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Original Research Article

# Electrical Load Forecasting using Machine Learning approach: simulation of a microgrid energy consumption with adaboost regressor

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## ABSTRACT

The dynamic evolution and variation of electrical loads is now, a priority for their optimal management and, above all, forecasting. Now, these dynamic load variations require computer tools that are able to implement optimal load forecasting models. Scientific research into automated models for forecasting abatrical load is therefore a la little of the science o electrical loads is therefore a challenge for sciencific researchers, and several studies have been carried out in this area. These include machine learning approaches such as Long Short-Term Memory, Support Vector Machine, Multilayer Perception, deep learning, probabilistic and others. These studies are often quite complex due to the number of elevated hyperparameters they contain, with considerable deviations in accuracy between the real and predicted data. Thus, in order to exploit methods with fewer hyperparameters and minunized prediction deviations between consumed and production, this paper proposes a method for three based on a regression ensemble method: adaboost regressor approach, to improve in energy consumption forecasting by application of advanced algorithm. So, this article presents learning and validation tests for the proposed model. The data used, were collected from a renewable energy source photovoltaic solar energy. While 80% of the data collected was used for learning purposes, the remaining 20% was used for validation testing. The results of this study give a coefficient of determination  $R^2$  between 0.9995 and 0.9997 for the learning results and between 0.83 and 0.95% for the validation test results. According to the metrics parameters, these results are representative The real data and reflect the performance of the proposed model. The proposed model is well adapted the management of electrical consumption load forecasts to ensure balance between supply and to demand.

# KEYWORDS

Optimal management, electricity demand, forecasting model, ensemble regression: adaboost regressor.

## **INTRODUCTION**

Electricity is at the heart of development [1]. The need to satisfy electricity demands to reduce energy insufficiency and, above all, environmental pollution, means that renewable

energy resources need to be prioritized, as recommended by the United Nations' global agreements 7 and 13 within its sustainable development goals [2]. However, the intermittent nature of these renewable resources is an important parameter that influences the quality and reliability of electrical energy and the balance between supply and demand, especially when these resources are less controlled [3]. Forecasting electrical energy production is becoming increasingly essential not only for the efficient and continuous operation of grid operating systems, but also for the optimal management of these renewable resources. Load forecasting is an integral process in the planning and operation of electric utilities [4]. It helps reduce the mismatch between supply and demand, thus ensuring the sustainability of energy systems.

Indeed, load forecasting is necessary for the consistent operation of the power grid and for the optimal management of the energy flows in these systems [5]. It also enables reserves to be estimated and managed for power system scheduling and for trading on the electricity market [6] and reducing penalties for grid imbalances [7]. Due to the sharp increase in electricity production from renewable energies, forecasting this production is becoming increasingly important. A number of research studies have been carried out to help power system operators to plan the distribution of electricity. However, a fairly significant discrepancy between actual demand values and those predicted by models would have technical and economic consequences [8] because forecasts should be optimized according to parameters that take prices into account [9].

The main objective of this study is to improve in energy consumption forecasting by application of advanced algorithm like adaboost regressor approach. These studies can help to identify the strengths and weakness of methods in that specific context and contribute to the advancement of knowledge in electrical load forecasting and energy management. Now, the methods consist to minimize the discrepancies between actual and predicted load values. The specific objective is to set up the adaboost regressor approach, for learning and validating electrical energy demands. For this, 80% of the data collected was used for learning purposes, the remaining 20% was used for validation testing. The data for learning and tests, were supplied by the Electrical Energy Company of Togo (CEET) and collected from a renewable energy production source: photovoltan solar energy.

The rest of this article is divided into four sections: the theoretical background materials is presented in Section 2; the material and methods are presented in Section 3; the results and discussion are presented in Section 4; and, finally, the conclusion is presented in Section 5.

# THEORETICAL BACKGROUND

In this section, bibliographical reviews, general forecasting approach, mathematical approach of the regression ensemble method and performance metrics, are shown.

