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Research article

Mathematical modeling of Ethiopia's energy demand by sectors and energy types, with forecasts for the next 30 years

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A R T I C L E I N F O

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Linear regression
Polynomial fit

A B S T R A C T

Due to the scarcity of economic resources, it is vital to optimize everything so that the supply and demand lines intersect in an optimized quantity, with no shortage or surplus of a provided item or service. Energy supply contains both surplus and shortage, thus estimating the amount of projected energy demand is a key work that must be completed. The objective of this paper is generating a mathematical model based on the actual data for thirty years forecasting. To create a mathematical model using actual data from the last fifteen years, a model that can represent the past trend and be used for future forecasting. This study provides a general overview of Ethiopia's current energy requirement with different energy type as well as sector-specific energy demand and estimates for different economic growth scenarios up to 2052. This model was created using a linear regression polynomial fit through Origin graphic and analysis software, and an econometric model was also applied. GDP was utilized as an independent variable in the economic model to determine the trend of energy consumption. Another input-output model is also used for multilinear regression to evaluate the change of four variables, GDP, population growth, urbanization growth rate, and general inflation rate, which was quantitatively linked with total energy requirement using Weka software. The mathematical model developed through linear and multilinear regression has been validated by using a different assumption on GDP growth based on past growth rate as low, medium and high growth rate and using the mathematical formula to generate an energy demand trend that can be compared with the actual trend; as a result, all the mathematical model that are generated has been found to be valid for the purpose of the intended work. Based on the generated mathematical model and different GDP growth rate scenario as low, medium, business as usual (BAU) and high a future energy demand was forecasted up to 2052 for thirty years. The model's results can help energy planners ensure that the country's supply capacity keeps up with predicted energy demand growth.

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1. Introduction

The capacity needed for future energy generation is determined by determining a society's long-term energy demand. These predictions are commonly used to assess the extent and content of an energy supply expansion project utilizing alternative energy sources [1,2]. To make reliable predictions, a complete forecasting effort is required that includes a range of future energy demand forecasts [3,4]. If the necessary macroeconomic and microeconomic data are available, the analysis should use them to make energy demand predictions more reliable and compatible with demographic, economic, and industrial development projections [5].

Long-term energy demand analysis is a critical component of integrated energy planning and policy in developing countries such as Ethiopia and throughout Africa [6]. To estimate future demand, planners and policymakers must first understand the elements that impact growth and energy consumption pattern. Bearing in mind the high capital intensity and extended gestation periods of energy investments, as well as supply limits and the negative effects of energy shortages, precise demand estimations at both the aggregate and sectoral levels are required. A study of the impact of price and non-price variables on energy consumption is also essential to establish energy-saving policies [5].

Sub-Saharan Africa's economy has grown rapidly, with energy consumption increasing by 45 % since 2000. Regional energy infrastructure, on the other hand, is underdeveloped and insufficient to meet people's demands. Despite the fact that there are abundant energy resources, access to modern energy services is limited. African countries aim to meet their population's growing energy demand and provide universal access to modern energy services while minimizing environmental impact [6]. To that aim, energy management systems that take into account all viable demand- and supply-side options while remaining consistent with global sustainability goals are critical [7]. Energy demand modelling is one of a critical component of energy management since it predicts future use of energy patterns and trends. It allows for the development of energy management plans and policy recommendations, as well as the efficient utilization of energy resources, improvements in energy efficiency and reliability, and emission reductions [6].

Energy is necessary for the majority of economic activity. As a result, energy is a majorly required but not fully sufficient condition for economic growth [8]. Energy sector models provide essential insights to policy and decision makers about energy demand and supply, least-cost energy technology mix, investment and finance requirements, and the synergies and trade-offs of energy sector development [9,10]. Energy models are becoming increasingly essential when considering the consequences of energy usage on the environment and climate change [11,12]. Energy models for developing nations should be customized to their unique structural elements (energy type, geography, macroeconomic) [13,14]. As a result, energy demand models were developed using economic methods and theories, with demand anticipated using macroeconomic characteristics such as GDP, GDP growth, and demographic changes such as population increase and urbanization [6].

Thus, unlike in industrialized countries, measuring energy demand in developing countries requires not just the collecting of consistent data, but is also hampered by a variety of factors [2]. As a result, it is even more necessary for developing countries than for industrial countries to analyze differences at a more disaggregated level, such as for core user sectors, chosen energy-intensive industries, or major end-uses such as household cooking, lighting, and transportation [5].

Historically, developing countries have estimated energy demand applying end-use methodologies. Top-down methodologies study the economy's response to policies and driving variables by analyzing end-use behavior and historical macroeconomic indicators such as income and population. Bottom-up optimization energy models were used to establish the least-cost technology combination and examine the cost and emission repercussions of alternative scenarios [13]. However, bottom-up optimization models have limits in terms of policy suggestions since they may overlook important components of developing countries' energy systems and economies. As a result, a top-down econometric model is highly suggested for the model of energy demand and for future forecasting of energy demand for developing nations [6].

Because of data scarcity, there is little literature on energy demand modeling in Africa. Existing African research generally focus on electricity's demand, where data is available. Several studies have forecasted power generation capacity, capacity expansion, and demand, including [7,15–19]. Some African sub-regions have performed regional electricity demand predictions [20,21]. [22]. [23].

There has been little study on modeling total energy demand in Africa [24]. forecasted South Africa's rural energy demand by 2018 using a bottom-up framework TIMES model, an extension of the MARKAL energy modeling system [25]. used the MESSAGE model to develop global energy scenarios that assessed universal energy availability in energy-poor regions such as Africa. In 2030, the ultimate energy need per capita is predicted to be around 10 GJ (GJ) [26]. estimated individual energy use by 2030 based on IEA World Energy Outlook estimates. Under normal circumstances (BAU), Africa's total household energy consumption is expected to be 9.5 EJ (EJ) by 2030. However, they concluded that alleviating energy poverty in Africa will necessitate an additional 9.7 EJ.

Developing reliable forecasting approaches for African energy demand is critical for policymakers, notwithstanding the difficulties encountered by developing country modelers. Proper energy management and planning policies are critical to achieving economic development and environmental security in Africa. Africa, which has 13 % of the world's population but just 4 % of global energy consumption, requires stable, clean, and affordable energy for development [6]. Hence, this study aims to address a gap in energy demand forecasting by forecasting overall energy requirement in Ethiopia.

According to Ref. [9], due to limited availability to modern energy sources to fulfill rising demand, Ethiopia's energy sector continues to rely significantly on traditional biomass energy. And proposed a Long-term energy demand forecasting which is forwarded as critical for guiding the country's energy supply system expansion plans. And, according to Ref. [10], the volume and mix of energy supply and consumption play significant roles in creating a country's sustainable development path. This is especially significant in developing countries where access to modern energy sources is still limited. The report reveals research gaps, notably in terms of connecting the energy sector to the rest of the economy and the environment through the use of multisectoral economic models. Among other things, the lack of a centrally coordinated energy data supply limits such advanced modelling.

This study proposes a more basic model that can be implemented utilizing only important variables such as macroeconomics (GDP), GDP growth, and other demographics such as urbanization rate, population, and inflation rate statistics for multivariate analysis. Parallel to the study, establishing a trustworthy and accurate mathematical model that can reflect the previous fifteen years' actual data can be viewed as the first step toward producing a simplified model that can function without the need for an immense quantity of data. The generated mathematical model was used to predict the energy use for the next 30 years. In the case of a multivariate linear equation, in addition to GDP, inflation rate, urbanization rate, and population growth were employed to calculate total energy demand over fifteen years.

The rest of this paper is structured as follows: Section 2 provides a brief overview of energy demand, economy and another demographic trend in Ethiopia. Section 3 provides a basic summary of the model approach, modelling scenarios and associated data. Section 4. provides detailed analysis of the modelling results Finally, Section 5 concludes.

2. Over view of energy demand, economy and another demographic trend in Ethiopia

2.1. Energy demand trend

The time series pattern of Ethiopia's energy consumption is characterized by massive use of biomass energy during the past fifteen years beginning in 2008, with a share of more than 85 % as shown in Fig. 1, this biomass figure included that derived biomass as well, like that of charcoal. Except for LPG (Light Petroleum Gas) and refinery gas, which did not have a linear rise and instead fluctuated, all energy sources for Ethiopia's energy demand are growing rapidly, as seen on Table 1.

With this fifteen - year data, overall energy demand climbed by roughly 15,500 ktoe (see Table 1), which is half of total energy consumption in 2008. To meet the energy demand of the next 20–50 years, this type of expansion requires accurate forecasting. The forecasting effort is crucial because the infrastructure and technology required to create this amount of energy may not be available, widening the gap between unmet energy demand.

In terms of energy origin (see Table 2), the majority of the energy is produced within the country. Beginning in 2012, some of the energy produced began to be sold to foreign countries, such as electricity to neighboring countries, and primary coal production began in 2017 with 2 ktoe and was expanded to 264 ktoe by 2022, reducing the amount of coal that must be imported by nearly 45.4 %. Energy from biomass and electricity are the country's two major locally produced energy sources; in 2022, about 5046 ktoe (11 %) of the total 46,283 ktoe energy demand was met by importing from abroad.

Within ten years, energy exports climbed from 29 ktoe in 2012 to 144 ktoe in 2022. Primary energy production has also increased from 28,765 to 41,328 ktoe in a period of fifteen years. Imported energy has also more than doubled in the last fifteen years, from 1971 ktoe to 5046 ktoe, as can be readily observed from Table 2,

The percentage share of each energy type by 2022 is shown in Fig. 2, indicating that traditional biomass energy dominated with 85.85 % and the remaining 14.15 % were covered by modern type of energy. With 6.22 % Heavy petroleum products, 3.61 % Light petroleum products, and 2.56 % Electricity, 1.26 % Hard coal, ignite and peat which accounts 13.65, % of the modern energy.

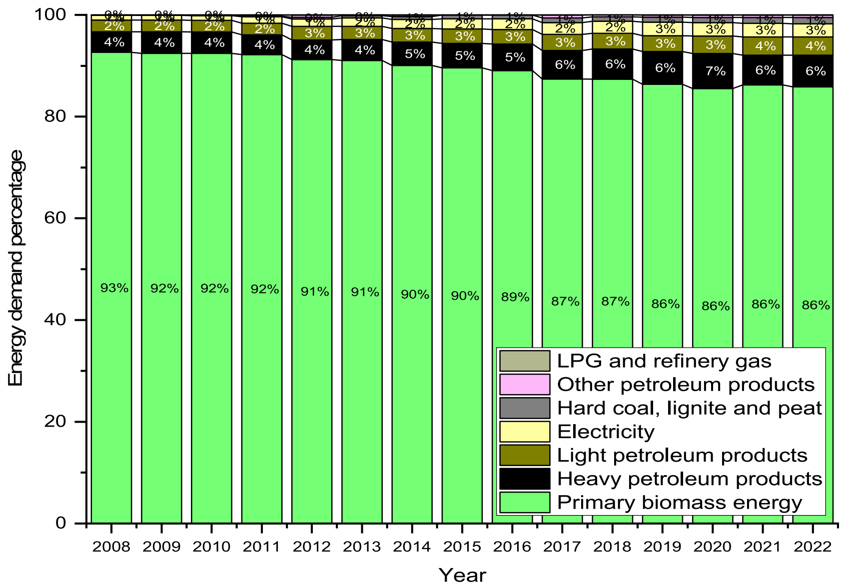


Fig. 1. Percentage share of different energy source for Ethiopia for fifteen years [27].

Table 1
Ethiopia's total energy requirements in energy types for the past fifteen years [27].

Year Unit: ktoe	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
LPG and refinery gas	7	7	9	9	6	5	8	8	8	9	5	7	7	9	11
Other petroleum products	5	13	13	80	162	48	112	0	0	238	154	197	221	219	220
Hard coal, lignite and peat	4	10	23	25	108	159	207	287	292	375	365	420	450	545	582
Electricity	290	285	305	426	511	604	665	757	839	966	1013	1161	1205	1214	1184
Light petroleum products	713	734	739	773	931	927	1010	1100	1134	1304	1306	1381	1554	1658	1672
Heavy petroleum products	1243	1340	1374	1313	1350	1485	1710	1854	2075	2339	2523	2820	3141	2675	2878
Primary biomass energy	28475	29294	30136	31001	31896	32766	33645	34489	35353	36230	37093	37953	38821	39682	39736
Total Energy Consumption	***30737***	***31683***	***32599***	***33627***	***34964***	***35994***	***37357***	***38495***	***39701***	***41461***	***42459***	***43939***	***45399***	***46002***	***46283***

Table 2
Energy balance of Ethiopia for the past fifteen years [27].

Year Unit: ktoe	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Production of primary energy	28765	29579	30446	31437	32442	33418	34392	35307	36252	37310	38231	39202	40114	41273	41328
Imports	1971	2119	2153	2192	2368	2592	3052	3281	3499	4253	4430	4857	5378	4863	5046
Exports					−29	−48	−82	−61	−60	−112	−123	−86	−86	−141	−144
Stock changes	1	−15		−2	183	32	−5	−32	10	10	−79	−34	−7	7	53
	30737	31683	32599	33627	34964	35994	37357	38495	39701	41461	42459	43939	45399	46002	46283

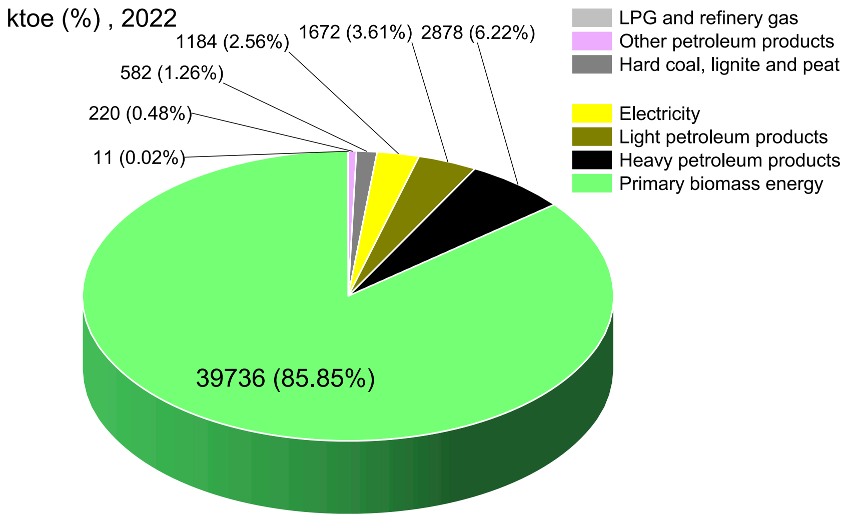


Fig. 2. Percentage share of different primary energy source, 2022 [27].

