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Review Article

Long Term Forecasting of Peak Demand and Annual Electricity Consumption of the West African Power Pool Interconnected Network by 2032

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Abstract

The uneven distribution of primary sources of electric power generation in Economic Community of West African States (ECOWAS) compelled the heads of states to create the West African Power Pool (WAPP). The vision of this system is to set up a common electrical energy market to satisfy the balance between supply and demand at an affordable price using the interconnected network. Forecasting maximum power demand and energy consumption is essential for planning and the coordination of new power plant and transmission lines building. This work consists of predicting maximum power demand and total energy that must transit through the WAPP interconnected network by the year 2032. We compare the performances of three time series models namely the Long Short-Term Memory (LSTM), Auto-Regressive Integrated Moving Average (ARIMA) and Fb Facebook Prophet. Electric power and energy data used for training the systems comes from the WAPP authorities. The results show that, for monthly peaks, the Facebook (Fb) Prophet model is the best, with a MAPE (mean absolute error percentage) of 3.1% and a low RMSE (root mean square error) of 1.225 GW. For energy prediction, ARIMA performances are the best compared to others with (RMSE 1.20 TWh, MAPE 1.00%). Thus, the forecast for total annual energy consumption and annual peak demand will be, respectively, 96.85TWh and 13.6 GW in 2032.

Keywords

Power Demand, Energy Supply, Maximum Power Peak, Forecasting, Energy Planning, Interconnected Network

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1. Introduction

The introduction plays an important role in providing background information (including relevant references), emphasizing the importance of the study, and outlining its objectives. It is crucial to conduct a thorough review of the current state of the research field and incorporate key publications into your work. By referencing other research papers, you can provide context and position your own work within the broader research landscape. The final paragraph should provide a concise summary of the main findings and conclusions, which will be helpful to the readers.

References will be consecutively numbered as they appear in the text by using numerals in square brackets (e.g., [1-3] or [4–7]). Further details on references can be found at the end of this document.

Forecasting peak electric power demand and energy consumption is important for the planning and use of electricity facilities. In fact, power prediction has a considerable influence on the decisions of electricity suppliers [1, 2]. For better sizing of power generation, transmission and distribution systems, a reliable data on future electricity demand is required [3]. Future electricity demand can be split into three horizons mainly short-term forecasting (STLF) (forecasts period less than twenty-four hours), medium-term forecasting (MTLF) (forecast period between twenty-four hours and one year), and long-term forecasting (LTLF) for durations of more than one year [4-6]. For proper planning infrastructures, it is necessary to make a long-term forecast.

Forecasting peak demand and long-term electricity consumption can be influenced by certain socio-economic parameters or criteria. Thus, authors link residential electricity demand to variables such as household income, climatic factor measured by temperature, household demographic structure, electricity price and the efficiency of electrical appliances [7, 8]. Furthermore, a positive statistical link between energy consumption and economic growth have been demonstrated in references [8-10]. The direct and indirect consequences of parameters such as gross domestic product (GDP), population trends, industrial growth and the use of coal in power generation were investigated as part of the study of China's energy demand [11]. The relationship between Iraq's real load and variables such as demographics, gross national product, consumer prices and temperature using linear logarithmic models and artificial neural networks (ANNs) was examined, and it emerged that there is a strong correlation between these different parameters [12]. Also, authors in [13] studied the relation between a time series and several influencing variables for long-term demand forecasting in Greece. The results of this study indicate that GDP brings a large variation in demand, and ordinal regression models perform better than multiple linear regression. ARIMA, ANN and exponential smoothing forecasting models were used to forecast household electricity demand. The conclusions drawn from the study show that forecast accuracy is influenced by the choice of techniques and input variables [14].

From the literature we can deduce that GDP, demography, temperature and humidity can be used as parameters influencing electricity demand. In our study, we used the average temperature and humidity data for the 14 ECOWAS countries [15], and the GDP and population data for the ECOWAS zone collected from the World Bank web page [16]. Figure 1 shows the evolution of average temperature and average humidity in the 14 ECOWAS countries.