# **Bibliographical reviews**

Electricity is a vector of development for countries. However, there is a major challenge in optimizing its production due to its integration of intermittent renewable energy sources. On the other hand, the most pressing concern is the efficient management of electrical load demands. Many studies have been carried out on the subject of more efficient and optimized energy management [10]. In this context, Izquierdo-Monge O and al. proposed, in their paper, a methodology for optimizing electrical energy consumption in a distribution network that involved equipping the network with intelligence [11]; in [12], the authors proposed microgrid optimization based on a hybridized system of renewable energy resources; Mah AXY and al. presented an optimization of the design and operation of an autonomous microgrid with electric and hydrogen loads, showing a significant reduction in load costs [13]; moreover, a strategy for controlling and managing the energy supply of a microgrid in order to achieve higher efficiency, reliability and economy was proposed in [14] with demand optimization by advanced algorithms such as particle swarm optimization [15].

All of these studies propose scientific methods and approaches with the aim of improving the management of renewable energy systems for the efficient exploitation of these resources to generate balance between supply and demand. To study the response to disruptions caused by the reduction of systems using non-renewable fossil resources in favor of renewable resources in microgrids, a robustness improvement study based on variable-shape LADRC technology for the electrical load interface was conducted [16]. A study on the dynamic analysis of microgrid systems for powering sailboat electrical loads using renewable energy was conducted [17]. S. Rajamand's objective in [18] is to manage energy consumption by adjusting demand based on supply conditions, often through incentives for consumption during peak periods. Amado and al. improve microgrid efficiency by integrating renewable energy [19].

Developing countries have conducted many studies on electricity to further their development [20] and explores the challenges and strategies for improving electricity access and affordability in these countries [21]. However, the growth of the population at present, causes on the one hand, an increase in electrical energy demand [22] with the modelling of the optimal electricity at long term [23]. The lack of electricity in rural areas then leads to a number of challenges in mobilizing the resources needed for optimal electrification planning [24] taking into account, the techno-economic assessment integrating renewable sources [25]. It is important to electrify rural areas and areas on the outskirts of critics, using power plants not far from these areas, to mobilize local natural resources [26] and to develop integrated energy systems for off-grid [27], in order to minimize distances and electrical losses. These available natural resources can thus be exploited by microgrids [28] with a necessary to optimize their design, operation and integration into conventional power systems [29]. At present, the management of these microgrids and all of electrical network management, are often robust [30] and a robust coordination framework of these microgrids is proposed in [31], because of the daily variation of short- and long-term loads due to the ever-increasing energy needs of the population. This difficulty in pairing the real-time adaptation of electricity production to the demand for electrical energy is explained by the lack of an efficient management program for these microgrids. The lack of a modernized predictive model for the management of these minigrids in most sub-Saharan countries is a difficulty in the operational planning of these power generation systems. It is therefore necessary to develop optimized prediction models for managing the evolution of microgrid loads.

Thus, machine learning techniques [32] and its importance for forecasting electrical energy consumption (load) [33] used to solve societal problems via different regression methods. In particular, prediction work based on neural network methods [34] for short term loads forecasting in morogrids environment [35] and with his radial basis functions [36] for modelling nunlinear and complex relationships in times series data [37]. Multilayer perceptron (MLPs) approach, and his convolution neural networks (CNNs) have also been presented in [10] and in N. Now, artificial neural network has the capacity to imitate biological neural systems [39] and to incorporate fuzzy logic principles to handle uncertainty and imprecision data [40] so their applications in science and engineering are presented in [41] and can be tested on real-world data under varying weather conditions such as for example, photovoltaic data [42]. Other models have also been developed, such as the LSTM (Long Short-Term Memory) technique [43] where authors propose and test a CNN and LSTM models reveal that the models behave differently when the number of layers changed over the different configurations; in [44], a short term load forecasting model that integrates a multi-scale CNN-LSTM hybrid approach neural network is proposed; for support vector regression : a proposition of algorithms, has been trained and tested with a significant encouraging result show an accuracy improvement from 20% to 23.4% in [45], and in [46], authors used support vector machine for the forecasting and recommended a combination of this approach with algorithms like artificial neural network (ANN) model and clustering; fuzzy polynomial regression methods is discussed in [47] showing how a fuzzy logic approach can be applied to

