



ECOWAS Sustainable Energy Journal

Ideas for evidence-based energy policies and strategies in West Africa

Volume II

The ECOWAS Sustainable Energy Journal (ESEJ)

The ECOWAS Sustainable Energy Journal (ESEJ) is a peer reviewed journal published annually by the Economic Community of West African States (ECOWAS) Centre for Renewable Energy and Energy Efficiency (ECREEE), Achada Santo Antonio, C.P 288, Praia, Cape Verde.

ESEJ is aligned with the objective of ECREEE which is to promote renewable energy and energy efficiency markets in West Africa by addressing technical, financial, policy and regulatory barriers. Moreover, with the ongoing energy landscape transformation in the region the importance of having relevant, evidence-based knowledge to aid in decision-making cannot be overemphasized.

By increasing the knowledge level of decision makers, science has played a key role in shaping the energy landscape, influencing decisions to cater for the needs of the present and, even, future generations. For the ECOWAS region, with issues of data availability and scarcity of country-specific research studies, the need to stimulate and cultivate the development of scientific, yet policy relevant, research projects have never been more pressing, especially in light of the region's sustainable development ambitions. Through its link with the ECOWAS Youth Leadership Development in Energy, ESEJ particularly aims to give a voice to West African youth, by providing a platform through which they may contribute to informing decisions in the energy sector in the region.

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The Konrad-Adenauer-Stiftung Regional Programme Energy Security and Climate Change in Sub-Saharan Africa realizes activities around the nexus of energy security and climate change in Sub-Saharan Africa. The programme particularly works to improve the political and social framework for achieving sustainable development. KAS also supports regional and international cooperation on energy security and climate action in the region. One of the key mechanisms through which the programme works to achieve its goals is by supporting knowledge development and transfer in order to influence policy decisions towards just and inclusive energy transition.

The ECOWAS Sustainable Energy Journal (ESEJ)

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Impact of COVID-19 on Electricity Supply-Demand in West-Africa

Oluwarotimi Delano Thierry Odoua^{*}, Aissatou N'diaye, Ghafi KONDI AKARAb, Windmanagda Sawadogoc, Abdou Latif Bonkaneyd, Tchégoun Michel Atchikpae, Rabani Adamoua

- a) Climate Change and Energy (CCE), West African Science Service Center on Climate Change and Adapted Land Use WASCAL (WASCAL), Niamey, Niger
- b) University of Felix Houphouët - Boigny; Côte d'Ivoire
- c) University of Augsburg; Germany
- d) Department of Physics, High School of Education, University Abdou Moumouni, Niamey, Niger
- e) University of Parakou; Benin

odou.o@edu.wascal.org

Abstract

COVID-19 has been an unprecedented situation that disrupted the stability of many socio-economic dynamics all over the world and in particular on the energy sector in West-Africa. This study seeks to provide technical based analysis to inform policy decision-making and experts in the sector on how the pandemic impacted the countries in the region and actions to reduce vulnerability. This study analyses the impact of COVID-19 on Electricity Supply-Demand in Benin, Togo, Côte d'Ivoire, Senegal and Niger using both quantitative and qualitative data. The latter is based on semi-structured interviews targeting power utilities in these countries. A comparative assessment is conducted between the observed consumption and forecasted in 2020. Advanced forecasting methods with machine learning algorithms are explored including ARIMA, Prophet, ETS, TBATS, NNAR, GLMNET, Random Forest and hybrid ones which are regressed with climatic factors (temperature, humidity and solar radiation) and calendar effect (working days). The best models after the performance evaluation are the NNAR and GLMNET which show good measure compared to others. The assessment shows globally that despite the pandemic the demand has risen above forecast averaging 3.28%. Three distinct periods can be discerned from the time series: a pre-COVID where the demand rose in all countries, and slowed down as the pandemic intensified (in COVID period) and the post COVID period where the consumption rose up back as a result of the release of restriction measures (economic recovery). From one country to another, the recovery time can be longer or shorter.

Keywords:

COVID-19, time series forecasting, West-Africa, electricity, machine learning

1.0 INTRODUCTION

In December 2019, a cluster of pneumonia cases, caused by a newly identified β -coronavirus, occurred in Wuhan, China (Yan-Rong Guo et al., 2020). On 30th January 2020, the WHO (World Health Organisation) declared the Chinese outbreak of COVID-19 to be a Public Health Emergency of International Concern (WHO, 2020). Many measures such as quarantine, social distancing and lockdown have been set to mitigate the coronavirus infection (Rochelle P. Walensky & Carlos del Rio, 2020). This involved not only the forced quarantine of the population, closing of schools and churches, shops, bar, restaurants, retail shops, but also shut down of national and international flights, closure of non-essential ports and airports and non-essential firms and industries (Ghiani et al., 2020) in Italy, there is an ongoing pandemic of coronavirus disease 2019 (COVID-19). These changes in population activities have a direct impact on all sectors including energy consumption. According to the International Energy Agency (IEA) (2020), countries in full lockdown are experiencing an average 25% decline in energy demand per week and countries in partial lockdown an average 18% decline. The energy system has seen a rapid and steady decline in electricity demand; this situation is compared to an “extended Sunday” (IEA, 2020).

Energy plays a central role in responding to emergencies such as the COVID-19 pandemic, from ensuring adequate healthcare services to supporting households during lockdowns (Broto and Kirshner, 2020). According to the IEA, the residential sector accounts for over 25% of global electricity consumption. With the COVID-19 pandemic, most commercial and professional services are shifting to homes. While this shift impacts on lower electricity consumption in the commercial and public services sector, a shift in the location of such services to residences may have impacted on a surge in residential electricity use for various energy services (Edomah & Ndulue, 2020).

The power sector has a vital role to play in ensuring the resilience of societies in their response to COVID-19, in driving the recovery of economies and stimulating socio-economic development (Boulle & Dane, 2020). In the path toward meeting the Sustainable Development Goals (SDG) 7, learning from this unprecedented situation and building a resilient power system to an extreme period like this one, is a necessity for sustainable development. Therefore, a clear diagnosis of the response of power utilities of the region against this pandemic and its impacts will elucidate the difficulties on one hand. And on the other hand, identify opportunities and help in formulating appropriate measures to address the situation.

Many studies have discussed the impact of the pandemic on the energy sector using multiple approaches like bottom-up and top-down analysis. The bottom-up research approach has been implemented by studying the effects of the pandemic on power systems in several countries, such as the United States (Agdas & Barooah, 2020), China (Norouzi et al., 2020), Italy (Ghiani et al., 2020), Spain (Santiago et al., 2021), Canada (Abu-Rayash & Dincer, 2020), India (Aruga et al., 2020), Sweden (Kanda & Kivimaa, 2020), and Finland (Navon et al., 2021). The top-down research efforts include new forecasting methods (Y. Chen et al., 2020), long-term business impacts (Paaso et al., 2020), the general effects of fast economic transitions (Kanda and Kivimaa, 2020), possible uses of machine-learning technologies (Wang et al., 2020), and the challenges related to the changing energy mix (Navon et al., 2021). In Africa, Andrade et al., (2020) explored the preliminary impacts caused by the COVID-19 pandemic in the South African electricity sector using seven weeks of data.

The results show the severe drops in electricity consumption and peak demand, which reached 28.1% and 20.2%, respectively. Another study done in Lagos, Nigeria by Edomah and Ndulue (2020) on the impact of COVID-19 electricity consumption on residential, commercial, and industrial sectors, shows that the industrial electricity consumption decreased by 24% and 18% under partial and total lockdown scenarios, respectively. The study of Edomah and Ndulue (2020) used a short time series data (five weeks during the lockdown period) to evaluate the impact of the COVID-19 on the electricity consumption, which is not robust to quantify the impact. In addition, their study is done at a local scale and not at national scale. An important question is how these disruptive shifts in the energy

sector imposed by the COVID-19 pandemic will affect the West African region. Therefore, there is a need to provide information at national level for different West Africa countries using a large dataset with new approaches.

The paper aims to assess the impact of COVID-19 on the electricity consumption in five different countries namely Benin, Senegal, Niger, Cote d'Ivoire and Togo. We used a new machine learning algorithm to forecast the electricity consumption for different countries and compare with the electricity consumption during the year 2020. Moreover, the paper provides detailed information on the impacts of the COVID-19 on the balance of power supply-demand from different power utilities. The following section presents the data and method used, while the results and discussions are in Section 3. The concluding remarks are presented in Section 4.

2.0 DATA AND METHODOLOGY

A comprehensive multi-approach was adopted in order to answer our research questions and infer the impact of COVID-19 on the power sector in the region. Given that, qualitative and quantitative data are collected. Quantitative data concerned electricity consumption and weather data to qualitatively assess the impact of the pandemic on a country's electricity consumption through time-series forecasting. Whereas qualitative data are semi structured interviews, helping to understand more in-country measures during the pandemic to meet the demand. This study was conducted in five countries namely Benin, Senegal, Côte d'Ivoire, Togo, and Niger in West-Africa countries with a direct interaction with countries main power utility.