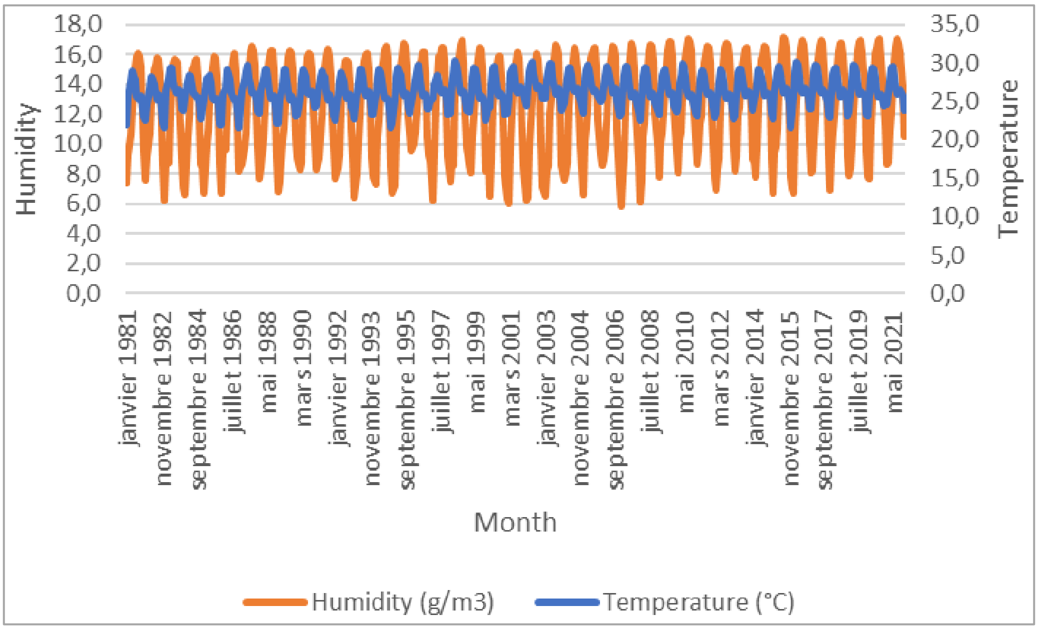

Figure 1. *Temperature and humidity trends from 1981 to 2021.*

The temperature trend shows that warming has continued in the ECOWAS zone, with an average temperature rise of around 0.3 ℃ per decade between 1991 and 2021, 0.2 ℃ higher than the rise recorded between 1981 and 1990. The year 2021 ranks as the fourth warmest on record, depending on the dataset used. It is characterized by a long period of drought and a short period of rain. As for humidity, since the mid-1990s, West Africa has become wetter, with fewer but more intense rainfall events in recent years. As for other parameters, figure 2 shows the evolution of GDP and population in the ECOWAS zone.