predict electrical load during holidays; multiple regression in [48] with the aims to improve the accuracy of electric load forecasting by a boosting-based approach ; deep learning in [49] advanced in short term load forecasting by combining deep learning with socioeconomic and infrastructural data, offering a practical solution for sustainable management in geographically or economically constrained environments; authors explore in [50], the application of neural networks in wind resource assessment and forecasting; probabilistic methods : in [51], the study likely aims to enhance the accuracy and reliability of industrial load forecasting by adopting a multivariate probabilistic approach involving characterizing the uncertainty in load predictions which is crucial for managing industrial energy systems effectively and an improvement of quantile regression neural network architecture can better capture complex patterns in load data and provide more accurate probabilistic forecasts [52].

Other authors such as, Yasameen F. and al. [53], have used the Structural Equations Modeling to forecast the impact of the environmental and energy factor to improve urban sustainability; for Afshin Balal and al. [54], it is possible to use the Random forest regression and the DSTM to forecast solar power generation; an application is being carried out an Eubbock, Texas. Meryem El Alaoui and al. [55] have used ARIMA and statistical methods for the prediction of energy consumption of an administrative building. Other works have been carried out to propose also, a model based on LSTM for enhancing power load forecasting accuracy [56] and in [57], a hybrid model based on Gated Recurrent Unit (GRU) and CNN.

Each of these methods has its own specificities; the number of hyperparameters to be defined, according to the model, is often high and the forecasting time is sometimes long. Table 1 provides an overview of the various methods used to forecast short- and long-term

expenses:

Methods	References
LSTM-MLP	[10][43][57]
ARIMA	[55]
SVM, kmeans-SVM	[45][46][58]
trical load Deep learning	[49][50]
casting Multilayer perceptron	[10]
Hybrid methods	[10][56][57]
Adaboost used in electrical load forecasting	[59]
Adaboost used in other areas	[60][61]

Table 1. Summary of electrical load forecasting models

## General forecasting approach

Forecasting is the study of a given quantity, whose future evolution can be estimated by calculation [62]. Let there be a training set D containing T pairs of input vectors x and scalars y according to relation eq. (1):

$$D = \{(x_t, y_t) | t = 1, \dots, T\}$$
(1)

where  $y_t$  is a time series and  $x_t$  is a vector of dimension d, defined by relation eq. (2):

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 $x_t = [x_1, \dots, x_d]^T$ 

All input vectors are often combined into matrix X, and the output values into output vector Y; relation eq. (3):

$$X = \begin{bmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_T^T \end{bmatrix}, Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_T \end{bmatrix}$$
(3)

The general model of a time series is given by relation eq. (4):

$$y_t = f(x_t, \theta) + \epsilon_t$$

where f is a function;  $x_t$  is the independent variables (or features) at time t;  $\theta$  is the parameter vector, it represents the parameters of the model that define the relationship between  $x_t$  and  $y_t$  and are typically estimated from historical data during the model training process; and  $\epsilon_t$  is a Gaussian noise. The forecast at a future time T+h is obtained by evaluating the function f at the test point  $x_{T+h}$  according to relation eq. (5):

$$y_{T+h} = f(x_{T+h}, \hat{Q})$$
<sup>(5)</sup>

where  $\hat{\theta}$  is the vector of parameters from the training data set D. It represents the estimated parameters of the model. Indeed,  $f(x_{T+h}, \hat{\theta})$  is a function that models the relationship between the explanatory variables and the target variable we want to predict.  $x_{T+h}$  represents the explanatory variables at the future time T+h. f is the function that can be linear, nonlinear, a regression odel, or any other type of function that describes the relationship between x and y. The choice of f, depends on the model used.

