2030 Energy Pathways in Côte d'Ivoire: "A Business as Usual" Analysis

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ABSTRACT---- *Forecasting future energy demand values is of paramount importance for proper resources planning. This paper examines energy outlook for the coming decade in Côte d'Ivoire presented as a business as usual scenario. We, therefore, build a forecasting model using the Autoregressive Integrated Moving Average (ARIMA) to estimate primary energy demand and energy demand by fuels. The results indicate that energy demand will increase steadily within the forecasted period (2017-2030). However, the annual growth rate of each fuel, including the primary energy demand item, will first rise from the year 1990 to the year 2016 and then decrease within the forecasted period except hydropower that will experience a steady increase from 1990 to 2030. Furthermore, it is noticed that the energy structure of the country will still be biofuels (fuelwood and charcoal) intensive with a significant presence of conventional sources of energy. Based on these findings, we propose some policy recommendations.*

Keywords----- primary energy demand, energy forecast, energy, ARIMA, forecasting, Côte d'Ivoire

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1. INTRODUCTION

Energy lies in the hearts of all countries' core interests[1]. This statement is fully justified, as energy is a capital driver of social and economic progress. As a result, long-term energy demand prediction is of paramount importance for the macro planning of not only the energy sector but also the society as a whole.

Côte d'Ivoire is an under-developed sub-Sahara African country. The country has experienced smooth growth over the past seven years, evidenced by a GDP growth that has been over 7% since 2012 [2]. Like any country in the developing phase, energy demand has increased during the period 1990-2016. Besides, biofuel (charcoal and fuelwood) makes up a fair proportion in the energy mix as discussed by [3]. The considerable population growth (2.5%/year since 2012)[2], and the high pressure exerted on forest resources and natural ecosystems make it urgent to predict energy demand in the long run for policy adjustments.

The forecasting methods can be broadly classified into two major categories, namely causal and time series models. In causal models, a relationship is established between the energy demand as the output and some input variables of various types (economic, social, weather parameters…). Support vector regression, artificial neural network, and general regression models are instances of causal models. On the other hand, time series models use historical data to estimate future values of a variable. In other words, they apply a simple known geological principle, which is that the past is the key to the future. Linear time series models such as the autoregressive integrated moving average (ARIMA) and exponential smoothing have been extensively used for forecasting energy consumption.

Forecasting future values of energy demand is a difficult task because of the involvement of many unknown external parameters [4]**.**

Several studies address energy demand forecasting using a kind of causal methods. Among them, the electricity demand in Japan is forecasted using a neural network from the year 1999 to 2020 [5]. Ten input factors, mostly economic data are used to feed the neural networks. [6] estimate the Greek electrical energy consumption for the period 2005-2015 using a neural network. [7] develop a deep neural network combining stacked autoencoder and multilayer perceptrons to predict electricity demand in Australia within a two-year range. They conclude that the deep neural network performs better than the classic one, especially for one to two-year prediction horizon. [8] predicts the electricity demand in Jordan from 2015 to 2029 using the back-propagation and the radial basis function neural networks. [9] apply wavelet and neural networks for long-term load forecasting. They use Gross State Product, consumers' price index, electricity tariff and population as input variables. [10] resort to support vector machines to forecast electricity within a five-year range. Similarly, other

authors including [11], [12], [13] rely on either neural network or support vector regression to come up to a long-term energy demand prediction.

Some studies shed light on time series models. ARIMA makes up a fair proportion of the energy demand forecast. Some of the works include [14], [15], [16], [17] and [18]. They either use ARIMA as a standalone forecasting method or for a comparison purpose. The predictive accuracy is regarded as being generally satisfying.

Causal methods using computational intelligence techniques such as neural networks and support vector machines can map non-linear relationships and overcome discontinuities, whereas linear models such as ARIMA can only model linear patterns.

