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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 electrical loads is therefore a challenge for scientific 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 Perceptron; 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 minimized prediction deviations between consumed and production, this paper proposes a method for forecasting 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 0.958 for the validation test results. According to the metrics parameters, these results are representative of the real data and reflect the performance of the proposed model. The proposed model is well adapted to the management of electrical consumption load forecasts to ensure balance between supply and 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: photovoltaic 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 *et 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 *et 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]. 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 *et 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 cities, 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 mini-grids 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 microgrids environment [35] and with his radial basis functions [36] for modelling nonlinear 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 [38]. 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 *et 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 *et al.* [54], it is possible to use the Random forest regression and the LSTM to forecast solar power generation; an application is being carried out in Lubbock, Texas. Meryem El Alaoui *et 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.

Table 1. Summary of electrical load forecasting models

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

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):

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

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

$$x_t = [x_1, \dots, x_d]^T \tag{2}$$

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

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

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

$$y_t = f(x_t, \theta) + \epsilon_t \tag{4}$$

where f is a function; x_t is the independent variables (or features) at time *t*; θ 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 ϵ_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):

$$y_{T+h} = f(x_{T+h}, \hat{\theta}\,) \tag{5}$$

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.

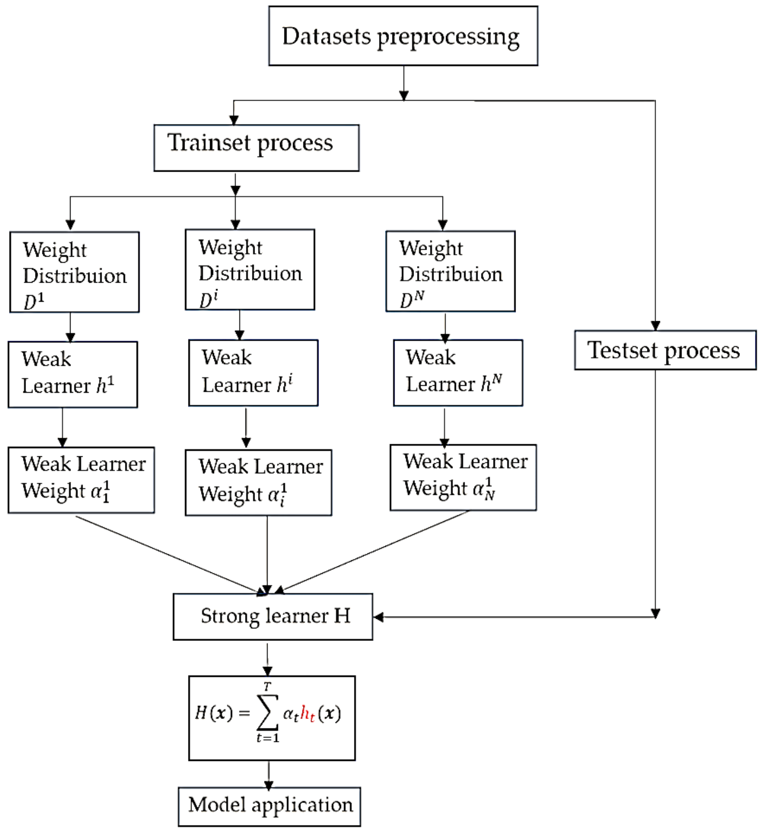


Figure 1. Flowchart of the adaboost regressor approach

The ensemble method thus provides a predictor $H(x)$, such that equations eqs. (6) - (8) [60]:

$$H(x) = sign\,(\sum_{t=1}^{T} \alpha_t . h_t(x)) \tag{6}$$

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

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

The goal is to find a sequence of predictor elements h_t and weights α_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), ..., (x_N, y_N): N training samples set;

(2) Initialize the weights vector of the sample: $D^1 = (\alpha_1^1, \ldots \alpha_i^1, \ldots \alpha_N^1)$, 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
$D^{t+1} = (\alpha_1^{t+1}, \ldots \alpha_i^{t+1}, \ldots \alpha_N^{t+1})$;
$\alpha_i^{t+1} = \alpha_i^t \beta^{1-|h_t(x_i)-y_i|}$, i = 1,2, …, 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 (eqs. (9), (10), (11)):

$$\min = \min(x_i);\ \max = \max(x_i)\,;\ i\ =\ 1, \ldots . N \tag{9}$$

$$\bar{X} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{10}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{X})^2} \tag{11}$$

where $\bar{X}$, x and σ 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.

The mean square error by eq. (12):

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

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

$$MAE = \frac{1}{n}\sum|y_{\text{real}} - y_{\text{predict}}| \tag{13}$$

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

$$RMSE = \sqrt{\frac{1}{n}\sum(y_{\text{real}} - y_{\text{predict}})^2} \tag{14}$$

The coefficient of determination by eq. (15):

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

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

MATERIAL AND METHODS

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**.

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.

