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Causality between residential electricity consumption and explanatory factors

Serge Guefano [a,*], Mokhtar Bozorg [a], Mauro Carpita [a], Pauline Darline Etet-Baha [b], Francis Lénine Djanna Koffi [c], Jean Gaston Tamba [c], Jacques Etame [d]

[a] Energy Institute, School of Management and Engineering Vaud, University of Applied Sciences Western Switzerland (HES-SO), Yverdon-les-Bains, Switzerland
[b] University Institute of Technology, University of Douala, Douala, Cameroon
[c] Laboratory of Technology and Applied Sciences, P.O BOX 8698, IUT Douala, Douala, Cameroon
[d] University of Douala, Department of Earth Sciences, Douala, Cameroon

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ABSTRACT

This research adds to the assessment of the causal relationships between residential electricity consumption and its explanatory factors. Johansen cointegration, autoregressive distributed lag model, the vector error correction model, and Wald causality tests are used. In both the short and long run, a unidirectional causality towards electricity consumption is identified. The sustainable development of the electricity sector in Cameroon, as defined by the national development strategy for 2030 and the long-term electricity sector development plan for 2030, requires an increase in GDP per capita, the adoption of a compact less energy-intensive urban model, the strengthening of control over the evolution of the number of subscribers on the distribution networks, and the reduction of CO2 emissions from thermal electricity generation.

1. Introduction

Modern energy services are essential to the long-term well-being of populations and to global sustainable development [1]. Access to clean energy is a goal shared by both developed and developing countries. In this case, access to electricity for households, healthcare facilities, schools and public services are shared priorities at all levels of development.

In the category of developing countries working to improve energy services, we find Cameroon, where 71% of households consume electricity on low voltage (LV), corresponding to an electrical voltage that varies between 220 V and 240 V [2]. A survey conducted in December 2018 grouped households according to electricity power consumption ranges, namely: 2.2 to 2.4 kW, 3.3 to 3.6 kW, and 6.6 to 7.2 kW, with current intensities of 10 Amperes (A), 15 A and 30 A, respectively [2,3]. There are also around 29% of small and medium-sized enterprises (SMEs) as well as small and medium-sized industries (SMIs) that consume electricity on medium voltage (MV) [4,5]. These companies take out a subscription with a power of between 0.036 MW and 4 MW, for a voltage range of between 3 kV and 33 kV [6].

Access to electricity for Cameroonian households differs according to the level of the local population [7]. In urban areas, for example, the rate of access to electricity is 93.19% for a population of more than 14 million inhabitants in 2019 [8]. The rate of access to this energy is estimated at 94.03% for a population estimated at over 15 million in 2020 [8]. In addition, the rate of access to electricity in rural areas is estimated at 24.18% for a population of 11,094,657 in 2019. In 2020, the rural population is estimated at 11,242,817, for an electricity access rate of 24.98% [8]. Over these two years, the rate of access to electricity increases as the population grows. However, the difference in access rates between rural and urban areas clearly shows that more needs to be done to improve electricity supply to the least satisfied sections of the population. With a 7% share of Cameroon's energy mix in 2016 (Fig. 1), electricity is the third most important energy source used by Cameroonian households, after wood energy and liquefied petroleum gas (LPG) [9]. Electricity consumption in households is mainly for lighting and powering household appliances, while the end uses of electricity in SMEs and SMIs include lighting and the production of goods. Given these end uses in the residential sector, electricity appears to be a clean energy whose production and supply in sufficient quality and quantity should be increased in order to bring the residential sector into line with sustainable development objectives.

Cameroon has one of the greatest hydroelectric potentials in sub-Saharan Africa (19.7 GW), of which only 5% is used for electricity generation [10]. To improve this situation, over the last two decades the government has approved various policies aimed at increasing

* Corresponding author.
E-mail address: serge.guefano@heig-vd.ch (S. Guefano).

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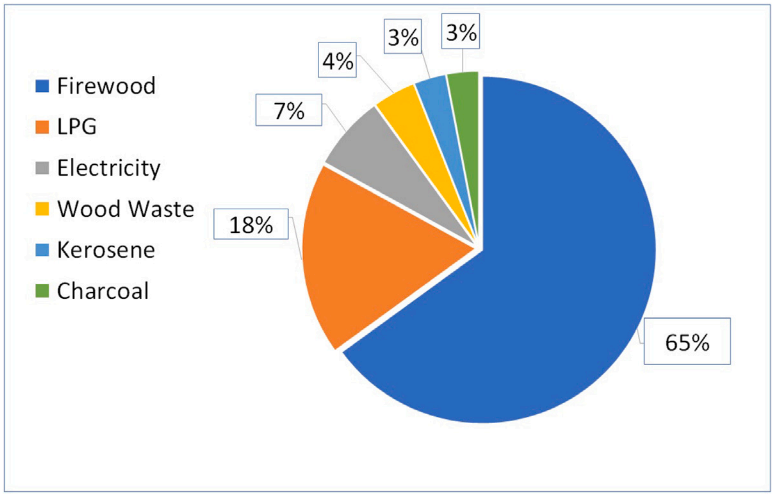


Fig. 1. Percentages of energy use in Cameroon.

its electricity generation capacity. These include the development of public–private partnerships, the diversification of projects aimed at increasing the number of electricity generation, transmission and distribution infrastructures nationwide, and the readjustment of laws regulating the activities of the various stakeholders in Cameroon's electricity sector [11]. Despite these many efforts, the quality of electricity supply remains mediocre. Consumers in Cameroon's residential sector are frequently subjected to untimely power cuts, which tarnish social well-being [3]. The gap between the rates of access to electricity in rural and urban areas remains wide in 2020. These rates are estimated at 94.03% in urban areas, compared with 24.98% in rural areas on the aforementioned date [8]. In view of these figures, the sustainable development objective, which in sub-section 7 – 1 supports access to available electrical energy for all households [12], is still a pipe dream in the Cameroonian context. As a result, electricity use in the residential sector seems to be linked to a number of factors that are holding back the achievement of sustainable development objectives. Consequently, this study aims to identify various economic, demographic and climatic factors that influence electricity consumption in the residential sector, and to highlight the causal relationships that exist between these factors and such consumption, with a view to suggesting development orientations that could contribute to the long run development of the electricity sector in Cameroon.

1.1. Literature review

Analyses of the causal links involving electricity consumption and various influencing factors give rise to policy recommendations capable of contributing effectively to the sustainable development of the various sectors of electrical energy consumption in Africa. In 2019, for example, [13] assessed the causal link between electricity use in Zimbabwe, gross domestic product per capita (GDPC) and CO2 emissions over the period 1971–2014. This analysis reveals the existence of a unidirectional causal relationship. Electricity consumption drives Zimbabwe's economic growth and leads to carbon dioxide emissions. The energy policies formulated recommend increasing electricity generation using various sources of renewable energy that are conducive to preserving the environment. Such an initiative should help the country to develop its economy while reducing its carbon dioxide emissions. [14] studied the relationship between renewable energy consumption and economic growth in 16 emerging countries, including Egypt and South Africa. No causal relationship was found between energy consumption and economic growth in these two African countries. This underlines the opportunity to develop energy efficiency policies without slowing down the country's economic growth. [15] studied the long run relationship between electricity consumption, public spending and sustainable development in Nigeria. The study reveals a negative impact of recurrent government spending on GDPC and electricity consumption. The policy recommendations arising from these observations emphasise the need to take account of real per capita needs when implementing development strategies and projects aimed at improving per capita electricity supply.

[16] investigated the existence of a causal relationship between electricity consumption (EC), economic growth and trade openness (TRO) of South Africa. Granger causality tests highlight the existence of a unidirectional causal relationship from electricity consumption to the country's GDP and trade openness, respectively. The energy policies highlighted suggest an increase in electricity generation in order to support the country's trade openness and economic growth. In addition, [17] examined the possible interactions between electricity consumption, CO2 emissions and economic growth in Cameroon. The investigations carried out show that there is no interaction between electricity consumption and economic growth, and that CO2 emissions are unidirectionally linked to economic growth. Electricity generation therefore appears to be insufficient to support the country's economic development, while fossil fuel consumption linked to generation activities sustains CO2 emissions on the one hand, and promotes the country's economic development on the other. The energy strategies formulated recommend increasing hydroelectric generation to support economic growth. In 2020, studies highlighting energy policies derived from causal relationship analyses involving electricity consumption in Africa are available. In the Nigerian context, [18] identifies a unidirectional causality from electricity consumption (EC) to urbanisation (UR) and economic growth, respectively. Policy recommendations encourage the enrichment of the energy mix to meet the growing energy demand in urban areas. [19] identifies a unidirectional causality from electricity consumption to South African economic growth. Electricity consumption with an energy intensity of less than 0.48% stimulates the country's economic growth.

1.2. Research gap and contributions

The analyses presented above demonstrate the relevance of the energy strategies proposed following studies of the causal relationships between electricity consumption and various factors interacting with this consumption in different African economies. However, very little research has focused on studying these interactions within the various African residential sectors. Table 1 summarises the results of causality studies involving electricity consumption in Africa over the timeframe 2011–2020. Based on these investigations, two studies were identified

Table 1
Summary of main causality studies involving electricity consumption in Africa.