2.2. Energy demand by sectors

As indicated in Table 1 and Fig. 3, energy consumption has increased by approximately 15,500 ktoe, accounting for 50 % of total energy consumption in 2008. As a result, this energy is used in three main sectors: industry and construction, transportation, and residential and other uses. When we look at the data alone, we can see that throughout the last fifteen years (2008–2022), households and other users consumed more than 85 % of the energy, followed by transportation at 5 %–10 % and industry and construction at 1 %–3 %. Fig. 3 a clearly illustrates that transport, industrial and construction energy consumption is growing in comparison to residences and other consumers.

Fig. 3 and Table 1 show that overall energy consumption in 2022 was 46,283 ktoe, with residences and other users accounting for 87.38 % (38,114 ktoe), transportation accounting for 9.92 % (4326 ktoe), and industry and construction accounting for the remaining 2.70 % (1178 ktoe). In 2008, the energy requirement for industry was 290 ktoe, which has nearly quadrupled by 2022. The energy demand for transportation increased in around triple in fifteen years, from 1519 ktoe in 2008. While the energy demand of households increased by more than one-third of the energy demand in 2008 from 27,338 ktoe to 38,114 ktoe within fifteen years, as seen from Fig. 3 a.

As shown in Fig. 4 a households and other users utilize the most energy, with biomass and derived biomass accounting for 98 % of total energy consumption. In addition to biomass and derived biomass, electricity and light petroleum products account for an average of 1.20 % and 0.65 % of household and other consumer energy use over the last fifteen years, respectively. Electricity consumption increase ranged from 28.54 % in 2017 to −13.20 % in 2022, with an average of 11.4 7 % across the 15-year study period. For the past fifteen years, the average LPG and refinery gas energy consumption share for households and other consumers was about 0.02 %

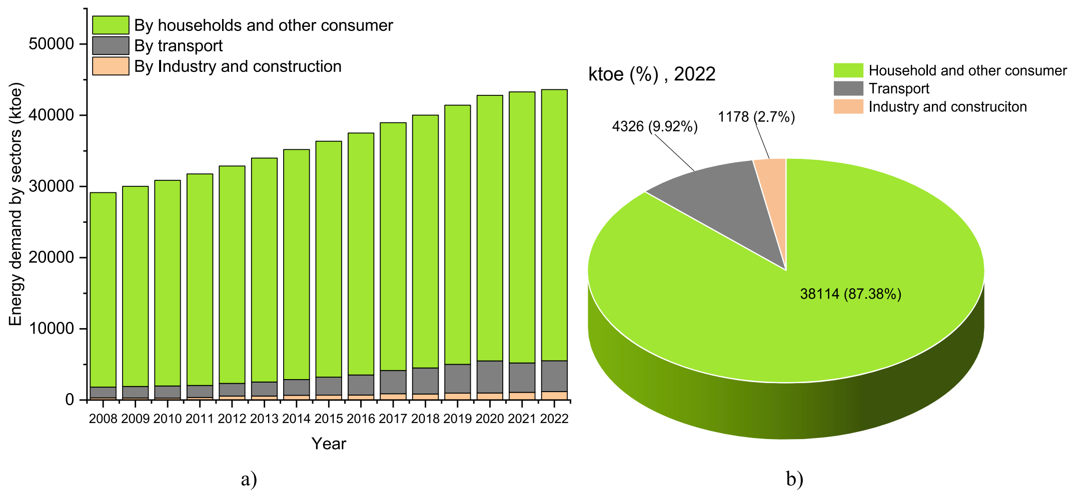
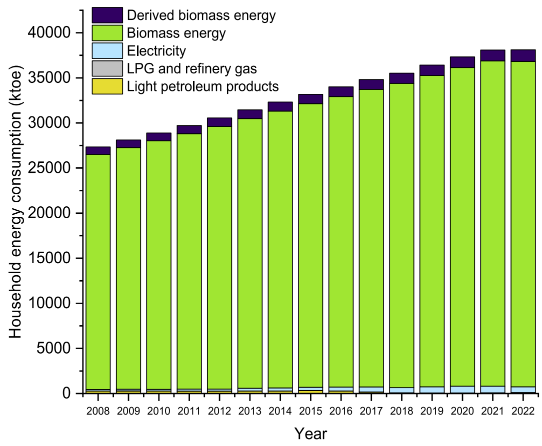
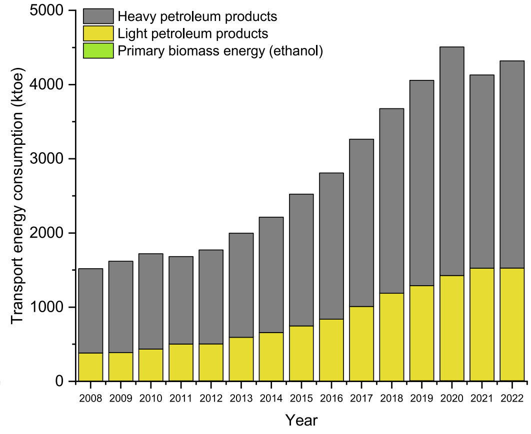


Fig. 3. a) Energy share of each sector from 2008 to 2022 b) Energy demand share of different sectors, 2018 [27].



a)



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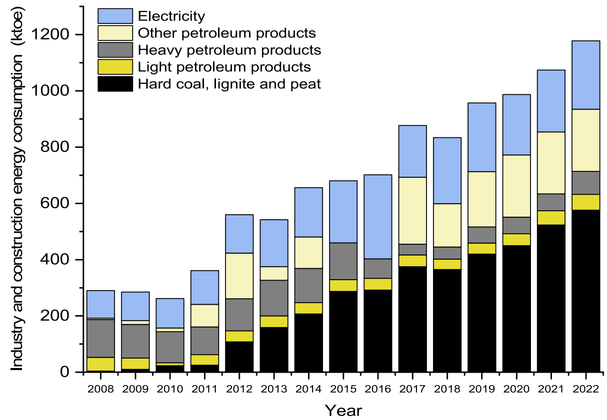


c)

Fig. 4. Energy consumption sector wise a) household and other consumers b) transport c) industry and construction energy consumption [27].

According to Fig. 4 b, heavy petroleum products accounted for the majority of energy utilized in the transportation sector from 2008 to 2022, with an average share of almost 70 %. This percentage share has decreased from 74.85 % (1137 ktoe), in 2008 to 64.65 % (2793 ktoe), in 2022 over the last fifteen years. Within the last fifteen years, the average contribution of light petroleum products has climbed from 25.15 % (382 ktoe), in 2008 to 35.19 % (1520 ktoe), in 2022. As shown in Fig. 4 b, the largest consumption year over this fifteen-year period was 2020, with a total of 4508 ktoe. The third fuel source for this sector was ethanol with a maximum of 7 ktoe,

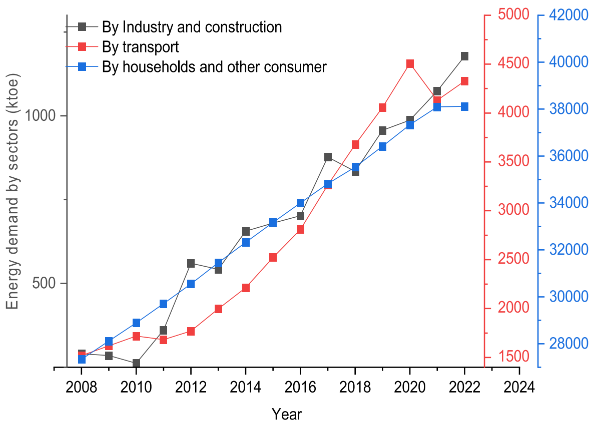


Fig. 5. Energy demand growth by those three sectors (Household and other consumer, transport, and Industry and construction), ktoe [27].

which is utilized for the blending of light petroleum (gasoline). Heavy petroleum usage climbed by two and a half times its value from 2008 to 2022. And this number is particularly large in the case of light petroleum use, which has increased fivefold over the last fifteen years. Electrical energy uses for Addis Ababa light rail began in February 2015 [28]. Furthermore, since 2018, Addis Ababa Djibouti Railway has used electricity as an energy source for transportation, and the data for this sector are not qualitatively organized, and its energy consumption is assumed to be less significant when compared to the rest of the sector's energy source [29]. But in the near future the involvement of electricity for the transport sector is expected to be significant since the government is forwarded a policy that appreciate the import of electric vehicle and put a legal restriction for the import of a car with internal combustion engine.

As indicated in Fig. 4 c, the industry and construction sectors' coal consumption grew from 4 ktoe (1.38 %) in 2008 to 576 ktoe (48.90 %) in 2022. The average increment rate during the last fifteen years was 58.06 %, with a peak of 332 % increase in coal consumption in 2012 and a negative 2.67 %, decline in coal consumption in 2018. Coal production began in 2017 at 2 ktoe and increased to 267 ktoe by 2022. In 2022, the industry and construction sector consumed 243 ktoe (20.63 %) of electricity, up from 98 ktoe (33.79 %) in 2008. From 2008 to 2022, the average increase in electricity use for the industry and construction sectors was 8.41 %, with a maximum increase of 35.91 % in 2016 and a high decrease of 38.46 % in 2017. Other petroleum products accounted for the third greatest energy share in the industry sector in 2022, at 18.76 % (221 ktoe), up from 1.72 % (5 ktoe) in 2008.

Heavy oil had the fourth highest energy share in the industry sector, accounting for 6.96 % (82 ktoe) in 2022, a decline from 46.21 % (134 ktoe) in 2008. The last energy utilized in the industry and construction sector is light petroleum; its percentage has declined from 16.90 % (49 ktoe) to 4.75 % (56 ktoe) from 2008 to 20222, but its usage has increased by an average of 13.64 %.

When we examine those three sectors in a single graph (Fig. 5), the time serious increment function for households, other customers, and transportation appears to be a smooth linear increment in most of the years, but there are some zigzags in the industry and construction sector. There is also a sharp decrease of transport energy demand in a year 2021 and the increment of energy demands for household and other user become almost similar in year 2021 and 2022, i.e. due to the increment of primary energy production was not significant as illustrated on Table 2. Based on the energy balance during the last fifteen years, the overall energy demanded by sector growth, and the percentage share of final consumption, useable energy accounts for approximately 94 % of total energy, with the remaining 5–6 % indicating various losses in conversion, transport and distribution, and statistical differences. The collected data on Table 1 included all the various losses and statistical difference that was 6 % through out those 15 years but Fig. 4 just examined a useful end user energy at the sector level which excluded those losses and statistical difference.

2.3. Economy

Energy demand and GDP growth are almost diagonally straight, as seen in Fig. 6 b, suggesting a linear relationship between the two. Over the previous five years, the GDP growth rate has decreased, falling from 9.50 % in 2017 to 5.32 % in 2022 (see Fig. 6 b). From 2000 to 2022, the average growth rate was 8.54 % as illustrated from Fig. 6 a.

Ethiopia's GDP grew from 732 billion birr (27.07 billion $) in 2008 to 2.35 trillion birrs (126.78 billion $) in 2022 [30,31], This growth demonstrated that there was more than triple GDP growth in the past fifteen years, as seen in Fig. 6 b. Fig. 6 a also shows that GDP has increased around sixfold in the last twenty-two years.

Ethiopia's inflation rate has been double-digit, especially since 2018 after 2012. There are some incidents that show a significant change, such as 2008, as a result of the global financial crisis. At the time, the general inflation rate was 55.2 %, with food inflation at 78.3 % and non-food inflation at 23.2 % (see Fig. 7). In 2022, the general inflation rate was 34 %, with 38.1 % food inflation and 28.4 % non-food inflation, as illustrated in Fig. 7. The inflation rate effect on energy requirement for the targeted years was employed as an independent variable in the multiple linear regression analysis.

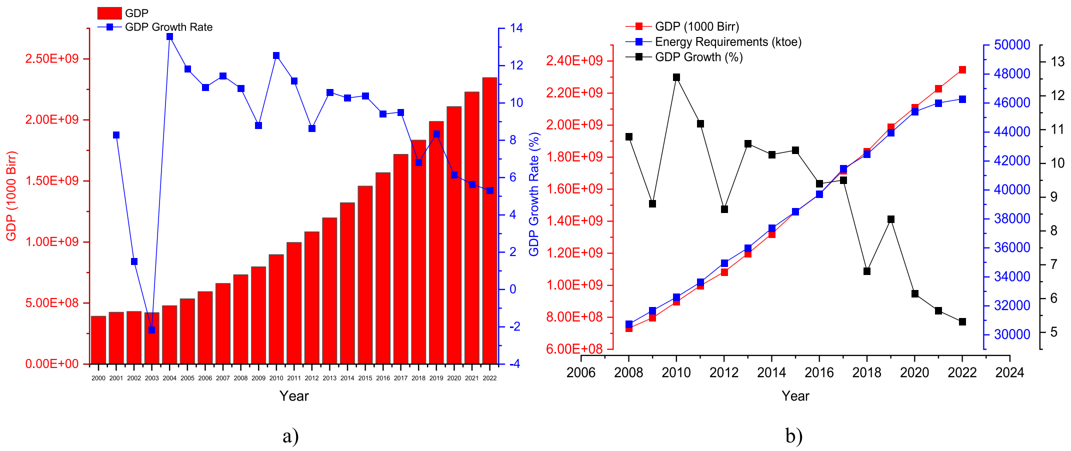


Fig. 6. a) GDP growth and GDP growth rate for the past twenty-three years (b) GDP, GDP growth rate and Energy consumption trend [27,30,31].