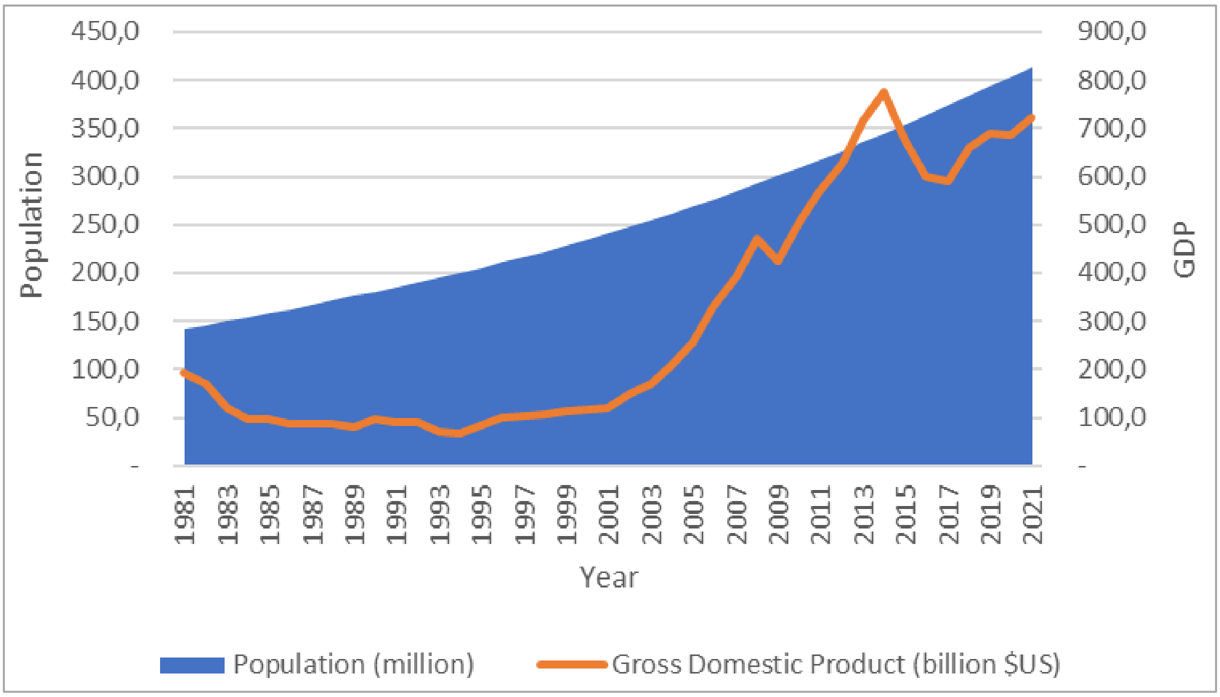

Figure 2. *Population and GDP trends, 1981-2021.*

These data from the World Bank database show that population growth is tending towards exponential growth. The population of West Africa in 2021 is estimated at 413 million, representing around 32% of Africa's total population, and is set to grow by slightly more, to 796 million in 2050 and 1.5 billion in 2100. The pace of population growth varies from country to country. The key factors in this demographic evolution are the high fertility rate and rising life expectancy. As for the zone's Gross Domestic Product (GDP) there is a remarkable growth since 2003, but following the COVID 19 crisis, it falls and resumes its growth from 2020 onwards. GDP in the western region is forecast to grow by 3.4% in 2023, compared with 3.7% in 2022. The zone's GDP is not uniform across the different countries.

In the literature, many authors have worked on the various problems of load forecasting or electrical energy consumption. Several models and methodologies are used to address these issues, and can be grouped into two (02) groups: Traditional models and artificial intelligence models [17-20]. Traditional models include exponential smoothing, regression, grey models and time series models [6, 18]. Artificial intelligence models, on the other hand, include models such as support vector regression (SVR) models, artificial neural networks (ANNs), machine learning (ML) models, deep learning (DL) models and genetic algorithm (GA) models [17, 18]. Each of these models can be combined to create hybrid models.

The association of the causality of the parameters (ecological degradation, GDP per capita and urban development) was used to predict Nigeria's energy consumption by 2030. The results obtained showed a sharp increase in energy demand and better forecast accuracy [21]. In [22], ARIMA is employed to forecast short-term energy demand in Spain. It is demonstrated that this model has short convergence time for the short-term prediction. The authors [23] used the ARIMA model to predict electricity consumption in Ghana up to 2030. The results showed that Ghana's consumption will grow to 9.5597 GWh. Jain and Al. [24] used ARIMA to predict electricity consumption. They concluded that the model performed well, achieving a MAPE of 6.63%. ARIMA has been used to forecast Turkey's sectoral consumption and total energy for the next 15 years. The authors highlight the evolution of electrical energy demand in the agricultural, transport, utilities and residential sectors [25]. Several other authors have used ARIMA for forecasting in various fields, for example electricity production to predict solar radiation in order to stabilize photovoltaic energy production over the long term [26], finance to maximize long-term investment profit at the level of three operators in India [27], and livestock farming to determine the average monthly cost of a kilogram of chicken meat in Egypt over the short term [28]. On the other hand, the

LSTM model was used for long-term road traffic forecasting [29]. The model has better accuracy and adequate stability. A new approach to long-term forecasting of photovoltaic energy in India using the LSTM model with the Nadam optimizer shows that the LSTM model works better with time-series data and is more efficient than the ARIMA and SARIMA models [30]. The LTSM model was also used to forecast domestic load for less than twenty-four (24) hours, based on consumption readings from domestic meters and knowledge gained from residents' behaviour [31]. The results of this work demonstrated the performance of LTSM in forecasting electricity demand. The LSTM model has also been used to predict oil production [32], the energy output of a photovoltaic field [33], and the quality of groundwater used for irrigation in northern Iran [34]. All these authors appreciate the results provided by this model. Also research conducted in [35] concerning medium- and long-term electric charge prediction using Facebook Profet was carried out. The authors showed the supremacy of the Prophet model over LSTM and ARIMA. Furthermore [36] studied the long-term power load forecast for Kuwait using the Prophet and Holt-Winters models. They concluded that Prophet provides excellent values and its errors are small. The author showed the supremacy of Prophet over SARIMA when evaluating solar and wind resources [37]. [38] to determine the future cost of electricity in order to improve the economic analysis in the feasibility study. The Prophet model would be suitable for Pakistan to predict the second wave of COVID-19 [39]. Given the capacity of the three models ARIMA, LSTM and Prophet, their application will be judicious for our work.