Author	Country	Year	Methodologies	Period	Causality
[22]	Ghana	2011	Toda and yamamoto; Granger causality	1971–2008	GDP → EC
[23]	Ivory Coast	2011	ARDL; VECM	1980–2008	ECC ↔ GDPC
[24]	Botswana	2011	ARDL	1980–2008	EC → GDP
[25]	Nigeria	2012	ARDL-VECM	1970–2008	EC → CO2
[26]	Nigeria	2013	VECM	1970–2005	GDP → EC
[27]	Nigeria	2013	Cobb–Douglas model; VECM	1980–2008	ECC ↔ GDP
[28]	Algeria	2013	VECM	1971–2010	EC ↔ GDP
[29]	Angola	2013	VECM	1971–2009	EC ↔ GDP; EC ↔ UR
[30]	Egypt, South Africa	2014	Panel Granger causality	1970–2011	GDP ↔ EC
[31]	24 African countries	2014	Granger causality	1971–2009	EC ↔ UR
[32]	Nigeria	2015	VECM	1971–2011	EC → GDP
[33]	South Africa	2015	Granger causality	1971–2009	ECC-no causality-GDPC
[34]	Nigeria	2015	ECM; Granger causality	1970–2012	EC ↔ GDP; EC ↔ EP
[35]	Ivory coast, Zambia	2015	VECM; Granger causality	1971–2011	FID → EC; GDP → EC
[36]	Ghana	2016	VECM; Granger causality	1970–2014	GDP → EC
[37]	Uganda	2016	VECM; Granger causality	2005–2016	EC → GDP
[38]	South Africa	2017	ARDL; Toda and Yamamoto	1971–2012	CO2 → EC
[39]	Ghana	2018	Toda and Yamamoto	1971–2014	EC → IG
[40]	Egypt	2018	VECM; Toda and Yamamoto	1971–2013	EC ↔ GDP
[20]	Algeria	2018	ARDL	1970–2013	GDP → REC
[13]	Zimbabwe	2019	Toda and Yamamoto	1971–2014	EC → GDP
[16]	South Africa	2019	Granger causality	1984–2015	
[18]	Nigeria	2020	FMOLS; DOLS; CCR	–	EC → GDP
[21]	Tunisia	2020	Granger Causality	1980–2018	REC → EP; REC → UR

Notes : → : unidirectional, ↔ : bidirectional, GDP: Gross Domestic Product, EC : Electricity Consumption, ECC : Electricity Consumption per Capita, GDPC : Gross Domestic Product per Capita, UR : Urbanisation, EP : Electricity Price, FDI: Foreign Direct Investment, CO2 : carbon dioxide; IG: Industrial Growth; REC : Residential Electricity Consumption, ECM : Error Correction Model, VECM : Vector Error Correction Model, ARDL : Autoregressive Distributed Lag, FMOLS : Fully-Modified Ordinary Least Squares, DOLS : Dynamic Ordinary Least squares.

as being interested in the analysis of causal relationships involving electricity consumption in the residential sector. In 2018, [20] studied the causal relationships between electricity consumption in the Algerian residential sector and its GDP. The study highlights the existence of a unidirectional causality from GDP to electricity consumption. An increase in per capita income would lead to an increase in the number of household appliances and higher electricity consumption in the residential sector. For this reason, energy efficiency measures are proposed, in particular the use of less energy-consuming appliances. In addition, it is recommended that the use of available renewable energies be stepped up in order to meet the growing demand for electricity driven by the country's economic growth. In 2020, [21] analyses the demand for electricity in the Tunisian residential sector using three explanatory factors: GDP, the price of electricity (EP) and urbanisation (UR). It is shown that there is a unidirectional causality from residential electricity consumption (REC) to the price of electricity and urbanisation, respectively. summarises the main directions and senses of causality identified. Unfortunately, this second study, which focuses on electricity consumption in the residential sector in Africa, fails to formulate energy strategies that will make it possible to meet the growing demand for electricity in the face of increasing urbanisation, and to adjust the price of electricity to consumers' wallets. Consequently, this work is a continuation of the two previous studies, with the aim of analysing, on the one hand, the causal relationships between electricity consumption in the Cameroonian residential sector and its main influencing factors, and on the other hand, the causal relationships identified should make it possible to develop energy strategies that should contribute to the sustainable development of the electricity sector in the Cameroonian residential sector.

1.3. Paper organisation

The remainder of this work is organised as follows: Section 2 details the theoretical framework of the study, Section 3 describes the data relating to the main factors which have a significant impact on residential electricity consumption, and which have been selected with regard to the conceptual framework described and similar studies. The econometric methodology used to identify the direction and sense of causal relationships between these influencing factors and electricity consumption is described in Section 4. Section 5 presents the results, Section 6 the main discussions, and Section 7 sets out the main conclusions and suggested energy strategies following the analyses of causal relationships discussed in the previous sections.

2. Theoretical framework of the study

Over the period 2010–2020, there are only two studies involved in analysing electricity consumption and its various influencing factors in Cameroon. In 2017, Tamba et al. [41]. conducted the first study, assessing the existence of a causal relationship between national electricity consumption and economic growth modelled by its GDP over the period 1971–2013. The econometric approach applied in this study combines stationarity tests, the Johansen cointegration test, the Granger causality test and vector autoregressive modelling (VAR model). The absence of cointegration and causality between the two variables is highlighted. National electricity generation up to 2013 appears to be insufficient to sustain economic growth. The energy strategies formulated are based on exploiting the strong existing potential, i.e. 294 Terrawatt-hours (TWh) exploited at 4.15% until 2013. The second study is scheduled for 2019. Njoke et al. [17]. carry out an empirical analysis of existing relationships between national electricity consumption, CO2 emissions and economic growth over the period 1971–2014. The econometric theory used reveals multifaceted interactions between the variables. ARDL (autoregressive distributed lag model) modelling and upper bound tests highlight the existence of long run cointegration between CO2 emissions and economic growth. The Toda and Yamamoto Granger causality test reveals the existence of unidirectional causality from CO2 emissions to economic growth. In addition, the Kuznets curve hypothesis reveals the existence of an inverted U-shaped curve between economic growth and the increase in CO2 emissions. The hypothesis of neutrality between national electricity consumption and economic growth is also supported by this second study. The energy strategies formulated recommend improving electricity generation using renewable energy sources, with the corollary of improving electricity access rates, estimated respectively at 94.03% and 24.98% in urban and rural areas in 2020 [8], and reducing CO2 emissions from thermal electricity generation, estimated at 6550 kt of CO2 in 2019 [1]. Due to the unavailability at national level of a wide range of balanced data for all the variables under study, the data collected generally comes from international institutions such as the World Bank (World Bank's development indicators) [17,41].

Until 2022, no study has analysed the interactions between sectoral electricity consumption and various influencing factors in Cameroon. However, during 2022, Tamba et al. [2] make an overview analysis of the Cameroonian electricity sector and identify factors that may interact with electricity consumption. These factors are called factors influencing electricity consumption in Cameroon, and are grouped into six main categories presented in this study under the label $((\alpha_i)_{1\leq i\leq 6})$.

(α_1) : Socio-economic factors have the particularity of increasing electricity consumption in the residential sector. These include GDP, GDP per capita, the number of households and the number of subscribers. It would therefore be interesting to verify this hypothesis on the basis of a structured econometric theory.

(α_2) : geographical factors are the second category presented, with the particularity of influencing the country's hydrology and national electricity generation, 61.7% of which will be supported by hydroelectricity in 2019 [1]. With dams capable of storing 99.92% of cubic metres of water during periods of high water, and only 6.12% of their capacity during periods of low water, electricity generation is subject to strong fluctuations. The consequences of this situation include instability of the electricity grids and frequent household blackouts [2].

(α_3) : The category of end users includes consumers in the residential sector, made up of households, SMEs and SMIs. In 2020, consumption reached the scale of 1470.3 Gigawatt-hours (GWh), behind that of the industrial sector, which is also listed in this category, and whose electricity consumption is high at 3845.8 (GWh), compared to 2019 when this consumption stood at 3618.3 GWh [1]. With regard to hydroelectricity generation in Cameroon, estimated at 5229 GWh in 2019 and 5434 (GWh) in 2020 respectively [1], it can be seen that electricity consumption in the industrial sector corresponds to 69.2% and 66.6% of previous generation between these two years. The hydrological disturbances described above, together with the frequent power cuts they cause, have a negative effect on industry in Cameroon. The average cost of an interruption varies between €3.62/kWh and €5.42/kWh for a one-hour outage [42], and between €1.96/kWh and €2.46/kWh for a 4-hour power cut [42]. This situation is undermining the country's industrial generation and economic growth.

(α_4) : Climatic factors capable of significantly influencing electricity consumption in the residential sector include meteorological factors such as rainfall, temperature and humidity [43]. Cameroon's climate is characterised by three main seasons [2]. (1) : The dry season, from November, December, January and February, with rainfall of less than 200 mm/month and temperatures between 24.5 °C and 26 °C/month. (2) : The short rainy season, which extends over April, May, June and October, with rainfall of between 200 mm and 400 mm/month, and average temperatures hovering around 25 °C/month. (3): the long rainy season, from July, August, September to May, including the first week of October. The corresponding rainfall is over 400 mm/month, with temperatures between 23.5 °C and 24 °C/month. Depending on the variations in these different meteorological factors, there are different peaks in electricity consumption on the two major existing electricity networks. On the southern interconnected network (SIN), which serves 6/10 of the existing regions (the South, Centre, Coast, West, North-West and South-West regions), electricity consumption peaks are recorded, fluctuating between 475 MWh/month and 570 MWh/month [43]. On the Northern Interconnected Network (NIN), which covers 3/10 of the country's regions (the North, Adamaoua and Extreme North), peak electricity consumption fluctuates between 35 MWh/month and 45 MWh/month [43].