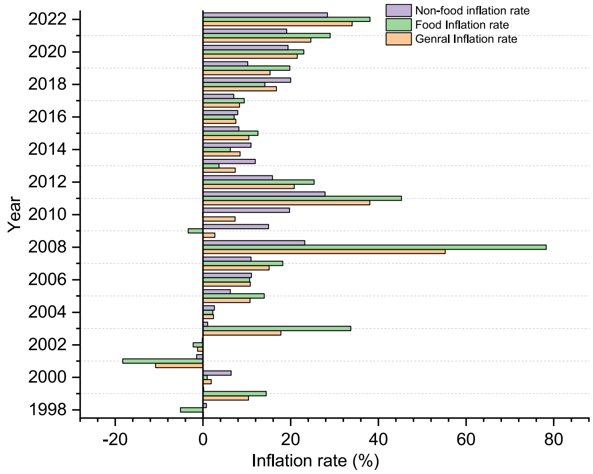


Fig. 7. Inflation rate [30,31].

2.4. Demographic trend

Population growth and urbanization growth rates are two other demographic parameters included as variables that can affect energy demand in multilinear regression analysis.

Ethiopia's population grew from 52 million in 1992 to 123 million in 2022, more than doubling in two decades (see Fig. 8), with an average annual growth rate of 2.92 %. This rapid population growth required effective energy demand forecasting in order to close future energy supply gaps generated by this phenomenon. The share of urban population has also expanded rapidly, nearly doubling in the last two decades from 13.2 % to 22.66 %, indicating that the share of rural population is less than 80 % (see Fig. 8). As we can see the pattern of urban population share growth, the urban population percentile has risen rapidly since 2007. Fig. 8 demonstrates that the two demographic trends were similar between 1992 and 2007.

3. Modelling approach

Energy models are characterized according to their objective, sectoral, energy type and geographical coverages, model structure, analytical technique, methodology, and time horizon [12]. Regardless of the classification criteria or parameters utilized, all energy models have relative strengths and disadvantages [32,33]. As a result, in practice, the circumstances of the economy being researched, the objective of the study, and data requirements and availability all influence the model used.

Once a consistent set of energy consumption/demand data is available, it is critical to understand why and how energy use varies across time, between sectors and energy types, industrial units, and household. Only a thorough assessment of the factors driving energy consumption can show the types of policy actions required to shift energy demand in terms of macroeconomic objectives. Such analyses can begin at the macro level, comparing energy consumption to population, economic activity level (gross output, GDP), economic activity structure, patterns of industrialization and urbanization, energy pricing, technical improvements, and so on. GDP,

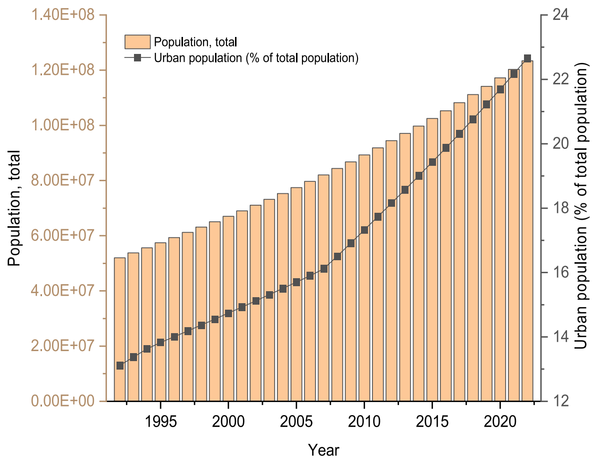


Fig. 8. Population growth and Urban population percentage share growth [31].

population, per capita income, and energy prices are common factors used to calculate demand [5].

Energy models are generally categorized according to their analytical methods (top-down and bottom-up). The top-down method reduces the complexity and number of components of the energy system [34,35]. The purpose of the analysis (forecasting, exploring or scenarios analysis, and backcasting), the underlying methodology (econometrics, macroeconomics, economic equilibrium, optimization, simulation, spreadsheet, backcasting, and multi-criteria methodologies), and the mathematical approach (linear programming, mixed integer programming, and dynamic programming), the data requirements (i.e., qualitative and quantitative, disaggregate and aggregate), the time horizon (i.e., short, medium, and long term), and the geographical coverage (i.e., local, national, regional, and global), [8,36,37].

This study used a top-down econometric and input-output analysis. Linear regression was used to tie national energy demand in general as a dependent variable to the total economic GDP predictor. In addition, certain forms of energy and sectoral energy demand are linked to national GDP. A multilinear regression revealed a linear relationship between four explanatory/predictor variables (GDP, total population, urban population, and inflation rate) and national energy demand responses. Regarding the research's goal, forecasting and scenario-based models are used. The long-term time horizon (fifteen years) was used to create the mathematical model and anticipate future 30-year energy consumption. The technique involved the use of aggregate quantitative data.

3.1. Overview of energy modelling approaches – State-of-the-Art

The analytical method is the first distinction that may be made in order to categorize energy system models: Top-down and bottom-up modelling methodologies are listed [32] as shown on Fig. 9 below.

Top-down (TD) models are commonly employed by governments and economists. The major purpose of these models is to connect the energy system to other macroeconomic sectors, which are then used to assess the macroeconomic links between the energy sector and the rest of the economy. It takes an economic approach, using aggregated economic data and a simplified description of technologies [37]. They often show the elements and complexity of the energy system in a simplified manner, rendering them effective for developing sector-specific policies which we implement this approach as a methodology for this research. These models try to depict the entire economy at the national level, as well as assess the aggregate implications of energy. Table 3 compares top-down and bottom-up modeling methodologies.

3.2. Energy demand model

Energy demand models can be static or dynamic, univariate or multivariate, and use approaches ranging from time series to hybrid models (Suganthi & Samuel, 2012). Energy models are created to ensure long-term progress for any nation. There are several methodological and mathematical techniques for estimating energy demand (Suganthi & Samuel, 2012). Several unique ways for managing energy demand were developed over the last decade in order to accurately forecast future energy needs. (Suganthi & Samuel, 2012) conducted an evaluation of various energy demand forecasting models. Traditional approaches to demand-side management include.

(i) time series,
(ii) regression,
(iii) econometrics, and
(iv) ARIMA (AutoRegressive Integrated Moving Average), as well as soft computing techniques like as fuzzy logic, genetic algorithms, and neural networks, are widely employed.

The goal of this research is to develop a mathematical model to accurately estimate future demand. The model takes into account variables including GDP growth rate, GDP structure, population growth, urbanization rate, and inflation rate. Econometric models tie energy consumption to other macroeconomic variables [38]. researched energy and economic growth in developed countries. Econometric models have been constructed to anticipate energy consumption in India based on factors such as GNP, energy price,

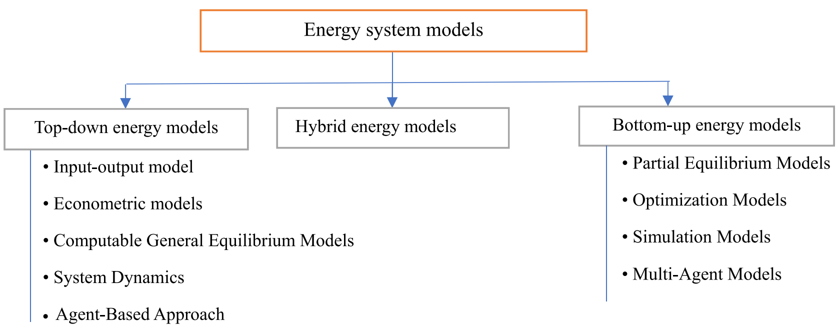


Fig. 9. Energy Modeling approach [34].

Table 3
Comparison of top-down and bottom-up models [8,37].

Criteria	Top-down	Bottom-up
Methodological approach	Econometrics or calibration for a single year Economic growth: estimated or exogenous	Engineering, spreadsheet-based analysis Simulation/optimization models
Level of disaggregation	Low: 1–10 sectors represented, use aggregated data to predict the future. Use aggregate economic indices to determine energy demand, but treat energy supply differently.	Hight: a variety of energy applications, use disaggregated data to explore the future Detail supply technologies employing disaggregated data but differ in managing energy demand.
Estimation	Provide pessimistic estimates for 'best' performance.	Provide optimistic estimates on 'best' performance
Behaviour representation	Thorough, but few energies relevant details	Detailed at end-user level but not comprehensive
Representation of technologies	Can not explicitly represent technologies. Based on macro input-output/econometric analysis. Reflect the market's adopted technology. Market behaviour determines the 'most efficient' technologies. Ignore the most efficient technology available, limiting possibilities for efficiency advancements.	Allow for extensive descriptions of technologies. Based on engineering and cost data Demonstrate technological potential. Efficient technologies can exist beyond the economic production frontier based on market behaviour. Overestimate the potential for efficiency improvements by disregarding market thresholds such as hidden costs and restrictions.
Market barriers and hidden costs of new technologies	Based on market behavior observations Cost of adopting new technologies is reflected in observed behavior Endogenize the behavioral interaction.	Are not influenced by market trends. Prevent the deployment of new technology Directly assess the cost of related to technology options.
Transaction costs of removing market barriers	High	Low
Trend and sectors interactions	Assume consistent historical patterns.	Assume insignificant interactions between the energy and other sectors.

technology, and population [39,40], and [41] [42,43]. found that these models are helpful in anticipating energy patterns in developing nations, like Ethiopia. Time series data of all those variables are collected for 15 years to project the future long term 30 years energy demand [44]. To do that linear regression and multilinear regression method are implemented to create a correlation between energy demand and those independent variables (GDP, population, urbanization rate and inflation rate).

The mathematical models relate GDP to total energy demand and various forms of energy demand that come from primary production such as biomass and electricity, as well as imported energy such as heavy petroleum, light petroleum, hard coal, and so on, as shown explicitly in Fig. 10 a. On the other hand, GDP is related to sectorial energy consumption, such as household and other consumers, transportation, industry, and construction, as illustrated in Fig. 10 b.

3.3. Forecasting process

In order to estimate the pattern of future energy consumption, demand forecasting is typically accomplished by projecting historical data or information into mathematical models [44]. Fig. 11 illustrates a typical energy demand forecasting procedure. Forecasting often begins with a solid and accessible historical energy database. The database should include energy demand data and other elements that impact energy use. The data are utilized as inputs for a forecast model, which produces the predicted energy consumption. This is a continual process that involves adding new data to the database and updating forecasts over time.

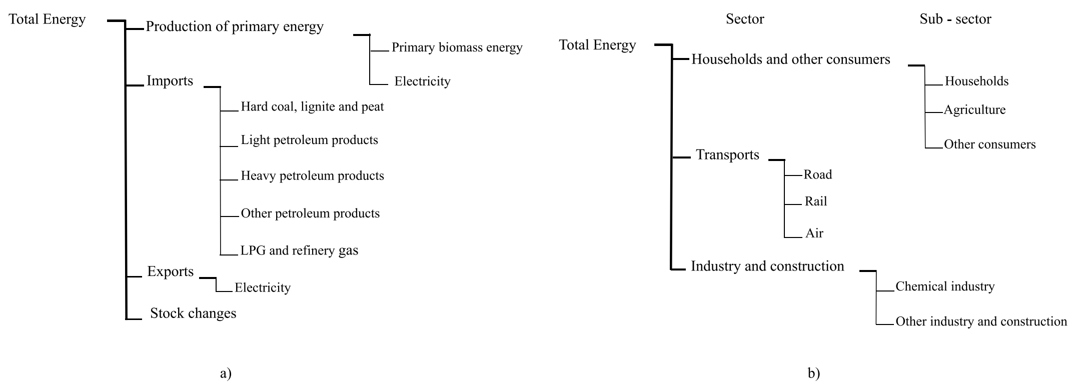


Fig. 10. Energy demand tree for demand projection, a) for the type of energy projection b) energy sector projection

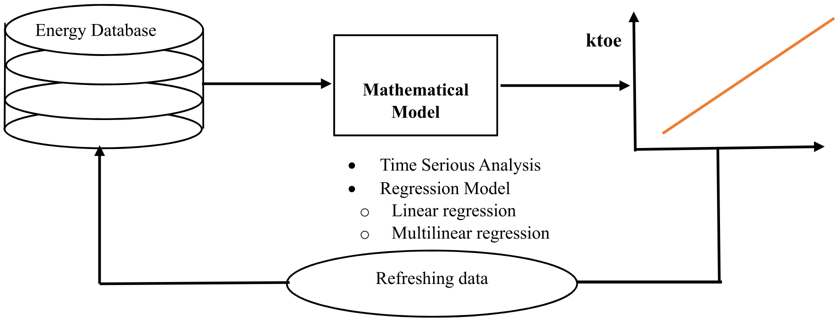


Fig. 11. Forecasting Model [44,45].

3.4. Forecasting methods

3.4.1. Mathematical model

Mathematical models will be used to describe the relationships between energy system inputs and outputs based on data analysis [45]. The two components can be explicitly chosen, in which case the model and curve-fitting techniques can be chosen independently or combined, as in the case of artificial intelligence-based or average approaches, in which the model and curve-fitting are inextricably linked [44].

Energy demand forecasting techniques can be categorized in a variety of ways. Curve fitting is one approach, while models such as static versus dynamic, empirical versus mathematical, univariate versus multivariate, etc., are used to classify the methodologies. Artificial intelligence technique versus statistics [44,46]. Statistical techniques with univariate mathematical dynamic model are used in this research.

Here, the following categories are used to guide discussions on the energy demand forecasting method.

- ❖ Averaging Method
- ❖ Mathematical Model based method
  - o Regression Method
  - o Autoregressive Method
- ❖ Artificial intelligence method

Here we use a mathematical model - based method, the regression method. One of the most prominent statistical tools for forecasting is regression (see Table 4). Regression analysis is used for forecasting energy demand. It includes two steps: The first step is to create a regression model that depicts the general relationship between variables that can influence demand (referred to as the forecaster/independent variable), here Gross Domestic Product (GDP), total population, urban population percentage and inflation rate are the forecaster for linear and multilinear regression, and energy demand (referred to as the response/dependent variable). Secondly, to perform regression analysis, which is an iterative method that entails repeatedly inspecting, validating, critiquing, and modifying the model's coefficients until a strong connection between the dependent and independent variables is discovered.