2. Methodology

A set of monthly peak demand and energy consumption data from the WAPP statistical reports [40-42], climate data (temperature, humidity) from the NASA website [15] and population and GDP data from the World Bank website [16] quoted above were used with the ARIMA, Prophet and LSTM forecasting models to predict the peak demand of the interconnected grid and the resulting energy.

2.1. Forecasting Method with ARIMA

The ARIMA forecasting model, also known as Box-Jenkins models in the literature, comprises the autoregressive (AR) model components (p) and the MA moving average (q) described by the following formula:

$$\mathrm{Y_t = \gamma_1 Y_{t-1} + \cdots + \gamma_p Y_{t-p} + \varepsilon_t - \theta_1 \epsilon_{t-1} - \cdots - \theta_q \epsilon_{t-q}} \quad (1)$$

where:

γ_i: coefficient at observation Y_{t-i};

ε_t white noise distributed as error;

p: the order of the first value included;

θ_i: coefficient at error ϵ_{t-i};

q: represents the oldest previous error.

Using the backshift operator:

$B^j y_t = y_{t-j}$, represents the rear offset.

can be rewritten as (2):

$$\mathrm{\gamma_p\,(B) Y_t = \theta_q(B)\epsilon_t} \quad (2)$$

where:

$\gamma_p\,(B) = 1 - \gamma_1 B - \cdots - \gamma_p B^p$: polynomial representation of the moving average operator's backward shift AR, as a polynomial in the backward shift operator $\theta_q\,(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$.

ARMA refers to the fact that the time series has at least a constant mean and variance, and that its covariance is based solely on the time difference. When non-stationarity is observed, data transformations are required. Given the non-stationarity of the variance, the logarithmic method is generally the most widespread, while the non-stationarity of the mean is generally suppressed by differentiation. It is modelled by the ARIMA (p, d, q) and is represented by the following equation:

$$\mathrm{\gamma_p\,(B)(1-B)^d\, Y_t = \theta_q(B)\epsilon_t} \quad (3)$$

with:

d: is the degree of differentiation

ARIMA modelling is carried out in six successive stages. Figure 3 shows a schematic diagram of the process.

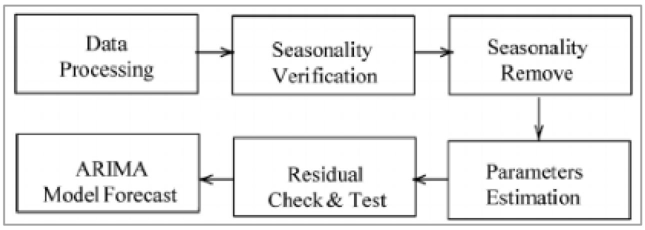

***Figure 3**. Block diagram of methodology ARIMA model.*

The autocorrelation model is used to characterize an ARIMA model. Fitting is a popular approach for determining the ARIMA order [43]. Model identification is based on the automated algorithmic comparison of models with different variables that best meet the fitting requirements [44-46]. Model validation is performed using the Ljung-Box test.

2.2. Forecasting Method with Prophet

This time-series prediction model incorporates seasonality, data trends and holidays to model complex characteristics. Seasonality can be adjusted in the form of daily, weekly and annual models. The decomposed mathematical representation is written as follows:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (4)$$

where:

$g(t)$: the data trend function;

$s(t)$: seasonality;

$h(t)$: the vacation effect, which can be added to specific data points;

ε_t: distinctive characteristics of data not adjusted by the model.

Linear growth by segments or saturation craters the prophetic function. Maximum load data show a linear evolution by part, a linear growth by segments model is used as follows:

$$g(t) = (k + a(t)^T \delta)t + (m + a(t)^T \gamma) \tag{5}$$

k: growth rate;

δ: adjustment rate;

m: offset parameter;

γ: represents trend reversal points S_j and is defined as $S_j \delta_j$

with aj (t) defined by:

$$a_j(t) = \begin{cases} 1 \; if \; t \geq s_j \\ 0 \; otherwise \end{cases} \tag{6}$$

Change points allow the linear growth model to change evolution and can be used by the user in the chain to better calibrate the model and provide reliable data forecasts. Prophet allows the user to insert the rate of trend adjustment or automatically detects points of change.

Fourier series can be used to describe the seasonality S(t) which is a function of repetition (daily, monthly, yearly). Seasonality is given by the following equation:

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right) \right) \tag{7}$$

Where:

P=1 for daily seasonality. For particular dates, the list of dates D defined by the analyst can be included in the vacancy matrix Z(t) to include the effects of these dates in the equation h(t), which must be inserted into the time series in the form of a regressor matrix.

$$Z(t) = [1(t \in D_1), \ldots., 1(t \in D_L)] \tag{8}$$

And

$$h(t) = Z(t) \, \kappa \tag{9}$$

with κ ~ (0,v 2) where v is the vacation smoothing parameter.