(α_5) : the category of technical factors includes outdated electricity networks, uncontrolled and fraudulent interconnections to distribution networks, and major losses on these networks. The dilapidated state of the SIN and NIN leads to significant losses during the transmission and distribution phases. For national electricity generations of 8476 GWh and 9008 GWh in 2019 and 2020 [1], electricity losses are 1864 GWh and 1981 GWh respectively [1]. Around 21.99% of the electricity produced is lost on the electricity networks before it reaches the end consumer. In addition, losses due to fraudulent connections, fires, power cuts and network maintenance are estimated at 914 GWh and 971 GWh [1], i.e. 10.78% of national electricity generation in 2019 and 2020 respectively. It is therefore urgent that the State of Cameroon adopt energy strategies to reduce these losses to a minimum, and contribute more effectively to the long run development of the electricity sector.

(α_6) : This last category of influencing factors concerns political factors [2]. These are all the strategies, decisions and projects contributing to the development of the electricity sector in the short and long run. Cameroon's electricity sector development projects include the national development strategy 2020–2030 (SND30), and the long run electricity sector development plan 2030 (PDSE-2030). In the SND30 [44], the government presents a reference framework to support multi-sector development up to 2030. In the electricity sector, the government is committed to reducing the gap between supply and demand by increasing installed electricity capacity to 5000 MW by 2030. This objective involves the construction of around ten hydroelectric power stations nationwide, with a combined installed capacity of 5226 MW. The government also plans to subsidise the construction of mini hydroelectric power stations in localities far from the main transmission and distribution networks, in order to meet household demand in those areas.

The PDSE-2030 provides for the extension of power lines and the interconnection of the SIN and NIN to form the National Interconnected Network (NI) by 2030 [45]. In this theoretical context, it is important to develop energy strategies that will contribute to the sectoral development of electricity over the long run. In the context of the residential sector, electricity consumption is considered as a proxy for electricity demand. The factors that influence this consumption over the short and long run are referred to as electricity consumption explanatory factors, following the example of several previous studies [46–49].

3. Data

This section describes the data relating to the various variables under study and their respective sources. These are mainly electricity consumption in the residential sector, GDP per capita, national CO2 emissions, urbanisation and the number of electricity-consuming subscribers on the medium-voltage and low-voltage networks. Research similar to this study recommends including the price factor in the analysis of causal relationships involving electricity consumption, in order to capture its effect on demand trends. However, the interval distribution of this factor makes it difficult to trace its evolution over previous years, and hence its inclusion in this causal analysis. This aspect is discussed in more detail in this section. Since the variable to be explained is electricity consumption, we also describe a number of tests to justify the statistical relevance of the explanatory factors selected.

3.1. Data description

In order to contribute to the enrichment of studies of causal relations linked to electricity consumption in the residential sector, four explanatory factors with an annual frequency are used. These include GDP per capita, an indicator of individual income, and the ability of each person to take out a continuous electricity subscription [50]. CO2 emissions are listed among the factors having a causal relationship with electricity consumption [51,52]. Although [17] formulates the hypothesis of an absence of causality between CO2 emissions and national electricity consumption in Cameroon, it would be interesting to carry out a targeted assessment within the residential sector. Following the

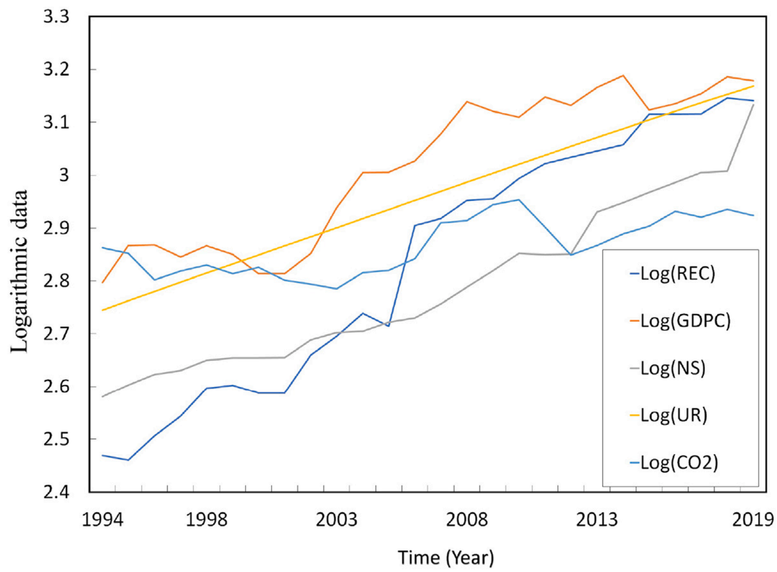


Fig. 2. Trends in specific variables.

analyses of Talbi et al. [21], we also retain the urbanisation factor within the framework of this study. However, the price factor is not taken into account in this study. Prices per kWh are stable and depend only on consumption ranges. For consumption below 110 kWh, the price is set at USD 0.09/kWh, between 111 kWh and 400 kWh, the price is USD 0.145/kWh, between 401 kWh and 800 kWh, the price is USD 0.170/kWh, while between 801 kWh and 2000 kWh, the price is set at USD 0.180/kWh [53]. This segmented distribution of electricity prices within the residential sector makes it difficult to take account of any price trends that might be compared with changes in electricity consumption. The number of subscribers is also included in the list of factors explaining electricity consumption. This is based on the assumption that there is a fairly close link with electricity consumption [54,55] Fig. 2 shows a similar trend for the variables selected, suggesting a very close interrelationship between their statistical indicators.

3.2. Data sources and statistical consistency

The databases of the International Energy Agency [1] provide information on electricity consumption in Cameroon's residential sector (REC in GWh). Data on GDP (in current US dollars), CO2 emissions from thermal electricity generation (in kilotonnes of CO2) and urban population (UR), are available in the World Bank database [8]. Finally, data on the number of subscribers (NS) are provided by the electricity distributor ENEO Cameroon [56]. These variables cover the period 1994–2019, during which the country's economy and demographic factors are growing overall. Table 2 shows some descriptive statistics based on these data. The mean, maximum and minimum values, standard deviation, skewness and kurtosis are all included. If the skewness of a given time series is in the range $[-3; 3]$ and its kurtosis is in the range $[-10; 10]$, then the series has a normal distribution [57]. In this context, the time series is representative of the physical process it describes [57]. Table 2 shows that the kurtosis and skewness of each time series meet the above reliability conditions. Consequently, the associated data are reliable representations of the real fluctuations of each variable.

These factors are among the indicators that best explain residential electricity consumption in Cameroon. Table 3 describes the strong correlation between REC and each explanatory factor, with correlation coefficients generally fluctuating around 1. Analysis of the relevance of the explanatory factors using the ordinary least squares method shows that they have t-statistics in absolute values above the reference of 1.96 and P-values overall below the 5% threshold. These factors are therefore 95% statistically significant and suitable for justifying the temporal variations in electricity consumption.

Fig. 3 shows the trends in growth rates for the five variables studied over the period 1995–2019. The very close link between the different trends confirms the results of the Table 3, which show a strong correlation between residential electricity consumption and each explanatory factor.

Table 4 confirms the hypothesis of a very close correlation between the variables. Most of the correlations between the growth rates are significant at the 1% level.

The steps involved in analysing the causal link between residential electricity consumption and each explanatory factor are described in this section. During these steps, statistical methods are used to figure out the best number of lags, the existence of cointegration and the direction of causality in the short and long run, respectively.

4. Empirical methodology

This section briefly describes the statistical tests used sequentially to model electricity consumption in the residential sector as a function of its determinants. These include the stationarity tests process (Section 4.1), the criteria for selecting the optimal lag number for the variables (Section 4.2), and the Johansen cointegration test process for determining the order of long-term cointegration of the variables in the model (Section 4.3). The Johansen test carried out here is based on variables relating to 26 annual observations, whereas the Johansen test generally requires a wider range of observations to be truly relevant. For this reason, Section 4.4 presents Autoregressive Distributed Lag (ARDL) technique developed to validate the results of the Johansen test. Section 4.5 presents the Vector Error Correction Model (VECM) used to assess the direction of the causal relationship between the different variables, in the short and long term, respectively. Finally, Section 4.6 describes some statistical tests to validate the robustness of the specified VECM model.

4.1. Stationarity tests process

The raw data for the majority of time series variables are non-stationary time series [58]. To avoid any biased causality analysis, it is necessary to ensure their stationary properties [59]. To do this, two statistical tests are used in this study: the Augmented Dickey Fuller

Table 2
Descriptive statistics of variables.

Descriptive statistics	*REC*	*GDPC*	*CO2*	*NS*	*UR*
Mean	782.2692	1089.2980	7392.3080	653.3980	9509759
Standard Deviation	391.4480	334.2153	906.2066	249.4699	2812682
kurtosis	1.5165	1.3749	1.6416	3.5183	1.889177
Skewness	0.1884	−0.1123	0.2322	1.0788	0.317098
Minimum	289.0000	626.7512	6100.0000	381.0340	5555026
Maximum	1400.0000	1542.6210	8990.0000	1360.0000	14741260
Sum	20339.0000	28321.7500	192200.0000	16988.3500	2.47E+08
Count	26	26	26	26	26

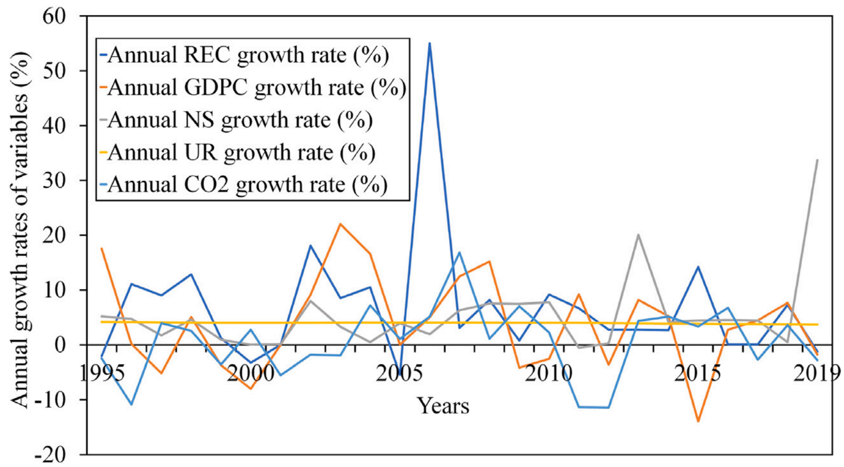


Fig. 3. Growth rates of variables.

