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Multiple Linear Regression to Predict Electrical Energy Consumption Based on Meteorological Data: Application to Some Sites Supplied by the CEB in Togo

[1,2,3]**Apaloo Bara Komla Kpomonè**, [1,2,3]**Palanga Eyouleki Tcheyi Gnadi**, [1,2,3]**Bokovi Yao**, [4]**Kuevidjen Dosseh** and [5]**Nomenyo Komla**

[1]*Department of Electrical Engineering, Ecole Polytechnique de Lomé (EPL), University of Lomé, Lomé, Togo*
[2]*Department of Electrical Engineering, Engineering Sciences Research Laboratory (LARSI), University of Lomé, Lomé, Togo*
[3]*Department of Electrical Engineering, Regional Excellence Center for Electricity Management (CERME) University of Lomé, Lomé, Togo*
[4]*Department of Operations Management, Electric Community of Benin (CEB), Lomé, Togo*
[5]*Laboratory Light, Nanomaterials and Nanotechnology - L2n CNRS UMR 7076, Troyes University of Technology, Troyes, France*

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Corresponding Author:
Apaloo Bara Komla Kpomonè
Department of Electrical Engineering, Ecole Polytechnique de Lomé (EPL), University of Lomé, Lomé, Togo
Email: espoirbara@gmail.com

Abstract: The prediction model developed in this article is based on the use of meteorological variables to estimate the consumption of electrical energy at the substations of the Electric Community of Benin. The objective is to predict this consumption in order to adapt production to it. The posts (Lomé Aflao, Légbasito, and Lomé port) are the targets that were used in the study. The input variables are Relative Humidity (H), Direct Normal Irradiance (I), Precipitation (P), Temperature (T), and wind speed (V). The data collection period extends from 2019 to 2021. Multiple linear regression is used as the algorithm. Mean Absolute Error (MAE), root Mean Square Error (MSE), root mean square error (RMSE), and linear correlation coefficient (R^2) were used to evaluate the performance of each model. A statistical characterization of each variable is carried out. It shows a good distribution of temperature, relative humidity, and wind speed values. This is not the case for direct normal irradiance, precipitation, and diffuse radiation. These latter at times have zero and extreme values at the same time. Furthermore, the modeling results show that the worst model is IPV giving MAE = 16.066; MSE = 385.847; RMSE = 19.643, and R^2 =21.021%, and is not good for consumption forecasting. On the other hand, the best model is obtained by the HIPTV configuration thus giving MAE = 13.214; MSE = 282.199; RMSE = 16.798, and R^2 = 77.284% showing that the parameters considered are necessary for its prediction. The correlation coefficient R^2 exceeds 50%, the results of this study show that from meteorological data, it is possible to predict the power to be consumed in the area considered. However, as it is not very close to 1, the exploration of other algorithms is necessary to resume this study.

Keywords: Electricity Consumption, Characterization, Meteorological Variables, Modeling, Multiple Linear Regression

Introduction

The electricity supply of a country is a criterion of economic, social, and industrial development today. Indeed, the availability of quantity and quality of electrical energy can offer new employment opportunities and socio-cultural emergence. In addition, investments in electricity production equipment lead to new innovations. Progress will also be seen in the areas of health, education, and access to new information and communication technologies (Pierre *et al.*, 2023). For Bronwyn and Rosenberg, the permanent electrification of industries makes it possible to intensify production by automating it; which has the effect of improving business productivity (Hall and Roserberg, 2010; Owolabi *et al.*, 2021). This electrification involves the establishment of electrical networks. In today's world, they are almost interconnected. This facilitates the flow of energy.

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In Benin as in Togo, the supply of electrical energy is assumed by the Electric Community of Benin (CEB), (Kuevidjen, 2023; Ntagungina, 2015). However, electricity supply constraints can hamper the ability to effectively meet ever-increasing demand. Among the constraints commonly encountered in electricity network management, an insufficient quantity of energy obtained as supply can lead to imbalances between supply and demand. In the CEB network, there are two means of supply: Internal production and import. If the estimation is not done well, we see electricity shortages, power outages, and disruptions in almost all sectors of activity. We can also list a financial loss linked to the production of undistributed energy or a waste of available primary energy sources.

Inspired by this context, it is therefore essential to estimate electrical energy consumption with good precision in order to plan production (Ali *et al*., 2023). This estimation involves machine learning for modern energy distribution systems (Marković *et al*., 2023). It uses artificial intelligence algorithms (Abdel-Basset *et al*., 2021) to plan production capacities in order to ensure sufficient availability to meet the needs of populations and industries. Among the algorithms commonly used in machine learning we can list: Random forests (Apaloo-Bara *et al*., 2019; Nti *et al*., 2019), artificial neural networks (Younès, 2006), support vector machines (Apaloo-Bara, 2020), multiple linear regression, (Supapo *et al*., 2017; Zhou *et al*., 2016; Almedeij, 2016; Tuaimah and Abdul Abass, 2014; Samhouri *et al*., 2009) etc. These algorithms make it easier to learn from the data. They enable the analysis of large historical data sets in real time to predict patterns, trends, and relationships between different factors influencing electrical energy consumption (Marković *et al*., 2023; Fan *et al*., 2014). These factors may include meteorological data (temperature, ambient relative humidity, precipitation, solar radiation, wind speed, etc.,) and other more relevant parameters.