#### Mathematical approach of the regression ensemble method

The regression ensemble method is a collection of regression models used to make prediction much faster and more efficient. It is defined by the following: the space of hypothesis H; a method for combining prediction elements  $h_t$ , such as  $h_t = 1...T \in H$ . Part of the regression ensemble method is the adaboost regression method, which is a set of machine learning procedures that consist of combining several sub-predictors to optimize better, prediction. Figure 1 shows the flowchart of the adaboost regressor approach:



The ensemble method thus provides a predictor H(x), such that equations eq. (6), eq. (7), and eq. (8) [60]:

$$H(x) = sign\left(\sum_{t=1}^{T} \alpha_t \cdot h_t(x)\right)$$
<sup>(6)</sup>

$$H = [(h_t, \alpha_t)]_{t=1...T} \in (\mathbf{H}, IR_+^*)^T$$
(7)

$$H_t(x) = H_{t-1}(x) + \alpha_t \cdot h_t(x)$$
 (8)

The goal is to find a sequence of predictor elements  $h_t$  and weights  $\alpha_t$  such that the previous global predictor achieves a small error.

The proposed algorithm is given:

- (1) As a given sample  $(x_1, y_1), (x_i, y_i), \dots, (x_N, y_N)$ : N training samples set
- (2) Initialize the weights vector of the sample:  $D^1 = (\alpha_1^1, \dots \alpha_i^1, \dots \alpha_N^1)$

D=1/N. N is the number of training samples

#### (3) While t < T, T the iteration numbers

(4) Under the probability distribution of training samples: the weak learner  $h_t(x)$  are trained

(5) The probability  $P = \frac{\alpha^t}{\sum_{i=1}^N \alpha_i^t}$ 

(6) Update weight distribution

$$D^{t+1} = (\alpha_1^{t+1}, \dots \alpha_i^{t+1}, \dots \alpha_N^{t+1})$$
$$\alpha_i^{t+1} = \alpha_i^t \beta^{1-|h_t(x_i)-y_i|}, i = 1, 2, \dots, N$$

With Weak learner weight  $\alpha_t = \frac{1}{2} \ln \left(\frac{1}{\beta_t}\right)$ ;  $\beta_t = \frac{\varepsilon_t}{1 - \varepsilon_t}$ 

(7) Calculate the combination of learners:  $H(x) = \sum_{t=1}^{T} \alpha_t h_t(x)$ 

#### **Performance metrics**

The statistical analyses of the data presented in the rest of this study are based on the minimum and maximum values of the data used and the mean, standard deviation and median of these data (eq. (9), eq. (10) and eq. (11)):

$$min = \min(x_i); max - \max(x_i) \neq i = 1, \dots, N$$
(9)

 $(-\bar{X})^2$ 

where  $\bar{X}$ , x and  $\sigma$  represent the mean, the variable and the standard deviation, respectively. The calculation of the errors inspired in [63] and [64], contained within the model, allowing to appreciate the difference between the predicted model and the real curve, is formulated as follows:

 $x_i$ 

The mean square error by eq. (12):

$$MSE = \frac{1}{n} \sum (y_{real} - y_{predict})^2$$
(12)

The average of the absolute errors by eq. (13):

$$MAE = \frac{1}{n} \sum |y_{real} - y_{predict}|$$
<sup>(13)</sup>

(14)

The square root of the mean square error by eq. (14):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum (y_{real} - y_{predict})^2}$$

The coefficient of determination by eq. (15):

$$R^{2} = 1 - \frac{\sum(y_{real} - y_{pred})^{2}}{\sum(y_{real} - \overline{y_{predict}})^{2}}$$
(15)

All of these regression metrics are calculated in order to evaluate the error, which is assumed to be minimal.

#### **MATERIAL AND METHODS**

Figur

Python 3.10 was used in this work. The following section presents the approach based on the forecasting method using adaboost regressor.