As no method strictly outperforms others in all situations [19], hybrid techniques have massively appeared to compensate both the aforementioned setbacks. Mostly, linear models such as ARIMA, exponential smoothing, multiple linear regression (MLR), moving average, and nonlinear models as artificial neural network (ANN) and support vector regression (SVR) are combined. Several hybridization techniques have been documented in the literature: ARIMA and ANN [20-25], ARIMA and SVR [26-28], seasonal autoregressive moving average (SARIMA) and SVR [29], MLR and ANN [30], exponential smoothing and ANN [31] and SVR and ARIMA[32].

In Côte d'Ivoire, the literature about energy forecast is inexistent. The nexus energy consumption and economic growth is discussed instead [33, 34].

The existing literature about energy demand forecast is particularly rich and elaborated. It constitutes a solid scientific basis. However, most papers focus on electricity demand, and as discussed earlier the topic of energy demand forecasting in Côte d'Ivoire is yet to be explored.

To fill these gaps, a case study of Côte d'Ivoire is proposed. It is going to contribute by enriching the literature with a forecasting model based on primary energy consumption. We assess the energy system in Côte d'Ivoire up the next decade under a business as usual scenario, which corresponds to the forecast scenario built with ARIMA.

The remainder of this paper is organized as follows: the methodology is first discussed in section 2. Section 3 describes the data, and the model evaluation adopted. The results and discussions are presented in section 4. Eventually, a conclusion is drawn in part 5.

2. METHODOLOGY

In this study, we utilize the ARIMA technique to predict total primary energy consumption and energy consumption by fuel. Also, we compute the energy coefficient to characterize the interaction between energy consumption and the national economy.

In fact, the main advantage of choosing ARIMA over other available forecasting methods is the fact that it only necessitates time-series data [22]. This feature avoids a common issue encountered with multivariate models: build a forecasting model with variables whose data are available only for a shorter period of time. In other words, with multivariate models, timeliness of data can be a problem. Thus, the prediction model is a conditional forecast based upon unavailable observations, adding a source of forecast error. It occurs with models using economic factors such as GDP (Gross Domestic Product) as input variables. In addition, ARIMA has been successfully applied for long-term forecasting.

Box and Jenkins first introduce the Autoregressive Integrated Moving Average [35]. It is made up of an Autoregressive part (AR) and a Moving average part (MA). Initially, it is an ARMA (p, q) model that is turned to an ARIMA (p, d, q) with p, q, and d parameters being respectively the AR, MA, and the differencing term. The differencing "d" is performed as a way to make the time series stationary. ARIMA model is applied only to stationary time series. In an ARIMA model, the future values of a variable is a linear combination of past observations and random errors and expressed as follows:

$$y_t = \theta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_p \varepsilon_{t-p}$$

(1)

where y_t is the actual value and ε_t is the random error at time t, and ϕ_i ($i = 1, 2. . ., p$) and θj ($j = 0, 1, 2. . ., q$) are the model parameters. p, d (as described above) and q are referred to as the order of the model, and random errors, εt, are assumed to be independently and identically distributed with a mean of zero and a constant variance of σ^2.

The stepwise procedure follows the Box and Jenkins methodology

i) Time series data are transformed in order to become stationary. Both variance and mean should be constant. In this study, we apply the Augmented Dicker Fuller (ADF) unit root test to check the stationarity of the time series of each fuel type.

ii) The parameters p and q are determined by studying the autocorrelation function (ACF) and the partial autocorrelation function (PACF).

iii) The model is chosen by assessing the relative quality of several competing models. We first give credits for models that reduce the Akaike Information Criteria (AIC) and the Sum of Squared Error (SSE). Then, the Ljung Box Q-statistics test is also performed to make sure the model does not exhibit any lack of fit. This test is applied to the residuals of each time series after fitting an ARIMA (p, d, q) model to the data. The Ljung Box Q-statistics test has two hypotheses:

Ho: No autocorrelation left in the residuals (Null hypothesis)

Hα: There is some autocorrelation left in the residuals.