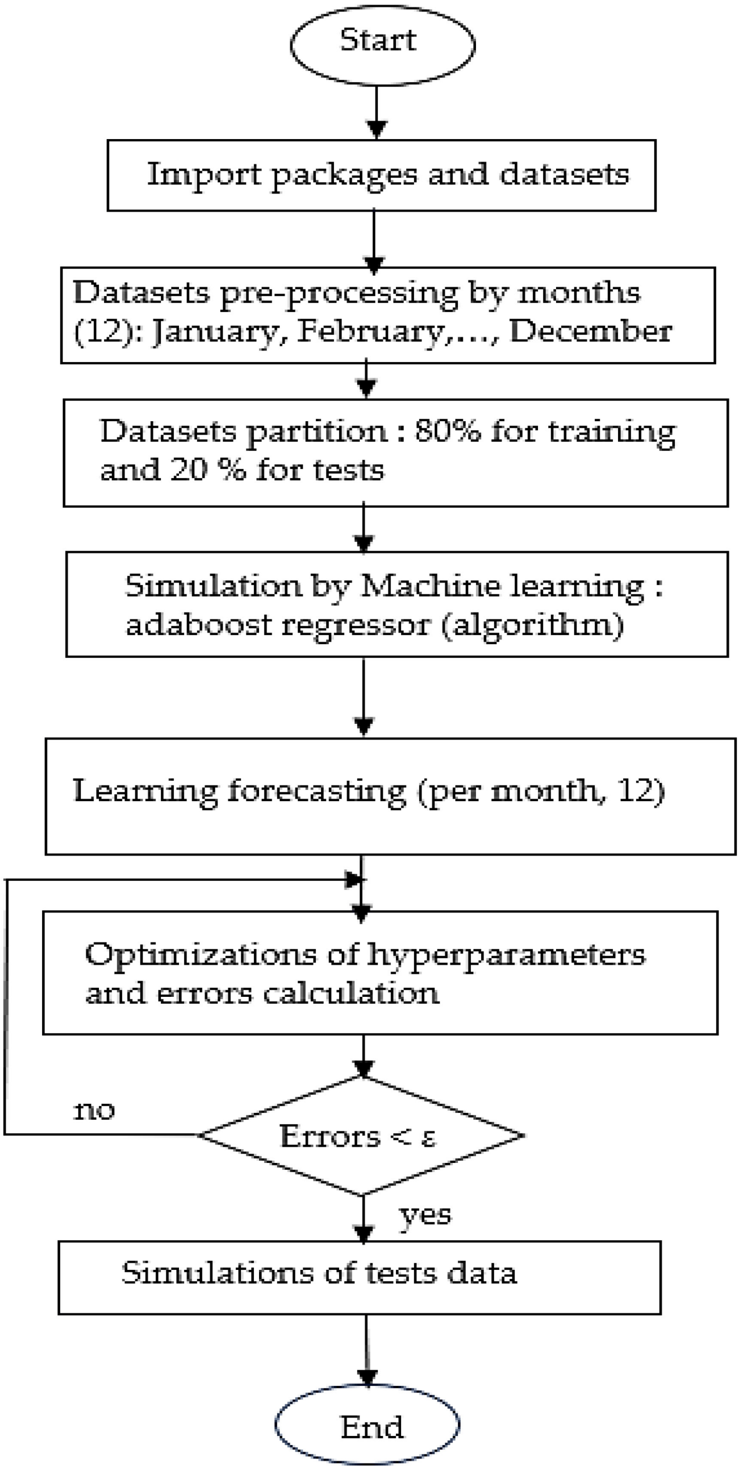
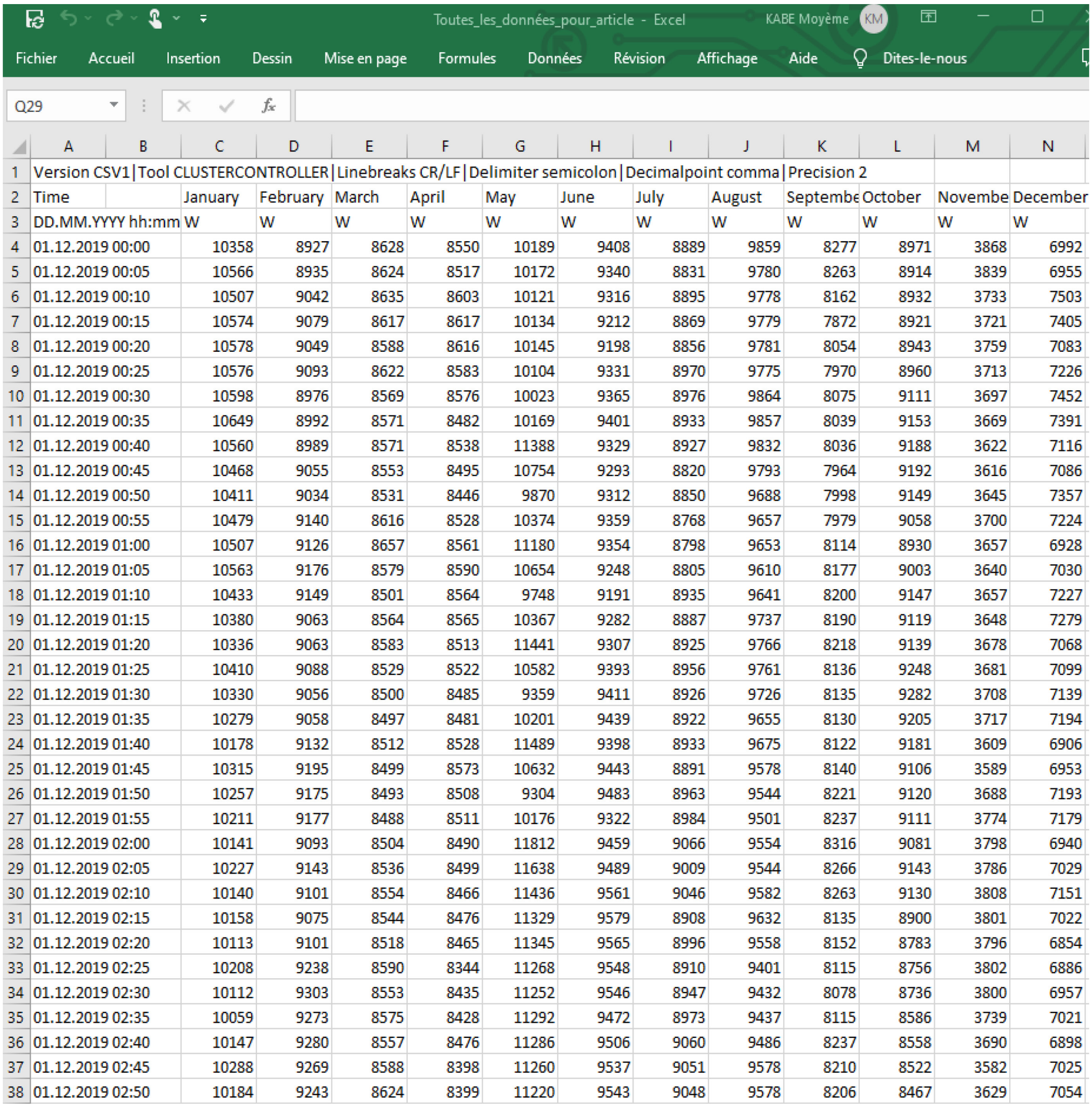


Figure 2. General flowchart used for electrical load forecasting and optimal model selection

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:



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Version CSV1|Tool CLUSTERCONTROLLER|Linebreaks CR/LF|Delimiter semicolon|Decimalpoint comma|Precision 2													
2	Time		January	February	March	April	May	June	July	August	Septembe	October	Novembe	December
3	DD.MM.YYYY hh:mm		W	W	W	W	W	W	W	W	W	W	W	W
4	01.12.2019 00:00		10358	8927	8628	8550	10189	9408	8889	9859	8277	8971	3868	6992
5	01.12.2019 00:05		10566	8935	8624	8517	10172	9340	8831	9780	8263	8914	3839	6955
6	01.12.2019 00:10		10507	9042	8635	8603	10121	9316	8895	9778	8162	8932	3733	7503
7	01.12.2019 00:15		10574	9079	8617	8617	10134	9212	8869	9779	7872	8921	3721	7405
8	01.12.2019 00:20		10578	9049	8588	8616	10145	9198	8856	9781	8054	8943	3759	7083
9	01.12.2019 00:25		10576	9093	8622	8583	10104	9331	8970	9775	7970	8960	3713	7226
10	01.12.2019 00:30		10598	8976	8569	8576	10023	9365	8976	9864	8075	9111	3697	7452
11	01.12.2019 00:35		10649	8992	8571	8482	10169	9401	8933	9857	8039	9153	3669	7391
12	01.12.2019 00:40		10560	8989	8571	8538	11388	9329	8927	9832	8036	9188	3622	7116
13	01.12.2019 00:45		10468	9055	8553	8495	10754	9293	8820	9793	7964	9192	3616	7086
14	01.12.2019 00:50		10411	9034	8531	8446	9870	9312	8850	9688	7998	9149	3645	7357
15	01.12.2019 00:55		10479	9140	8616	8528	10374	9359	8768	9657	7979	9058	3700	7224
16	01.12.2019 01:00		10507	9126	8657	8561	11180	9354	8798	9653	8114	8930	3657	6928
17	01.12.2019 01:05		10563	9176	8579	8590	10654	9248	8805	9610	8177	9003	3640	7030
18	01.12.2019 01:10		10433	9149	8501	8564	9748	9191	8935	9641	8200	9147	3657	7227
19	01.12.2019 01:15		10380	9063	8564	8565	10367	9282	8887	9737	8190	9119	3648	7279
20	01.12.2019 01:20		10336	9063	8583	8513	11441	9307	8925	9766	8218	9139	3678	7068
21	01.12.2019 01:25		10410	9088	8529	8522	10582	9393	8956	9761	8136	9248	3681	7099
22	01.12.2019 01:30		10330	9056	8500	8485	9359	9411	8926	9726	8135	9282	3708	7139
23	01.12.2019 01:35		10279	9058	8497	8481	10201	9439	8922	9655	8130	9205	3717	7194
24	01.12.2019 01:40		10178	9132	8512	8528	11489	9398	8933	9675	8122	9181	3609	6906
25	01.12.2019 01:45		10315	9195	8499	8573	10632	9443	8891	9578	8140	9106	3589	6953
26	01.12.2019 01:50		10257	9175	8493	8508	9304	9483	8963	9544	8221	9120	3688	7193
27	01.12.2019 01:55		10211	9177	8488	8511	10176	9322	8984	9501	8237	9111	3774	7179
28	01.12.2019 02:00		10141	9093	8504	8490	11812	9459	9066	9554	8316	9081	3798	6940
29	01.12.2019 02:05		10227	9143	8536	8499	11638	9489	9009	9544	8266	9143	3786	7029
30	01.12.2019 02:10		10140	9101	8554	8466	11436	9561	9046	9582	8263	9130	3808	7151
31	01.12.2019 02:15		10158	9075	8544	8476	11329	9579	8908	9632	8135	8900	3801	7022
32	01.12.2019 02:20		10113	9101	8518	8465	11345	9565	8996	9558	8152	8783	3796	6854
33	01.12.2019 02:25		10208	9238	8590	8344	11268	9548	8910	9401	8115	8756	3802	6886
34	01.12.2019 02:30		10112	9303	8553	8435	11252	9546	8947	9432	8078	8736	3800	6957
35	01.12.2019 02:35		10059	9273	8575	8428	11292	9472	8973	9437	8115	8586	3739	7021
36	01.12.2019 02:40		10147	9280	8557	8476	11286	9506	9060	9486	8237	8558	3690	6898
37	01.12.2019 02:45		10288	9269	8588	8398	11260	9537	9051	9578	8210	8522	3582	7025
38	01.12.2019 02:50		10184	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.

Table 2. General statistical data indicators

Months	Points	Step (min)	min	max	mean	std	median
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			0	80.453	16.58	16.11	10.28
June	4100-4300	5	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	9.37

std = standard deviation

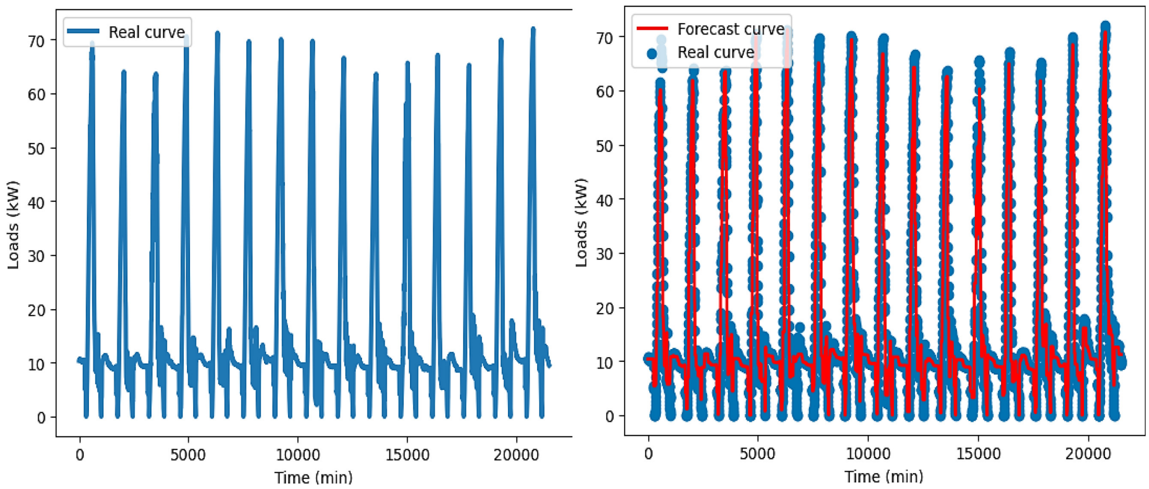
Table 2 shows the minimum, maximum, mean, standard deviation and median values of the electrical load data. The number of data analyzed per month is about 4100 to 4300. The maximum value recorded during these half months is 71.974. The overall mean was 16.2, with a standard deviation of around 15.7, 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.