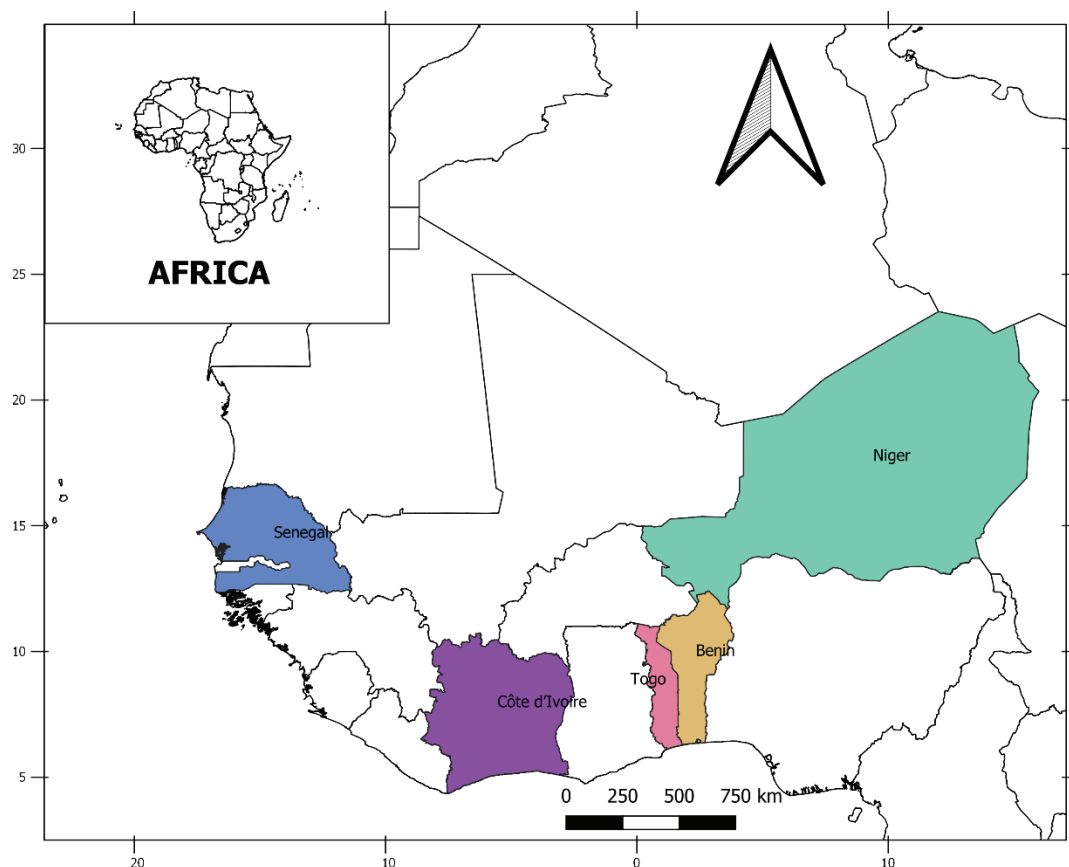


Figure 1: Study areas map: Countries of study highlighted

2.1 Data

Electricity demand is significantly affected by nonlinear factors and in electricity consumption forecasting the main factors that affect the accuracy of forecast are deterministic variables and weather variables. This includes climatic condition, calendar and other seasonality variables which have been widely reported in the literature (Chapagain et al., 2020; Chapagain & Kittipiyakul, 2018). Under West-Africa region and in literature as a whole, studies demonstrated that weather parameters such as: temperature, solar radiation and relative humidity have a considerable effect on the electricity consumption (Bonkaney, 2020; Friedrich & Afshari, 2015).

Given the sparse weather observation data over the region, spatial weather parameters data are retrieved from the latest climate reanalysis produced by European Centre for Medium-Range Weather Forecasts (ECMWF), the 5th generation of European ReAnalysis (ERA5). ERA5 is produced within the Copernicus Climate Change Service of the European Commission. It is widely used for many climate impact studies in West-Africa as they have demonstrated good performance to bridge data gaps (Danso et al., 2020; Sawadogo et al., 2020; Sterl et al., 2020) and knowing the best location for the implementation of solar and wind energy projects is important within this context. The purpose of this study is to assess the impact of climate change on solar and wind energy potential over Africa under low end (RCP2.6. ERA5 climate reanalysis, a numerical description of the recent climate by combining models with observations and are invaluable to numerous users around the world. It embodies a detailed record of the global atmosphere, land surface and ocean waves from 1950 onwards. ERA5 is based on the Integrated Forecasting System (IFS) Cy41r2 which was operational in 2016 (Hersbach et al., 2020) ECMWF is producing the ERA5 reanalysis which, once completed, will embody a detailed record of the global atmosphere, land surface and ocean waves from 1950 onwards. This new reanalysis replaces the ERA-Interim reanalysis (spanning 1979 onwards).

Calendar effects are captured by creating a dummy variable where special days such as holidays were considered as week-end. The dummy variable takes value 1 corresponding to “yes - normal working days” and 0 corresponding to “no-weekend or public holidays”. Table 1 below summaries the data collected and sources.

Table 1: Weather and energy data collected

Type of data	Spatial Resolution	Time range	Temporal Resolution	Source
Weather parameters:				https://cds.climate.copernicus.eu/c
Solar radiation (RSDS)	Country wide	2017:2020	Hourly	
Relative Humidity (RH)	Country wide		Hourly	
Temperature (°C)	Country wide		Hourly	
Electricity consumption	Spatial Resolution	Time range	Temporal Resolution	Source
Load	Country aggregation	2017:2020	Hourly	SBEE: Beninese Company of Electrical Energy
Load			Hourly	CEET: Togo Electric Energy Company
Electricity consumption			Daily	SENELEC: National Electricity Company of Senegal
Electricity consumption			Daily	CIE: Ivorian Electricity Company
Load			Hourly	NIGELEC: Nigerien Electricity Company
Semi-structured interviews				SBEE, CEET, SENELEC, CIE, NIGELEC
Public Holidays (Wday)				Literature

The semi-structured interviews consists of a series of questions around four sections including Impacts, Challenges, Opportunities and Perspectives to better understand the response and strategies of West-African power companies during the early period of coronavirus (pre-vaccine).

2.2 Methodology

Electricity consumption forecasting implies the use of various approach ranging from simple regression to complex and modern ones where some are based on machine learning algorithm. In order to have the best model for each forecasting exercise per country, this paper tested the performance of nine models to predict historical electricity consumption regressed with climatic variables (air temperature, relative humidity, and solar radiation) and calendar effect. These models can be divided in three categories: automatic, Machine Learning and hybrid Machine Learning.

2.2.1 Automatic Models

2.2.1.1 ARIMA

Auto Regressive Moving Average (ARIMA) is an adaptation of time filtering methods developed in the 1930's — 1940's by electrical engineers. Later in the 1970's, two statisticians George Box and Gwilym Jenkins developed a systematic method for applying them in business and economic data. This model assumes that the time series is generated from a linear process. But in real world phenomena, systems are nonlinear pretty often (Benrhmach et al., 2020). These models predict time series' future values based on a linear combination of its previous values and disturbances (Kalimoldayev et al., 2020). The ARIMA model with parameters p (the autoregressive order or the lag of the model), d (the integration or differencing order), q (the moving average order) with additional regressors fit an equation:

$$y_t - \phi_1 y_{t-1} - \dots - \phi_p y_{t-p} = \mu - \theta_1 e_{t-1} - \dots - \theta_q e_{t-q} + \beta^1 (x_t^1 - \phi_1 x_{t-1}^1 - \dots - \phi_p x_{t-p}^1) + \dots + \beta^n (x_t^n - \phi_1 x_{t-1}^n - \dots - \phi_p x_{t-p}^n) \quad \text{Eq. 1}$$

where μ is the constant, ϕ_k and θ_k are the AR and MA coefficients at lag k , and y_{t-k} and $e_{t-k} = y_{t-k} - \hat{y}_{t-k}$ the values of the dependent variable and of the forecast error at lag k , respectively. N represents the number of exogenous variables, β^i is every constant and x_{t-k}^i is indicator i at lag k (Robert Nau, 2021).