Given a series Y of length m, the test is defined as:

$$Q = n(n + 2) \sum_{k=1}^{m} \frac{\hat{r}_k^2}{n-k} \quad (2)$$

Where $\hat{r}_k$ is the estimated autocorrelation of the series at lag k, and m is the number of tested lags. The null hypothesis is rejected (meaning the model has a significant lack of fit) if

$$Q > X_{1-\alpha,h}^2 \qquad (3)$$

where $X_{1-\alpha,h}^2$ is the chi-square distribution table value with h ($h = m - p - q$) degrees of freedom and significance level α. p and q are the parameters of the ARIMA model as aforementioned. Eventually, the parsimony principle is considered [36]. According to this principle, the model with the smallest amount of parameters is to be selected to provide an adequate representation of the time-series data [36]. In other words, the simplest model that describes accurately the time series data is chosen.

In addition, the model assumptions about the residuals being white noise have to be met.

The modeling procedure is performed using the statistical software R version 3.6.0 and all necessary graphs produced from it. For the forecasting results, we consider the upper limits of the 95% confidence level.

Furthermore, for a better understanding of the relationship between energy consumption and economy, we calculate the ratio energy consumption rate/GDP rate from 1990 to 2016.

3. DATA AND MODELS' EVALUATION

3.1 Data

This current study uses the yearly data of total primary energy consumption and that of fuel consumption in Côte d'Ivoire between 1990 to 2016. Fuel consumption comprises oil, natural gas, hydropower, and biofuels. The data originate from the International Energy Agency (IEA) website [37]. The electricity consumption in the original data has been replaced by their equivalent oil, natural gas, hydropower, and biofuels consumption. An annual share of each fuel type in the electricity consumption was calculated. Thus, this share was used to calculate the amount of each fuel type corresponding to given yearly electricity consumption. This way, we have been able to retrieve for each year the amount of each fuel contained in the bulk electricity consumption given originally. The data in the year 2016 come from [38]. Each time series is divided into a training set and testing set in the respective range of 85% (1990 to 2012) and 15% (2013-2016).

3.2 Model evaluation

The performance of each model is assessed with the test set before the final choice for the forecast model is built over the entire time-series data.

Quantitative error measurements.

Three types of quantitative error measurements are considered; namely the root mean squared error (RMSE), the mean absolute percentage error (MAPE), and the mean absolute error (MAE). Their mathematical expressions are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_t - \hat{y}_t)^2} \qquad (4)$$

$$MAPE = \sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times \frac{100}{n} \qquad (5)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \qquad (6)$$

4. RESULTS AND DISCUSSIONS

The models' information of each fuel type in terms of ARIMA parameters (p, d, q), the AIC, the SSE as well as the quantitative error measurements (MAE, RMSE, and MAPE) on the respective test sets are tabulated in Table 1.

The Augmented Dicky Fuller (ADF) unit root tests demonstrate that none of the time series are stationary. That justifies the differencing carried out, which is materialized by the parameters d in each model. The p-values obtained from the Ljung Box Q-statistics test suggest that the null hypothesis cannot be rejected. There is, therefore, no autocorrelation left in the residuals of each time series. Furthermore, the residuals of each model are not significantly different from white noise. Besides, the parsimony principle influenced the final model choice. As observed in Table 1, the highest parameter is 2.

Table 1: Forecasting Models' description

Fuel	ARIMA (p,d,q)	MAE	RMSE	MAPE	SSE	P-value	AIC
TFC	0,1,1	0.38	0.42	0.05	3.19	0.62	30.99
Oil	1,2,1	0.08	0.08	0.04	0.27	0.99	-28.68
Nat.gas	0,2,1	0.42	0.34	0.65	0.36	0.98	-16.21
Hydro	0,1,2	0.03	0.04	0.39	0.00	0.56	-143.26
Biofuels	0,2,1	1.54	1.76	0.34	1.49	0.66	23.58

p.s. *TPE= total primary energy, Nat. gas= natural gas, Hydro= Hydropower*

The quantitative error statistics are computed to assess the quality of each model over the test set before the model is constructed on the whole time series. The magnitude of MAE values ranges from 0.034 to 1.539; that of RMSE goes from 0.036 to 1.758, while MAPE's ones vary from 0.051 to 0.647. These values are judged satisfying. In a nutshell, all the conditions to ensure the goodness of each model are applied.