Table 3
Correlation with REC.

Correlated variables	REC & GDPC	REC & NS	REC & UR	REC & CO2
correlation coefficients	0.961	0.941	0.982	0.772
t-statistics	−2.726	−3.467	4.529	−2.575
P-value	0.0489*	0.0023*	0.0002*	0.0177*

* denotes significance at the 5% threshold.

Table 4
Pairwise correlation.

Variables	REC	GDPC	CO2	NS	UR
REC	1.000				
GDPC	0.665*	1.000			
CO2	0.599*	0.633*	1.000		
NS	0.471*	0.928*	0.724*	1.000	
UR	0.478*	0.255*	0.686*	0.05*	1.000

* denotes correlations that are significant at 1% level.

(ADF) test, and the Phillip-Perron (PP) test [59]. The ADF tests, in fact, are based on the ordinary least squares estimation of the three model systems given by the relation Eq. (1).

$$\begin{cases} \Delta y_t = \rho y_{t-1} + \sum_{j=2}^{p} \Phi_j \Delta y_{t-j+1} + \varepsilon_t \\ \Delta y_t = \rho y_{t-1} + \sum_{j=2}^{p} \Phi_j \Delta y_{t-j+1} + c + \varepsilon_t \\ \Delta y_t = \rho y_{t-1} + \sum_{j=2}^{p} \Phi_j \Delta y_{t-j+1} + bt + c + \varepsilon_t \end{cases} \tag{1}$$

where t is the time index, c is an intercept constant called a drift, b is the coefficient on a time trend, ρ is the coefficient presenting process root, i.e. the focus of testing, p is the lag order of the first-differences autoregressive process, ε_t is an independent identically distributes residual term. The difference between the three equations concerns the presence of the deterministic elements c (a drift term) and bt (a linear time trend) [60].

These equations represent autoregressive models of order 1 with a constant and a trend, respectively. The specification error ϵ_t is assumed to be a process of white noise [61]. Machine execution results highlight a probability (P-value) at which the test performed is significant [58]. Generally, this probability is compared to the critical threshold (α) for rejecting or validating test results [17]. Thus, if $P - value < \alpha$ we accept the null hypothesis H_0: there is at least one unit root. The process is said to be stationary at the critical threshold α. Otherwise, if $P - value > \alpha$, the null hypothesis is rejected : there is no unit root. The process is non-stationary. As a result, the stationarity of these chronological series must be determined using the sequence of first differences [62]. The results of the ADF tests are reinforced by the unit root tests developed by Philipps-Perron (PP) [63]. Indeed, ADF tests do not take into account any heteroscedasticity in the error term, but assume that the errors within the model are independent of each other and constitute white noise. The unit root test developed by Philipps and Perron (PP) overcomes the shortcomings of ADF tests and highlights the existence of a unit root more precisely. Constructed to take heteroskedastic errors into account, the test (PP) is subdivided into four steps structured as follows [64]:

- Ordinary least squares estimation of the three basic models of the Dickey–Fuller tests and calculation of the associated statistics and the residual e_t;
- Short term variance estimation: $\hat{\sigma}^2 = \frac{1}{n}\sum_{t=1}^{n} e_t^2$;
- Estimation of the corrective factor s_t^2 called long term variance, and defined by Eq. (2):

$$s_t^2 = \frac{1}{n}\sum_{t=1}^{n} e_t^2 + 2\sum_{i=1}^{l}\left(1 - \frac{i}{l+1}\right)\left[\frac{1}{n}\sum_{t=i+1}^{n} e_t e_{t-i}\right] \tag{2}$$

where l is the number of lags defined by the Newey–West truncation as a function of the number of observations n: $l \approx 4(n/100)^{2/9}$;
- Calculation of pp statistic by relation Eq. (3) :

$$pp = \sqrt{v} * \frac{(\hat{\phi} - 1)}{\hat{\sigma}_\phi} + \frac{n(v-1)\hat{\sigma}_\phi}{\sqrt{v}} \tag{3}$$

with $\upsilon = \frac{\hat{\sigma}^2}{s_t^2}$ which takes the value 1 if e_t is white noise.

4.2. The optimal lag number

This refers to the time lag λ retained simultaneously by the majority of the chosen tests and capable of tracing the endogenous variable's trends as accurately as possible [65]. The Schwarz (Sc), Hannan-Quinn (HQ), Akaike (AIC) and Lagrande criteria are used to numerically select the right number of lags of the demand explanatory factors.

4.3. The Johansen cointegration test process

The Johansen test, is a procedure for testing cointegration of several, say k, I(1) time series. This test permits more than one cointegrating relationship [66]. There are two types of Johansen test, either with trace or with eigenvalue, and the inferences might be a little bit different. The null hypothesis for the trace test is that the number of cointegration vectors is $r = r^* < k$, vs. the alternative that $r = k$. Testing proceeds sequentially for $r^* = 1, 2, etc.$ and the first non-rejection of the null is taken as an estimate of r [66]. The null hypothesis for the maximum eigenvalue test is as for the trace test but the alternative is $r = r^* + 1$ and, again, testing proceeds sequentially for $r^* = 1, 2, etc.$, with the first non-rejection used as an estimator for r [66]. Once the stationarity of all variables in the same order has been established, the Johansen cointegration test is performed using trace statistics (λ_{trace}) and eigenvalue statistics ($\lambda_{\max}$) [67]. At the 5% tolerance level, each of these statistics is compared to its number-based critical value. The possible orders of cointegration that may exist between the variables are tested according to the values of the number $r \in N$. The accepted order of cointegration is the one in which the values of (λ_{trace}) and ($\lambda_{\max}$) are less than the critical values and significant at the 5% level [67].

4.4. ARDL approach for validating a long-run equilibrium

In order to validate the hypothesis of a long-run equilibrium between the variables, in addition to the Johansen test, this study uses ARDL modelling and upper-bound tests based on F-statistics. The ARDL technique has the advantage of being more efficient in the case of small and finite samples. In addition, the application of this technique makes it possible to obtain unbiased long-run estimates. According to Barkhordari et al. [68], the F-statistic is compared with the lower bound (Lb) and upper bound (Ub), respectively. If F-statistic > Ub, the hypothesis of non cointegration is rejected. If F-statistic < Lb, the null hypothesis of non cointegration cannot be rejected. Nevertheless, if Lb < F-statistic < Ub, the null hypothesis of no cointegration is not conclusive.

4.5. Vector error correction model

For a general VAR(p) model: There are two possible specifications for error correction: that is, two vector error correction models (VECM): the long run VECM and the transitory VECM [69]. The existence of cointegration means that there is at least one equilibrium relationship between the variables. According to Engel and Granger [70], the existence of an integral vector between the variables suggests that there is a causal relationship between them, at least in one direction. Since the variables are integrated we can continue the estimation of the error correction model that integrates short-term dynamics with long-term equilibrium [71,72].

The VECM makes it possible to detect the direction of causality in the long run, under the condition of stationarity of the different variables in first difference [73]. In this context, the error-correction term in the model must have a negative sign and be significant at the tolerance threshold [74]. Furthermore, the Wald causality test proves to be significant for assessing the direction of short-term causality, given the significance of the nullity test for the coefficients of the specified VECM model [75]. In the specific case where electricity consumption in the residential sector is the objective variable, the associated VECM is defined by the equation Eq. (4). In this equation, the white noise error term is ϵ_t, and the error correction terms is $ECT_{r,t-j}$ where r corresponds to the accepted order of cointegration as discussed in Section 4.3. ϕ_j denote the adjustment coefficients used to assess the level of imbalance correction within the model [59]. α is the intercept, l, m, n, p and s are lag numbers. β_i, γ_i, λ_i, ψ_i and η_i are estimated coefficients, Δ is the symbol for the first difference.

$$\begin{aligned} \Delta(REC)_t = \quad & \alpha + \sum_{i=1}^{l} \beta_i \Delta(REC)_{t-i} + \sum_{i=1}^{m} \gamma_i \Delta(GDPC)_{t-i} \\ & + \sum_{i=1}^{n} \lambda_i \Delta(CO_2)_{t-i} + \sum_{i=1}^{p} \psi_i \Delta(NS)_{t-i} \\ & + \sum_{i=1}^{s} \eta_i \Delta(Ur)_{t-i} + \phi_j ECT_{r,t-j} + \varepsilon_t \end{aligned} \tag{4}$$

4.6. Diagnostic tests

Diagnostic tests are used to validate the statistical consistency of the specified VECM and its relevance to the study of causal relationships. These include tests for Ramsey Reset specification, heteroskedasticity, normality of error terms and overall model stability [76–78].

4.6.1. Ramsey reset test

To ensure that the explanatory factors selected are sufficient to model residential electricity consumption, we carry out the Ramsey specification error test. The P values associated with the t-statistic, the F-statistic and the likelihood ratio of the test must be, respectively, greater than the tolerance threshold set at [79].

4.6.2. Heteroscedasticity test

When the variance of the error term within the model is not constant, the specified model is subject to heteroskedasticity [76]. This may be due to a number of statistical inconsistencies including:

- the repetition of the same value of the variable to be explained for different explanatory variable values;
- the relationship between errors and the values of an explanatory variable;
- The observations are averages calculated from various sample sizes.