3.4.1.1. Simple linear regression. The mathematical expression of simple linear regression is as follows Eq (1), for linear fitting and Eq (2) for polynomial fitting [47,48],:

$$Y = (\beta_0 \pm c) + (\beta_1 \pm c)X + \varepsilon \qquad \text{Eq (1)}$$

$$Y = (\beta_0 \pm c) + (\beta_1 \pm c)X^1 + (\beta_2 \pm c)X^2 + \varepsilon \qquad \text{Eq (2)}$$

Where:

Y is the dependent or response variable, energy demand (ktoe);
X is the forecaster or independent variable, GDP 1000 birr;
β_0 and β_1 are the coefficients of regression; and c is constant value the upper and lower margin of the slop and the Y intercept
ε refers to Residual Sum Square (RSS) to calculate the difference between forecasted and observed data.

Table 4
Linear regression techniques classification [47].

Regression type		Response parameters	Predictor parameters	Regression equation
Univariate	Simple	1	1	$\widehat{Y} = \widehat{\beta}_0 + \widehat{\beta}_1 X$
	Multiple	1	≥2	$\widehat{Y} = \widehat{\beta}_0 + \widehat{\beta}_1 X_1 + \widehat{\beta}_2 X_2 + \ldots\ldots\ldots\ldots + \widehat{\beta}_p X_p$
Multivariate		≥2	≥1	$\widehat{Y}_i = \widehat{\beta}_{i,0} + \widehat{\beta}_{i,1} X_1 + \widehat{\beta}_{i,2} X_2 + \ldots\ldots\ldots\ldots + \widehat{\beta}_{i,p} X_p$

The error term is ε determined as the sum of squared differences between expected and observed data points and this value need to be very small closer to zero to have the best fit between the observed data point and expected linear data point. The sum of squared differences (error sum of square (ESS)) or residual sum of square (RSS) between predicted data points ($\hat{y}_i$) and observed data points (y_i) is shown in Eq (3)

$$ESS..or..RSS(\varepsilon) = \sum (y_i - \hat{y}_i)^2 \quad \text{Eq (3)}$$

3.4.1.2. Multiple linear regressions. Multiple linear regression uses more than one predictor variable. The mathematical expression for multiple linear regression is as follows in Eq (4) [47,48],:

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots\ldots\ldots + \beta_p X_p + \varepsilon \quad \text{Eq (4)}$$

Where:

Y is the dependent or response variable, energy demand (ktoe);

Predictor parameters (X_1 = GDP (1000 birr); X_2 = Total population; X_3 = Urbanization percentage;

X_4 = Inflation rate)

Regression coefficients (β_0, β_1, β_2 and β_4) are the coefficients of regression;

ε is the error to estimate the deviation of a forecasted value from the observed data.

The forecasted value from multiple linear regression is expressed in Eq (5)

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \ldots\ldots\ldots\ldots\ldots + \hat{\beta}_p X_p \quad \text{Eq (5)}$$

Where, $\hat{Y}$ is known as forecasted value and

β_1, is the regression coefficients need to estimate from the previous data

Weka 3.9.6 machine learning software, a powerful artificial intelligence software, is used for multi linear analysis.

3.5. Scenarios

The scenarios in this model are based on GDP growth rates. GDP average growth during the last twenty-two years, beginning in 2000, has been 8.54 %, and hence the scenarios offered for energy projection are based on that data. As a consequence, we advocated 10 % GDP growth as a high GDP growth, with of 8.5 % as business as usual (BAU), medium growth of 7.5 %, and low growth of 5 %. The basis for choosing this scenario was because the average GDP growth for the ten years beginning in 2008 and ending in 2017 was 10.03 %, the rest year from 2017 to 2022 was 6.45 %, and the overall average GDP growth for these fifteen years was 8.83 %. The expected GDP growth for the next 30 years is based on these assumptions, and the projected energy demand is matched with those scenarios, as are the energy demand calculations.

3.6. Validation

The mathematical model is validated with the actual energy demand by comparing the expected linear data with the observed actual data using those different scenarios. And that will justify whether that the mathematical model that are generate; the expected linear data will align the observed data.

4. Results and discussions

Energy forecasting begins with the creation of an acceptable mathematical model in relation to macroeconomic variables for the projection process, using 15 years of total energy consumption time series data and the assistance of certain statistical software such as Origin Graphing and Analysis 2022. This mathematical model is based on an econometric technique for the linear regression statical model, which examines the relationship between total energy growth and economic growth. The second form of top-down model is econometric models, which link energy use to other macroeconomic variables such as GDP. This strategy investigates the economic connections between the energy sector and macroeconomic indices such as GDP, employment, and gross value added [34]. To obtain the best representation of the actual data using the created mathematical formula, the fitting of the mathematical model is assessed with the actual data using linear and polynomial fit, with the assumption of alternative GDP growth rate scenarios.

A second multilinear regression is conducted using a powerful machine learning software, with total energy demand as the dependent variable and GDP, population growth, urbanization population share growth, and inflation rate as independent factors. The effect of those independent variables on energy consumption is analyzed using Weka 3.9.6 machine learning software, and the result is a mathematical model that combines the effect of those four independent variables on future energy demand prediction. This technique is based on the first top-down model, which is an input-output model that considers a variety of macroeconomic factors influencing specific energy demands.

In general, this energy forecasting mathematical models are characterized using a top-down analytical technique for forecasting and scenario analysis, using macroeconomics as the underlying methodology and linear functions with linear and polynomial fitting. The data needs are quantifiable and aggregated, with a 30-year forecast time horizon and nationwide geographic coverage.

4.1. Linear mathematical model based on actual energy demand data

For linear and polynomial fits, a linear mathematical model based on the econometric model technique is built, as shown in Fig. 12 a and b respectively. The linear fitting mathematical model between GDP growth from 732 billion birr in 2008 to 2.35 trillion birrs in 2022 and total energy requirement increase from 30,737 ktoe in 2008 to 46,283 ktoe in 2022 is related to the formula on Eq (6) which is developed based on Eq (1) and the value of Eq (3) or residual sum of square error for this formula is 2,125,500. Pearson's r correlation factor is 0.99737, R - Square (COD) value of 0.99475, and Adj R - Square of 0.99434, indicating that the linear relationship has a very strong linear fitting; however, because the Residual Sum of Squares (RSS) or Error Sum of Square (ESS) is high (2,125,500.56), additional analysis is required. After running the model, the RSS calculates the amount of error left between the regression function and the data set. In other words, the regression model explains the data better when the sum of squared residuals error is lower. A score of 0 indicates that the model is a perfect fit, however the values for this linear fit are extremely high, necessitating a polynomial fit.

$$y = \left(1.00{*}10^{-8} \pm 2.02{*}10^{-10}\right)x + (23,842.65 \pm 317.28) + 2,125,500 \qquad \text{Eq (6)}$$

$$y = \left(1.00{*}10^{-5} \pm 3.03{*}10^{-20}\right)x + \left(1.52{*}10^{-29} + 9.74{*}10^{-30}\right)x^2 + \left(23847.65 \pm 2.17{*}10^{-11}\right) + 3.63{*}10^{-22} \qquad \text{Eq (7)}$$

Furthermore, as illustrated in Fig. 12 b, the linear link is established using polynomial fitting for future investigation. The linear regression between GDP and energy demand with polynomial fitting produces the formula in Eq (7) based on the formula stated on Eq (2). The residual sum square error is very negligible less than 0.005, or $3.63{*}10^{-22}$, and the R-square (COD) and Adj R-square values are both 1. All of these numbers are acceptable, indicating that the model is a perfect fit, with a very modest RSS that is near to zero. The R-squared number and Adj-R value of 1 also indicate that the model is a perfect fit to the real data.

4.2. Linear mathematical model for different sectors

A similar method is used to explore the relationship between energy consumption growth in the three sectors (household and other consumer, transportation, and industry and construction) and GDP growth. Fig. 13, 14 and 15 show a clear linear regression of those three sectors with GDP using linear and polynomial fit. The linear regression with linear fit and polynomial fit is studied, and the linear fit, like the previous total energy consumption, fails to qualify due to its high Residual Sum of Squares (RSS) value. RSS values for households and other consumers, transport, and industry and construction are 1,697,662.28, 728,393.27, and 24,213.82 respectively.

The linear regression with polynomial and linear fit for those three sectors are investigated, and the linear regression equation for the polynomial fit is used for future forecasting plans based on the Residual Sum of Squares (RSS) value, which is very small and close to zero.

The linear equations for those three sectors are stated as follows: Eq (8), Eq (9) and Eq (10), with slop and y-intercepts, plus and minus constants to set their upper and lower limits, for the household and other consumer, transportation, industry, and construction sectors, respectively. The last number in those equations represents the residual sum of squares, which is significantly different from the expected result, which is 0.

$$y = \left(6.77{*}10^{-6} \pm 1.80{*}10^{-7}\right)x + (23,008.50 \pm 283.56) + 1,697,662.28 \qquad \text{Eq (8)}$$

$$y = \left(2.02{*}10^{-6} \pm 1.18{*}10^{-7}\right)x + (-215.87 \pm 185.74) + 728,393.27 \qquad \text{Eq (9)}$$

$$y = \left(5.53{*}10^{-10} \pm 2.15{*}10^{-11}\right)x + (-145.02 \pm 33.86) + 24213.82 \qquad \text{Eq (10)}$$

However, due to their RSS value, we go on to the polynomial fit, in which the RSS value for all sectors is close to zero, as illustrated in Figs. 13–15 b. As a result, the formula that will be used for projecting sectorial energy demand based on Eq (2) will be Eq (11), Eq (12) and Eq (13) as follows for those three sectors:

$$y = \left(6.77{*}10^{-6} \pm 1.44{*}10^{-20}\right)x + \left(-6.02{*}10^{-30} \pm 4.62{*}10^{-30}\right)x^2 + \left(23008.50 \pm 1.03{*}10^{-11}\right) + 8.17{*}10^{-23} \qquad \text{Eq (11)}$$

$$y = \left(2.02{*}10^{-6} \pm 1.07{*}10^{-21}\right)x + \left(-2.72{*}10^{-31} \pm 3.39{*}10^{-31}\right)x^2 + \left(-215.87 \pm 7.57{*}10^{-13}\right) + 4.41{*}10^{-25} \qquad \text{Eq (12)}$$

$$y = \left(5.53{*}10^{-10} \pm 3.46{*}10^{-25}\right)x + \left(4.50{*}10^{-38} \pm 1.11{*}10^{-37}\right)x^2 + \left(-145.02 \pm 2.48{*}10^{-13}\right) + 4.74{*}10^{-26} \qquad \text{Eq (13)}$$

4.3. Linear mathematical model for different energy type

The growth of those different energy types is briefly shown in Table 1, and this growth in relation to GDP growth for primary biomass energy, heavy petroleum, light petroleum, and electricity, which accounted for more than 98 % of total energy consumption, is shown in Fig. 16, 17, 18 and 19.

The association between different types of energy growth and GDP growth is similar to the one between different sectors of energy growth and GDP growth. Because biomass accounts for more than 85 % of total energy consumption and more than 98 % of household and other consumers use this primary biomass energy source, the growth in primary biomass energy demand follows a similar pattern to the growth in total energy demand, household and other consumer in relation to GDP, (see Figs. 12, Figs. 13 and 16).

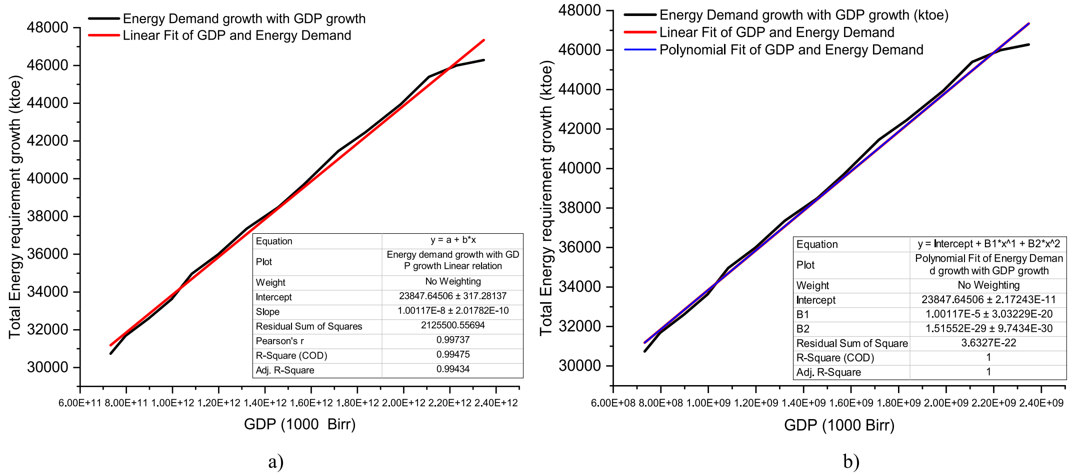


Fig. 12. Linear regression of Energy demand versus GDP growth with a) linear fit b) polynomial fit