2.2.1.2 TBATS

TBATS is an alternative to autoregressive approach developed by De Livera, Hyndman, & Snyder (2011) which uses a combination of Fourier terms with an exponential smoothing state space model and a Box-Cox transformation, in a completely automated manner for univariate data. TBATS constitutes the following elements: Trigonometric terms for seasonality, B: Box-Cox transformations for heterogeneity, A: ARMA errors for short-term dynamics, T: Trend and S: Seasonal (including multiple and non-integer periods). The general representation of TBATS model Eq. 2, includes level Eq. 3, trend Eq. 4, seasonal Eq. 5, ARMA error term Eq. 6 :

$$y_t^{(w)} = l_{t-1} + \phi b_{t-1} + \sum_{i=1}^T s_t^{(i)} + d_t \quad \text{Eq. 2}$$

$$l_t = l_{t-1} + \phi b_{t-1} + \alpha d_t \quad \text{Eq. 3}$$

$$b_t = (1 - \phi)b + \phi b_{t-1} + \beta d_t \quad \text{Eq. 4}$$

$$s_t^{(i)} = s_{j,t-1}^{(i)} + \cos \lambda s_j^{(i)} + \sin \lambda s_j^{(i)} + y_i d_t \quad \text{Eq. 5}$$

$$d_t = \sum_{p=1}^p \varphi_i d_{t-i} + \sum_{p=1}^p \theta_i \varepsilon_{t-i} + \varepsilon_t \quad \text{Eq. 6}$$

Here $y_t^{(w)}$ is Box-Cox transformed observations at time t with the parameter ω ; l_t is the local level at time t ; b is the long-run trend; b_t is the short-term trend at time t ; seasonal periods; $s_t^{(i)}$ is the i th seasonal component of the series at time t ; d_t is an ARMA(p , q) error process; ε_t is the Gaussian white-noise process with zero mean and constant variance; α , β , γ_i are smoothing parameters; ϕ is damped parameter; $s_{j,t-1}^{(i)}$ is the stochastic level; k_i is the number of harmonics for the i th seasonal component, $\lambda s_j^{(i)} = 2\pi j/m_i$ where m_i is period of the i th seasonal cycles (Benrhmach et al., 2020; de Livera et al., 2011).

2.2.1.3 Multiple Seasonality Regression Models - Exponential Smoothing (ETS) Model

ETS refers to Error, Trend and Seasonal. ETS is an Exponential Smoothing Model technique based on the methods described by Hyndman et al. and is made available through the forecast package in the R software environment (Rob J. Hyndman & Yeasmin Khandakar, 2008). The seasonal component can be either which can be additive (A), multiplicative (M), or none (N). The optimum model method between the additive and multiplicative error models, was chosen based on either the minimum of Akaike information criterion (AIC), the corrected Akaike information criterion (AICc), or Bayesian information criterion (BIC) (Liu et al., 2020; Rob J. Hyndman & Yeasmin Khandakar, 2008). The general model involves a state vector and state space equations of the form

$$y_t = w(x_{(t-1)}) + r(x_{(t-1)})\varepsilon_t \quad \text{Ep 7}$$

$$x_t = f(x_{(t-1)}) + g(x_{(t-1)})\varepsilon_t \quad \text{Ep 8}$$

where $\{\varepsilon_t\}$ is a Gaussian white noise process with mean zero and variance σ^2 , and $\mathbf{1}_t = w(x_{(t-1)})$. The model with additive errors has $r(x_{(t-1)}) = \mathbf{1}_t$, so that $y_t = \mathbf{1}_t + \varepsilon_t$. The model with multiplicative errors has $r(x_{(t-1)}) = \mathbf{1}_t$, so that $y_t = \mathbf{1}_t(1 + \varepsilon_t)$. Thus, $\varepsilon_t = (y_t - \mathbf{1}_t)/\mathbf{1}_t$ is the relative error for the multiplicative model. The models are not unique. Clearly, any value of $r(x_{(t-1)})$ will lead to identical point forecasts for y_t (Rob J. Hyndman & Yeasmin Khandakar, 2008).

2.2.1.4 Prophet Model

The Prophet Model implements a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well (Taylor & Letham, 2018). It can be implemented in open source software such as Python and R, called Prophet. They are combined in the following equation:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t. \quad \text{Eq. 9}$$

Here $g(t)$ is the trend function which models non-periodic changes in the value of the

time series, $s(t)$ represents periodic changes (e.g., weekly and yearly seasonality), and $h(t)$ represents the effects of holidays which occur on potentially irregular schedules over one or more days. The error term represents any idiosyncratic changes which are not accommodated by the model; later we will make the parametric assumption that ϵ_t is normally distributed (Taylor & Letham, 2018).

2.2.2 Machine Learning Models

2.2.2.1 NNAR

Neural networks are a kind of statistical model, popularly used in machine learning. The concept of Artificial Neural Network (ANN) is inspired from the biological neural network of the central nervous system (Panigrahi & Behera, 2017). A large literature has evolved to forecast time series using various linear, nonlinear and hybrid linear–nonlinear models. Recently, hybrid models by suitably combining linear models like autoregressive integrated moving average (ARIMA). Neural Network Auto Regressive (NNAR) is one kind of ANN's in which lagged values of the time series can be used as inputs to a neural network (Sena & Nagwani, 2016). In this article, we only consider feed-forward networks with one hidden layer, and we use the notation NNAR(p,k) to indicate there are p lagged inputs and k nodes in the hidden layer. A NNAR(p,o) model is equivalent to an ARIMA(p,o,o) model, but without the restrictions on the parameters to ensure stationarity. With seasonal data, it is useful to also add the last observed values from the same season as inputs. More generally, an NNAR(p,P,k)_m model has inputs $(y_{t-1}, y_{t-2}, \dots, y_{t-p}, y_{t-m}, y_{t-2m}, \dots, y_{t-pm})$ and k neurons in the hidden layer. A NNAR(p,P,o)_m model is equivalent to an ARIMA(p,o,o)(P,o,o)_m model but without the restrictions on the parameters that ensure stationarity. For seasonal time series, the default values are P=1 and p is chosen from the optimal linear model fitted to the seasonally adjusted data. If k is not specified, it is set to $k=(p+P+1)/2$ (rounded to the nearest integer) (Rob J Hyndman and George Athanasopoulos, 2018). The NNETAR() function in R package forecast fits an NNAR(p,P,k)_m model.

2.2.2.2 Generalized Linear Model Elastic Net (GLMNET)

The elastic net procedure is a form of regularized optimization for linear regression that provides a bridge between ridge regression and the lasso. The estimate that it produces can be viewed as a Bayesian posterior mode under a prior distribution implied by the form of the elastic net penalty (Hans, 2011). The Elastic Net (ENET) uses a mixture of the l_1 (lasso) and l_2 (ridge regression) penalties and can be formulated as:

$$\hat{\beta}(\text{enet}) = \left(1 + \frac{\lambda_2}{n}\right) \left\{ \underset{\beta}{\operatorname{argmin}} \| \mathbf{y} - \mathbf{X}\beta \|_2^2 + \lambda_2 \| \beta \|_2^2 + \lambda_1 \| \beta \|_1 \right\} \quad \text{Eq. 10}$$

On setting $\alpha = \lambda_2 / (\lambda_1 + \lambda_2)$, the ENET estimator Eq. 7 is seen to be equivalent to the minimizer of:

$$\hat{\beta}(\text{enet } 2) = \underset{\beta}{\operatorname{argmin}} \| \mathbf{y} - \mathbf{X}\beta \|_2^2, \text{ subject to } P_\alpha(\beta) = (1 - \alpha) \| \beta \|_1 + \alpha \| \beta \|_2^2 \leq s,$$

for some s where $P_\alpha(\beta)$ is the Elastic Net penalty (Hans, 2011; Ogutu et al., 2012; Zou & Hastie, 2003).

2.2.2.3 Random Forest

Random Forest (RF) is a machine learning method for classification and regression. This modeling approach uses an ensemble of decision trees $\{h_{X_k}(\cdot), 1, \dots, \beta_k\} = \mathcal{H}$ for mapping a relationship between a vector of predictors and dependent variables. For each tree, X is the input vector, β_k is an independent stochastic variable which decides the growth of every tree (Jiang et al., 2019). Tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. The generalization error for forests converges to a limit as the number of trees in the forest becomes large. (BREIMAN, 2001). Statistically, Random Forests are appealing because of the additional features they provide such as measures of variable importance,

differential class weighting, missing value imputation, visualization, outlier detection and unsupervised learning (Cutler et al., 2012).

2.2.3 Hybrid Models

We have included two hybrid models (arima_boost() and prophet_boost()) that combine both automated algorithms with the machine learning algorithm XGBoost. In the case of The Prophet Boost algorithm combines Prophet with XGBoost to get the best of both worlds. The algorithm works by firstly modeling the univariate series using Prophet and then using regressors supplied via the preprocessing recipe which generate new features, and regressing the Prophet Residuals with the XGBoost model. The model can be created using the fit() function using the following engines: “prophet_xgboost” (default) - Connects to prophet::prophet() and xgboost::xgb.train() which is implemented in the R package Modeltime (T. Chen et al., 2018; Dancho, 2021).