2.3. LSTM Forecasting Method

LSTM have been specifically developed to overcome the problem of dependency. Composed of four neuronal layers which collaborate differently, it has a serial architecture with an iterative module.

The typical LSTM is made up of storage modules called "cells". Cell state and hidden state are entrusted to the neighbouring cell. The cell state is the main data sequence, which routes data in the same way. In this way, certain linear adaptations can take place. Data can be introduced or subtracted from the cell state via sigmoid gates. A gate is similar to a layer or series of matrix operations, which contain different individual weights. LSTM can be modelled in three essential steps:

Step 1: The mechanism for identifying and excluding information when creating an LSTM network is provided by the sigmoid operation, which is connected to the last LSTM cell (ht-1) at time t - 1 and to the current input X at time t. This forgetting gate (ft) is a vector containing the variables 0 to 1 indicating the number in each cell state [47]. The equation of the forget gate is:

$$f_t = \sigma\left(W_f [h_{t-1}, X_t] + b_f\right) \tag{10}$$

Where:

σ is the sigmoid equation;

Wf and bf are the weight matrices and parameter bias vectors and the forgetting gate, respectively.

Step 2 consists in determining and storing the data of the future input Xt in the cell, as well as updating the cell state. This operation is carried out in two stages: the sigmoid layer and the $tanh$ layer. In fact, the sigmoid layer indicates whether the latest data will be updated or rejected (0 ou 1) and the $tanh$ function assigns a weight to the data received (-1 to 1). The two data are multiplied to update the new state of the cell. the old memory Ct-1 is completed to new memory, causing Ct to be forgotten [47].

$$i_t = \sigma(W_i [h_{t-1}, X_t] + b_i) \tag{11}$$

$$N_t = \tan h \, (W_n [h_{t-1}, X_t] + b_n) \tag{12}$$

$$C_t = C_{t-1} f_t + N_t i_t \tag{13}$$

With:

Ct-1 and Ct the cell statuses at instant t - 1 and t respectively. W and b are the weight and parameter vector matrices of the bias and cell behaviour, respectively.

In step 3, the data at the ht output are based on the Ot cell behaviour output, but this is a sieved variant. Next, the response of the sigmoid Ot is multiplied by the data created by the layer $tanh$ from the cellular behaviour Ct, with a data ranging from -1 to 1.

$$O_t = \sigma(W_o [h_{t-1}, X_t] + b_o) \tag{14}$$

$$h_t = O_t \tan h \, (t) \tag{15}$$

With:

Wo and bo respectively, the weight matrices and bias, of the output gate.

To compare and determine the accuracy of each of the models used, several other criteria are used, including simple statistical measures [48, 49].

According to authors in [50], the most common methods to evaluate the accuracy of a prediction model are the computation of MAPE and RMSE. Equation (16) and (17) are the formula for calculating RMSE and MAPE respectively:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \quad (16)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\hat{y}_t - y_t}{y_t}\right| \times 100\% \quad (17)$$

With:

y_t: Measured value;

$\hat{y}_t$: Predicted value

n: number of values tested.