Indeed, adaBoost regressor is an ensemble learning algorithm that combines several weak models to enhance regression performance. It takes into account, the number of estimators to combine: increasing this number, can improve performance, but it also increases the risk of overfitting; the learning rate that reduces the contribution of each estimator: a smaller value makes the algorithm more robust but requires a larger number of estimators to compensate; the loss function to minimize. The choice of loss affects how sample weights are updated; the base estimator (the base model or weak learner used to "boosting"); and the random state (by default, none).

However, the input variables are time (min) and the output variables are electrical power (in kW).

The general flowchart use for electrical load forecasting and the model selection is shown in





Figure 2. General flowchart used for electrical load forecasting and optimal model selection

# Data presentation

Electrical load consumption data are presented and averaged over a population of more than 500 households. These data were collected from a renewable energy source photovoltaic solar energy and were obtained from the Electrical Energy Company of Togo. These are the data on which the forecasts were based and, in fact, represent only 0.87 % of the total consumption data for the electrical loads used during this period. The total dataset is around 4100 to 4300. To perform simulations using Machine Learning techniques, a considerable quantity of datasets is required. In fact, this data represents the consumption of electrical loads over several days by months. Figure 3 shows a part of the global datasets:

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1	Versio	n CSV1	Too	I CLUSTERCO	ONTROLLER	Linebreak	cs CR/LF   D	elimiter se	micolon	Decimalpoi	nt comma	Precision	2		
2	Time			January	February	March	April	May	June	July	August	Septembe	October	Novembe	December
3	DD.MN	1.YYYY I	nh:m	m W	W	W	W	W	W	W	W	W	W	W	W
4	01.12.2	019 00:	00	10358	3 8927	8628	8550	10189	9408	8889	9859	8277	8971	3868	6992
5	01.12.2	019 00:	05	10566	5 8935	8624	8517	10172	9340	8831	9780	8263	8914	3839	6955
6	01.12.2	019 00:	10	1050	7 9042	8635	8603	10121	9316	8895	9778	8162	8932	3733	7503
7	01.12.2	019 00:	15	10574	1 9079	8617	8617	10134	9212	8869	9779	7872	8921	3721	7405
8	01.12.2	019 00:	20	10578	3 9049	8588	8616	10145	9198	8856	9781	8054	8943	3759	7083
9	01.12.2	019 00:	25	10570	9093	8622	8583	10104	9331	8970	9775	/9/0	8960	3/13	7220
10	01.12.2	019 00:	30	10590	5 8970 9000	0571	8570	10023	9303	8970	9804	8075	9111	3097	7452
12	01.12.2	019 00.	33 40	1056	0000	0571	0402	11200	0220	0700	2007	0035	0100	2622	7351
12	01.12.2	019 00.	40	10/69	2 9055	8552	8/195	10754	9323	8927	9792	7964	9100	2616	7110
14	01.12.2	019 00.	4J 50	10400	9034	8531	8446	9870	9312	8850	9688	7998	91/19	3645	7357
15	01 12 2	019 00.	55	1047	9140	8616	8528	10374	9359	8768	9657	7979	9058	3700	7224
16	01.12.2	019 01:	00	1050	7 9126	8657	8561	11180	9354	8798	9653	8114	8930	3657	6928
17	01.12.2	019 01:	05	1056	9176	8579	8590	10654	9248	8805	9610	8177	9003	3640	7030
18	01.12.2	019 01:	10	10433	3 9149	8501	8564	9748	9191	8935	9641	8200	9147	3657	7227
19	01.12.2	019 01:	15	10380	9063	8564	8565	10367	9282	8887	9737	8190	9119	3648	7279
20	01.12.2	019 01:	20	10330	5 9063	8583	8513	11441	9307	8925	9766	8218	9139	3678	7068
21	01.12.2	019 01:	25	10410	9088	8529	8522	10582	9393	8956	9761	8136	9248	3681	7099
22	01.12.2	019 01:	30	10330	9056	8500	8485	9359	9411	8926	9726	8135	9282	3708	7139
23	01.12.2	019 01:	35	10279	9058	8497	8481	10201	9439	8922	9655	8130	9205	3717	7194
24	01.12.2	019 01:	40	10178	9132	8512	8528	11489	9398	8933	9675	8122	9181	3609	6906
25	01.12.2	019 01:	45	10313	5 9195	8499	8573	10632	9443	8891	9578	8140	9106	3589	6953
26	01.12.2	019 01:	50	1025	7 9175	8493	8508	9304	9483	8963	9544	8221	9120	3688	7193
27	01.12.2	019 01:	55	10211	l 9177	8488	8511	10176	9322	8984	9501	8237	9111	3774	7179
28	01.12.2	019 02:	00	10141	L 9093	8504	8490	11812	9459	9066	9554	8316	9081	3798	6940
29	01.12.2	019 02:	05	10227	7 9143	8536	8499	11638	9489	9009	9544	8266	9143	3786	7029
30	01.12.2	019 02:	10	10140	9101	8554	8466	11436	9561	9046	9582	8263	9130	3808	7151
31	01.12.2	019 02:	15	10158	3 9075	8544	8476	11329	9579	8908	9632	8135	8900	3801	7022
32	01.12.2	019 02:	20	10113	9101	8518	8465	11345	9565	8996	9558	8152	8783	3796	6854
33	01.12.2	019 02:	25	10208	3 9238	8590	8344	11268	9548	8910	9401	8115	8756	3802	6886
34	01.12.2	019 02:	30	10112	2 9303	8553	8435	11252	9546	8947	9432	8078	8736	3800	6957
35	01.12.2	019 02:	35	10059	9273	8575	8428	11292	9472	8973	9437	8115	8586	3739	7021
36	01.12.2	019 02:	40	1014	7 9280	8557	8476	11286	9506	9060	9486	8237	8558	3690	6898
37	01.12.2	019 02:	45	10288	9269	8588	8398	11260	9537	9051	9578	8210	8522	3582	7025
38	01.12.2	019 02:	50	10184	4 9243	8624	8399	11220	9543	9048	9578	8206	8467	3629	7054