Knowing that weather forecasts these days are very precise with new technologies, the objective of this study is to use multiple linear regression to predict electrical energy consumption in Togo. The goal is to rely on data collected by the CEB from 2019-2021 and to use certain meteorological variables (relative humidity, direct normal irradiance, precipitation, temperature, and wind speed) to design models. We will draw inspiration from certain performance evaluation criteria commonly used in the literature (Apaloo-Bara *et al*., 2019; Pierre *et al*., 2023; Djandja *et al*., 2019); such as Mean Absolute Error (MAE), root Mean Square Error (MSE), Root Mean Square Error (RMSE) and coefficient of determination R^2 to confirm or refute the validity of the models. Characterization of the electricity consumption data and the aforementioned meteorological variables of the city of Lomé will be carried out for this purpose.

The result of this study will help the CEB to detect the impact of the variables used in this study on the consumption of electrical energy in Lomé, Togo, in order to extend it to all areas placed under its coverage. Also through the results obtained, the company will have a sophisticated means of forecasting the electrical energy needs necessary to make available to customers.

Materials

The values of the power consumed in Lomé are recorded at the LOME AFLAO, LEGBASSITO, and LOME PORT substations daily at an interval of 1 h and then stored in an Excel file whose appearance is presented in Fig. 1. In this table, the power recording can be found on the aforementioned sites. The values are collected per day and at each hour of the day then collected per month. Thus, we can find the values of the powers consumed on the sites considered in Megawatt and the accumulation can be distinguished in the last column.

The meteorological data are, for their part, collected on the fr.tutiempo.net sites and on the open-meteo.com site on the same days and times as those of the powers recorded as shown in Fig. 2. On this site, there is the ability to get records of all-weather parameters from any location on earth for free. The biggest advantage lies in the fact that we can even obtain this data in an Excel file by entering the georeferenced coordinates of the location. This made it easier to carry out and achieve the effectiveness of the work presented in this article. Figure 3 outlines the arrangement of data for modeling.

This figure contains weather in dates and times, Temperature (T) in degrees Celsius (°C), Relative Humidity in percentage (RH%), wind speed (V) in meters per second (m/s), Direct Normal Irradiance (DNI) of the sun in Watts per square meter (W/m²) and Precipitation (P) in millimeters (mm) in Lomé.

DATE	HEURE	LOME AFLAO P(MW)	LEGBASSITO P(MW)	LOME PORT P(MW)	LOME P(MW)
01/01/2019	1	81	6,48	31	118,48
01/01/2019	2	81	6,21	33	120,21
01/01/2019	3	77	6,03	31	114,03
01/01/2019	4	77	5,67	31	113,67
01/01/2019	5	76	5,4	30	111,4
01/01/2019	6	59	5,22	23	87,22
01/01/2019	7	59	4,68	22	85,68
01/01/2019	8	58	4,68	22	84,68
01/01/2019	9	56	4,59	23	83,59
01/01/2019	10	56	4,59	22	82,59
01/01/2019	11	57	4,59	23	84,59
01/01/2019	12	4	4,59	22	30,59
01/01/2019	13	61	4,68	22	87,68
01/01/2019	14	61	4,68	22	87,68
01/01/2019	15	59	4,68	23	86,68
01/01/2019	16	62	4,68	22	88,68
01/01/2019	17	61	4,68	20	85,68
01/01/2019	18	69	5,04	23	97,04
01/01/2019	19	84	6,93	27	117,93
01/01/2019	20	86	7,38	27	120,38
01/01/2019	21	88	7,38	27	122,38
01/01/2019	22	87	7,38	27	121,38
01/01/2019	23	79	6,84	27	112,84

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Fig. 1: Overview of the electricity consumption record sheet in Lomé from 2019-2020

Table 1: Production fleet for the CEB network

Type of plant	Instantaneous installed power in MW	Production power Available in MW
Lomé thermal power plant headquarters (SULZER)	16	12.0
Lomé B thermal power plant (CTLB)	12	11.9
Kara Thermal Power Plant	16	4.0
Sokodé Thermal Power Plant	4	1,5
Kpimé hydraulic power plant	1,6	1,5
Nangbéto Hydraulic Power Plant	75	75
Contour global thermal power plant	99,6	100