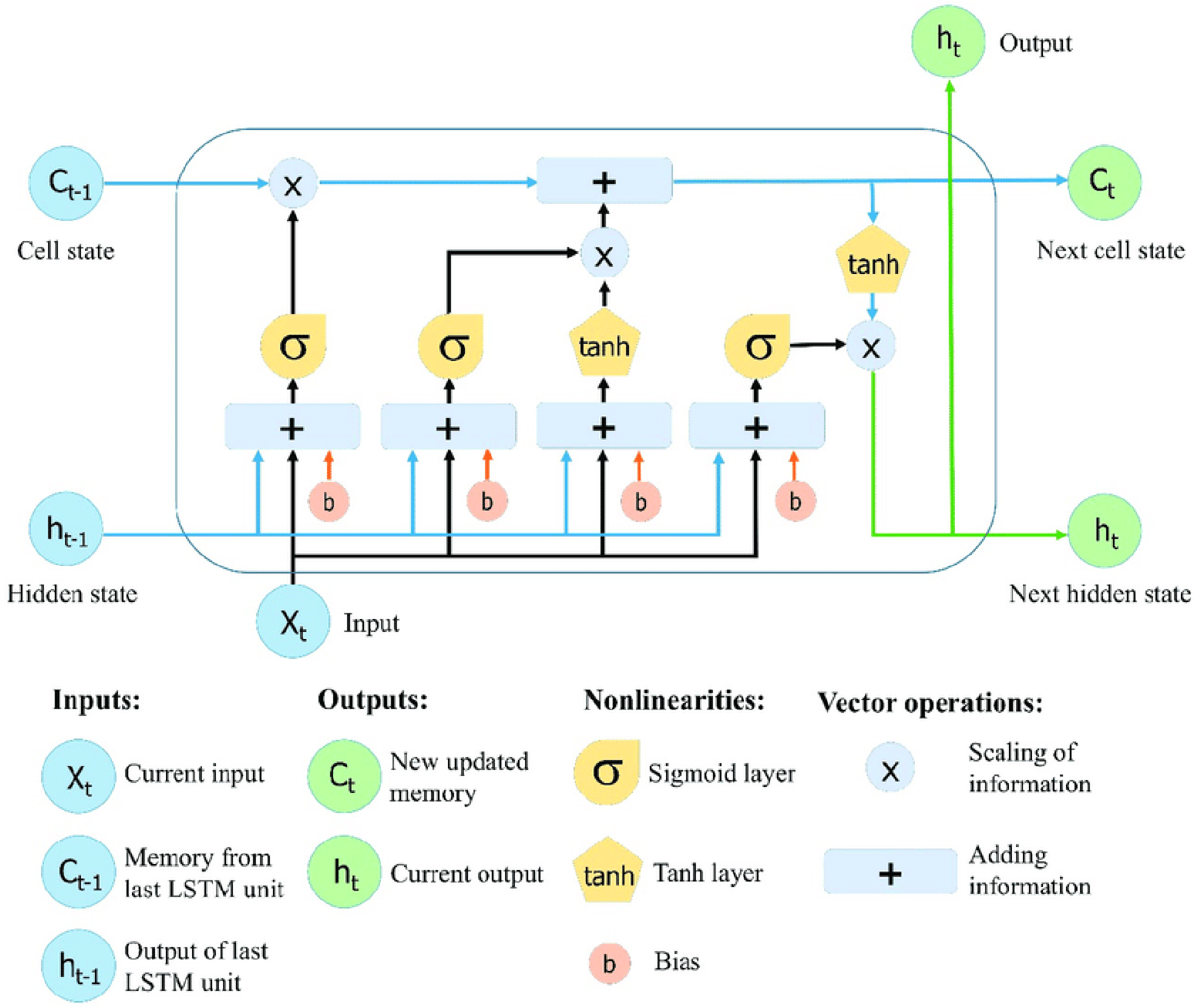

Figure 4. *LSTM architecture (Hochreiter & Schmidhuber, 1997).*

3. Result of Simulation

The three models ARIMA, LSTM and Prophet were trained with 80% of the monthly historical peak demand values available. Once trained, we proceeded to validate each model with the remaining 20% of historical data. Figure 5 shows the data validation test for the three models:

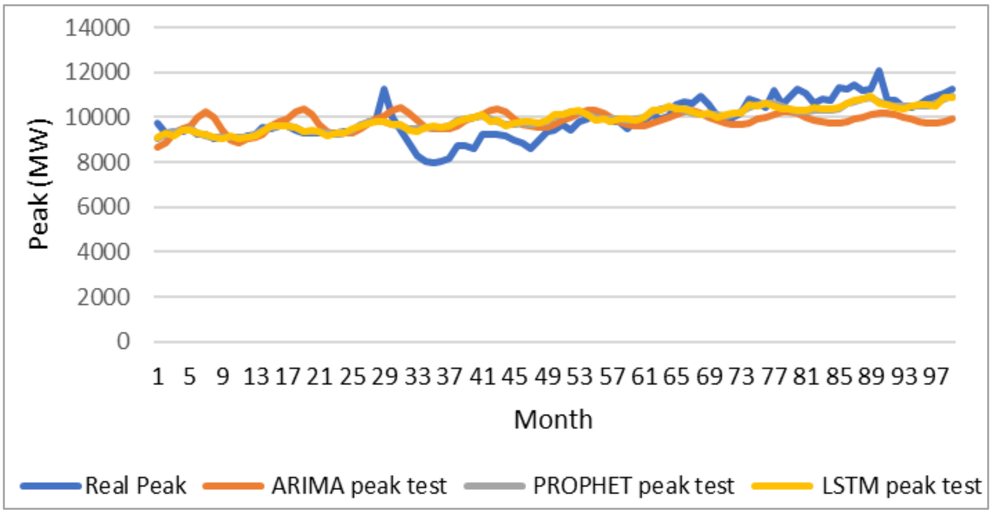

Figure 5. *Superpositions of the LSTM, ARIMA and Prophet validation graphs for peak electrical demand.*