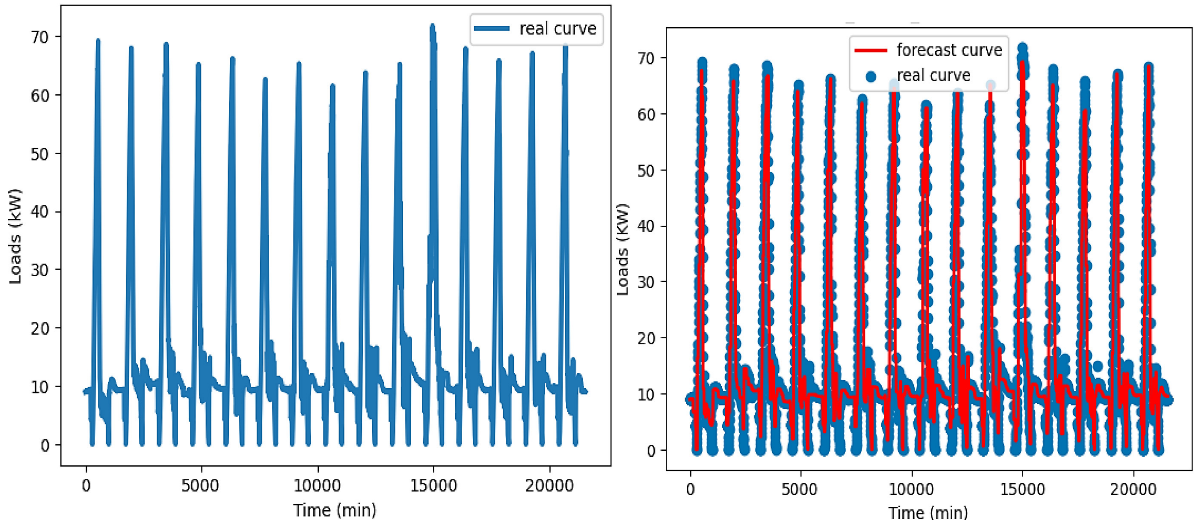
(a) (b)

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

Figure 4a and Figure 4b, 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 5a** and **Figure 5b**, **Figure 6a** and **Figure 6b**, **Figure 7a** and **Figure 7b**, **Figure 8a** and **Figure 8b**, **Figure 9a** and **Figure 9b**, **Figure 10a** and **Figure 10b**, **Figure 11a** and **Figure 11b**, **Figure 12a** and **Figure 12b**, **Figure 13a** and **Figure 13b**, **Figure 14a** and **Figure 14b**, and **Figure 15a** and **Figure 15b**.

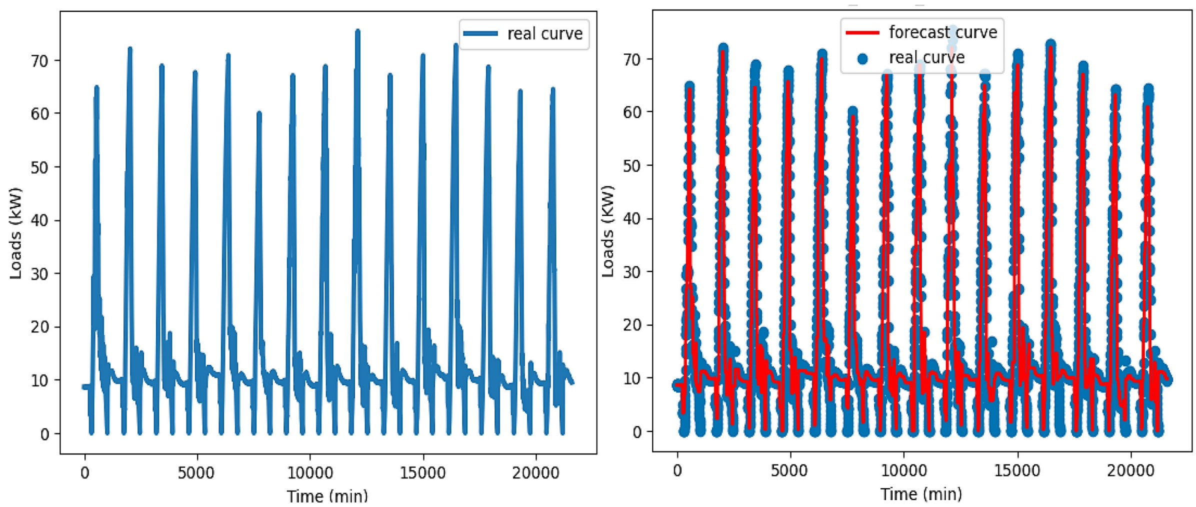
Figure 5a and **Figure 5b** show respectively the real curve and the forecast curve for the month of February.



(a) (b)

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

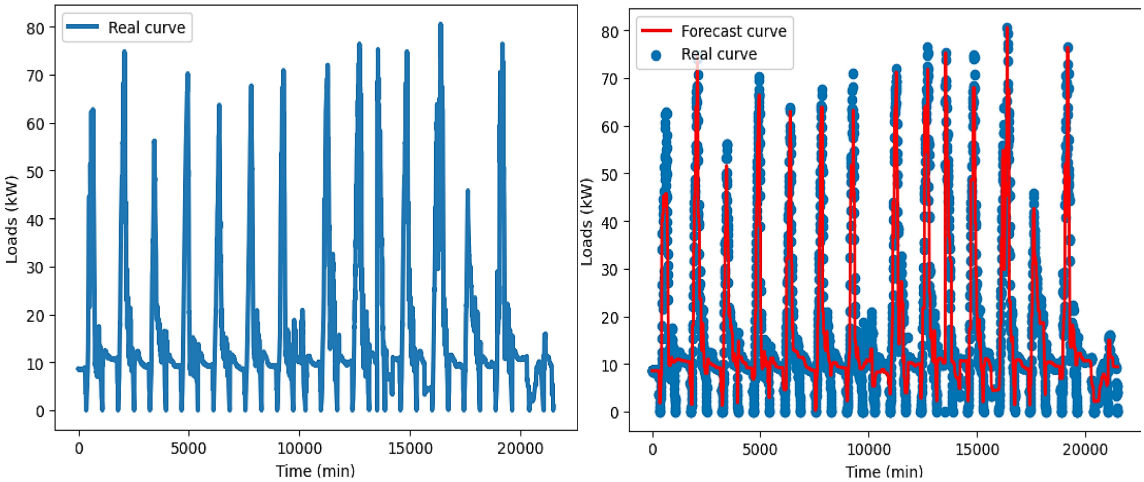
The real curve and the forecast curve are shown respectively in **Figure 6a** and **Figure 6b** for the month of March.