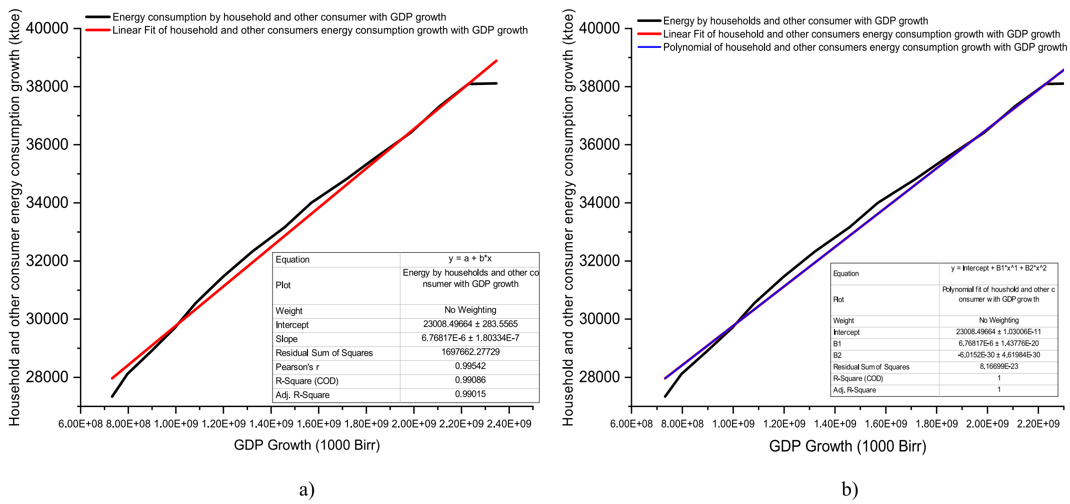


Fig. 13. Linear regression for household energy consumption versus GDP with a) linear and b) polynomial fit

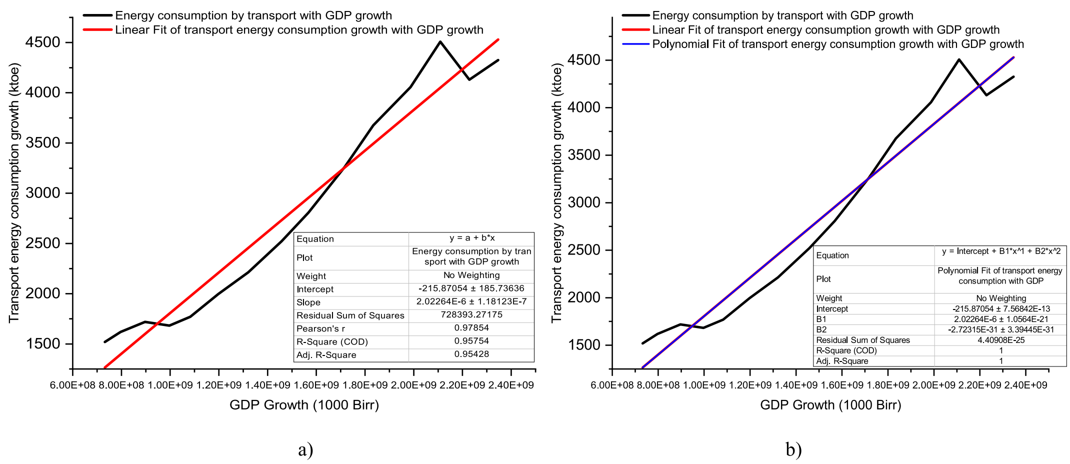
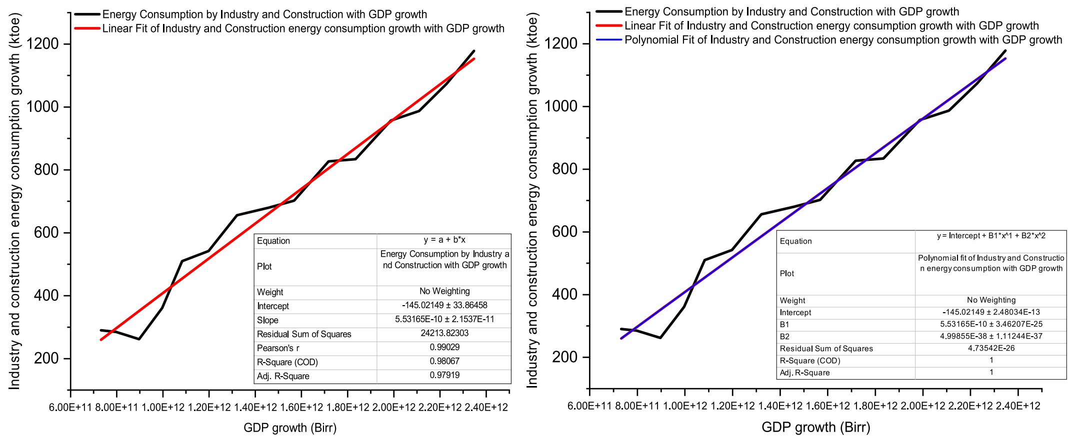
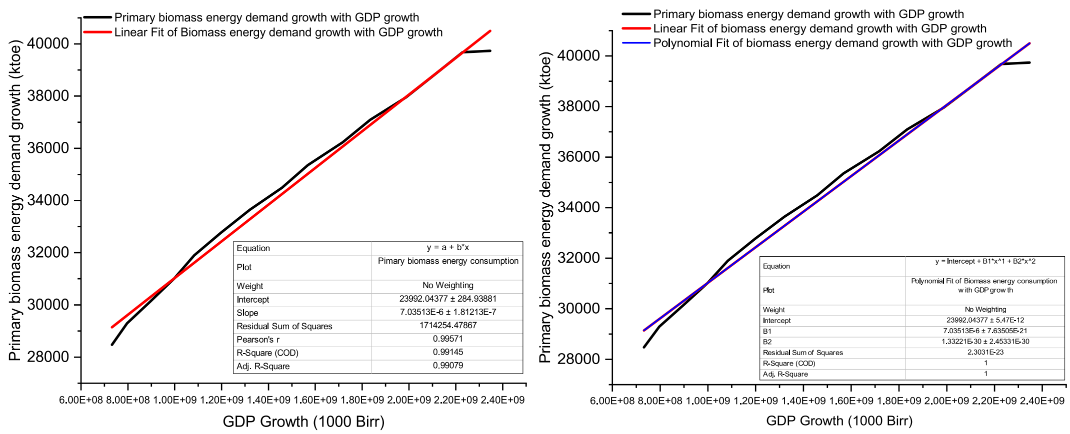


Fig. 14. Linear regression for transport energy consumption versus GDP with a) linear and b) polynomial fit



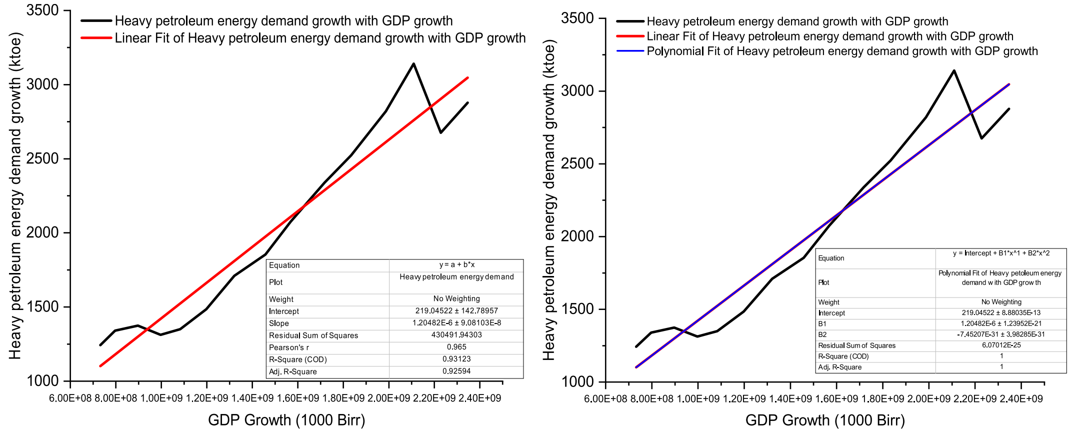
a) b)

Fig. 15. Linear regression for industry and construction energy consumption versus GDP with a) linear and b) polynomial fit



a) b)

Fig. 16. Linear regression for primary biomass demand versus GDP with a) linear and b) polynomial fit



a) b)

Fig. 17. Linear regression for heavy petroleum demand versus GDP with a) linear and b) polynomial fit

Similarly, heavy petroleum growth follows a similar pattern to that of the transport sector, with heavy petroleum accounting for more than 64 % of the transport sector's energy consumption over the last 15 years (see Figs. 14 and 17). Light petroleum follows a somewhat similar growth path to the industrial and construction sectors, due to comparable growth rates (see Figs. 15 and 18).

The electrical demand trend is a combination of household and other consumer, as well as industrial and construction sectors; it has a straight line like the household consumption trend and a bend curve at the beginning, similar to the industry and construction graph. As seen in Figs. 13, 15 and 19, more than half of the electricity used is for residential consumption, with the rest going to industry. For the four energy sources, primary biomass, heavy petroleum, light petroleum, and electricity, Eqs (14)–(17) respectively indicate the linear regression of those energy types with GDP growth using a polynomial fit.

$$y=(7.04*10^{-6}\pm 7.64*10^{-21})x+(1.33*10^{-30}\pm 2.45*10^{-30})x^2+(23992.04\pm 5.47*10^{-12})+2.30*10^{-23} \qquad \text{Eq (14)}$$

$$y=(1.20*10^{-6}\pm 1.24*10^{-21})x+(-7.45*10^{-31}\pm 3.98*10^{-31})x^2+(219.05\pm 8.88*10^{-13})+6.07*10^{-25} \qquad \text{Eq (15)}$$

$$y=(6.23*10^{-10}\pm 5.95*10^{-25})x+(2.14*10^{-37}\pm 1.91*10^{-37})x^2+(203.99\pm 4.26*10^{-13})+1.40*10^{-25} \qquad \text{Eq (16)}$$

$$y=(6.57*10^{-10}\pm 2.02*10^{-25})x+(1.79*10^{-39}\pm 6.50*10^{-38})x^2+(-219.70\pm 1.45*10^{-13})+1.62*10^{-26} \qquad \text{Eq (17)}$$

4.3.1. Validation of the mathematical model with actual data for total energy demand

After developing these two formulas, linear regression with linear and polynomial fit, with positive and negative constant values on the slop and y-intercept, the next step is to validate the linear mathematical models with linear and polynomial fit under the assumption of different GDP growth rates. In this case, the average GDP growth rate over the last two decades has been 8.54 %. Validation was carried out using four scenarios with growth rates of 5 %, 7.5 %, 8.5 %, and 10 % (low, moderate, business as usual and high GDP respectively). For the initial attempt, the slops and y-intercept values are used without adding or subtracting the constant values indicated in the computed formula Eq (6) and Eq (7), and the resulting graph is displayed in Fig. 20. According to Fig. 20, the graph is drawn with the base year 2008 initial GDP of 732,242,115,909 birr and four GDP growth rate scenarios, 5 %, 7.5 %, 8.5 %, and 10 %, to obtain the various energy demand growth with the given linear and polynomial function, and the line that is closest to the actual data is the one with 10 % GDP growth. This is because the average GDP growth rate during those ten years from 2008 to 2017 was 10.03 %, but this growth declined after 2017, and the average five-year GDP growth was 6.45 %, resulting in a reduction in energy demand increase after 2017, as shown in Fig. 2. The average GDP growth for those fifteen years starting from 2008 to 2022 was 8.83 %.

Fig. 21 depicts the energy demand variance of the two scenarios, namely energy demand increases with a 10 % GDP growth and 8.5 % with actual energy consumption. The gap between energy demand growth at a 10 % GDP growth rate and actual energy demand growth is very close to zero for the first ten years, and after 2017, the energy demand difference with 10 % GDP begins to vary greatly, whilst GDP at 8.5 % gets close to zero. Even if the residual sum of squares (RSS) of the linear fit is considerable in Eq (6) and very small in Eq (7) for the polynomial fit, the graphs of the two scenarios, high GDP growth, 10 % and business as usual (BAU), 8.5 %, with linear fit and polynomial fit exhibit similar lines as can be seen from Fig. 21.

As shown in Figs. 20 and 21, the effect of residual square sum (RSS) for linear fit was identical to that of polynomial fit; however, if the constant coefficient is used, the linear fit will provide a range for those various scenarios, as shown in Fig. 22 a and b. The top range is when the constant value is added to the slope and y-intercept, whereas the lower range is when the constant coefficient is deducted from the slope and y-intercept (see Fig. 22 b).

This circumstance did not work for polynomial fit; the constant coefficient for the slope and y-intercept made no impact on the

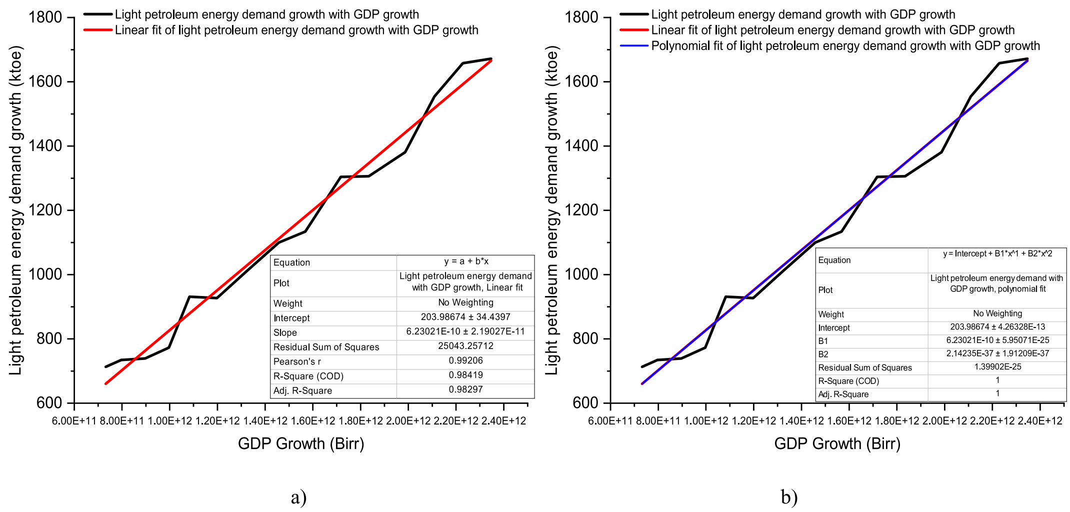


Fig. 18. Linear regression for light petroleum consumption versus GDP with a) linear and b) polynomial fit

