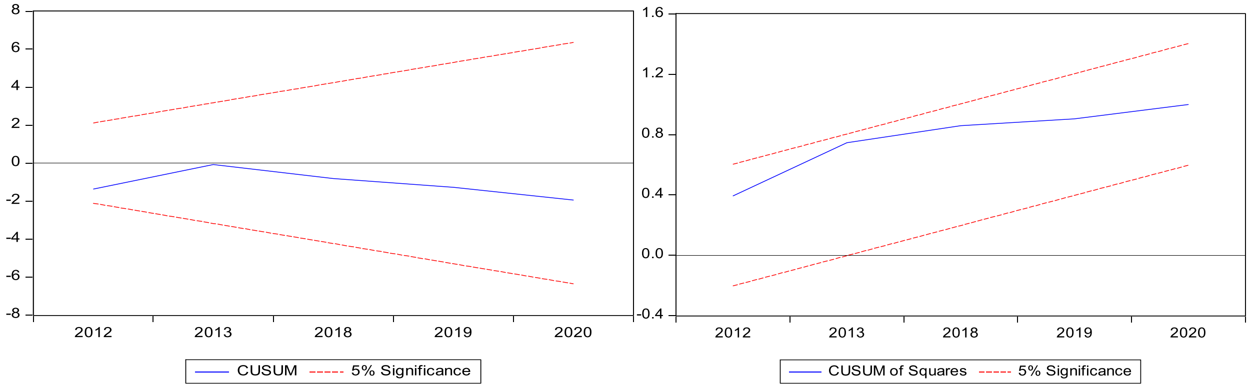

Fig. A1. ARDL model stability test.

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