(a) (b)

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

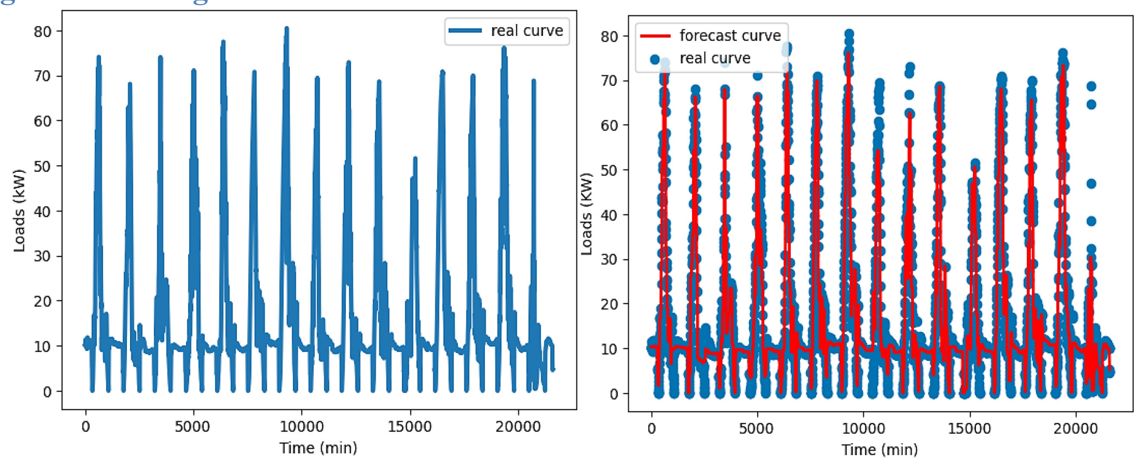
The variation of the curves depends on the variation of the data for each month. **Figure 7** shows the results of the real (a) and the forecast (b) curves for the month of April.



(a) (b)

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

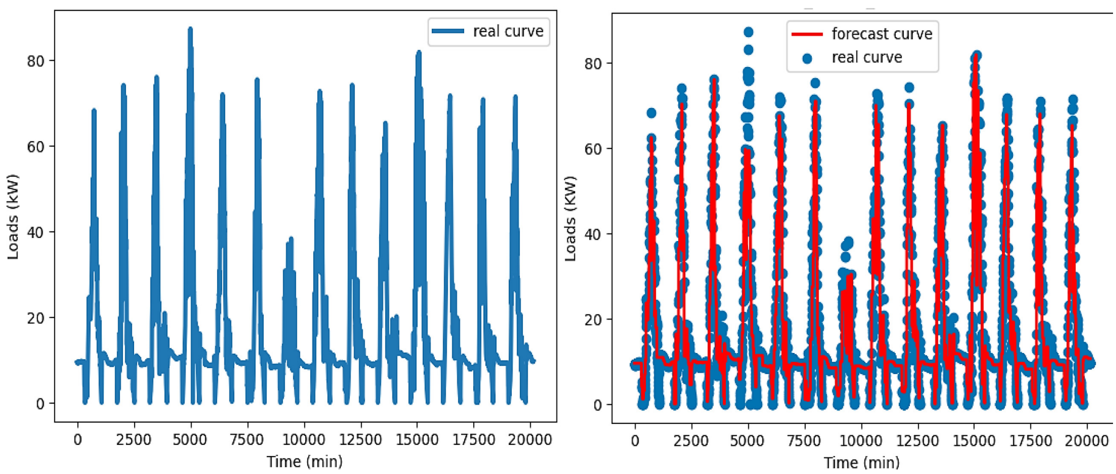
The real curves and the forecast curves for the month of May are presented respectively in **Figure 8a** and **Figure 8b**.



(a) (b)

Figure 8. Real curve for the month of May (a); real and forecast curves for May (b)

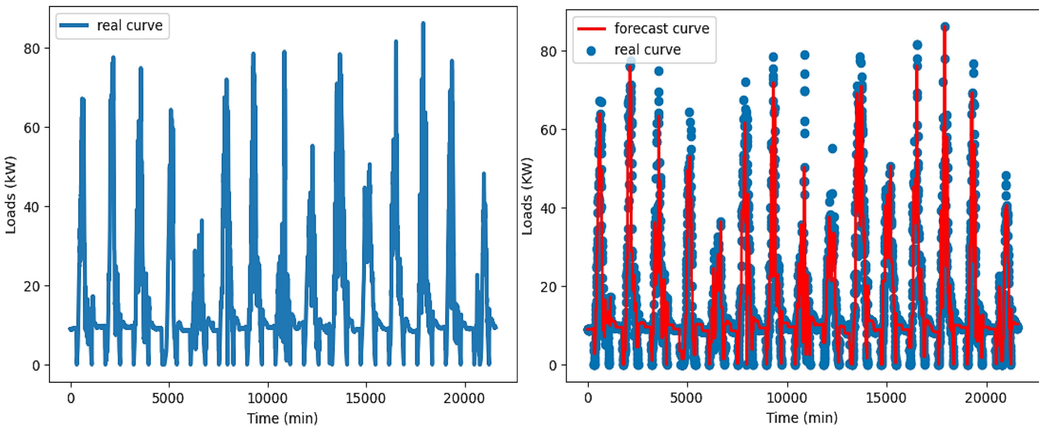
Figure 9a and **Figure 9b** show respectively the real curve and the forecast curve for the month of June.



(a) (b)

Figure 9. Real curve for the month of June (a); real and forecast curves for June (b)

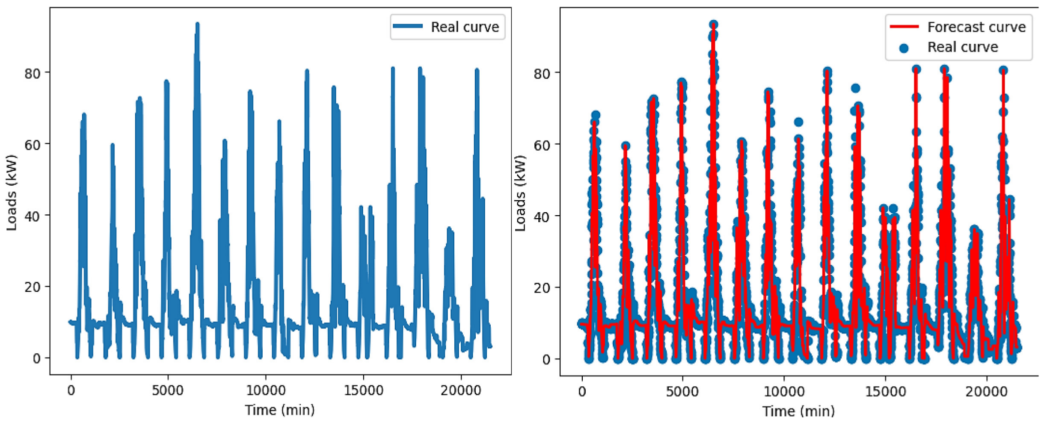
However, Figure 10a and Figure 10b show respectively the real curve and the forecast curve for the month of July.