We used XGBoost, a gradient boosting framework, introduced back in 2014. XGBoost can be used as a forecasting technique for feature selection and load prediction of a time lag. From prediction to classification XGBoost has proved its worth in terms of performance (Barolli, 2019).

2.3. Evaluation metrics - Model Adequacy and forecast accuracy

Best of models per country was selected based on the one that minimized as much as possible the error and had an accurate forecast on testing period. Therefore, various metrics were computed including Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), Mean Absolute Scaled Error (MASE) and R-squared for model adequacy. The RMSE and MAE measures the average magnitude error between the model outputs and the observations. The RMSE value indicates larger differences, while the MAE does not introduce weighting and gives the sign of the error. The smaller the RMSE, the better the performance of the models (Rivera & Arnould, 2020).

Hyndman and Koehler (2006) recommend that the Mean Absolute Scaled Error (MASE) be the standard when comparing forecast accuracies in which the forecast error is scaled by the in-sample mean absolute error obtained using the naïve forecasting method. This new measure is also easily interpretable: values of MASE greater than one indicates that the forecasts are worse, on average, than in-sample one-step forecasts from the naïve method. For the model fit we need to check significance of the coefficients, overall model adequacy and stability, correspondence to the model assumptions: no serial correlation, homoscedasticity and normal distribution of residuals. The model adequacy is estimated on the basis of residual standard error (σ_2), coefficient of determination (R^2) that refers to the percentage of target variable variance explained by the model (Kalimoldayev et al., 2020). The metrics equations are presented below:

$$MAE = \frac{1}{m} \sum_{i=1}^m |f(i) - y(i)| * 100 \% \quad Eq. 11$$

$$RMSE = \sqrt{\frac{1}{M} + \sum_{i=1}^m (f(i) - y(i))^2} \quad Eq. 12$$

$$q_t = \frac{e_t}{\frac{1}{n-1} \sum_{i=2}^n |Y_i - Y_{i-1}|} \quad \text{and} \quad MASE = \text{mean}(|q|) \quad Eq. 13$$

$$R^2 = \left[1 - \frac{\frac{1}{n} \sum_{i=1}^n (y_t - \hat{y}_t)^2}{\text{var}(y)} \right] \times 100 \quad Eq. 14$$

Let Y_t denote the observation at time t and F_t denote the forecast of Y_t . Then define the forecast error $e_t = Y_t - F_t$ (Hyndman & Koehler, 2006; Shaub, 2020).

To evaluate the prediction accuracy, the historical electricity consumption data were split into two. Models were trained over two years (2017-2018) and testing on 2019 respectively

(Figure 2). The performance metrics were calculated on the test set to get an unbiased estimation of the best model performance. The Tidymodels Extension for Time Series Modeling “Modeltime” package on its version 0.7.0 is used in R open source software for the data processing (Dancho, 2021).

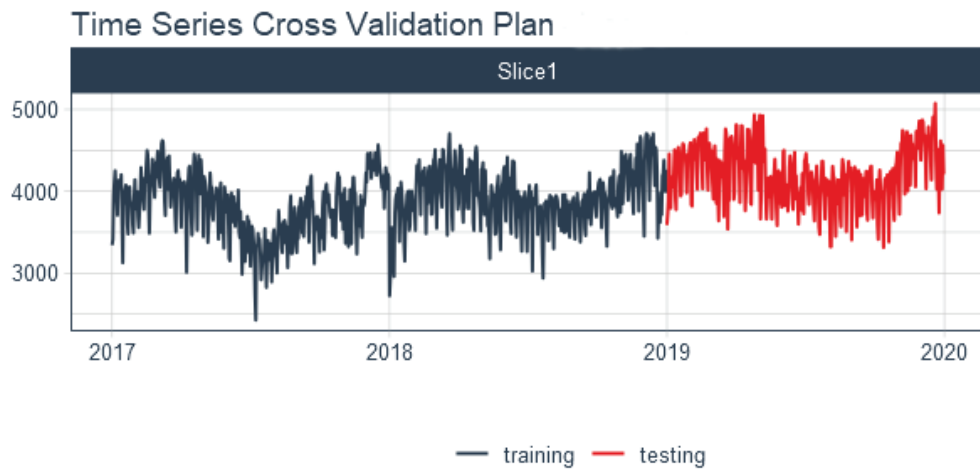


Figure 2: Time series cross validation - Training and testing period
Results and Discussions

Seasonal load profile is shown in Figure 4 for each of the countries over the years - a monthly average of three years data from 2017-2019 representing the training period. Daily energy electricity consumption is obtained by summing hourly load profiles.

Benin, Togo and Cote d'Ivoire had the same electricity consumption pattern. It was characterized by two peaks in the early period of the year during the month of March and later one during the month of December and lowest off-peak occurring during the month of August. The average daily energy consumption ranges respectively [2.87-5.1] GWh, [2.42 - 5.6] GWh and [17.37 - 32.27] GWh in Benin, Togo and Cote d'Ivoire. The seasonal pattern is consistent with the recent study of Kondi et al., (2019) on Weather Sensitivity of Electricity Demand in West African Megacities. This could be explained by the fact that Benin, Togo and Cote d'Ivoire share the same climatic zone (Figure 3) and therefore weather-based influence on electricity consumption of the population is the same. As a matter of fact, for the above countries, the temperature (TEMP), relative humidity (RH) and solar radiation (RSDS) follows the same pattern (Figure 5). In all cases, RH is an opposite of temperature whereas the RSDS has an opposite profile to RH in such a way that when RH is high, RSDS is low and reciprocally. Temperature range [25ffC-32ffC], the humidity [35 - 87] %, and solar radiation between [178 - 261] W/m²/day. A perfect matching is found between the load consumption seasonal profile and the weather parameters positively for RSDS and temp or negatively for RH, correlation wise. RSDS and TEMP increases are followed by an increase of load while the opposite is observed for the relative humidity.

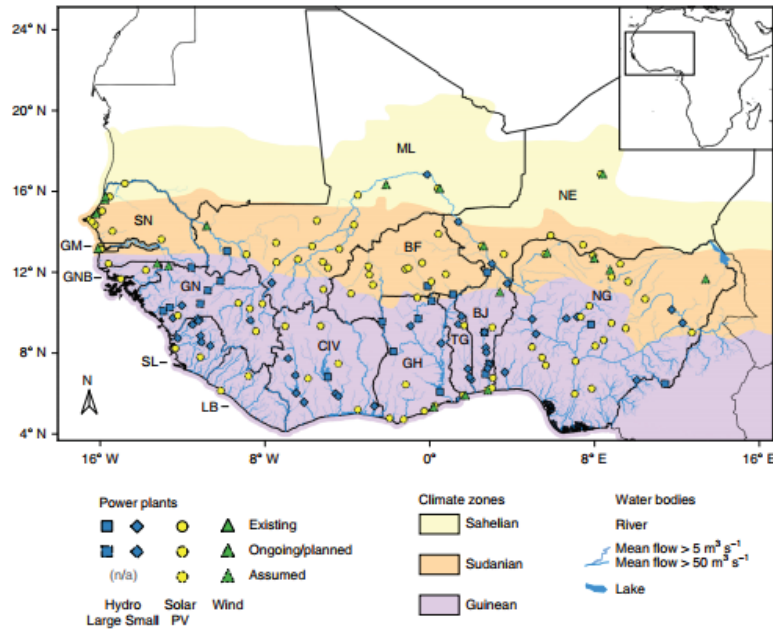


Figure 3: Climatic zones and power plants in West Africa, derived from (Sterl et al., 2020)

Niger and Senegal have distinct seasonal profiles compared to Benin, Cote d'Ivoire and Togo. Niger displays two peaks in its seasonal profile occurring respectively in May (2.79 GWh) and October (2.38 GWh) and the lowest in the months of December and January.

The temperature increases as we move northward to the Sahelian region. Hottest and coldest temperatures of all studied countries are observed in Niger ranging from 24.7 to 35.5 fflC (this value represent average mean temperature). The weather and electricity consumption pattern observed in the case of Niger match with the study of Bonkaney (2020) air temperature (T mean. In contrast, unlike the other countries of the study that depict two peaks, Senegal exhibits only one peak occurring in October with an average value of 13.56 GWh. The lowest consumption is observed in January with an average of 9.62 GWh.

As of the other countries, the same remark is observed for Niger and Senegal where the electricity consumption has positive correlation with temperature and radiation and negative correlation for the relative humidity.

Hence, for all the countries, the electricity consumption positively correlates with temperature and radiation and negatively with relative humidity. In a nutshell, we observed that load demand profile follows the weather seasonal trend and this trend varies depending on the climatic zone the countries mostly fall into. This explains why Benin, Cote d'Ivoire and Togo display the same seasonal pattern as they are in the same climatic zone (Guinea climatic zone) and Niger in Sahelian and Senegal in Soudanian zone have different pattern from those in Guinean Zone. See countries in their climatic zone (Figure 3).