Such circumstances may skew the quality of the results, resulting in incorrect analyses and conclusions. Several tests can be used to detect and correct heteroscedasticity in a time series. A Lagrange test, for example, can be carried out by computing the statistic $LM = n' * R^2$ (n'=n-p:difference between the number of observations n and the order of autocorrelation p) [77]. R^2 is the associated determination coefficient, which describes the averaging of the series' values. Then we compare $\chi^2_\alpha(p)$ to the α threshold in the order p. If $LM = n' * R^2 > \chi^2_\alpha(p)$, the hypothesis of error independence is rejected; in other words, the F-statistic and $\chi^2_\alpha(p)$ probabilities associated with the Lagrange test are less than the set critical value α. In this case, a first-order difference filter can correct the autocorrelation and produce a homoscedastic time series [77].

4.6.3. Normality test

The objective is to ensure that the ϵ_t error terms within the model are independent and identically distributed within the specified model, and therefore constitute white noise [78]. This test is based on the validity of the Jarque–Bera (JB) statistic defined by equation Eq. (5). The results of this test must be such that $JB < 5.99$ for a P-value > 5% [80], for the hypothesis of a normal distribution of the error terms within the model to be accepted.

$$JB = (n/6)\beta_1 + (n/24)(\beta_2 - 3)^2 \tag{5}$$

β_1 and β_2 are respectively coefficients of Skewness and Kurtosis.

Table 5
Outcomes of unit root test.

Variables	ADF test			PP-test			Decision
	At level P-value	In first difference P-value	Lg	At level P-value	In first difference P-value	Lg	
REC	0.959	0.0001*	2	0.975	0.0001*	2	I(1)
GDPC	0.615	0.006*	2	0.569	0.005*	2	I(1)
CO2	0.171	0.034**	2	0.334	0.034**	2	I(1)
NS	0.875	0.0127**	2	0.875	0.013**	2	I(1)
UR	1.000	0.0015*	2	1.000	0.0000*	2	I(1)

(*), (**) indicate significance at 1% and 5% respectively.
Lg indicates the Lag length of the dependent variable.
The Lag length for the ADF was selected using Schwarz information Criterion.
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel.

4.6.4. Model stability test

The stability test is performed using the cumulative sum of the recursive residuals $S(t)$ and the cumulative sum of the squares of the recursive residuals $S'(t)$ defined by the Eqs. (6) and (7) suggested by Brown et al. [81]. The trends in the $S(t)$ and $S'(t)$ statistics must be contained within the interval defined by the relationship Eq. (8) for the validation of the long run stability hypothesis of the model specified [82]. Furthermore, as a last step to analyse the stability of the ARDL model estimated in this study, we check all its inverse roots with respect to the unit cycle. All the roots must be contained in the unit circle to validate the stability of the model.

$$S(t) = (n-k)\left(\sum_{j=k+1}^{t} \tilde{\varepsilon}_j\right) / \left(\sum_{j=k+1}^{t} \tilde{\varepsilon}_j^2\right) \tag{6}$$

$$S'(t) = \left(\sum_{j=k+1}^{t} \tilde{\varepsilon}_j^2\right) / \left(\sum_{j=k+1}^{n} \tilde{\varepsilon}_j^2\right) \tag{7}$$

(t = k+1, …, n). The number of variables is k, and the number of observations is n.

$$I = \left[\pm\beta\,(2t+n-3k)/\sqrt{(n-k)}\right] \tag{8}$$

In this relation $\beta = 0.948$ at the critical threshold $\alpha = 5\%$ [83].

5. Empirical results

This section presents the results of statistical tests relating to the modelling of electricity consumption as a function of explanatory factors. Overall, the statistical analysis highlights the existence of unidirectional causality from all the explanatory factors to electricity consumption in the short and long runs, respectively. Therefore, reliable development strategies can be formulated for decision-makers to help manage electricity demand in Cameroon's residential sector.

5.1. Stationarity assessments

Table 5 shows the results of the stationarity test for the different variables. At level, the ADF and PP tests have P-values above the critical threshold of 5%. For first difference variables, the P-values associated with the tests are well below the 5% threshold. As mentioned in Section 4.1, the variables used in this analysis are non-stationary at level and stationary at first difference. This result suggests the existence of long run cointegration between the variables [84]. However, the cointegration test should fully confirm this observation.

5.2. Optimal lag number

According to the Schwarz (SC), Hannan-Quinn (HQ), Akaike (AIC), Final prediction error (FPE) and Lagrange (LR) criteria, $l = m = n = p = s = 2$ is the best lag number as shown in Table 6. As specified in Section 4.2, the time response function is therefore a linear two-period combination of electricity consumption $(\Delta REC)_t$ and the set of explanatory factors.

Table 6
Selected optimal lag number.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−983.01	NA	3.94e+29	82.33	82.57	82.39
1	−788.11	292.33	2.95e+23	68.17	69.64	68.56
2	−725.54	67.78*	1.77e+22*	65.04*	67.74*	65.76*

* Indicates the lag order currently selected by the criteria.

5.3. Outcomes of Johansen cointegration test

Table 7 presents the results of an incremented test of the order of cointegration of the various variables based on the estimators ($\lambda_t race$) and ($\lambda_{\max}$). We see that for a null order of cointegration, $r = 0$, $\lambda_t race = 131.239$, and $\lambda_m ax = 68.876$ are greater than their respective critical values of 69.818 and 33.876. The null hypothesis of cointegration is rejected. The previous observation holds true for $r = 1$ and $r = 2$. The cointegration null hypothesis is rejected once more because the estimators remain above their critical values. We see that for $r = 3$, $\lambda_{trace} = 9.026 < 15.494$ and $\lambda_{\max} = 6.767 < 14.264$. At the tolerance threshold of 5%, the hypothesis of three cointegrating relationships between the five correlated variables is accepted. Thus, the order of cointegration highlighted by this test is $r = 3$ as outlined in Section 4.3. Each estimated model therefore contains three error-correction terms. The hypothesis of a long run equilibrium between the variables is accepted. However, as the data used in this analysis cover only 26 observations, we also perform upper bound tests to verify the results of the Johansen tests, in relation to the approach proposed in Section 4.4.

5.4. ARDL modelling and long run equilibrium of variables

5.4.1. ARDL modelling and statistical proofing

Before evaluating the long run cointegration by the ARDL technique, it is necessary to check the statistical validity of the model. Table 8 shows the statistics related to the estimation of the ARDL model, with electricity consumption as the dependent variable. The R^2, the adjusted R^2, the P-values, and the probability of the F-statistic are better for a maximum number of lags mostly equal to 2. Exception observed for GDP per capita (GDPC), where the optimal number of lags is 1. This difference supports the hypothesis of an almost immediate effect on the REC variable of any shock observed within the GDPC.

5.4.2. Serial correlation and heteroskedasticity tests for ARDL model

The results of the Breusch–Godfrey serial correlation LM test presented in Table 9 show that the P-value associated with the test is $16.75\% > 5\%$. The hypothesis of the existence of a serial correlation between the variables is rejected at the 5% threshold. Moreover, the P-value associated with the $\chi^{(2)}$ of the heteroskedasticity test is $51.45\% > 5\%$. As indicated in Section 4.6.2, the residuals of the model are homoscedastic, identically and independently distributed. They therefore constitute white noise.

Table 7
Outcomes of Johansen cointegration tests.

Rank (r)	λ_{trace}	P-value***	λ_{trace} critical value	$\lambda_{\max}$	P-value***	$\lambda_{\max}$ critical value
r=0	131.2391	0.000*	69.8188	68.8760	0.000*	33.8768
r=1	62.3630	0.0012*	47.8561	30.7440	0.0190*	27.5843
r=2	31.6190	0.0305*	29.7971	22.5923	0.0309*	21.1316
r=3	9.0266	0.3629**	15.4947	6.7675	0.5170**	14.2646

* denotes rejection of the nomber of cointegrating equations at 5% level.
** denotes acceptation of the number of cointegrating equations at 5% level.
*** MacKinnon-Haug-Michelis (1999) p-values, at the 5% critical threshold.

Table 8
ARDL modelling.

Variable	Coefficient	Std.Error	t-statistic	P-value
C	−801.31	314.05	−2.55	0.03
$\Delta(REC(-1))$	0.39	0.31	1.27	0.23
$\Delta(REC(-2))$	0.51	0.25	1.96	0.08
$\Delta(GDPC(-1))$	−0.44	0.15	−2.85	0.02
$\Delta(CO2(-1))$	−0.02	0.03	−0.69	0.50
$\Delta(CO2(-2))$	0.07	0.02	3.44	0.008
$\Delta(NS(-1))$	3.33	0.90	3.68	0.006
$\Delta(NS(-2))$	2.25	0.65	3.44	0.008
$\Delta(UR(-1))$	−0.06	0.01	−4.30	0.002
$\Delta(UR(-2))$	0.06	0.01	4.19	0.003
REC(−1)	−1.31	0.36	−3.64	0.006
GDPC(−1)	−0.08	0.20	−0.41	0.69
CO2(−1)	9.44E−05	0.02	0.003	0.99
NS(−1)	−4.20	1.08	−3.88	0.004
UR(−1)	0.0005	0.0002	2.19	0.059
R^2	0.912			
Adjusted R^2	0.76			
Log Likelihood	−100.93			
F-statistic	5.97			
Prob.(F-statistic)	0.007			
ECT	−1.838			

Dependent variable: $\Delta(REC)$.
Method: least squares.
Sample (adjusted): 1997–2019.
* indicates significance at 5% threshold.

Table 9
LM and Heteroscedasticity tests for ARDL model.