(a) (b)

Figure 10. Real curve for the month of July (a); real and forecast curves for July (b)

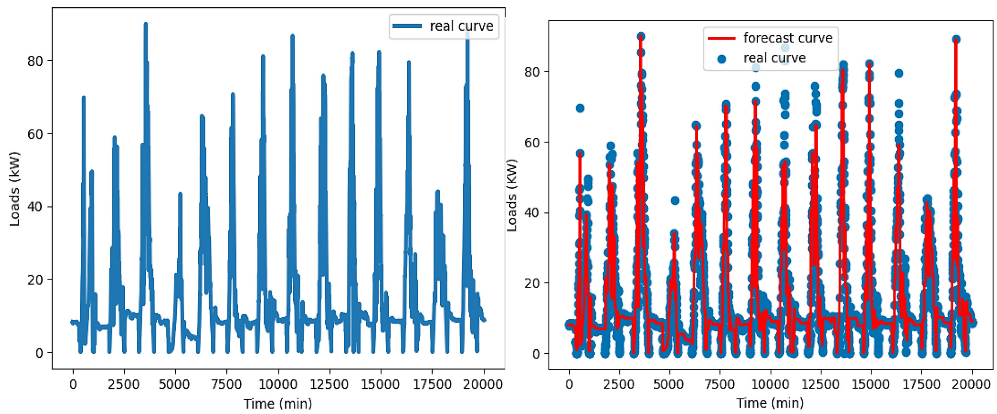
Figure 11a and Figure 11b show respectively the real curve and the forecast curve for the month of August.



(a) (b)

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

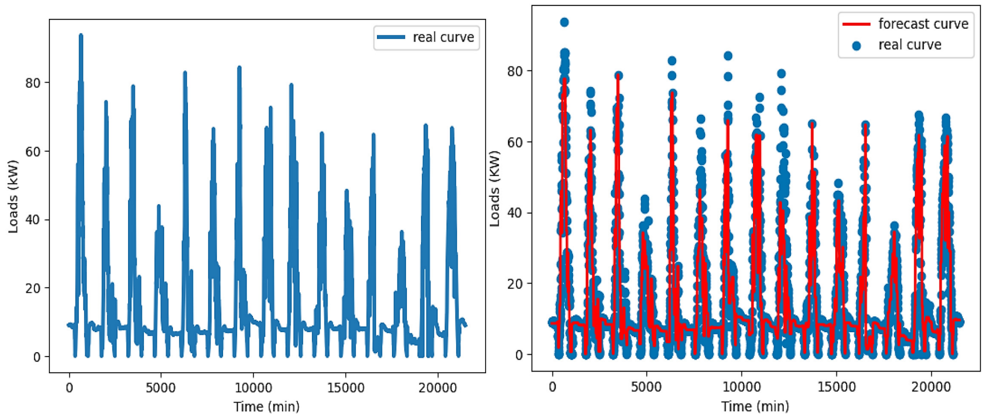
In Figure 12a and Figure 12b, the real curve and forecast curve of the month of September are presented.



(a) (b)

Figure 12. Real curve for the month of September (a); real and forecast curves for September (b)

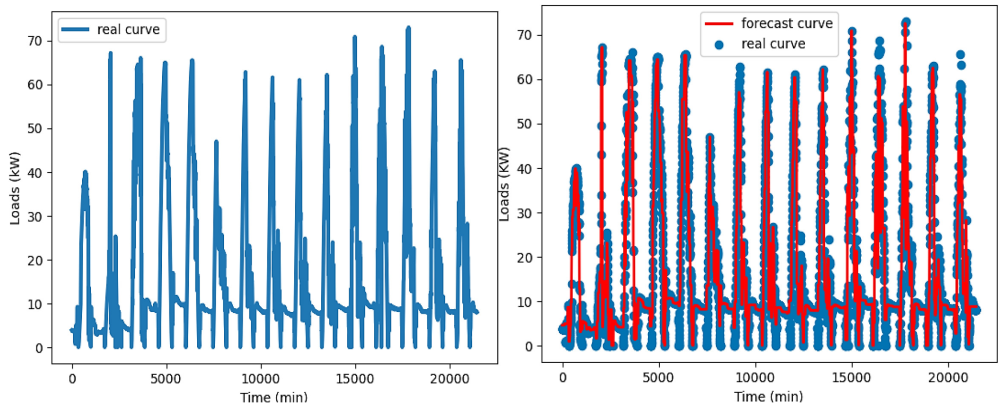
Figure 13a and **Figure 13b** show respectively the real curve and the forecast curve for the month of October.



(a) (b)

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

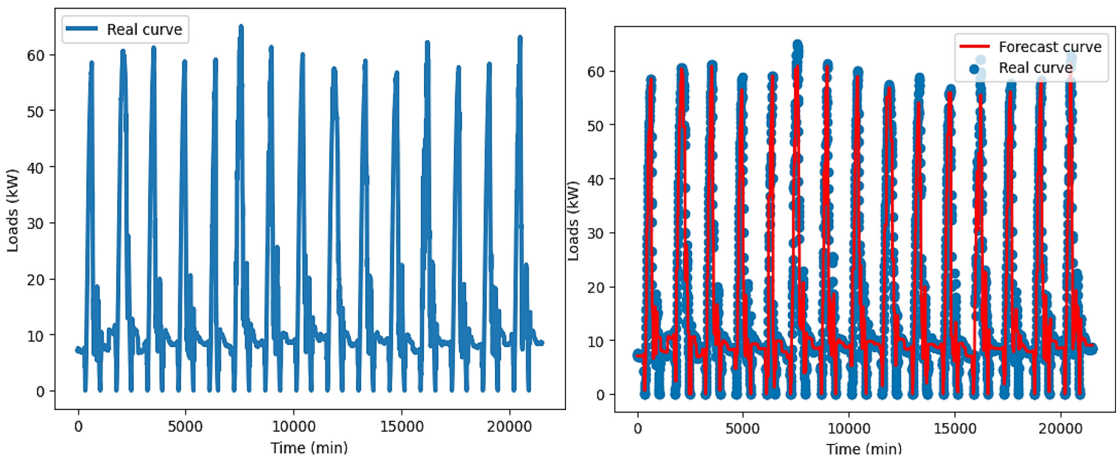
Figure 14a and **Figure 14b** show respectively the real curve and the forecast curve for the month of November.