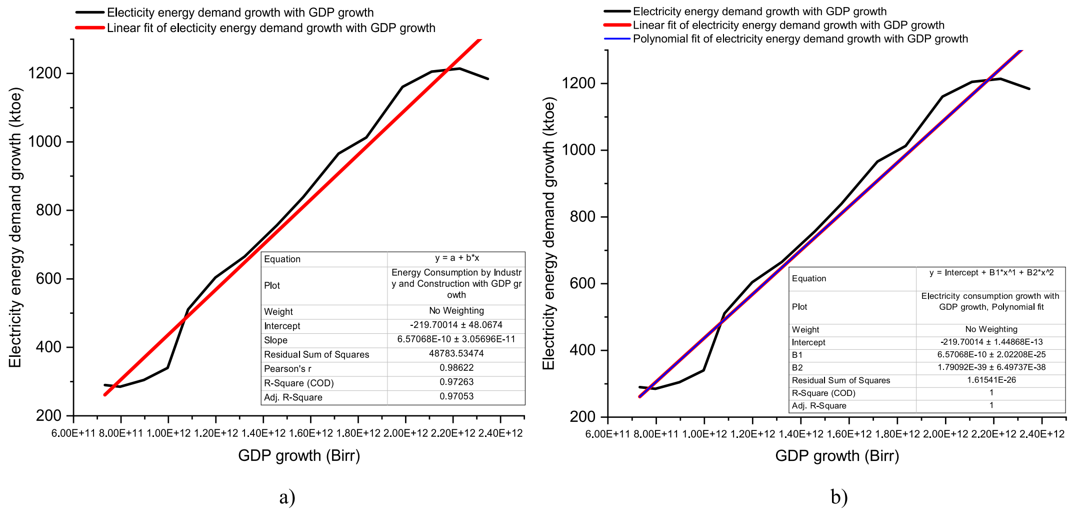


Fig. 19. Linear regression for electricity consumption versus GDP with a) linear and b) polynomial fit

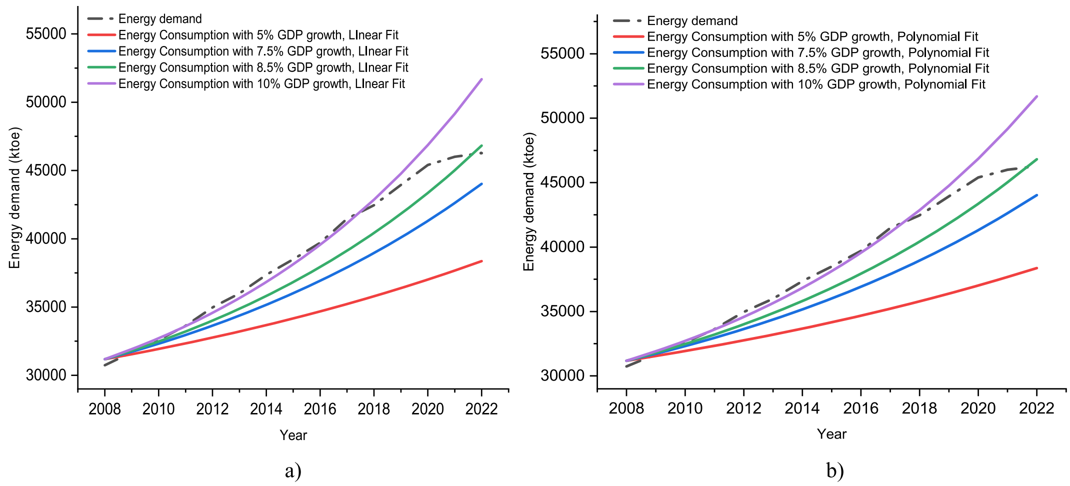


Fig. 20. Linear regression with a) Linear fit and b) polynomial fit, with different GDP growth rate

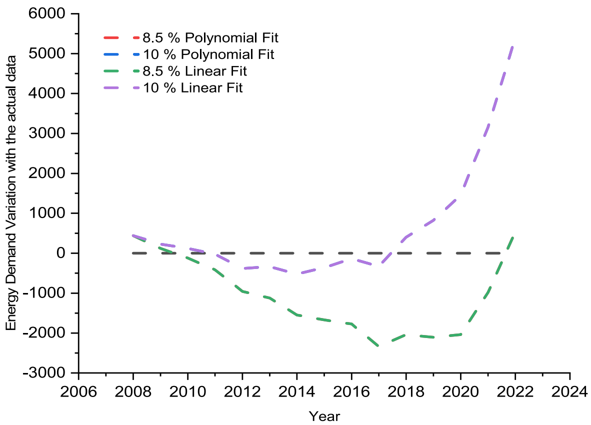


Fig. 21. Energy demand difference of those two scenarios with the actual energy demand

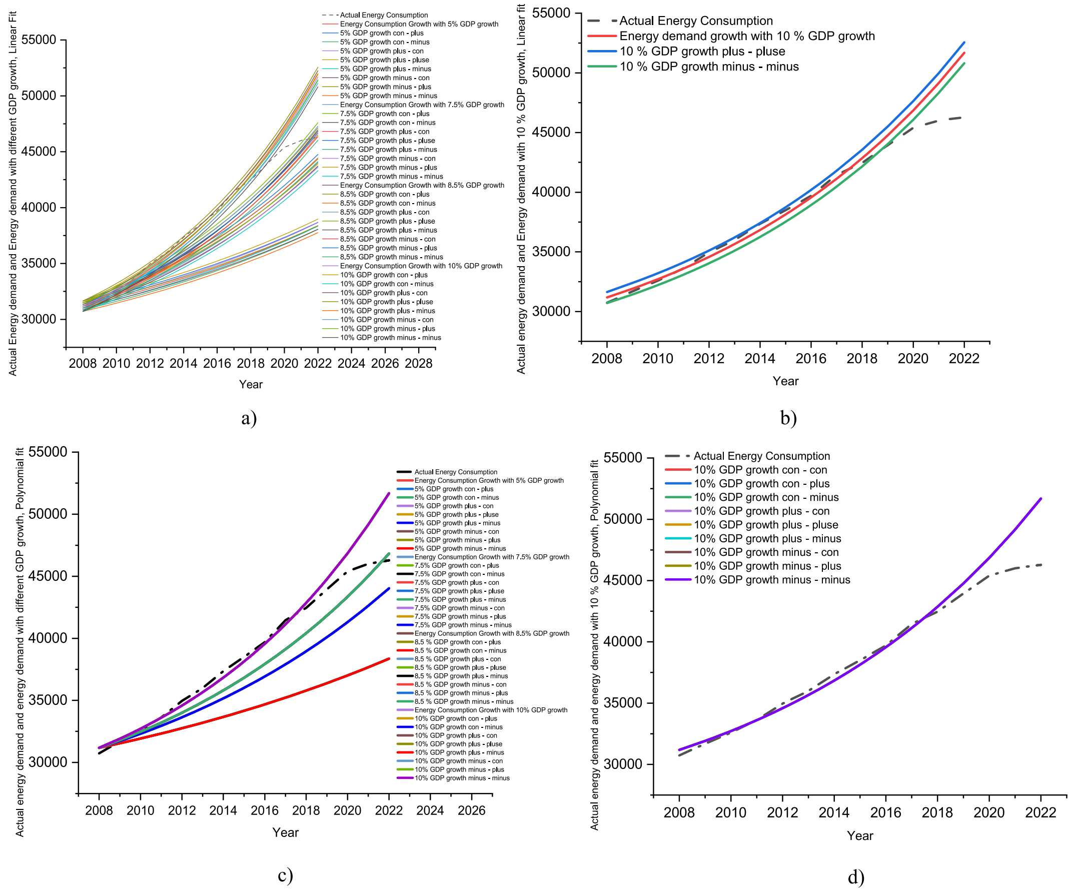


Fig. 22. Effects of those constant coefficient value to the slope and y-intercept, actual energy demand with a) Linear regression, linear fit and energy demand growth with different GDP growth assumption and different combination of constant coefficient on slope and y intercept b) Linear regression with linear fit for energy demand growth with 10 % GDP growth, plus and minus constant coefficient on the slope and y-intercept for the upper and lower range c) Linear regression with polynomial fit and energy demand growth with different GDP growth assumption and different combination of constant coefficient on slope and y intercept d) Linear regression with polynomial fit for energy demand growth with 10 % GDP growth and different combination of constant coefficient on the slope and y-intercept. Plus, minus and constant.[1].

[1] Plus, minus, or constant refers to adding, subtracting, or avoiding the constant coefficient on the slope or y-intercept.

linear regression graph for energy demand growth with varying GDP growth. As a result, we can use linear regression with linear fit without using the constant coefficients of the slope and y-intercept. The same is true for linear regression with polynomial fit, and whether we use the constant confidence for the slope or y-intercept makes no difference, as shown in Fig. 22 c and d. As a result, we can utilize Eq (6) and Eq (7) without the constant coefficients to predict energy consumption over the next thirty years. But here since the residual sum of square for the polynomial fit approach to zero we used Eq (7) for the forecasting process. Other validations for sectorial energy consumption and diverse energy type energy demand growth have yielded similar results to the validation for overall energy demand during the last fifteen years. The average percentage variation of energy consumption with the suggested linear regression formula with a polynomial fit and a 10 % GDP growth assumption, based on actual data, was 1.90 %, 3.02 %, and −3.35 % for households, transportation, and industries. A great percentage variation was after 2018 and this is due to the fact that the assumed GDP growth and the real GDP growth after this time create a great variation. Table 5 clearly shows all the linear regression with polynomial fit and all the statistical parameters that are produced from the linear regression with polynomial fit.

4.4. Multilinear regression

The multilinear regression is carried out using Weka 3.9.6 (Waikato Environment for Knowledge Analysis), a strong machine learning software package published under the GNU General Public License. It was created at the University of Waikato in New Zealand as a supplement to the book "Data Mining: Practical Machine Learning Tools and Techniques." Weka is a machine learning

Table 5
Total energy demand and Energy demand by sector and type of energy with its linear regression polynomial fit formula and its statistical figures

Description of the Energy Consumptions	Linear Regression Formula with Polynomial fit	Linear Fit Pearson's r	Polynomial Fit		
			Residual Sum of Square	R – Square (COD)	Adj. R – Square
Total energy consumption	$y = 1.00*10^{-3}x + 1.52*10^{-29}x^2 + 23847.65$	0.99737	$3.63*10^{-22}$	1	1
Household and other consumer	$y = 6.77*10^{-6}x - 6.02*10^{-30}x^2 + 23008.50$	0.99542	$8.17*10^{-23}$	1	1
Transport	$y = 2.02*10^{-6}x - 2.72*10^{-31}x^2 - 215.87$	0.97854	$4.41*10^{-25}$	1	1
Industry and Construction	$y = 5.53*10^{-10}x + 4.50*10^{-38}x^2 - 145.02$	0.98543	$4.74*10^{-26}$	1	1
Primary biomass	$y = 7.04*10^{-6}x + 1.33*10^{-30}x^2 + 23992.04$	0.99571	$2.30*10^{-23}$	1	1
Heavy petroleum	$y = 1.20*10^{-6}x - 7.45*10^{-31}x^2 + 219.05$	0.96500	$6.07*10^{-25}$	1	1
Light petroleum	$y = 6.23*10^{-10}x + 2.14*10^{-37}x^2 + 203.99$	0.99206	$1.40*10^{-25}$	1	1
Electricity	$y = 6.57*10^{-10}x + 1.79*10^{-39}x^2 - 219.70$	0.98622	$1.62*10^{-26}$	1	1

workbench designed to help apply machine learning techniques to a variety of real-world issues [49].

Multiple linear regression (MLR) is used to find a mathematical relationship between numerous random variables (see Table 4). In other words, MLR investigates how several independent variables are connected to a single dependent variable. The data in Table 6 are organized to see the effect of those four independent variables on the overall energy demand, which was initially written on a note pad with all of the required procedures and exported to Weka for analysis, all of the statistical data associated with each variable on Table 6 that are analyzed on Weka, illustrated on Table 7.

Because Waikato Environment for Knowledge Analysis (Weka) is a powerful machine learning tool, it is used to examine the multilinear regression relationship between the dependent variable, total energy demand, and the independent variables, population growth, urbanization growth rate, GDP growth, and overall inflation rate. In this situation, there are fifteen instances or raw data, i.e., fifteen years of data, and five attributes, which are five variables, one dependent and four independents.

Before beginning the analysis, all attributes (variables) must be normalized, or changed to a scale data range of 0–1, so that the quantitative impacts of all variables will be compared equally. Following the normalization technique, all attributes are quantified on a scale of 0–1, and the minimum, maximum, mean, and standard deviation of those four attributes are displayed in Table 8. In this case, the dependent variable is total energy demand, which is not subjected to min/max normalization because it is the value that will be forecast and is not changed in any way.

There are six tabs on the top of a Weka visual user interface (see Fig. 24). The first tab is the Preprocess tab, where all of the data will be imported and normalized on the software; the second is the Classify tab, where all of the statistical analysis will be performed and the final tab is Visualize, where the graphic relationships of each variable with each other in the order are displayed as shown in Fig. 25.

Under the Classify tab, the following test options are evaluated in conjunction with Linear Regression, Simple Linear Regression, Multilayer Perception, Gaussian Process, and Random Forest: Use training set, Cross-validation, and Percentage split with different percentages. A great result was produced for a percentage split of 85 % with tree M5P, Simple Linear regression, Linear regression with different attributes as illustrated in Fig. 24 and Table 9. That is a linear relationship between total energy demand, population growth, and actual GDP growth, urbanization expansion, as well as general inflation growth rate as it can be seen from Fig. 23 and 24. All associations have a correlation coefficient of one: with different, mean absolute error, root mean squared error, relative absolute error and root relative square error. This resulted in the multilinear regression model for total energy demand (TED), as shown in Table 9. Fifteen years data of Explanatory/Predictor/Independent variables were used to predict the response variable with the relationship shown in Fig. 23.

Where:
y = Total energy demand (ktoe)
x_1 = Population growth (individuals)
x_2 = Actual growth domestic product (GDP) growth (birr)
x_3 = General Inflation rate (%)
x_4 = Urbanization population share (%)

4.4.1. Validation for the multilinear regression

$$x_{normalized} = \frac{(x - x_{\min})}{(x_{\max} - x_{\min})} \qquad \text{Eq (22)}$$

Fig. 25 clearly indicates the ties of one characteristic to the other; with the exception of the general inflation rate, all variables have

Table 6
Data for Multilinear regression [27,30,31].