As presented in the methodology, all the time-series forecasting models are multivariate and forced with regressors (RH, RSDS, TEMP and Wday) except for ETS and TBATS which are univariate models. The models are evaluated against each other on testing period (in the year 2019) and the best is selected based on the level of adequacy and forecast accuracy through minimizing error. The performance of regression models used differ from one country to the other.

Table 2 shows the results of the different performance metric computed for all the models. In Senegal, RF, Prophet, and GLMNET models are the best in fitting the electricity consumption and capturing as much as possible the variance on the observation with an R-squared of 81%, 83% and 84% respectively. Except the ETS, TBATS and auto. ARIMA all the rest of models have a R-squared beyond 75%. Above all, the GLMNET model provides

the least error with the lowest MASE of 1.82, which makes it the best model in forecasting 2020 electricity consumption without COVID-19 in Senegal.

In the case of Cote d'Ivoire, except the univariate based models which R-squared is below 25% the other models have reached a R-squared above 60%. Therefore, this shows that the considered predictors have significant impact on model estimation and explanation of the dependent variable. The GLMNET comes to be the best model while presenting the lowest error possible with MAE (37), RMSE (52) and best accuracy MASE (0.6) as shown in Table 2 compared to other models.

Regarding model's performance in capturing Niger electricity consumption in testing period, from Table 2, it can be observed that univariate models are under-performing with an R-squared nearly equal to 0 while the other have a good fitting above 0.85. NNAR, Prophet and GLMNET are the top models with an R-squared higher than 0.9. On the basis of the MAE, MASE and RMSE measures, NNAR Artificial intelligence model coefficients were low enough to outperform Prophet and GLMNET model with respectively 159.5, 1.34 and 195.13. Hence, the NNAR is used to model the electricity consumption in Niger with 10 neurons in the hidden layer with a weekly seasonality (NNAR (1,1,10) [7]).

In the case of Togo, regressed models outperformed univariate one (ETS and TBATS) with R-squared above 0.5 except NNAR of 0.43. As in Table 2 shows, in all cases, GLMNET model shows very good accuracy compared to others, as all the values are much lower in RMSE, MAE and MASE with an R-squared of 0.59. Finally, in the case of Benin, NNAR (1,1,10) [7] showed better performance both in predictive ability with highest R-squared of 0.67 and also in forecasting capabilities by minimizing the level of error.

From the above, it was found that for all the countries, the electricity consumption exhibits seasonality driven by climatic and calendar effects that have been taken into account in building the regressions models. Thus, the multivariate models outperform the univariate ones in west Africa. Furthermore, Generalized Linear Model Elastic Net (GLMNET) and Neural Network Auto-Regressive (NNAR) are the top models with good performances for forecasting electricity consumption in the countries considered. The seasonal profile difference and relative change between the observed and forecasted are shown in Figure 8 and Figure 9.

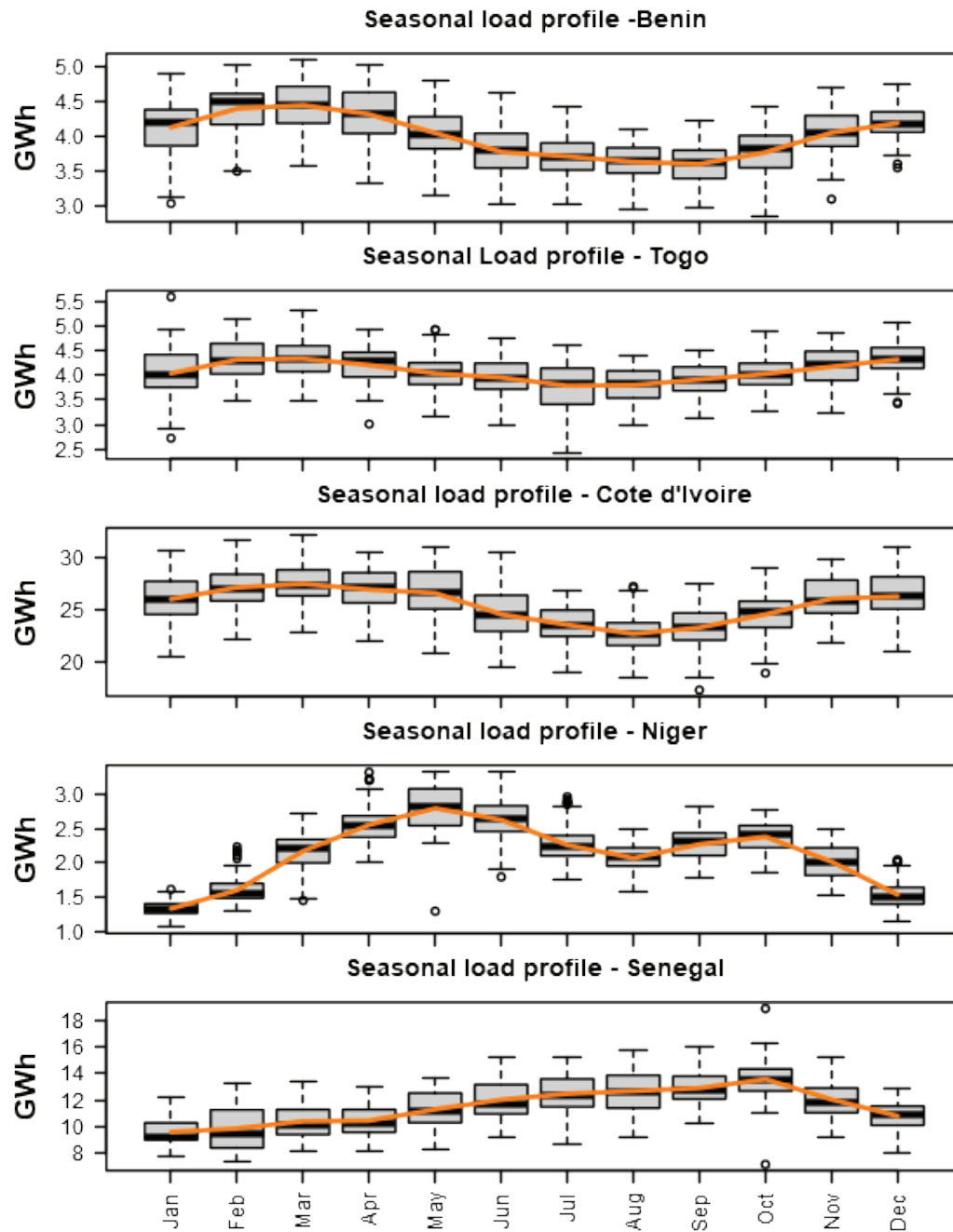


Figure 4: Seasonal daily energy load and consumption profile of countries

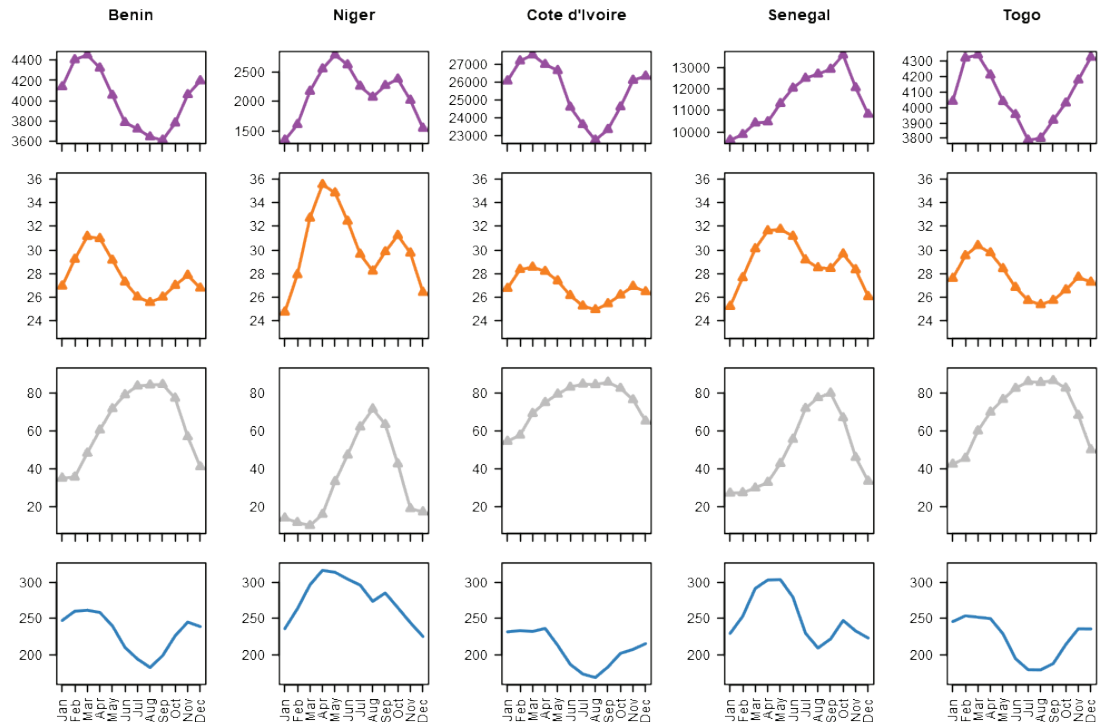


Figure 5: Seasonal electricity consumption profile against meteorological parameters, RSDS: surface downward solar radiation, TEMP: air mean temperature, RH: Relative Humidity. All parameters are monthly average from 2017-2019.