Figure 3. Presentation of a part of load data for simulation

The results are presented and discussed in the next section.

# **RESULTS AND DISCUSSIONS**

This section shows the different results of the forecasting and the discussions.

## Results

This section presents a study based on forecasting results. The studies present the statistical indicators of the data, then, the various prediction results and the correlation results between the predicted and the real value.

## Statistical results

The forecasting results obtained were based on load data recorded on a monthly basis, the statistical indicators of which are presented in Table 2:

	points	Step	min	max	mean	std	median
Months		(min)					
January			0	71.97	16.3	16.44	10.237
February			0	71.778	16.00	15.80	10.1
March			0	75.369	16.179	15.93	10.285
April			0	80.59	16.37	15.67	10.64
May	4100-	5	0	80.453	16.58	16.11	10.28
June	4300		0	87.4	16.67	16.06	10.26
July			0	86.127	15.98	14.757	9.937
August			0	93.5	15.9	15.21	9.68
September			0	90.014	15.02	14.92	9.083
October			0	93.73	14.95	15.34	8.467
November			0	73.001	16.42	16.28	9.14
December			0	65.0	16.25	15.6	<mark>9</mark> .37

Table 2. General statistical data indicators

std = standard deviation.

Table 2 shows the minimum, maximum, mean, standard deviation and median values of the electrical load data. The number of data analyzed per month is about 4100 to 4300. The maximum value recorded during these half months is 71.974 the overall mean was 16.2, with a standard deviation of around 15.7, showing the non-homogeneity of the consumption load each month and the variance in the data: the load of the installed microgrid therefore varies dynamically.

The results of the electrical loads forecasting, are presented.

## Forecast results on selected monthly data

The statistical indicators are presented in Table 2.

The following figure, Figure 4, shows the variation over time (by step of 5 min) of the electrical consumption loads (in kW). The forecast results over time, are also shown:



Figure 4. (a) Real curve for the month of January; (b) Real and forecast curves for January

Figure 4 (a) and (b), respectively show the actual and predicted electrical loads for the month of January. During this month, the electrical consumption loads recorded are to the order of 70

kW. These loads vary over the course of the month. The results of the learning and test model are shown in Table 3.