Year	Population Growth (individual)	Urbanization Population Share (%)	General Inflation Rate (%)	Actual GDP Growth (1000 birr)	Total Energy Consumption (ktoe)
2008	84,357,105	16.51	55.2	732,242,116	30737
2009	86,755,585	16.91	2.71	796,697,628	31683
2010	89,237,791	17.32	7.32	896,687,512	32599
2011	91,817,929	17.74	38.04	996,921,821	33627
2012	94,451,280	18.16	20.81	1,083,133,744	34964
2013	97,084,366	18.58	7.39	1,197,753,878	35994
2014	99,746,766	19.00	8.46	1,320,688,074	37357
2015	102,471,895	19.43	10.45	1,457,857,586	38495
2016	105,293,228	19.87	7.50	1,568,097,451	39701
2017	108,197,950	20.31	8.36	1,717,127,215	41461
2018	111,129,438	20.76	16.77	1,834,066,487	42459
2019	114,120,594	21.23	15.30	1,987,157,533	43939
2020	117,190,911	21.70	21.50	2,109,180,096	45399
2021	120,283,026	22.17	24.60	2,228,170,139	46002
2022	123,379,924	22.66	34.04	2,346,644,085	46283

Table 7
Statistical result from Weka related to those variables

Description	Minimum	Maximum	Mean	Standard Deviation
Population Growth (individual)	84,357,105	123,379,924	103,034,519	12,485,004
Urbanization Population Share (%)	16.51	22.66	19.49	1.959
General Inflation Rate (%)	2.71	55.2	18.563	14.447
Actual GDP Growth (birr)	732,242,115,909.40	2,346,644,085,000	1,484,828,357,559.43	535,564,387,751.17
Total Energy Consumption (ktoe)	30737	46283	38713.33	5376.06

Table 8
Normalized value of those four independent variables

Description	Minimum	Maximum	Mean	Standard Deviation
Population Growth (individual)	0	1	0.479	0.320
Urbanization Population Share (%)	0	1	0.485	0.319
Actual GDP Growth	0	1	0.302	0.275
General Inflation Rate (%)	0	1	0.466	0.332
Total energy demand (ktoe)	30737	46283	38713.33	5376.06

a strong association with each other, as seen by the diagonal line on the relationship of those different attributes.

The validation of the multilinear regression was performed by applying the formulas from the previous section Eq (18)for M5P classifier trees which the software selected with its criterial the most influential parameter, in this case it is the population growth, Eq (19) simple linear regression classifier that correlate actual GDP growth with total energy demand, Eq (20) linear regression with M5 or Greedy attribute selection method and the last formula Eq (21) was for linear regression classifier with "No attribute" (attribute selection method) to obtained the assumed total energy demand which is related with those variables to the actual data. The outcomes of those four linear regression formulas using those four variables with their normalized values and two attribute selection methods are compared to the actual data as illustrated in Fig. 26. All those four variables will be used on those formula after the data is normalized using Eq (22).

The results in Fig. 26 are very impressive; the maximum variance value for the M5P classified, Simple linear regression of GDP with actual EDG (energy demand growth), M5 or Greedy attribute method with actual EDG and "No attribute" with actual EDG was 1164.41 ktoe (2.52 %) of the actual data, 1058.59 ktoe (2.29 %), 827.38 ktoe (1.79 %) and 822.72 ktoe (1.74 %) respectively. The highest percentage variation of all multi linear regression is between 1.74 % and 2.52 % of the actual data. The overall average variation is 2.98 ktoe, 31.55 ktoe, 6.64 ktoe and 6.12 ktoe for M5P classified, Simple linear regression of GDP with EDG, M5 or Greedy attribute method and No attribute selections respectively, as shown in Fig. 27, the maximum variation occurred on the last year. Except for the last year the maximum percentage variation was between positive and negative 1.5 %.

4.5. Ethiopian energy demand forecasting for the next 30 years

The total energy demand forecasting for the next 30 years is based on linear regression with polynomial fit and multilinear regression formula, using these formulas and the GDP growth assumptions of 5 %, 7.5 %, 8.5 % and 10 %. The total energy demand for the next 30 years based on linear regression with polynomial fit is projected, as shown in Fig. 28.

Table 9
Simple linear and Multilinear regression formula

Classifier	Attribute Selection Method	Test Options – Percentage split 85 %	Summary					
			Correlation coefficient	Mean absolute error	Root mean squared error	Relative absolute error	Root relative square error	Total number of Instances
trees.M5P	-	$y = 16752.10x_1 + 30695.31$ …… ….. Eq (18)	1	53.69	54.93	0.7936%	0.775%	2
Simple Linear Regression	-	$y = 16162.94x_2 + 31178.65$…… ….. Eq (19)	1	370.0944	398.3877	5.4709%	5.6212%	2
Linear Regression	*M5 or Greedy method*	$y = 16155.45x_2 - 770.67x_3 + 31414.91$… ….. Eq (20)	1	439.3955	439.8999	6.4953%	6.2069%	2
Linear Regression	*No attribute selection*	$y = 16530.75x_2 - 781.54x_3 - 391.48x_4 + 31432.93$. Eq (21)	1	439.3955	439.8999	6.4953%	6.2069%	2

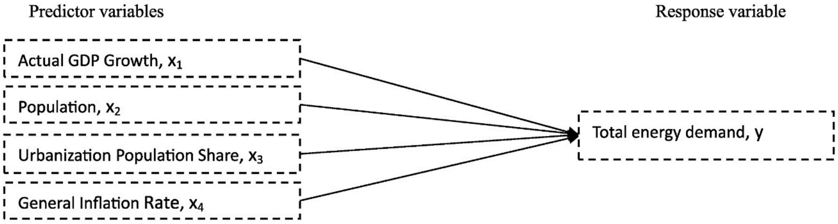


Fig. 23. Relationship of predictor variables with response variable

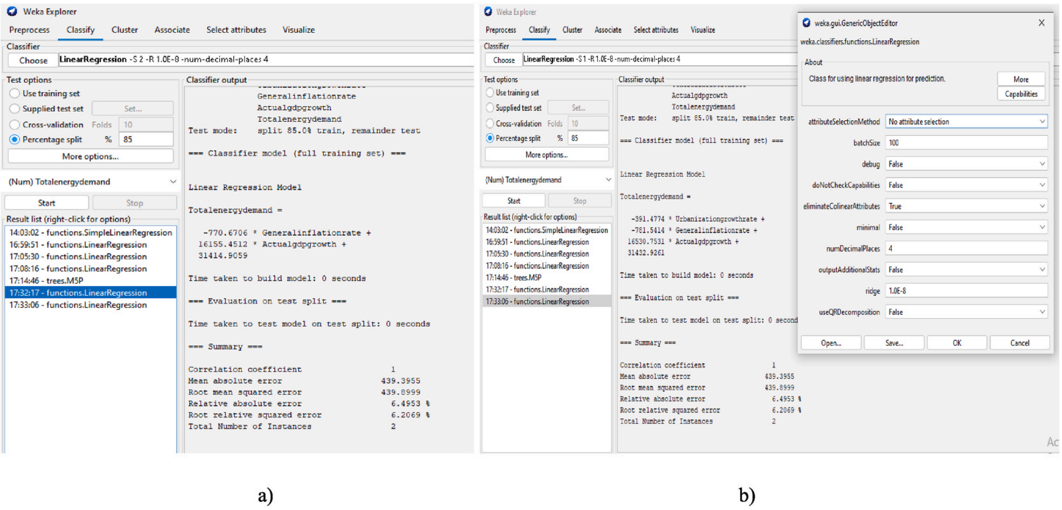


Fig. 24. Different test option under Classify tab a) GDP growth with general inflation rate with b) GDP growth, urbanization growth rate and general inflation rate

With a high GDP growth rate of 10 % projected, overall energy demand at the end of the 30th year will be 433,802.1 ktoe, approximately nine times the energy consumption in 2022. With 8.5 % Business as usual (BAU) GDP growth rate estimated, total energy demand will be 295,396 ktoe, or more than six times the 2022 energy demand. If GDP growth is assumed to be medium at 7.5 %, total energy demand is predicted to reach 229,536 ktoe, roughly five time that of 2020. With lower GDP growth of 5 % the estimated project shows us the energy demand will be 125,387 ktoe which is more than 2.5 time of the energy demand in 2022. As a result, based on projected GDP growth, it is simple to estimate the amount of energy required in the future for 30 years, as shown in Fig. 28. The projection can also be tested using multilinear regression with various classifier and attribute selection methods, such as M5P classified population growth with GDP, Simple linear regression of GDP with actual EDG (energy demand growth), M5 or Greedy attribute method with actual EDG, and "No attribute". Since there is little difference between these methods based on their relationship with the actual data of those fifteen years estimation graph shown on the validation part of these four methods, Fig. 26, it is preferable to use the M5P classified and Simple linear regression approaches to anticipate energy demand over the next 30 years. When we employed this technique, we projected three variables: the population number, the rate of urbanization and actual GDP growth. The average population growth rate over the last thirty years from 1992 to 2022 was 2.92 %, while urbanization growth was comparable, at 1.84 %. With a population growth rate of 2.92 % and urbanization growth rate of 1.84 %, Fig. 29 show that the population and urbanization growth rates are expected to be around 293 million and 39 %, respectively at 2052. As we can illustrated from Fig. 28 the GDP growth for those four different scenarios is projected and for the second attribute of a multilinear regression of Eq (19), BAU is selected to project the total energy demand as shown in Table 10.

4.5.1. Energy demand projection for different sectors and energy types

In comparison to the previous stage, the energy demand projections for those three sectors are determined by the GDP growth rate. After 30 years, the residential, transportation, and industrial sectors have the biggest energy demand at 300,148.39 ktoe, 82,606.25 ktoe, and 26,695.29 ktoe, respectively. Their minimum forecasts are: 57677.97 ktoe, 20297.87 ktoe, and 5465.21 ktoe. Household and other consumer demand are predicted to increase by approximately 8-fold for maximum growth and 1.5-fold for minimum GDP growth. The transport sector's growth is expected to increase 19-fold for maximum growth and 5- fold for minimum GDP growth rate. Finally, industry and construction are expected to increase around 23-fold for maximum growth and 4.5-fold for minimum GDP growth as it can be clearly seen from Table 10. The growth rate in the industry and construction sectors is predicted to accelerate.

The numerous energy sources are forecasted for thirty years in the same way as the various energy-consuming sectors are, as shown

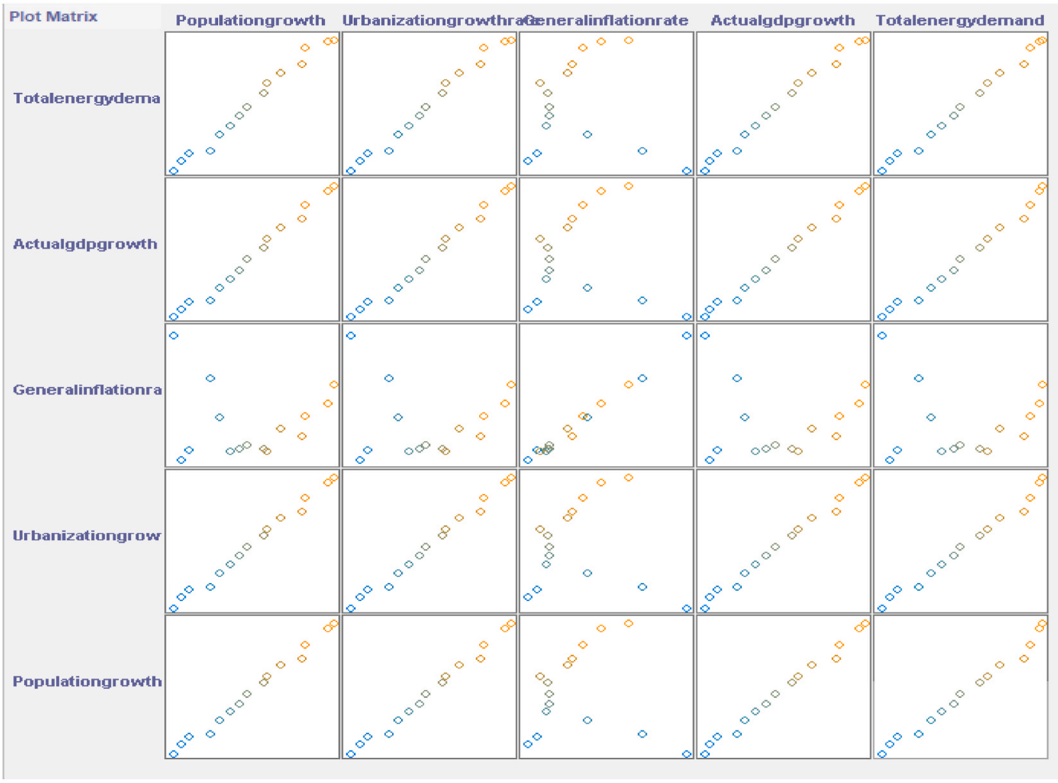


Fig. 25. Plot Matrix of those five variables

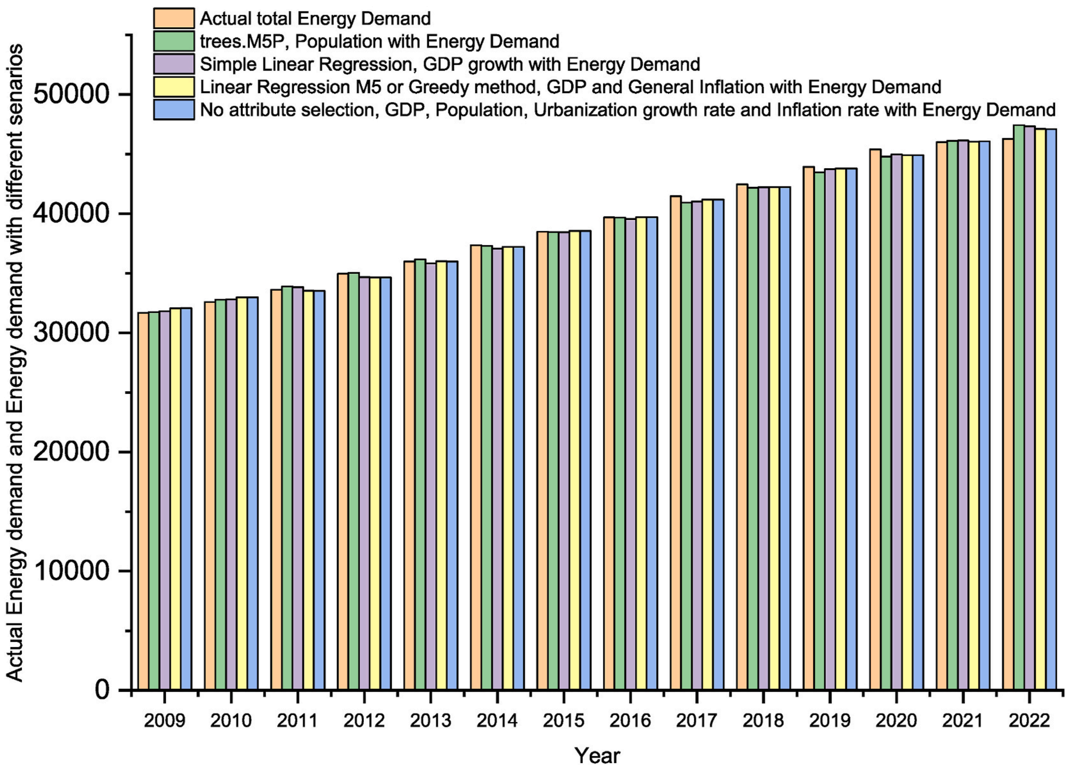


Fig. 26. Validation graph for Multilinear regression with different attribute selection method