Table 2: Accuracy table of model per country, * A part from Senegal which values are in kWh, for the other countries the statistical metrics are computed in MWh unit

Accuracy table - SENEGAL *

.model_id	.model_desc	.type	mae	mase	rmse	rsq
1	REGRESSION WITH ARIMA(1,1,1) (1,0,1)[7] ERRORS	Test	2086417	3.96	2510997	0.03
2	PROPHET W/ REGRESSORS	Test	1491121	2.83	1604519	0.83
3	NNAR(1,1,10)[7]	Test	1442738	2.74	1603605	0.75
4	SEASONAL DECOMP: ETS(M,N,N)	Test	2012124	3.81	2415022	0.06
5	TBATS(0, {2,1}, -, {<7,3>})	Test	1927273	3.65	2334254	0.07
6	GLMNET	Test	957460.7	1.82	1065989	0.84
7	RANDOM FOREST	Test	1377272	2.61	1500802	0.81
8	PROPHET W/ XGBOOST ERRORS	Test	1238263	2.35	1368443	0.79
9	ARIMA(0,0,0) WITH NON-ZERO MEAN W/ XGBOOST ERRORS	Test	1353598	2.57	1494758	0.78

Accuracy table - Cote d'Ivoire

.model_id	.model_desc	.type	mae	mase	rmse	rsq
1	REGRESSION WITH ARIMA(3,1,2) (0,0,2)[7] ERRORS	Test	58.71	0.95	70.96	0.58
2	PROPHET W/ REGRESSORS	Test	44.6	0.72	57.81	0.77
3	NNAR(1,1,10)[7]	Test	76.8	1.24	86.18	0.77
4	SEASONAL DECOMP: ETS(M,N,N)	Test	83.21	1.35	97.37	0.2
5	TBATS(0, {2,1}, -, {<7,3>})	Test	84.17	1.36	98.68	0.22
6	GLMNET	Test	37.06	0.6	51.78	0.78
7	RANDOMFOREST	Test	70.38	1.14	81.48	0.72
8	PROPHET W/ XGBOOST ERRORS	Test	53.97	0.87	68.14	0.7

9	ARIMA(0,0,0) WITH NON-ZERO MEAN W/ XGBOOST ERRORS	Test	65.56	1.06	78.99	0.68
Accuracy table – Niger						
.model_id	.model_desc	.type	mae	mase	rmse	rsq
1	REGRESSION WITH ARIMA(1,0,2) (2,0,2)[7] ERRORS	Test	324.47	2.72	399.15	0.85
2	PROPHET W/ REGRESSORS	Test	352.95	2.96	394.73	0.92
3	NNAR (1,1,10)[7]	Test	159.5	1.34	195.13	0.96
4	SEASONAL DECOMP: ETS(M,N,N)	Test	879.29	7.37	1006.72	0.03
5	TBATS(0, {0,2}, 0.966, {<7,3>})	Test	965.79	8.1	1088.75	0
6	GLMNET	Test	217.97	1.83	250.14	0.94
7	RANDOMFOREST	Test	212.52	1.78	252.25	0.9
8	PROPHET W/ XGBOOST ERRORS	Test	288.4	2.42	322.53	0.89
9	ARIMA(0,0,0) WITH NON-ZERO MEAN W/ XGBOOST ERRORS	Test	214.26	1.8	254.35	0.89
Accuracy table – Togo						
.model_id	.model_desc	.type	mae	mase	rmse	rsq
1	REGRESSION WITH ARIMA(3,1,1) (2,0,0)[7] ERRORS	Test	199.68	0.74	254.94	0.51
2	PROPHET W/ REGRESSORS	Test	238.77	0.89	286.93	0.62
3	NNAR(1,1,10)[7]	Test	317.21	1.18	372.59	0.5
4	SEASONAL DECOMP: ETS(A,N,N)	Test	243.91	0.91	291.89	0.33
5	TBATS(1, {1,2}, -, {<7,3>})	Test	234.27	0.87	286.9	0.33
6	GLMNET	Test	197.2	0.73	241.83	0.59
7	RANDOMFOREST	Test	272.37	1.01	318.5	0.65
8	PROPHET W/ XGBOOST ERRORS	Test	263.26	0.98	317.41	0.56
9	ARIMA(0,0,0) WITH NON-ZERO MEAN W/ XGBOOST ERRORS	Test	219.18	0.81	275.31	0.6
Accuracy table – Benin						
.model_id	.model_desc	.type	mae	mase	rmse	rsq
1	REGRESSION WITH ARIMA(0,1,2) (0,0,2)[7] ERRORS	Test	494.85	2.13	584.43	0.57
2	PROPHET W/ REGRESSORS	Test	406.18	1.75	482.72	0.63
3	NNAR(1,1,10)[7]	Test	250.72	1.08	308.89	0.67
4	SEASONAL DECOMP: ETS (M,N,N)	Test	575.03	2.47	683.94	0.11
5	TBATS(1, {1,3}, -, {<7,3>})	Test	513.61	2.21	603.06	0.13
6	GLMNET	Test	378.06	1.63	453.4	0.63
7	RANDOMFOREST	Test	264.31	1.14	320.32	0.64
8	PROPHET W/ XGBOOST ERRORS	Test	376.33	1.62	457.38	0.52
9	ARIMA(0,0,0) WITH NON-ZERO MEAN W/ XGBOOST ERRORS	Test	266.22	1.14	327.34	0.64

Early cases of COVID-19 confirmed in 2020 were recorded in the beginning of February and start increasing to peak on the first wave in May and slow down a bit before taking an ascendant to peak in July (second wave of contamination) to reverse down through the end of year. This is due to the various restriction's measures put in place. As things are getting back to normal and the release of some restrictions, the contamination is peaking again in early 2021 and now experienced a decreasing rate in the mid-term part of 2021. Now with the new variant, the contamination is going up again (Figure 6). This sinusoidal pattern is also observed in overall confirmed cases in countries with some stagnant period of the year (Figure 7). Cote d'Ivoire and Senegal are the countries with the highest rate of cases confirmed followed by Togo, Benin and Niger on the last update of 23 July 2021 with 55861, 49386, 14970, 8324 and 5594 number of cases recorded respectively (Figure 7).

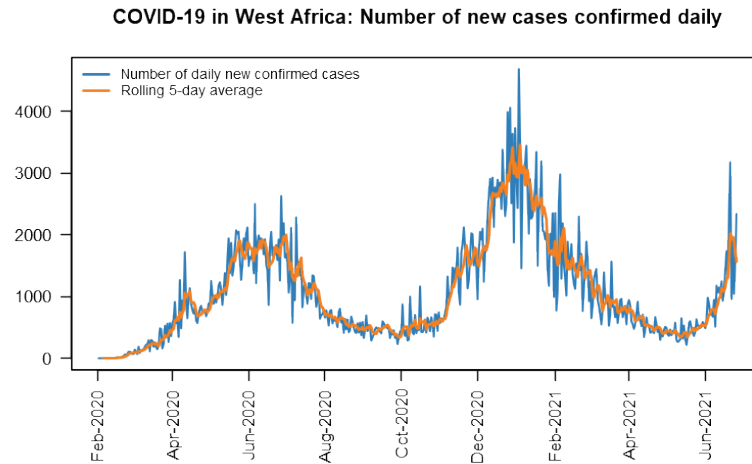


Figure 6: COVID-19 in West Africa, (Johns Hopkins University & Medicine, 2021)

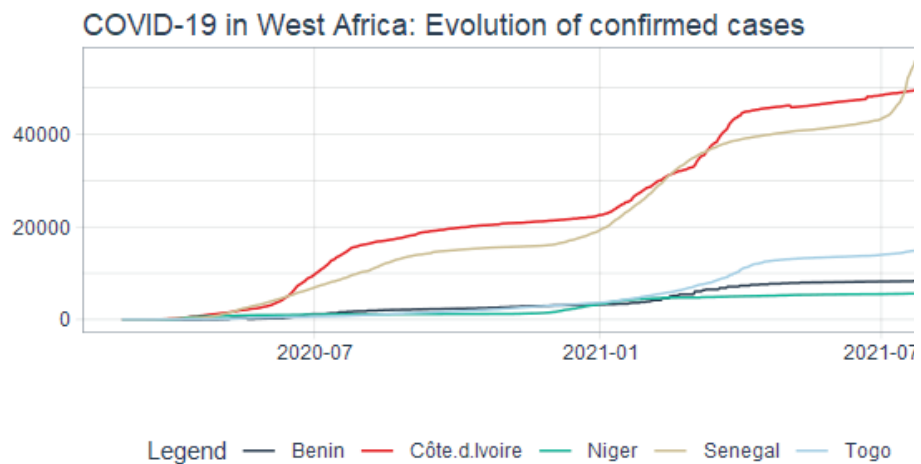


Figure 7: COVID-19 in West Africa: Evolution of confirmed cases (Johns Hopkins University & Medicine, 2021)

As a result of COVID-19 increase cases in West-African countries, this affected drastically the consumption pattern due to the restriction measures put in place. How this external factor affected the demand in the year 2020, is displayed in Figure 8 and Figure 9. The best model from the study above is used to forecast the electricity consumption for the year 2020 regressed with climatic and the calendar effect.