Serial correlation LM test	F-statistic	obs*R-squared	Prob.F	Prob.chi2
	0.551	–	0.602	0.167
Heteroscedasticity test	0.763	13.15	0.685	0.514

Table 10
Wald test for ARDL model coefficients.

Statistic	Value	df	Probability
F-statistic	6.65	(7, 8)	0.0079
chi2	46.60	7	0

Null hypothesis: C(4) = C(5) =...= C(10) = 0.

5.4.3. Cusum tests results for ARDL model

Fig. 4 shows the Cusum and Cusum of squares of the model contained within the 95% confidence interval. The specified ARDL model is therefore statistically robust. This model can be used to perform a long run cointegration analysis between the variables.

5.4.4. Upper bounds tests

By assigning the explanatory factors $\Delta(GDPC(-1))$, $\Delta(CO2(-1))$, $\Delta(CO2(-2))$, $\Delta(NS(-1))$, $\Delta(NS(-2))$, $\Delta(UR(-1))$ and $\Delta(UR(-2))$ the notations C(4), C(5), C(6), C(7), C(8), C(9) and C(10) in accordance with the order of appearance in the model, the non-cointegration of the variables is consistent with hypothesis $H0 : C(4) = C(5) = C(6) = C(7) = C(8) = C(9) = C(10) = 0$, while the alternative hypothesis is $H1 : C(4) \neq C(5) \neq C(6) \neq C(7) \neq C(8) \neq C(9) \neq C(10) \neq 0$. Table 10 shows the results of the Wald test. The F-statistic associated with the test is F = 6.65 for an associated P-value of 0.79%. This value is compared to the critical value of Pesaran et al. [68], at 5%. Our model being unrestricted with an intercept and no trend, the upper bound corresponding to the F-statistic = 6.65 is Ub = 4.85, while the lower bound is Lb = 3.78. We see that F-statistic = 6.65 > 4.85. We can therefore reject the H0 hypothesis of non-cointegration. The alternative hypothesis H1 is accepted. There is a long run cointegration relationship between the variables as mentioned in Section 4.4. The estimation of the error correction term indicated in Table 8 gives ECT(−1) = −1.838. The system is getting toward long run equilibrium at a speed of 183.8%.

5.5. Vector error correction models estimation

Table 11 presents the estimated coefficients of the model specified by Eq. (4) for $\Delta(REC)_t$ as objective function. By integrating the coefficients values estimated by the software, the objective function $\Delta(REC)_t$ is rewritten in the form given by Eq. (9).

$$\begin{aligned}\Delta(REC)_t &= -1.629((REC)_{t-1} - 0.04(CO_2)_{t-1} + 0.00015(UR)_{t-1} - 1996.529)\\ &-4.731((NS)_{t-1} + 0.0076(CO_2)_{t-1} - 0.0002(UR)_{t-1} + 1359.98)\\ &-0.235((GDPC)_{t-1} - 0.046(CO_2)_{t-1} + 0.0005(UR)_{t-1} - 6340.36)\\ &+0.648\Delta(REC)_{t-1} + 0.720\Delta(REC)_{t-2} + 3.99\Delta(NS)_{t-1} + 2.63\Delta(NS)_{t-2}\\ &-0.69\Delta(GDPC)_{t-1} - 0.18\Delta(GDPC)_{t-2} - 0.06\Delta(CO_2)_{t-1} + 0.06\Delta(CO_2)_{t-2}\\ &-0.06\Delta(UR)_{t-1} + 0.05\Delta(UR)_{t-2} + 3797.96 + \varepsilon_t\end{aligned}$$

Table 11
Vector error correction models.

Functional variable	Model description	Coefficients at j = 1	*P*-value at j = 1	Coefficients at j = 2	*P*-value at j = 2	ECT	*P*-value
	$\Delta(REC)_{t-j}$	0.648	0.015	0.720	0.002	−1.629	0.0005*
	$\Delta(GDPC)_{t-j}$	−0.691	0.003	−0.187	0.190	−0.235	0.0034*
$\Delta(REC)_t$	$\Delta(CO2)_{t-j}$	−0.062	0.011	0.065	0.007	−4.731	0.0007*
	$\Delta(NS)_{t-j}$	3.999	0.0008	2.635	0.0017		
	$\Delta(UR)_{t-j}$	−0.066	0.0006	0.058	0.0011		
R^2	0.905	Adjusted R^2	0.769	F-stat.	6.641	Prob.(F-stat.)	0.003
	$\Delta(GDPC)_{t-j}$	0.559	0.084	0.267	0.249	−0.107	0.835
	$\Delta(REC)_{t-j}$	0.442	0.245	0.352	0.256	−1.379	0.651
	$\Delta(CO2)_{t-j}$	0.004	0.888	0.001	0.964	−2.661	0.118
$\Delta(GDPC)_t$	$\Delta(NS)_{t-j}$	2.238	0.129	−0.244	0.808		
	$\Delta(UR)_{t-j}$	−0.036	0.126	0.054	0.023		
R^2	0.863	Adjusted R^2	0.665	F-stat.	4.372	Prob.(F-stat.)	0.016
	$\Delta(NS)_{t-j}$	0.091	0.951	−0.016	0.988	0.012	0.983
	$\Delta(REC)_{t-j}$	0.035	0.930	−0.086	0.793	0.243	0.586
	$\Delta(GDPC)_{t-j}$	−0.086	0.792	0.031	0.898	−1.663	0.353
$\Delta(NS)_t$	$\Delta(CO2)_{t-j}$	0.035	0.342	−0.0218	0.542		
	$\Delta(UR)_{t-j}$	−0.028	0.269	0.017	0.451		
R^2	0.733	Adjusted R^2	0.347	F-stat.	1.902	Prob.(F-stat.)	0.168
	$\Delta(CO2)_{t-j}$	0.022	0.935	0.263	0.342	5.342	0.236
	$\Delta(REC)_{t-j}$	0.400	0.896	0.134	0.756	−1.954	0.566
	$\Delta(GDPC)_{t-j}$	−1.125	0.652	3.127	0.120	−24.239	0.093
$\Delta(CO2)_t$	$\Delta(NS)_{t-j}$	24.273	0.059	12.177	0.173		
	$\Delta(UR)_{t-j}$	−0.278	0.156	0.178	0.318		
R^2	0.635	Adjusted R^2	0.108	F-stat.	1.205	Prob.(F-stat.)	0.398
	$\Delta(UR)_{t-j}$	1.629	0.0001	−0.789	0.0048	−1.781	0.743
	$\Delta(REC)_{t-j}$	1.312	0.734	2.945	0.359	3.652	0.398
	$\Delta(GDPC)_{t-j}$	−5.442	0.106	−3.221	0.193	−25.291	0.152
$\Delta(UR)_t$	$\Delta(CO2)_{t-j}$	−0.246	0.489	0.461	0.195		
	$\Delta(NS)_{t-j}$	1.629	0.0001	−0.789	0.0048		
R^2	0.999	Adjusted R^2	0.999	F-stat.	43,435.98	Prob.(F-stat.)	0.000

(*) indicates significance at 1% threshold.

(9)

5.5.1. VECM and assessment of long run causality

For the four explanatory factors, namely, $\Delta(GDPC)_t$, $\Delta(NS)_t$, $\Delta(CO2)_t$, and $\Delta(UR)_t$ the estimated coefficients are also presented. The estimated model for these four explanatory factors are derived in a similar way as Eq. (9) in order to provide a more detailed analysis of causality. So we have five equations based on the change in the functional variable among the five variables chosen.

For the model with the functional variable $\Delta(REC)_t$, the three associated error correction terms are negative and significant at the tolerance threshold of 1%. This finding supports the hypothesis of long-run causality from all explanatory factors considered simultaneously to electricity consumption. We can make a definitive statement about the direction of the interaction by observing the signs and significance of the error-correction terms in the other four models. Consistent with the results presented in Table 11, the error correction terms in the functional variable models $\Delta(GDPC)_t$, $\Delta(NS)_t$, $\Delta(CO2)_t$, and $\Delta(UR)_t$ are insignificant at the 1% tolerance level. According to the $\Delta(REC)_t$ model, long run causality is thus unidirectional, from all explanatory factors to electricity consumption.

5.5.2. Wald tests and assessment of short-term causality

An analysis of the direction of short-term causality is performed using the model in Table 11. The Wald causality test results are presented in Table 12. The tests on the nullity of the directing coefficients $C(i)$ associated with each explanatory factor are significant at the 1% threshold for the functional variable model $\Delta(REC)_t$. This finding supports the hypothesis of short-term causality from each explanatory factor to electricity consumption. The observations of the models $\Delta(GDPC)t$, $\Delta(GDPC)t$, $\Delta(CO2)t$, $\Delta(NS)t$, and $\Delta(UR)t$ reveal that the results of the tests on the nullity of the coefficients are globally non-significant. The results in bold indicate that there is no short-term causality from electricity consumption to each of the explanatory factors. As a result, the short-term causal relationship discovered is unidirectional, running from all explanatory factors to electricity consumption. Additional statistical tests are used to validate the effectiveness of the identified causal relationship.

5.6. Diagnostic tests

5.6.1. Ramsey reset test results

Table 13 shows the results of the regression error specification test, performed with a number of fitted terms equal to 1. The P-values of the t-statistic, F-statistic, and Likelihood ratio are all above the tolerance threshold of 5%. The explanatory factor $\Delta(GDPC)$, $\Delta(CO2)$, $\Delta(NS)$, and $\Delta(UR)$ are considered necessary and sufficient to explain the trends of the dependent variable $\Delta(REC)$. Any modelling based on these variables is free of specification errors.

Table 12
Wald causality tests results.