(a) (b)

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

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



(a) (b)

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

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.

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

Months / indicators	***MAE***	***RMSE***	**Learning (R^2)**	**Test (R^2)**
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	2.19	4.46	0.9996	0.919
May	2.11	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

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 16a and Figure 16b, Figure 17a and Figure 17b, Figure 18a and Figure 18b, Figure 19a and Figure 19b, Figure 20a and Figure 20b, Figure 21a and Figure 21b.

Figure 16a and Figure 16b show respectively correlation curve for January and February.

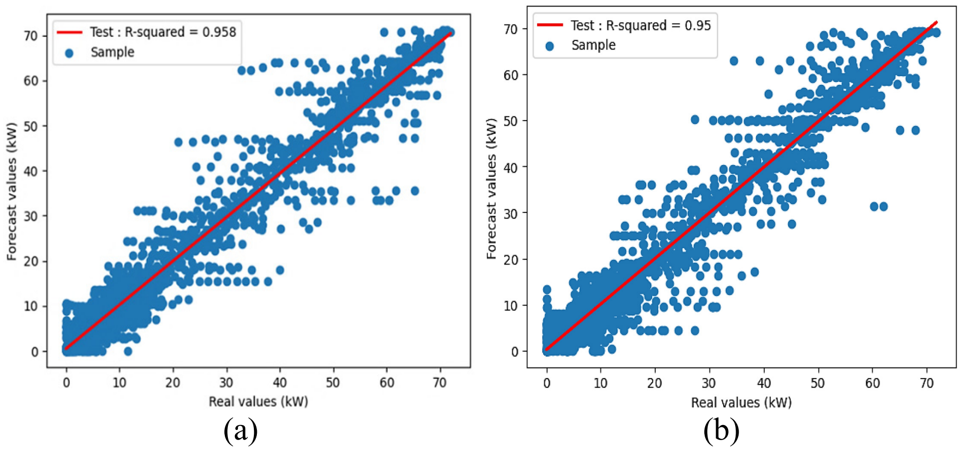
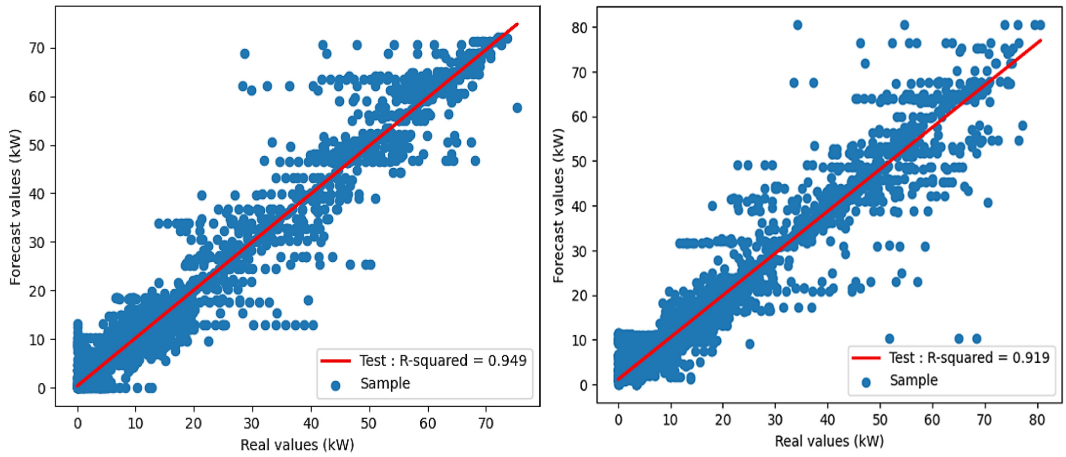


Figure 16. Correlation curve for January (a); correlation curve for February (b)

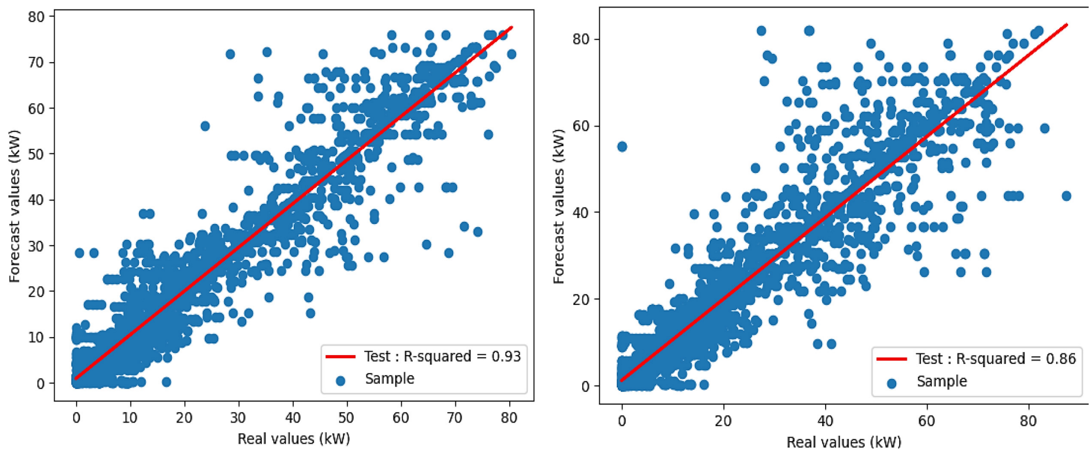
Figure 17a and **Figure 17b** show respectively correlation curve for March and April.