The forecasted values for each item and the total primary energy consumption from 2017 to 2030 are compiled in Table 3 and displayed in Figure 2. The results for the total primary energy consumption are emphasized in Figure 1. The graph combines the primary energy consumption from 1990 up to 2016 and the forecasted values.

As noticed from the table, all the fuel types will be increasing within the forecasted period including the total primary energy consumption. For a better analysis of the annual growth rate of each item, we create three cut-offs of the time period from 1990 to 2030. The three-time slices are 1990-2002, 2003-2016 and 2017-2030. They have respectively 13, 14 and 14 years. Table 2 indicates that the annual growth rate for each item exhibits the same pattern, unlike hydropower. They all rise from the first period 1990-2002 to the second time slice 2003-2016, then start a decline within the forecasted period 2017-2030. Hydropower instead is increasing from 1990 to 2030. It translates the effort made by the government, even if it is still low in developing hydroelectric energy. The irregularly high growth rate magnitude of 79.27% of natural gas is because the fuel was first introduced in the mid-nineties. So, the quick increase of natural gas input during the first four years of its introduction gets the annual growth rate to a considerably high value. Then, happened the stabilization from the year 1999 that more or less confine the yearly growth rate to more reasonable amounts. If the four years are regarded as outliers and omitted, the annual growth rate of natural gas turns to -6.39% for the first time slice 1990-2002. The total primary energy demand increases from the first time slice (3.38%) to the second (4.44%), then decreases for the period up to 2030 (1.85%).

Table 2: Annual growth rate results in percentage (%)

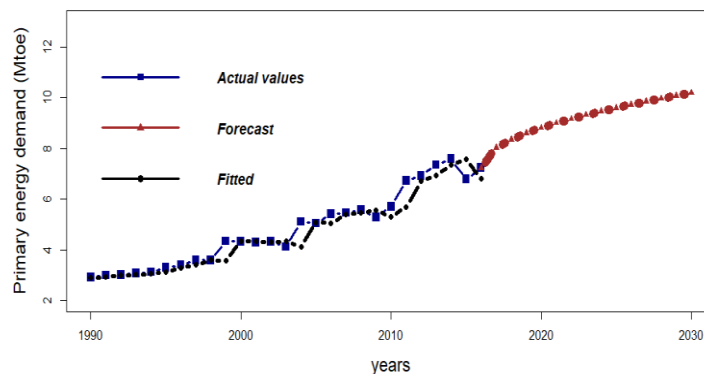| Years	TFC	Oil	Nat. gas	Hydro	Biofuels
1990-2002	3.38	1.62	79.27	-1.88	2.65
2003-2016	4.44	7.58	3.68	-0.07	3.60
2017-2030	1.85	5.56	3.60	0.03	1.84

Figure 1: Total primary energy demand forecast modeling

Table 3: Forecasted values for each item and total primary energy demand (TPE) in million tons of oil equivalent (Mtoe)