Explained variable	Explanatory variables	Null hypothesis	$\chi^{(2)}$	df	P-value
$\Delta(REC)_t$	$\Delta(REC)_{t-j}$	C(4) = C(5) = 0	16.995	2	0.0002*
	$\Delta(GDPC)_{t-j}$	C(6) = C(7) = 0	17.960	2	0.0001*
	$\Delta(NS)_{t-j}$	C(8) = C(9) = 0	16.909	2	0.0002*
	$\Delta(CO2)_{t-j}$	C(10) = C(11) = 0	25.240	2	0.0000*
	$\Delta(UR)_{t-j}$	C(12) = C(13) = 0	26.075	2	0.0030*
$\Delta(GDPC)_t$	$\Delta(REC)_{t-j}$	**C(18) = C(19) = 0**	**1.864**	**2**	**0.393**
	$\Delta(GDPC)_{t-j}$	C(20) = C(21) = 0	3.767	2	0.152
	$\Delta(NS)_{t-j}$	C(22) = C(23) = 0	0.028	2	0.985
	$\Delta(CO2)_{t-j}$	C(24) = C(25) = 0	11.393	2	0.0034
	$\Delta(UR)_{t-j}$	C(26) = C(27) = 0	11.685	2	0.0029
$\Delta(CO2)_t$	$\Delta(REC)_{t-j}$	**C(32) = C(33) = 0**	**0.109**	**2**	**0.946**
	$\Delta(GDPC)_{t-j}$	C(34) = C(35) = 0	7.407	2	0.024
	$\Delta(NS)_{t-j}$	C(36) = C(37) = 0	1.141	2	0.565
	$\Delta(CO2)_{t-j}$	C(38) = C(39) = 0	4.986	2	0.082
	$\Delta(UR)_{t-j}$	C(40) = C(41) = 0	3.235	2	0.198
$\Delta(NS)_t$	$\Delta(REC)_{t-j}$	**C(46) = C(47) = 0**	**0.179**	**2**	**0.914**
	$\Delta(GDPC)_{t-j}$	C(48) = C(49) = 0	0.243	2	0.885
	$\Delta(NS)_{t-j}$	C(50) = C(51) = 0	1.143	2	0.564
	$\Delta(CO2)_{t-j}$	C(52) = C(53) = 0	0.018	2	0.990
	$\Delta(UR)_{t-j}$	C(54) = C(55) = 0	1.945	2	0.378
$\Delta(UR)_t$	$\Delta(REC)_{t-j}$	**C(60) = C(61) = 0**	**1.030**	**2**	**0.597**
	$\Delta(GDPC)_{t-j}$	C(62) = C(63) = 0	3.313	2	0.190
	$\Delta(NS)_{t-j}$	C(64) = C(65) = 0	2.081	2	0.353
	$\Delta(CO2)_{t-j}$	C(66) = C(67) = 0	2.214	2	0.330
	$\Delta(UR)_{t-j}$	C(68) = C(69) = 0	105.310	2	0.000

$j = (1; 2)$ is the time lag of the explanatory factors, and for which the coefficients $C(i)$ are tested. (*) denotes the test's significance at 1% threshold.

Table 13
Ramsey reset test findings.

Statistics	Value	df	P-value
t-statistic	0.381	19	0.707
F-statistic	0.145	(1, 19)	0.707
Likelihood ratio	0.190	1	0.663

Table 14
Heteroscedasticity tests.

Test	Statistics	P-value	Observation
LM-test	$\chi_p^{(2)} = 0.083$	0.920	P-value > 5% Homoscedasticity of error terms
	F-statistic = 0.783	0.548	

5.6.2. Heteroscedasticity test for VECM

As seen in Table 14, the probabilities associated respectively with the F-statistic and the $\chi_p^{(2)}$ are relatively higher than the error threshold of 5%. Consequently, the model is homoscedastic at the critical threshold of 5%. There is no correlation between variations in GDPC, CO2, NS and UR, but there is a direct correlation between each of these explanatory factors and residential electricity consumption.

5.6.3. Normality test

The results of this test confirm the earlier conclusion. With a confidence level of 95%, the distribution of the error terms in the $\Delta(REC)_t$ model follows a Gaussian distribution. Consequently, the residuals of the model are independently and identically distributed (iid). Any statistically valid explanatory factor added to this model will have no effect on the four existing explanatory factors, but a direct correlation with electricity consumption.

5.6.4. Stability tests

Cusum and Cusum-squared curves are contained within the range of 95%, as shown in Fig. 4. The $\Delta(REC)t$ model has been shown to be statistically valid and stable. Since there is unidirectional causality from all the explanatory factors to residential electricity consumption, any impetus within one of these factors will have a direct effect on consumption, without feedback.

As a final step to analyse the stability of the estimated VECM, we check all its inverse roots in relation to the unit cycle. Fig. 5 presents the results of the inverse roots of AR characteristic polynomial. All the roots are inside the unit cycle, confirming the stability of the model.

6. Discussions

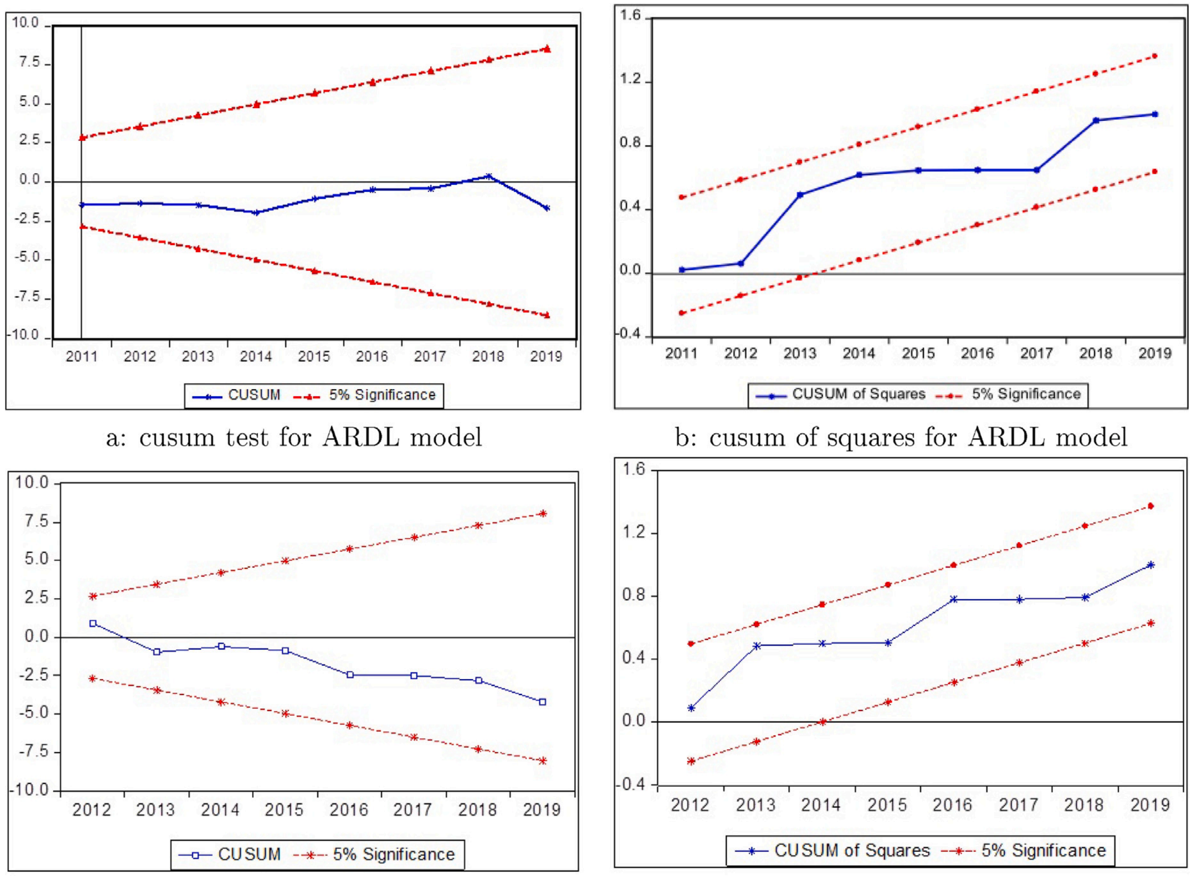
In this section, we discuss how the explanatory factors selected can contribute to ensuring the sustainability of electricity consumption in the residential sector over the short and long run. This is in line with the results highlighted in Section 5. Strategies for better managing electricity consumption are also outlined.

6.1. GDP per capita as sustainability factor of residential electricity consumption

According to [20], GDP had a significant impact on residential electricity consumption in Algeria from 1970 to 2013. Any increase in Algeria's GDP leads to an increase in residential electricity consumption. Our findings support this hypothesis. With a unidirectional causality from GDP per capita to electricity consumption (see Sections 5.5.1 and 5.5.2), any increase in GDP per capita in Cameroon would result in an increase in electricity consumption. Improving per capita GDP is a pre-requisite for achieving the 7–1 Sustainable Development Goals. With a GDP per capita of around USD 1500 in 2019 [8], just under USD 5 per day, it is difficult for a cameroonian household to meet its basic needs and subscribe to a regular energy service. This causes problems like less access to energy services, more unpaid bills, and the spread of electricity fraud because of uncontrolled connections that the national electricity distributor doesn't know about. Per capita GDP thus appears to be a key factor in the sustainability of electricity consumption in the residential sector. This factor is closely linked to the proliferation of electrical appliances in households, with the corollary of increased electricity consumption in the residential sector [85].