Figure 5 shows the behaviour of each of the trained models in the face of 20% historical data in blue. We note that the ARIMA model fails to follow the trend of the historical values. We can see that the LSTM and Prophet models are virtually indistinguishable and tend to follow the trend of the historical data. Only the performance of each model can enable us to choose the best-performing model. Table 1 shows the performance of each model.

Table 1. *Performance of LSTM, ARIMA and PROPHET for peak electrical demand.*

PERFORMANCE	MAPE (%)	RMSE (GW)
ARIMA	4,59	1,276
PROPHET	3,10	1,255
LSTM	3,17	1,259

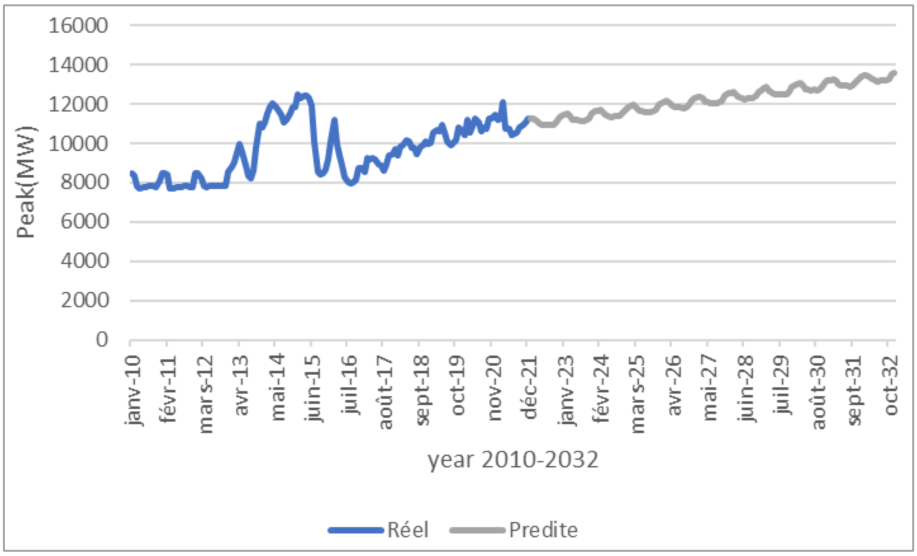

Figure 6. *2032 WAPP monthly peak electricity demand forecast using Prophet model.*

In the table, we see that the errors of the ARIMA model are higher than those of the other two models. The Prophet model has the lowest errors, with a MAPE of 3.10% and RMSE of 1.255 GW. We can conclude that it is the best model to use for predicting peak demand in 2032. Figure 6 shows WAPP's monthly forecast of peak electricity demand using Prophet model.

Figure 6 shows that the peak is increasing. This peak will be 12GW in 2026 and will reach 13.6GW in 2032, i.e. an increase of 12.58% compared to 2021, and will occur in December 2032. The peaks for the other months are shown in table 2:

Table 2. *Forecast of monthly electricity demand in 2032.*

Month	1	2	3	4	5	6	7	8	9	10	11	12
GW	13,45	13,49	13,37	13,25	13,18	13,13	13,17	13,18	13,19	13,3	13,52	13,6

As for annual energy forecasting of the WAPP, two models were the subject of our study: the ARIMA and Prophet models. After training the models with 80% of historical data, we validated the models with the remaining 20% of data. Figure 7 shows the behaviour of the two models in relation to real values.