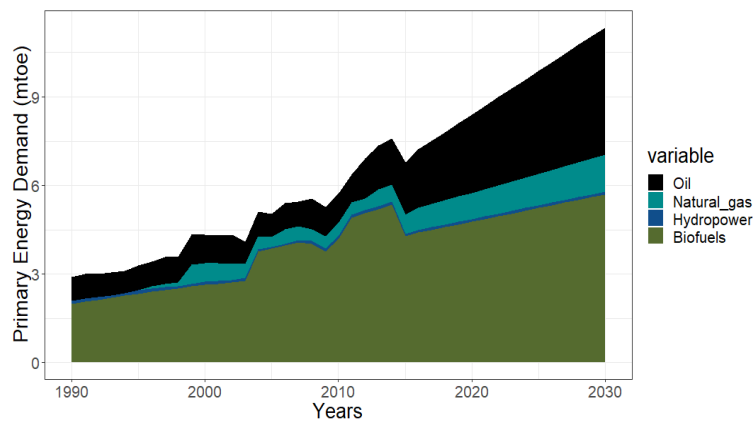| Years	TPE	Oil	Nat. gas	Hydro	Biofuels
2017	8.0325	2.1412	0.7851	0.0925	4.4913
2018	8.3556	2.3153	0.8204	0.0925	4.5840
2019	8.6053	2.4805	0.8556	0.0925	4.6766
2020	8.8164	2.6489	0.8909	0.0925	4.7693
2021	9.0027	2.8161	0.9262	0.0925	4.8619
2022	9.1713	2.9838	0.9615	0.0925	4.9545
2023	9.3264	3.1513	0.9967	0.0925	5.0472
2024	9.4709	3.3189	1.0320	0.0925	5.1398
2025	9.6066	3.4865	1.0673	0.0925	5.2325
2026	9.7351	3.6540	1.1025	0.0925	5.3251
2027	9.8573	3.8216	1.1378	0.0925	5.4178
2028	9.9740	3.9892	1.1731	0.0925	5.5104
2029	10.0860	4.1567	1.2084	0.0927	5.6030
2030	10.1938	4.3243	1.2436	0.0929	5.6957

Figure 2: Cumulative graph of realized and forecasted energy demand by fuels from 1990 to 2030

The ratio energy consumption rate / GDP rate known as the energy coefficient can portray energy/economy interaction. The period from 1990 to 2016 is parted in 5; each part has five years except the last that has six. The energy consumption and GDP rate are calculated for each piece and the ratio (energy coefficient) is then deducted for each section. An overall average of all energy coefficient values is computed. Figure 3 shows that the energy coefficient values range from -0.09 to 3.17 with a mean of 1.59. These figures confirm that an increase of 1% GDP necessitates a 1.5% increase in energy consumption in an economy undergoing industrialization as discussed by [39]. It is indeed the case of Côte d'Ivoire, who is still developing. As a result, primary energy demand should increase until the energy peak is reached. The decrease in the annual growth rate of the primary energy demand (Table 2) could be the sign that energy peak is about to be achieved in the coming decades.
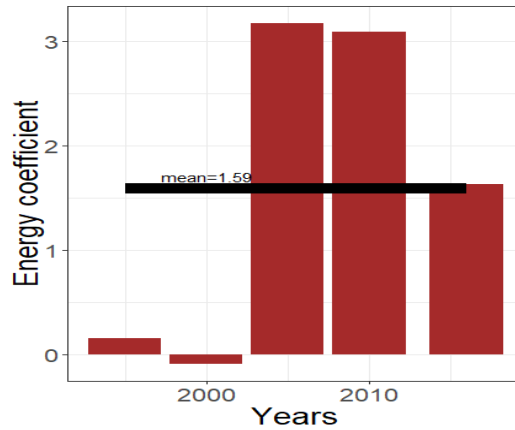
Figure 3: Energy coefficient

Investigating the energy consumption and economic growth nexus in Côte d'Ivoire, both [33] and [40] found bidirectional causality between economic growth and energy consumption. If we consider the growth hypothesis, meaning that energy consumption drives economic growth, any decrease in energy demand will slow down the economic growth during the forecasted period. However, if we consider the conservation hypothesis instead, meaning that economic growth influences energy consumption, no relevant conclusion can be drawn on the economic growth if any decline of energy consumption is observed during the forecasted period. Furthermore, for the financial development and energy consumption nexus, [40] established a unidirectional causality running from financial development to energy consumption. Therefore, within the forecasted period, the only reliable way to pinpoint whether the decline of primary energy demand rate is caused by the energy peak is to assume an increase of financial development. In this condition, any decrease in energy demand rate will be a sign that the energy peak is about to be reached. Such a scenario will only be clarified with future country performance.