6.2. Compact urbanisation for long run sustainability of residential electricity consumption

Urbanisation remains inextricably linked to electricity consumption in the Cameroonian residential sector, just as it was in Tunisia in 2020, according to [21]. However, the opposite directions of causality show that population migration from rural to urban areas increases electricity demand. Cameroon's urbanisation rate is increasing. According to [8], 58.15% of the population will live in cities by 2021, up from 55.18% in 2016. In this situation, it is critical for the government to design an urban model that allows for the containment of displaced populations, the implementation of energy efficiency measures, and the control of electricity demand in order to satisfy it. The urbanisation in Cameroon follows mostly the spread-out urbanisation model as opposed to the compact urbanisation model. Cities grow under this model by consuming more land and air space. As a result, the overhead electricity network is more branched and extended over long distances. As a result, power poles are spread across a larger land area. This increases the likelihood of incidents on electricity networks as well as the projected maintenance costs. Limiting the spread of construction is therefore necessary to combat this type of expensive and energy-consuming urban planning. Sustainable urban planning, which includes limiting urban sprawl, would help Cameroon's electricity system and



a: cusum test for ARDL model

b: cusum of squares for ARDL model

c: cusum test for VECM

d: cusum of squares for VECM

Fig. 4. Cusum and Cusum of squares tests.

residential sector develop more sustainably. The adoption of the compact urban model, supported by energy efficiency measures shared by all residences, will ensure the long-term sustainability of the electricity demand imposed by urbanisation.

6.3. CO2 emissions and residential electricity consumption

Table 15 depicts additional factors that influence residential electricity consumption. The role of $CO2$ in influencing residential electricity demand is not by chance. In fact, hydroelectric production is still insufficient to meet the growing population's electricity demands. As a solution to this problem, Cameroon's government has chosen to generate electricity through oil or gas power thermal stations. The release of CO2 into the atmosphere is a direct result of these conditions. In fact, Cameroon has approximately twenty thermal power stations that run on heavy or light fuel oil, with a total capacity of 374.26 MW in 2015. There are also two operational gas power plants with a combined capacity of 266 MW. The combined installed capacity of the three operational hydroelectric power stations is 732.2 MW. In 2015, heavy fuel oil, light fuel oil, and gas-fired thermal power stations accounted for 46.65% of the total installed production capacity of 1372.46 MW. Furthermore, self-generators, which accounted for 22% of total production capacity in 2016 [9], run primarily on diesel, contributing to CO2 emissions from self-generation of electricity. Furthermore, the residential sector's estimated electricity consumption is 1383 GWh, which is lower than the industrial sector's estimated consumption of 3619 GWh in 2019 [1]. This value order indicates that a significant portion of thermal production is made available to households, SMIs, and SMEs.

The electricity supply system for the residential sector in Cameroon is such that generation follows demand. The electricity produced by thermal power stations in Cameroon is used to support hydroelectric generation in order to meet demand from the residential sector. Consequently, any increase in thermal generation leads to an increase in CO2 emissions and a satisfaction of household electricity consumption. In other words, the increase in CO2 emissions from thermal electricity generation helps to meet the demand for electricity from the residential sector, and therefore has a positive effect on consumption. However, the opposite effect is not necessarily true. An increase in electricity consumption in the residential sector may not lead to an increase in CO2 emissions. In fact, the increase in GDP per capita, the proliferation of energy-consuming household appliances, the increase in the number of electricity consumers per household, the proliferation of small and medium-sized industries and small and medium-sized enterprises that use electricity to produce goods and services, can all support an increase in residential electricity consumption, without any increase in CO2 emissions due to thermal electricity generation.

Taking into account that CO2 emissions due to hydroelectricity are negligible [86], this analysis remains consistent with the unidirectional causality from CO2 emissions to residential electricity consumption as outlined in Sections 5.5.1 and 5.5.2. This means that thermal electricity generation and its associated CO2 emissions are central to the sustainability of residential electricity consumption in Cameroon. Cameroon still needs to step up its thermal generation in order to sustainably support residential demand. However, this intensification must be accompanied by a plan for the gradual reduction of CO2 emissions in order to contribute effectively to the objective of reducing national emissions by 35% by 2030, as agreed by the State of Cameroon

Table 15
Author's contribution.

Sector	Authors	Country	Year of study	Empirical method	Period	Results
Residential	[20]	Algeria	2018	ARDL	1970–2013	GDP → REC
	[21]	Tunisia	2020	Granger Causality	1980–2018	REC → EP REC → UR
	Writers	Cameroon	2022	ARDL, VECM	1994–2019	GDPC → REC CO2 → REC UR → REC NS → REC

Note : → represents unidirectional.

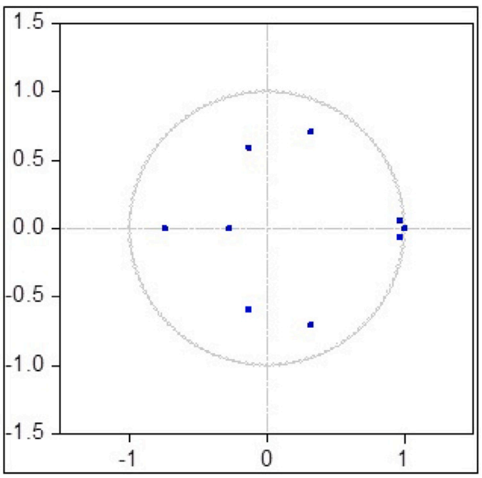


Fig. 5. Inverse roots of AR characteristic polynomial.

in 2021 at the 26th conference of the parties (COP26) in Glasgow, United Kingdom. This objective of −35% of CO_2 emissions can be achieved by significantly involving the residential sector. This will involve stepping up hydroelectric, solar and wind generation, which account respectively for 66.48%, 0.24% and 0.0% of the country's electricity generation in 2020 [1]. CO_2 emissions therefore appear to be a major energy factor in the sustainability of electricity demand in the residential sector.

6.4. The number of subscribers and the sustainability of residential electricity consumption

An increase in the number of subscribers to the distribution network leads directly to an increase in electricity consumption. This logical consequence supports the idea of a unidirectional causality from the number of subscribers to residential electricity consumption. However, the increase in the number of subscribers to the electricity network highlights two problems: saturation of the network and deterioration in the quality of supply, with the corollary of unsatisfied demand. To ensure that all Cameroonians have access to reliable and modern electricity services, the government should combat fraudulent connections to the distribution networks, renovate obsolete and saturated power lines, and carry out extension work. The number of subscribers, which is often neglected in causality studies, is therefore a determining factor in the long run sustainability of electricity demand in the residential sector.

7. Conclusions and policy implications

The analysis of causal relationships involving various factors of electricity demand sustainability is a useful approach for identifying energy strategies to be implemented in order to contribute to the long-term development of various consumption sectors. The residential sector is one of the energy consumption sectors in Cameroon that has seen an increase in demand for electricity over the last ten years. The scarcity of literature in Cameroon on studies of the causal relationship between electricity demand and its explanatory factors justifies the importance of this reflection. In fact, between 2012 and 2022, only two scientific studies in the African region looked closely at the possible causal links between residential electricity consumption and its main factors. This also explains why there are not many energy strategies for decision-makers that could help the residential sector reach its goals for sustainable development.

Controlling variations in the most influential factors that dictate the direction of electricity fluctuations on transmission and distribution networks is critical to ensuring universal access to adequate electricity. In addition, to GDP and urbanisation, which have been identified as factors with a direct causal relationship with residential electricity consumption in Africa in the literature, this study identifies GDP per capita, CO_2 emissions from thermal electricity generation, and the evolution of the number of subscribers, as additional parameters to be included in the analysis of causal relationships involving residential electricity consumption. The Johansen cointegration model, the autoregressive distributed lag model, the vector error correction model, and the Wald-Granger causality tests are still very useful for analysing cointegration between variables and determining causality direction over time.

In both the short and long run, the results show unidirectional causality from each explanatory factors to residential electricity consumption. An increase in GDP per capita has been identified as a necessary measure to improve consumers' ability to afford a regular energy service. The spread-out model of urbanisation currently being observed in Cameroon favours a strong branching of distribution lines, uncontrolled electrical interconnections, and increased fraud. In this situation, it is recommended that a compact urban model be adopted. Implementing such a measure in the majority of urban areas will limit power line overhead densification, reduce the risk of impacts, impose common energy efficiency measures on residences, and better control electricity consumption. The study's recommendations include reducing CO_2 emissions from thermal electricity generation and further controlling the evolution of the number of subscribers on distribution networks, which will aid in the achievement of sustainable development goals in the residential sector. CO_2 capture and storage is one of the technologies that will be used to reduce the carbon footprint of thermal power plants. Prepaid metres can be used to ensure that electricity consumption is proportional to each subscriber's wallet. This would prevent unpaid bills from causing power outages and disputes between the electricity distributor and its customers.

Although statistical tests indicate that the ARDL and VECM models in this study are stable and free of specification errors, other variables such as the price of electricity, the number of households, thermal electricity generation, hydroelectric generation, and per capita electricity consumption, can be included in the models in order to shed light on their respective effects on electricity demand, and to bring out more factors in the sustainability of electricity consumption in the residential sector.

CRediT authorship contribution statement

Serge Guefano: Conceptualization, Data curation, Software, Methodology, Investigation, Preparation, Writing – original draft, Writing – review & editing. **Mokhtar Bozorg:** Formal analysis, Methodology, Writing – original draft, Writing – review & editing, Validation, Funding acquisition, Resources. **Mauro Carpita:** Supervision, Writing – original draft, Project administration, Funding acquisition, Resources, Validation. **Jean Gaston Tamba:** Supervision, Conceptualization, Formal analysis. **Jacques Etame:** Supervision, Funding acquisition.

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.

Data availability

I give permission for my data to be published at the same time as this work. I make my data available in this submission

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Appendix A. Supplementary data

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