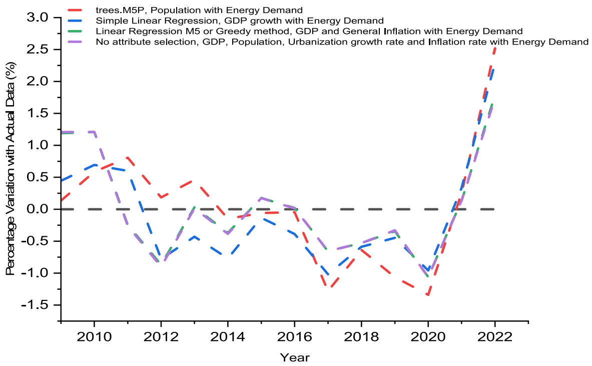


Fig. 27. Percentage variation of those alternatives' multilinear regression EDG with the actual EDG

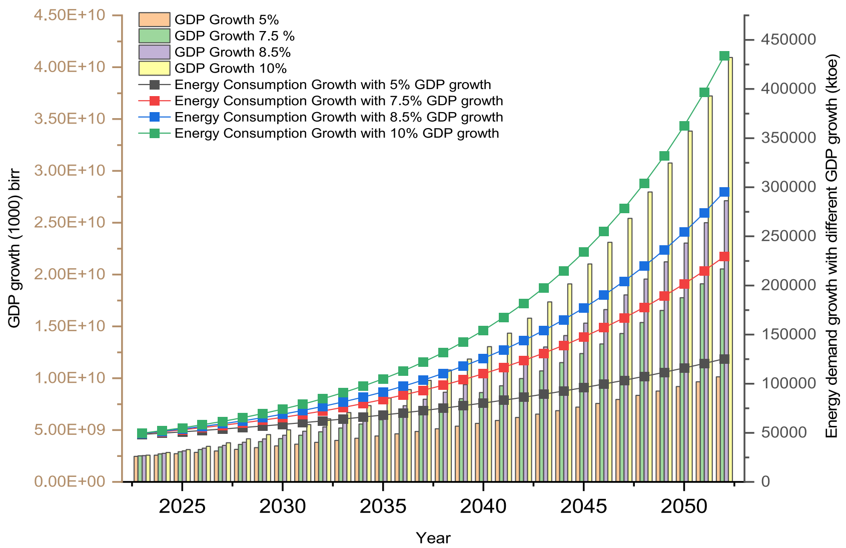


Fig. 28. Total energy demand for future 30 years

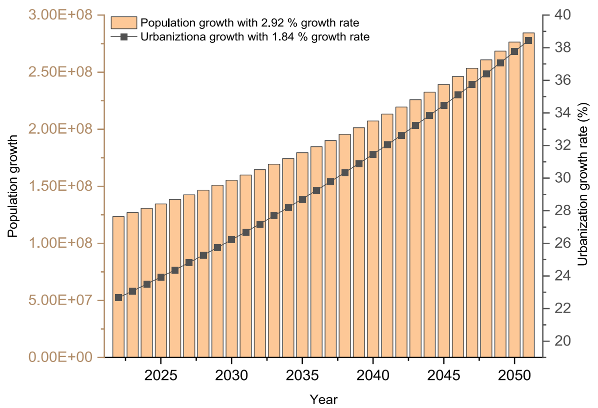


Fig. 29. Population and Urbanization population share projection for 30 years

in Table 11. The estimated energy demand for the various forms of energy over the next thirty years is given. Similarly to the last fifteen-year energy trend, biomass will continue to dominate in the future. Based on a 10 % GDP growth forecast, the percentage of biomass in contrast to other energy types is expected to be 75.37 %, 11.97 % for heavy petroleum, 6.45 % for electricity, and 6.21 % for light petroleum. Within the next 30 years, electricity will overtake light petroleum as the third-largest source of energy.

Table 10
Total and different sector energy demand forecasted for 30 years

Different Mathematical models and sectors	GDP growth	Energy Demand Projection (ktoe)							
		2024	2028	2032	2036	2040	2044	2048	2052
Total Energy demand (ED) Projection	8.5 %	51,505.25	62,177.17	76,966.96	97,463.50	125,868.82	165,234.58	219,789.96	295,396.01
trees M5P, with Population growth		49,115.73	53,076.92	57,341.99	61,934.22	66,878.74	72,202.56	77,934.77	84,106.71
Simple Linear Regression (SLR)	8.5 %	49,782.54	56,961.01	66,909.35	80,696.36	99,803.19	126,282.57	162,979.24	213,835.65
	10 %	54,353.17	65,108.47	80,855.30	103,910.23	137,664.96	187,085.25	259,441.51	365,378.30
With Linear Regression and Polynomial fitrowhead									
House hold and other consumer energy demand forecast	5 %	40,518.94	42,313.76	44,292.55	46,474.16	48,879.39	51,531.16	54,454.73	57,677.97
	7.5 %	41,362.69	47,519.96	55,742.80	66,724.15	81,389.40	100,974.40	127,129.55	162,058.95
	8.5 %	41,705.76	48,920.26	58,918.53	72,774.74	91,977.47	118,589.75	155,470.61	206,582.27
	10 %	42,226.30	51,145.29	83,322.21	51,145.29	111,313.81	152,296.30	212,298.77	300,148.39
Transport energy demand forecast	5 %	5017.05	6144.78	7515.54	9181.71	11,206.95	1, 3668.63	16,660.83	20,297.87
	7.5 %	5269.21	7109.28	9566.64	12,848.37	17,231.03	23,083.92	30,900.28	41,338.79
	8.5 %	5371.73	7527.75	10,515.70	14,656.57	20,395.23	28,348.20	39,369.89	54,644.40
	10 %	5527.29	8192.70	12,095.11	17,808.64	26,173.81	38,421.26	56,352.76	82,606.25
Industry and construction energy demand forecast	5 %	1286.11	1594.53	1969.42	2425.09	2979.97	3652.20	4470.53	5465.21
	7.5 %	1355.07	1858.31	2530.37	3427.87	4626.47	6227.16	8364.83	11,219.62
	8.5 %	1390.70	2103.42	3146.92	4674.72	6911.56	10,186.51	14,981.38	22,001.54
	10 %	1716.18	2579.96	3844.62	5696.21	8407.13	12,376.18	18,187.27	26,695.29

Table 11
Different energy type demand forecasted for 30 years

Energy Type	GDP growth	Energy Demand Projection (ktoe)							
		2024	2028	2032	2036	2040	2044	2048	2052
With Linear regression polynomial Fit									
Primary biomass	5 %	42,193.16	46,115.61	50,883.38	56,678.63	63,722.79	72,285.02	82,692.45	95,342.76
	7.5 %	43,070.19	49,470.33	58,017.50	69,431.99	84,675.70	105,033.19	132,219.99	168,527.13
	8.5 %	43,426.79	50,925.85	61,318.50	75,721.23	95,681.39	123,343.35	161,678.92	214,806.60
	10 %	43,967.87	53,238.65	66,812.00	86,684.74	11,5780.42	158,379.40	220,748.58	312,063.29
Heavy Petroleum	5 %	3336.13	4007.88	4824.39	5816.87	7023.24	8489.59	10,271.94	12,438.40
	7.5 %	3486.32	4582.40	6046.17	8000.99	10,611.59	14,097.96	18,753.91	24,971.79
	8.5 %	3547.39	4831.67	6611.49	9078.07	12,496.40	17,233.72	23,798.98	32,897.50
	10 %	3640.06	5227.75	7552.29	10,955.65	15,938.51	23,233.91	33,915.11	49,553.46
Light petroleum	5 %	1815.85	2163.22	2585.44	3098.66	3722.48	4480.74	5402.41	6522.70
	7.5 %	1893.52	2460.31	3217.23	4228.08	5578.04	7380.87	9788.50	13,003.81
	8.5 %	1925.10	2589.21	3509.56	4785.05	6552.69	9002.40	12,397.34	17,102.25
	10 %	1973.02	2794.02	3996.06	5755.96	8332.63	12,105.14	17,628.46	25,715.16
Electricity	5 %	1480.25	1846.60	2291.90	2833.17	3491.08	4290.77	5262.81	6444.32
	7.5 %	1562.16	2159.92	2958.21	4024.31	5448.04	7349.39	9888.59	13,279.61
	8.5 %	1595.47	2295.87	3266.52	4611.71	6475.95	9059.53	12,640.00	17,602.02
	10 %	1646.00	2511.88	3779.60	5635.68	8353.16	12,331.83	18,156.99	26,685.62

Similarly, to the prior assessment for sectoral energy demand forecasting, the rate of GDP growth influences energy demand predictions for those four energy types. After 30 years, the following maximum energy demand levels are expected: 312,063.29 ktoe, 49,553.46 ktoe, 25,715.16 ktoe, and 26,685.62 ktoe, from biomass, heavy petroleum, light petroleum and electricity respectively for the high GDP growth. Their respective minimum projections are 95,342.76 ktoe, 12,438.40 ktoe, 6522.70 ktoe, and 6444.32 ktoe. The expected demand increases for biomass, heavy petroleum, light petroleum, and electricity are 214,806.60 ktoe, 32,897.50 ktoe, 17,102.25 ktoe, and 17,602.02 ktoe, respectively, with business as usual (BAU) GDP growth of 8.5 % as it is illustrated on Table 11.

The energy demand for biomass is expected to increase around eight - fold under the assumption of 10 % GDP growth, and 2.4 times under the assumption of 5 % GDP growth. Heavy petroleum production is anticipated to increase 17 -fold from 2878 ktoe to 49,553.46 ktoe for maximum growth and more than fourfold for minimal GDP growth rate. Heavy petroleum is expected to reach 32,897.50 ktoe if GDP growth remains as business as usual at 8.5 % as it can clearly see from Table 11. With high, moderate, and low GDP growth, light petroleum is anticipated to increase 15-fold, 7.8-fold, and around 4-fold from 1672 ktoe. Finally, at maximum and minimum GDP growth rates, electricity is anticipated to rise 22.5- fold (from 1184 ktoe to 26,685.62 ktoe) and 5.4-fold (from 1184 ktoe to 6444.32 ktoe), respectively. This energy type is anticipated to develop roughly to elevenfold, 13,279.61 ktoe, if GDP growth is assumed to be modest (7.5 %). All the detail figurative description of those different energy type expected growth are depicted on Table 11.

5. Conclusion

All portion of the work was devoted to developing a forecasting model based on fifteen years of real data. A linear regression with polynomial fit was used to forecast overall energy demand, energy for the three sectors (residential, transportation, and industrial), and four energy types (biomass, heavy petroleum, light petroleum, and electricity) over a 30-year period. The development of mathematical models using various methodologies is done correctly, and multiple formulas for projecting total energy, distinct sectorial energy demand, and energy types have been proposed. The formulas have been tested with different scenarios using actual data, so there will be no problems with their use. Estimating the appropriate GDP growth rate for future projections is one of the critical tasks that must be done in order to achieve the desired results for the following 30 years. Reliable GDP projections can accurately predict future energy demand, assisting policymakers in determining which type of energy to generate or import and how much to invest. This allows for more efficient allocation of finance towards prioritized energy types and sector. Total energy is raised from 46283 ktoe in 2022 to 6.4-fold in 2052 to 295,396.01 ktoe with the assumption of 8.5 % GDP growth, while this number is predicted to be 7.9-fold or 365,378.30 ktoe under the 10 % GDP growth scenario.

A multi-linear regression with GDP, population growth, urbanization growth rate, and general inflation rate as independent factors and total energy consumption as a dependent variable was also conducted. This method also anticipates energy use for the next 30 years, employing trees M5P, with Population growth, Simple Linear Regression (SLR) with different GDP growth.

CRediT authorship contribution statement

Arkbom Hailu: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Geremew Teklu:** Writing – review & editing, Supervision, Conceptualization. **Antigen Birhan:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Yiheyis Eshetu:** Writing – review & editing, Resources, Investigation, Formal analysis, Data curation. **Ebisa Regasa:** Resources, Investigation, Formal analysis, Data curation. **Tinsae Wondimu:** Resources, Investigation, Formal analysis, Data curation.

Data availability statement

Data included in article/supplementary material/referenced in article.

Additional information

No additional information is available for this paper.

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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.

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