As regards the energy structure as displayed in Figures 4 and 5, fossil fuels are expected to experience a significant increase, rising from 38.96% to 49.03% share between 2017 and 2030. It demonstrates that the economy will still be fossil fuel-intensive within the next decade. In fact, the figure is actually an underestimation since coal is about to come in the fossil fuels interplay by 2021 [41]. This sharp upward trend is caused by the increase of oil's share that goes from 28.51% to 38.08%, accounting for a nearly 10% increase from 2017 to 2030. The transport and the industry sectors consume a fair proportion of oil and petroleum products. Therefore, those sectors are expected to expand. However, renewable energies exhibit a downward trend ranging from 61.04% to 50.97% share that makes up a 10.07% drop from 2017 to 2030. This decline is not only provoked by the increase of fossil fuels but also by the interaction between biofuels and natural gas. Biofuels are the primary sources of energy used by the population. Fuelwood and charcoal are massively used in the respective proportion of 66% and 20% for cooking [42]. The effort made by the government to promote clean cooking technologies such as liquefied petroleum gas (LPG) got their share to 18.23% in 2016 [2]. This trend should be rising slowly by 2030, thus, reducing the share of renewable energies, mostly made up of biofuels.

Furthermore, biofuels in the form of fuelwood and charcoal are strictly not considered as renewable energies since they do harm the natural ecosystems jeopardizing future generations to meet their own needs [43]. In this perspective, the real renewable energies that are hydropower will make up only nearly 1% by 2030, which is considered very low. To date, only 36% of the Ivorian hydropower potential is operational [44, 45]**.** Besides, other renewable energy sources such as solar and the use of agricultural residues and urban wastes for various applications such as power production still need to be harnessed.
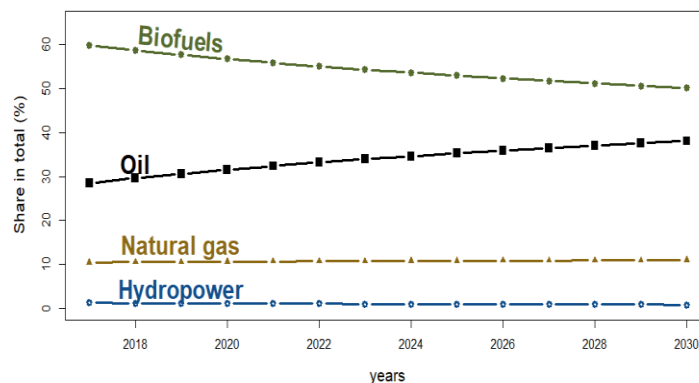

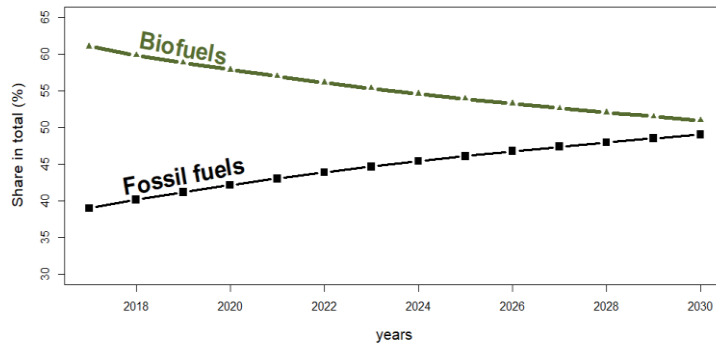**Figure 4:** Future trends of each fuel item

Figure 5: Future trends of each fuel category

The configuration of the energy structure by 2030 demonstrates that biofuels in the form of fuelwood and charcoal will still predominate the Ivorian energy sector with a fair proportion of carbon-based energy. Such an energy structure depicts a country that is still developing but does not find appropriate alternatives to leapfrog the conventional sources of energy and embrace a more sustainable energy regime.