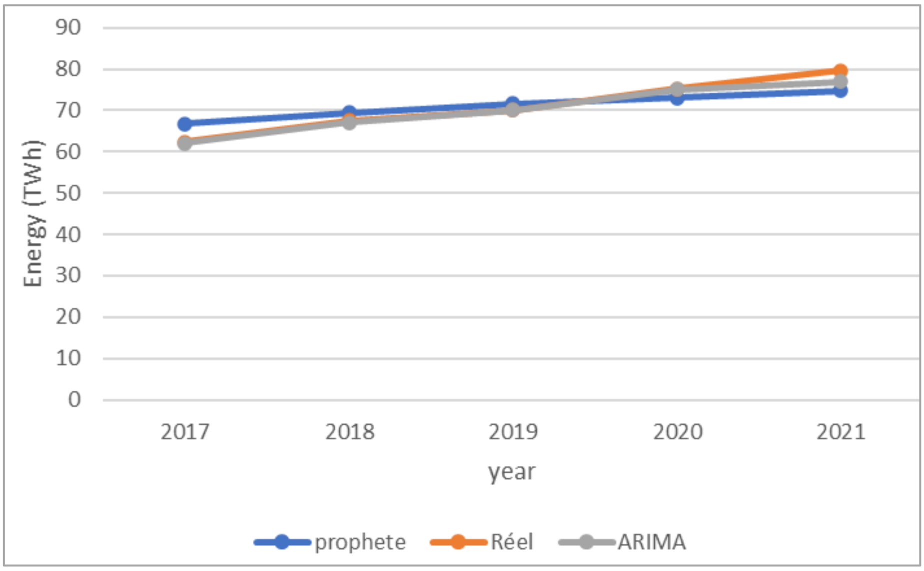

Figure 7. *Superpositions of ARIMA and Prophet validation graphs for electricity consumption.*

From this graph we can see that, over the validation period 2017 to 2021, the ARIMA model more closely followed actual values, whereas Prophet overestimated energy consumption from 2017 to 2019 and underestimated it after this period.

To select the best model, we calculated the errors shown in the following table:

Table 3. *ARIMA and PROPHET performance for electric energy consumption forecast.*

PERFORMANCE	MAPE (%)	RMSE (TWh)
ARIMA	1,00	1,20
PROPHET	4,19	3,24

Of these models, we have chosen the ARIMA model for forecasting electricity consumption, as it has the lowest errors. Figure 7 shows the evolution of electrical energy consumption up to 2032 using the ARIMA model.

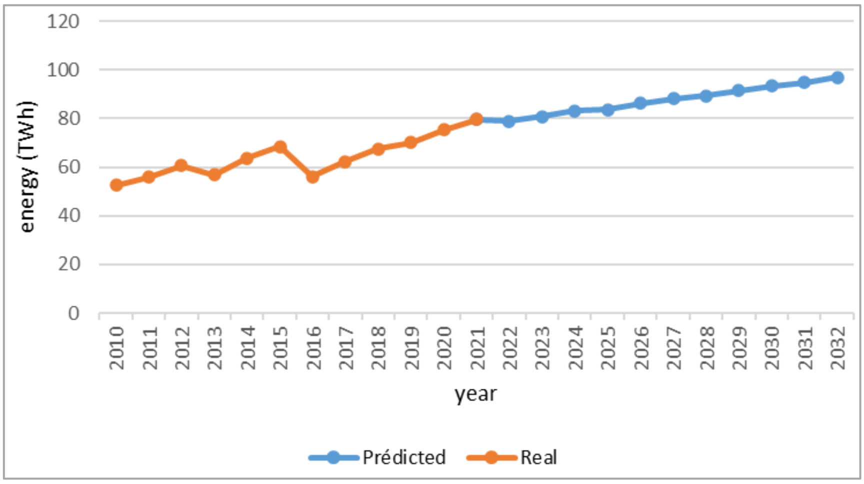

Figure 8. *Electricity consumption forecast for 2032 using ARIMA model.*

Electricity consumption according to the implemented ARIMA model will reach 86.14 TWh in 2026, rising to 96.85 TWh in 2032, an increase of 12.17% compared to 2021.

4. Conclusion

This work made it possible to choose the best models in for forecasting peak electricity demand and annual electricity consumption. It showed that the ARIMA model is better for forecasting electricity consumption, while Prophet model is better for forecasting monthly peak demand.

Indeed, by 2032, annual peak demand will be 13.6GW, with electricity consumption of 96.85TWh.

The future prospects of this work will focus on matching supply and demand, in order to plan power generation sources effectively.

The models are recommended for use in predicting peak electricity demand and annual electricity production, in order to plan generation and transmission infrastructures and avoid over-investment.

Abbreviations

ECOWAS: Economic Community of West African States
WAPP: West African Power Pool
LSTM: Long Short-Term Memory
ARIMA: Auto-Regressive Integrated Moving Average
MAPE: Mean Absolute Error Percentage
RMSE: Root Mean Square Error
GDP: Gross Domestic Product
GW: Gigawatt
TWh: Terawatt hour

Conflicts of Interest

The authors declare no conflicts of interest.

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