One general observation, that can be easily perceived from Figure 8 and Figure 9 is that prior COVID-19 cases being confirmed, all countries' demand rose, due to the economic progress that was being recorded in the region. Five out of the ten fastest-growing economies in 2019 were in West Africa: Côte d'Ivoire (the highest GDP growth rate: 7.3%), Ghana (7%), Benin (6.4%), Senegal (6.3%) and Niger (6.3%) (World Bank 2020).

It is worth noting that the seasonal pattern of consumption in all countries had not changed despite the pandemic, which follows the same path as described in Figure 4 (see Figure 4 against Figure 8 & Figure 9). However, as the covid-19 cases increase leading to various dynamics in the societies, the level of consumption changes compared to the normal (normal represents the forecasted consumption of 2020) which is different from one country to another.

In the case of Benin, three main time slots period can be observed. The pre-COVID, in-COVID and post-COVID in the year 2020. Table 3 gives the total consumption difference between the observed and forecasted consumption for 2020 and daily average.

The pre-COVID span from January to March where the demand rose with a total +11,096 MWh compared to the forecast for 2020 obtained from time series modeling above. During the in-COVID period (April-September) the demand decreased by about -13,851.61 MWh (with a daily decrease of 76.52 MWh) in the period. As activities are getting back to normal post restriction measures the demand starts to increase with +9,795.19 MWh (Table 3) during late September to December. Globally an increase in the consumption of about +7040.45 MWh is noted despite the pandemic, which is about 0.46 % $\pm$ 6 of increase in overall compared to the normal (Table 4 and Figure 8, B2). The normal refers to the demand without COVID-19 as business as usual.

On the supply side the country was fortunate to finish his new plant on time the year before and that have played a critical role in helping the country meeting the demand as well as having a stable power importation as stated in the interview had with the SBEE Governance and Risk Management Department in the following “The efforts since 2019 with the construction of the MARIA-GLETA 2 Thermal Power Plant have not only reduced the country’s import rate but also kept up with demand during the COVID-19 period. Imports from the suppliers (Ghana and Nigeria) were stable, which made it possible to avoid any additional production costs that would have required the rental of a reserve generator.”

Among the countries studied Niger had the lowest COVID-19 confirmed cases and therefore was not subjected to the same pressure and socio-dynamic as the other countries (Figure 7). This low rate of contamination and economic progress recorded in 2019, could explain why they were not a significant decrease in consumption (Figure 8, NIG2) in 2020 in Niger. Over 2020, there was an increase of about 3777 MWh which represents an average increase of about 10.32% $\pm$ 8.20 compared to the forecasted consumption expected for the given year. The slight decrease below forecast at the end recorded could be due to the seasonal pattern. At the early period of contamination in March, the pandemic drives down consumption but still stay above the forecast, before resuming to an increasing trend.

Togo is a neighboring country of the Benin republic, and in term of relative change, the countries have similar trend. The pre-COVID, in-COVID and post-COVID periods are discernable as of Benin (Figure 6, B2 and Figure 6, TG2). Until a recent past till 2020, Benin and Togo shared a common body for electricity import for their country known as Communauté Electrique du Benin (CEB). This could be an underlying reason. During in-COVID period (April-September) the demand decreases by about -193 MWh and resumes back to an increasing trend for the last two months of year (post- COVID) with -8907.57 MWh (average 49.48 MWh). The pre- COVID total increase observed is about +17,030.75 MWh (average of 187.151 MWh). On average over the year the demand relative change shows an increase of 0.84% $\pm$ 5.54 (Table 4).

For the case of Cote d’Ivoire, the three periods were observed but the trend of consumption increase resumed quicker than other countries previously discussed after the in-COVID period. The in-COVID period (beginning of early cases confirmed of COVID-19) span from April to June where there is a slight decrease but still the consumption remains above forecast with +16802.34 MWh (averaging +161.56 MWh) surplus with regards to the normal (forecast) (Figure 8, CI1& CI2). The surplus from July to December is about 12,0414.12MWh (averaging +747.91 MWh) above forecast. Despite the context of COVID-19, the relative change is about 2.18% $\pm$ 3.52 (Table 4).

Cote d’Ivoire and Senegal experienced a quick recovery in consumption after a slow decrease during the first months after the recording of the first cases of COVID-19. In the case of Senegal, the early increase in consumption pre-COVID is observed from January (+35514.86 MWh) to March followed by a period of decrease spanning from April to May (-5503.12 MWh) and the post-COVID from June to December (+95,192.87 MWh) where consumption resume increasing above forecast (Figure 9, SN1 & SN2). The demand increased by 2.64 % $\pm$ 5.93 compared to the expected (Table 3).

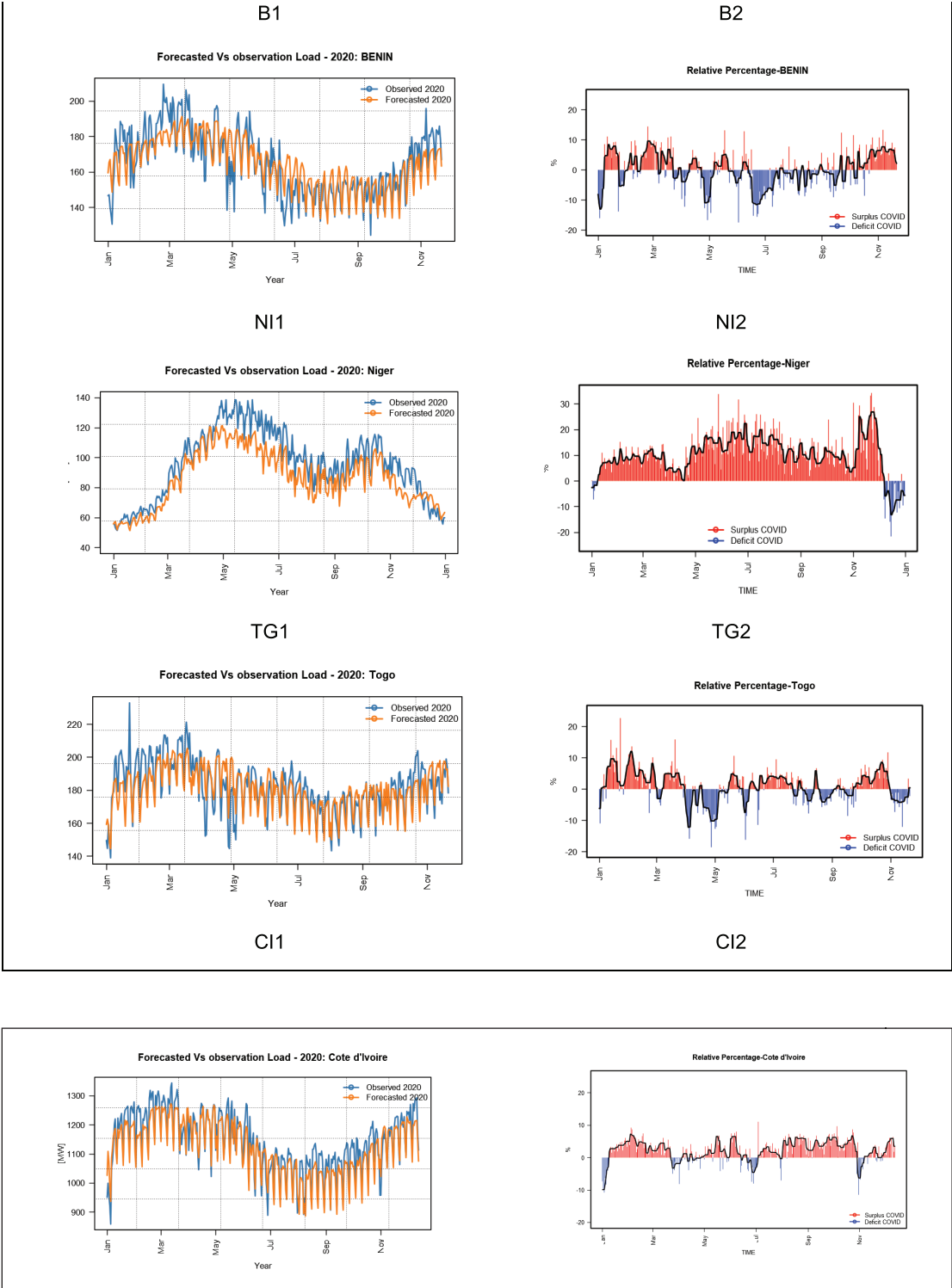


Figure 8: Time series forecasting of load without COVID and relative change: $100 \times (\text{Observed} - \text{forecast} / \text{forecast})$ in Benin, Togo, Niger and Cote d'Ivoire