Furthermore, we also notice that the ARIMA forecasted value of the primary energy demand is different from the summation of the individual ARIMA forecasted valued obtained with each fuel item (Figure 6). The ARIMA predicted values are higher from 2017 to 2023. It is precisely the reverse from 2023 to 2030. The difference is minimum in 2023 (0.039 mtoe) and maximum in 2030 (1.163 mtoe).

Eventually, the forecasting scenario assumes that economic development has more or less the same trend of the past, especially that of the seven past years characterized by marked economic progress. However, the main uncertainties remain the political and social environment. Political and social tensions are noticeable in the run-up of the presidential elections of 2020. Any political instability will slow down the GDP growth and compromise financial development, thus investments. The energy demand in this scenario is bound to decrease.
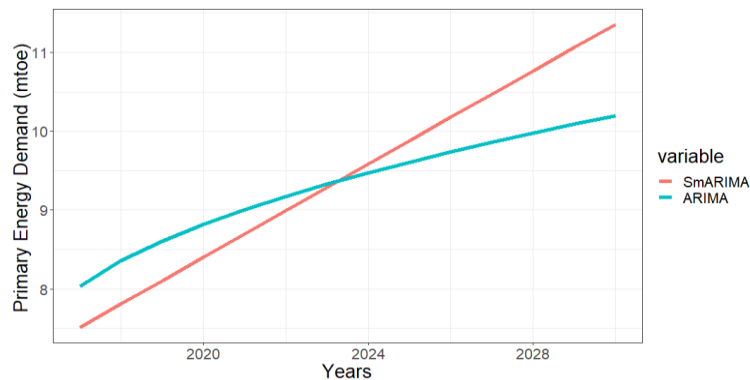

Figure 6: Comparison between the forecasted values of primary energy demand and the summation of the predicted values of each fuel item

p.s. SmARIMA is the summation of the predicted values of each fuel item
ARIMA is the forecasted value of the total primary energy demand

5. CONCLUSION

The goal of this study is to examine energy outlook in Côte d'Ivoire for the coming decade based on a forecasting model (ARIMA) to present a business as usual scenario. The results show that energy demand for each fuel item will increase until 2030. However, the annual growth rate for each fuel item first increases, then declines within the forecasted, except hydropower that increases from 1990 to 2030. Furthermore, the energy structure, by 2030, will be predominantly comprised of biofuels in the form of fuelwood and charcoal (50.97% share) to which should be added conventional sources of energy (49.03% share). Another major piece of finding is that oil is experiencing the highest increase with a magnitude of 5.56% within the forecasted period.

Based on the conclusions above, the policy implications are framed as follows.

Firstly, the country should invest in energy efficiency and promote research and development in energy-saving technologies. That will reduce primary energy demand, public expenditures, and especially the imports of fossil fuels. Côte d'Ivoire mostly imports fossil fuels to cover its needs since the local resources are insufficient.

Secondly, an endeavor has to be made by the Ivorian government to come up to a sustainable energy mix by giving an impetus to the dissemination of renewable energies to lower the share carbon-based energies and their global warming effects. It can take the form of the introduction of a law framework in favor of the renewable energy sector that puts forward manifest incentives with gentle tax regulations, especially for private investors. Côte d'Ivoire has a considerable potential to develop solar and hydropower energy for applications such as power production, home heating cooling, and lighting. However, the renewable energy field is still at its early development stage and does not benefit full attention of the decision-makers.

Thirdly, as noticed in the study, most households will still be using biofuels (fuelwood and charcoal) in the next decade for their basic needs, such as cooking. With the adverse effects linked to the use of this primitive type of energy, the authorities should subsidize clean cooking technologies such as liquefied petroleum gas (LPG) to maintain the equilibrium of the local ecosystems and ensure people's welfare.

Last but not least, financial resources have always been a critical challenge for developing countries such as Côte d'Ivoire to pursue their development obligations. In this regard, a climate of peace and politic stability, proper management of public finances, and a struggle to eradicate corruption can make a significant contribution in leveraging the investment levels and secure substantial financial resources.

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