The same results are shown for the others months : February, March, April, May, June, July, August, September, October, November and December, respectively in Figure 5 (a) and (b), Figure 6(a) and (b), Figure 7 (a) and (b), Figure 8 (a) and (b), Figure 9 (a) and (b), Figure 10(a) and (b), Figure 11(a) and (b), Figure 12(a) and (b), Figure 13(a) and (b), Figure 14(a) and (b), and Figure 15(a) and (b).

Figure 5 (a) and (b), show respectively the real curve and the forecast curve for the month of February:



Figure 5. (a) Real curve for the month of February; (b) Real and forecast curves for February

The real curve and the forecast curve are shown respectively in Figure 6 (a) and (b) for the month of March:



Figure 6. (a) Real curve for the month of March; (b) Real and forecast curves for March

The variation of the curves depends on the variation of the data for each month. Figure 7, shows the results of the real and the forecast curves for the month of April:



Figure 7. (a) Real curve for the month of April; (b) Real and forecast curves for April

The real curves and the forecast curves for the month of May are presented respectively in Figure 8 (a) and (b).



a) and (b) show respectively the real curve and the forecast curve for the month

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of Jun





Figure 11. (a) Real curve for the month of August; (b) Real and forecast curves for Aug

And in Figure 12 (a) and (b), the real curve and forecast curve of the month of September are presented:



Figure 13 (a) and (b) show respectively the real curve and the forecast curve for the month of October.



Figure 13. (a) Real curve for the month of October; (b) Real and forecast curves for October

Figure 14 (a) and (b) show respectively the real curve and the forecast curve for the month of November.



Figure 14. (a) Real curve for the month of November; (b) Real and forecast curves for November

Figure 15 (a) and (b) show respectively the real curve and the forecast curve for the month of December.



Figure 15. (a) Real curve for the month of December; (b) Real and forecast curves for December

The results obtained for the various months show the variance in electrical load demands. In fact, these loads are dynamic and show a good correlation with the predicted data.

The results of the forecasting model's performance indicators, in relation to the actual loads, are shown in Table 3, and the model's learning and test results are thus obtained:

Months/ indicators	MAE	RMSE	Learning (R <sup>2</sup> )	Test (R <sup>2</sup> )
January	1.62	3.39	0.9995	0.958
February	1.63	3.35	0.9997	0.954
March	1.63	3.567	0.9997	0.949
April	219	4.46	0.9996	0.919
May		4.49	0.99975	0.93
June	2.64	5.93	0.9998	0.86
July	2.90	6.87	0.9990	0.78
August	1.38	4.11	0.9997	0.928
September	2.59	6.147	0.99975	0.83
October	2.71	6.085	0.9997	0.84
November	2.215	5.118	0.9998	0.90
December	1.66	3.4	0.9996	0.953

Table 3. Results of the forecasting model's measurable performance indicators

The analysis of the various indicators of the model's performance in Table 3 demonstrates the level of variation present in the data compared to the model, as seen in all the real and forecast curves. In fact, these results show a fairly significant coefficient of determination, indicating that the model is representing real data with a low MAE, MSE and RMSE. This reflects the minimal nature of the errors made by the model, showing that the errors are much smaller than the variance present in the data, which explains the model's performance.

## Correlation results between actual and predicted data

The correlation results between the microgrid-generated consumption loads and predicted consumption loads for all months, are shown respectively in Figure 16 (a) and (b), Figure 17(a) and (b), Figure 18(a) and (b), Figure 19(a) and (b), Figure 20(a) and (b), Figure 21(a) and (b).





Figure 16. (a) Correlation curve for January; (b) Correlation curve for February

Figure 17 (a) and (b) show respectively correlation curve for march and April.



Figure 18 (a) and (b) show respectively correlation curve for May and June.