(a) (b)

Figure 17. Correlation curve for March (a); correlation curve for April (b)

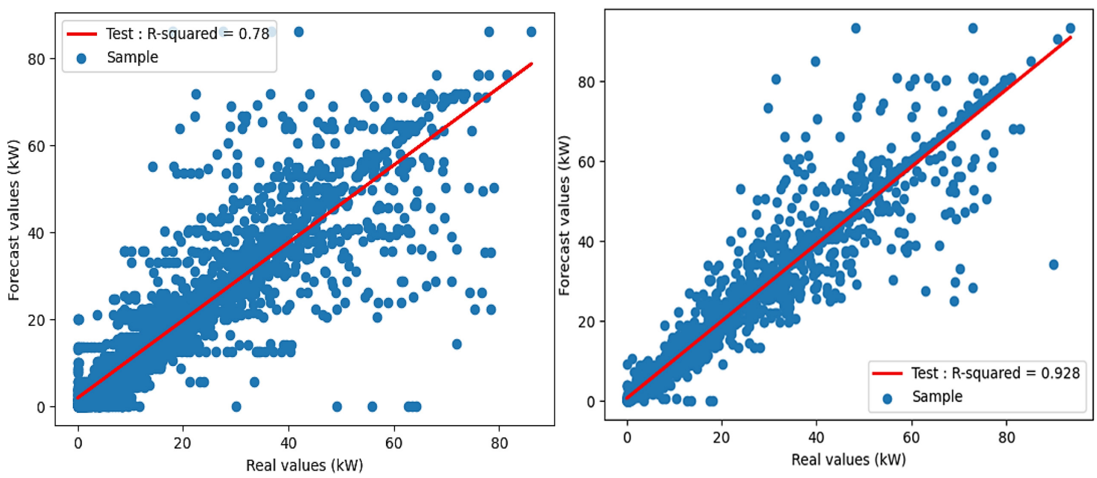
Figure 18a and **Figure 18b** show respectively correlation curve for May and June.



(a) (b)

Figure 18. Correlation curve for May (a); correlation curve for June (b)

Figure 19a and **Figure 19b** show respectively correlation curve for July and August.



(a) (b)

Figure 19. Correlation curve for July (a); correlation curve for August (b)

Figure 20a and **Figure 20b** show respectively correlation curve for September and October.

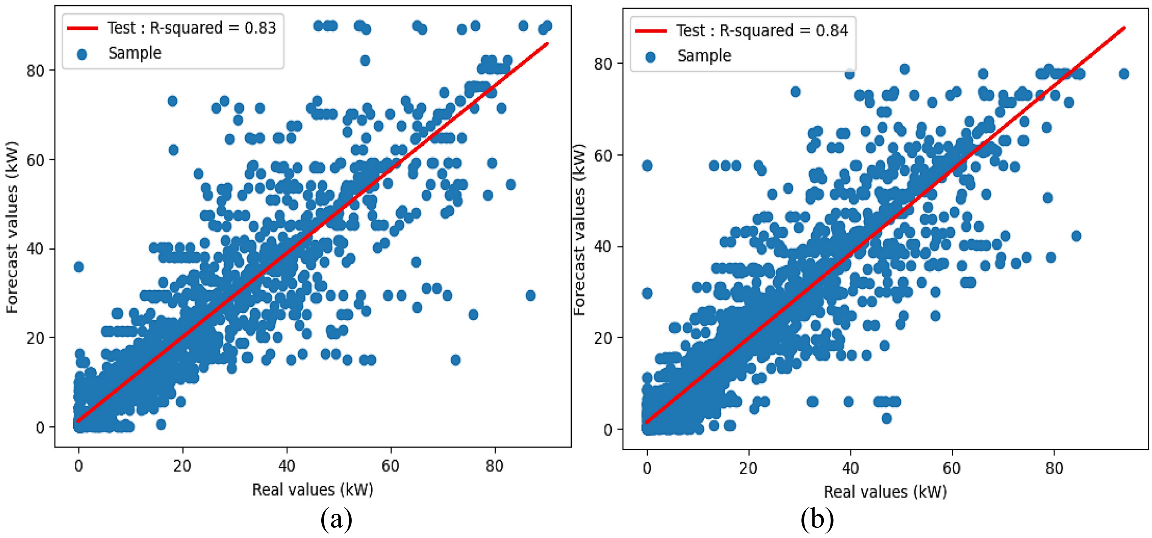


Figure 20. Correlation curve for September (a); correlation curve for October (b)

Figure 21a and **Figure 21b** show respectively correlation curve for November and December.

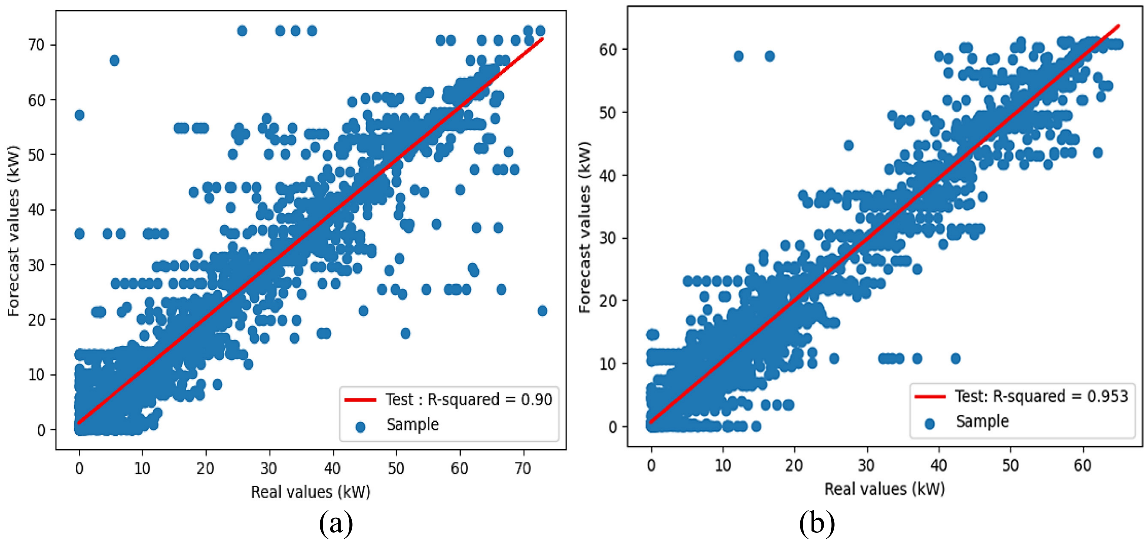


Figure 21. Correlation curve for November (a); correlation curve for December (b)

In the previous figures *R*-squared denotes R^2.

These figures show the test results of the developed model by month. The more points nearer the line, means 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^2 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 *et 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^2 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 demand 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 satisfactory, minimizing the error gap between the actual and predicted data. First, the results of this study give a coefficient of determination R^2 between 0.9995 and 0.9997 for the learning results and second, a coefficient of determination R^2 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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Conflicts of Interest: The authors declare no conflicts of interest.

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