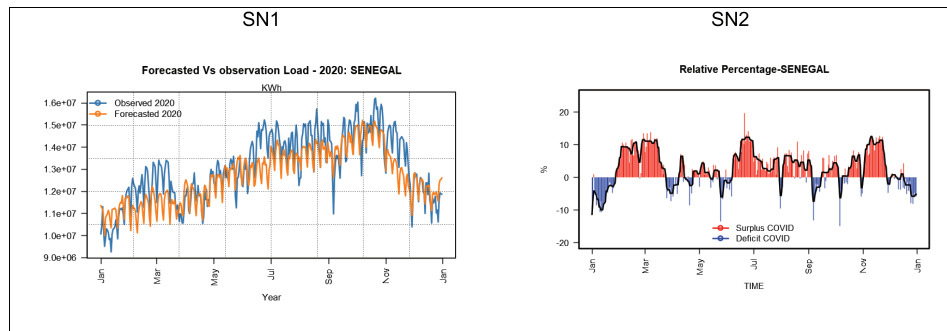


Figure 9: Time series forecasting of load without COVID and relative change: $100 \times (\text{Observed} - \text{forecast}) / \text{forecast}$ in Senegal

Table 3: Total consumption and average daily consumption bias (observed – forecast) per COVID period.

COUNTRIES	TIME PERIOD	TOTAL CONSUMPTION (MWH)	DAILY AVERAGE (MWH)
COTE D'IVOIRE			
Pre-COVID	01/01/2020 - 3/22/2020	64636.59	788.25
In-COVID	3/23/2020 – 7/4/2020	16802.34	161.56
Post-COVID	7/4/2020 – 12/31/2020	120414.12	747.91
SENEGAL			
Pre-COVID	01/01/2020 - 3/24/2020	35514.86	422.79
In-COVID	3/25/2020 – 6/7/2020	-5503.12	-77.374
Post-COVID	6/8/2020 – 12/31/2020	95192.87	459.86
TOGO			
Pre-COVID	01/01/2021 - 3/31/2020	17030.75	187.151
In-COVID	4/1/2020 - 9/27/2020	-8907.57	-49.48
Post-COVID	9/28/2020 – 12/31/2020	3348.64	60.88
NIGER			
COVID year	01/01/2021 - 12/31/2020	81234.25	221.951
BENIN			
Pre-COVID	01/01/2021 - 3/23/2020	11096.87	133.69
In-COVID	3/24/2020 - 9/20/2020	-13851.61	-76.52
Post-covid	9/21/2020 – 12/31/2020	9795.19	157.98

Table 4: Descriptive statistics of observed and forecast

BENIN				
	mean	sd	min	max
Observed (MW)	3966.81	444.68	2984.25	5032.48
forecast (MW)	3945.21	328.51	3166.87	4573.65
Relative Bias (%)	0.46	6.17	-17.01	14.14
Observed - Forecast	21.60	116.17	-182.62	458.83
NIGER				
Observed (MW)	2300.86	539.96	1235.11	3327.34
forecast (MW)	2078.91	441.48	1226.56	2925.32
Relative Bias (%)	10.32	8.20	-21.20	34.06
Observed - Forecast	221.95	98.47	8.55	402.02
TOGO				

Observed (MW)	4360.08	378.13	3338.13	5592.69
forecast (MW)	4324.89	305.07	3468.69	4937.18
Relative Bias (%)	0.84	5.54	-18.64	22.73
Observed - Forecast	35.19	73.06	-130.56	655.51
COTE D'IVOIRE				
Observed (MWh)	27409.49	2415.71	20616.66	32274.50
forecast (MWh)	26827.78	2229.21	21290.67	30553.74
Relative Bias (%)	2.18	3.52	-11.49	11.01
Observed - Forecast	581.71	186.50	-674.01	1720.76
SENEGAL				
Observed (kWh)	13041887.36	1507418.68	9260175.30	16214307.00
forecast (kWh)	12699798.20	1214440.57	10017888.72	15212461.16
Relative Bias (%)	2.64	5.93	-14.83	19.77
Observed - Forecast	342089.17	740274.98	-2212620.63	2441785.68

4.0 CONCLUSIONS AND RECOMMENDATIONS

This study sought to understand the impact of COVID-19 on the electricity supply-demand side in selected countries in West-Africa (Benin, Togo, Cote d'Ivoire, Senegal). Several types of models were inventoried including Automated (Auto.ARIMA_REGRESSORS, PROPHET_REGRESSORS, NNAR, ETS, TBATS), machine learnings (GLMNET, RANDOMFOREST) and hybrid Model (PROPHET_XCGBOOST, ARIMA_XCGBOOST ERRORS) to explore the best of algorithm that have the highest predictive ability and forecasting accuracy electricity consumption per country of study. Various performance metrics are computed to assess models against each other. Mean air temperature, Solar radiation (RSDS), Relative Humidity (RH), Temperature (°C) and Workind days (Wday) are used as explanatory variables in multivariate models. We observed that the seasonal electricity consumption pattern was the same with the temperature, and solar radiation. As the temperature and RSDS increase, the electricity demand also increases while it decreases with increasing RH. Furthermore, it was also found that countries within the same climatic zones depicted the same seasonal pattern. This explains why the same seasonal pattern was observed between Cote d'Ivoire, Benin, and Togo on one hand Niger, and Senegal on the other hand. From the time-series modelling and model selection, we found that machine learning algorithms namely NNAR and the GLMNET were the best models that perform better in capturing variability and accuracy for forecasting. GLMNET was best for Senegal, Cote d'Ivoire and Benin while NNAR for Niger and Togo. These models are then used to forecast the electricity consumption for the year 2020 assuming no COVID-19 happened. On the observed consumption as regards to the pandemic, three main periods were detected namely pre-COVID, in-COVID and post-COVID period.

The pre-COVID is the first months before the recording of first cases of contamination and the results show that the electricity consumption was increasing above the forecast without COVID. This was explained by the economic progress noticed in the region. Then during the in-COVID period, as the cases are increasing and because of panic alert and rapid deployment of restriction measures, the consumption goes down in all countries. Nevertheless, in some countries the demand was much more pronounced like in Benin and Togo. The third period is the post-COVID which represents the period after the release of restrictions measures. It was a resurgence of rising demand in all countries. In overall, for all countries, during the 2020 as a result of COVID-19, the electricity consumption increased by about 0.46%, 10.32%, 0.84%, 2.18%, 2.64% respectively in Benin, Niger, Togo, Côte d'Ivoire, and Senegal with an average of 3.28%. Niger having the highest increase in consumption despite this special year could be explained by the evolution of the country and also that it had the least number of infected people of all countries. Therefore, the restriction measures were highly enforced as compared to the surrounding countries. This study was amongst the first of kind on forecasting electricity consumption in West-

Africa using advanced techniques and assessing the impact of the COVID-19 pandemic on supply-demand. Advanced modern techniques model is fitted on historical data and tested before being used for forecasting. However, this modelling practice requires high temporally scale and long historical data to produce accurate results. To promote more research and increase finding, it is highly recommendable that more effort is put into collecting and make available high-resolution electricity consumption data. This data is essential for proper demand analysis which can support proper power system planning.

Code availability

The R code is available upon request to the corresponding author. The analyses were performed in R Programming Language.

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**ECOWAS Centre for Renewable Energy
and Energy Efficiency**
Achada Santo Antonio, C.P. 288, Praia,
Cape Verde
Tel: +238 26046630
Email: info@ecreee.org
Website: www.ecreee.org



Konrad-Adenauer-Stiftung e.V.
Regional Programme Energy Security and Climate
Change in Sub-Saharan Africa
P.O.Box 66471-00800
Nairobi, Kenya
TEL: +254 20 2610021
Website: <https://www.kas.de/en/web/climate-energy-africa>

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