Figure 20. (a) Correlation curve for September; (b) Correlation curve for October





Figure 21. (a) Correlation curve for November; (b) Correlation curve for December

R-squared  $= R^2$ 

These figures show the test results of the developed model by month. The more points nearer the line, the better the prediction performance. However, it should be noted that the model is not actually fitted directly to the test data, as the latter have the effect of minimizing the model's overfitting for testing purposes. These results therefore show the good correlation between the measured and predicted values. The dynamic variation in load by month, shown in the figures above, demonstrates the usefulness of this study and the accuracy with which a model should forecast trends. The initial results from the forecasting tests in this study are conclusive, with satisfactory performance indicators.

## Discussions

The forecasting results obtained and the calculated performance indices MAPE, MSE, RMSE and  $R^2$  have allowed to evaluate the proposed model. In fact, these different indicators, by month, reflect the minimization of the error between the actual electrical load consumption

data and those predicted. The first MAE results, according to the different months studied (January, February, March, April, May, June, July, August, September, November and December) have values ranging from 1.38 to 2.9. These differences can be explained by the variances in the data for each month, as there were variations in the dynamic loads recorded. Although these values are low, it provides information on the difference between the actual values and those predicted. The results obtained for the MAE therefore show the minimum variation between the actual and predicted data. In addition, the values recorded for the MSE and RMSE of the forecasting model enabled to determine whether deviating values would interfere with the forecasting data. These values being relatively low indicates that the accuracy of the model is high. Finally, the R<sup>2</sup> coefficient, which expresses the correlation between actual and predicted data, shows that, on average, over 90% of the actual load data is represented by the proposed model. This indicates the accuracy of the predictive model in relation to the electrical consumption data.

In general, the minimization of performance indicators reflects the optimal forecasting of electricity demand, necessary to minimize the cost of energy supply or production. Indeed, if the deviations (errors) between actual and predicted data are significant, this would mean that the model would be less efficient and, consequently, could lead to significant financial losses; hence the importance of developing models that minimize errors as much as possible. In addition, these studies contribute to the management of the electrical load and are necessary for any study contributing to the optimization, for example, of the electrical network installation (microgrids): previous studies carried out by kabe and al. [65].

Indeed, the model of adaboost regressor proposed, learns better and minimize significant errors. It is therefore recommended that network managers opt for more accurate models with minimized errors, such as the one proposed in this article. The proposed model demonstrates its excellent performance in forecasting electrical loads. The minimization of its performance coefficients such as MAPE, MSE, RMSE and R<sup>2</sup> show the accuracy of the proposed model. However, a more extensive study with other approaches of forecasting electrical loads consumption could be envisaged in order to appreciate the limitations of the model.

## CONCLUSION

The study of the efficient management of the evolution of electrical consumption loads is essential to satisfy the domand for electrical loads, ensuring a balance between supply and demand. Studies have been carried out to improve the learning accuracy of forecasting models; these studies continue today, with the aim of minimizing the errors that forecasting models can make in predicting real data. This paper proposes a model made up of ensemble regression method: adaboost regression approach, based on a machine learning technique, to predict the temporal evolution of the variation in electrical loads. The initial test results for the model were satisfactor, minimizing the error gap between the actual and predicted data. First, the results of this study give a coefficient of determination R<sup>2</sup> between 0.9995 and 0.9997 for the learning results and second, a coefficient of determination R<sup>2</sup> between 0.83 and 0.958 for the validation test results. The coefficient of determination of the proposed model is in perfect agreement with the experimental results obtained according by month. This coefficient demonstrates that the proposed model is a suitable representation for the actual prediction of electrical loads in future forecasts. The high number of data, shows that, the model can predict as short and long terms the electrical load consumption. The results of these studies conducted in this article, will contribute to optimal decision-making in energy system management and planning, especially in daily, monthly and annual forecasts of electrical energy demands. However, updates of electrical load forecasting models can be considered with other forecasting models, in order to regularly adapt electrical load forecasts to the new forecasting models.

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