TIME	T(°C)	HR (%)	V (m/s)	DNI(W/m²)	P (mm)	RD (W/m²)
2019-01-01T00:00	26,8	87	4,04	0	0	0
2019-01-01T01:00	26,6	89	3,92	0	0	0
2019-01-01T02:00	26,5	90	3,67	0	0	0
2019-01-01T03:00	26,1	90	3,45	0	0	0
2019-01-01T04:00	25,9	91	3,4	0	0	0
2019-01-01T05:00	24,9	92	2,96	0	0	0
2019-01-01T06:00	25,5	90	2,46	0	0	0
2019-01-01T07:00	25,6	89	2,36	0	0	12
2019-01-01T08:00	27,3	84	1,79	181,2	0	78
2019-01-01T09:00	28,2	77	1,21	352,5	0	241
2019-01-01T10:00	31,7	58	1,36	572,2	0	458
2019-01-01T11:00	31,8	55	1,25	702,7	0	584
2019-01-01T12:00	31,9	54	1,66	770,5	0	699
2019-01-01T13:00	32	54	2,19	812,1	0	696
2019-01-01T14:00	32,2	54	2,92	811,1	0	648
2019-01-01T15:00	31,4	62	4,22	794,4	0	522
2019-01-01T16:00	30,8	68	5,61	731	0	346
2019-01-01T17:00	29,2	72	6,32	596,8	0	150
2019-01-01T18:00	28,6	78	6,53	254,4	0	19
2019-01-01T19:00	28,9	81	5,54	0	0	0
2019-01-01T20:00	27,9	83	4,95	0	0	0
2019-01-01T21:00	27,3	82	4,88	0	0	0
2019-01-01T22:00	26,1	90	4,2	0	0	0
2019-01-01T23:00	26	90	4,22	0	0	0
2019-01-02T00:00	26,2	89	4,6	0	0	0
2019-01-02T01:00	26,3	89	4,72	0	0	0
2019-01-02T02:00	25,8	91	4,65	0	0	0
2019-01-02T03:00	25	91	4,25	0	0	0
2019-01-02T04:00	24,5	92	3,42	0	0	0

Fig. 2: Weather data collection page

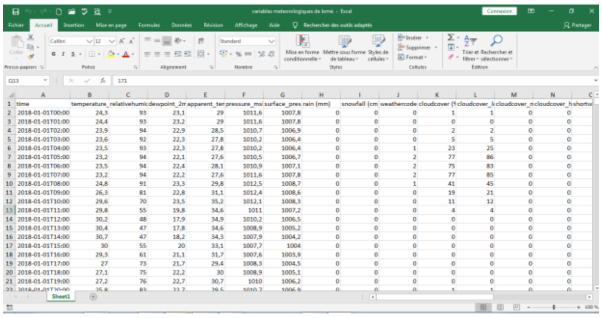

Fig. 3: Appearance of the weather data sheet in Lomé from 2019-2021

The electricity consumption data samples used in our study are collected from databases provided by the Benin Electric Community (CEB). They contain relevant information on electrical energy consumption, as well as weather data in Lomé, Togo. Initially, data is taken on a daily basis to facilitate overall analysis and visualization of longer-term trends. However, in order to obtain more detailed information and explore short-term variations, we further decomposed the daily-level aggregated data into hourly data. Togo's independent electricity supply sources are grouped in Table 1 (Kuevidjen, 2023, Ntagungina, 2015). Apart from these sources, to cover the energy needs, there are supplies coming from other countries in the sub-region.

Through Table 1, we can understand that only the central global contour is more felt. This is why we are able to operate it at 100 MW instead of 99.6 MW installed. Unlike in other cases, the aging of others is well seen. This concerns in particular the Kara Thermal Power Plant which is only used 25% for production; 37.5% for Centrale Thermal Sokodé and 75% for Centrale Thermal de Lomé headquarters (SULZER). Regarding the hydraulic power plants of Nangbéto) used to produce 100% of its power, Kpimé used 93.75% and the Lomé B thermal power plant which produces 11.9 MW instead of 12 MW installed, the problem is not really alarming. The difficulty lies in the types of power plants they are dealing with. Given all this, in the CEB network, it is necessary to forecast consumption in order to define the energy capacity to be produced per plant. This will avoid waste or overloads that could lead to load shedding.

Methods

The quality of a prediction model is closely linked to the choice of the algorithm used and the different performance evaluation metrics. As an algorithm for our study, we opted for the use of multiple linear regression. It is a machine-learning technique that makes it possible to model the linear relationship between a target variable and a set of explanatory variables. It is widely used to predict continuous values and is well suited to cases where the relationship between variables can be approximated by a regression line. Multiple linear regression takes into account the evolution of independent variables relative to dependent variables in a synchronized manner (Almedeij, 2016). Equation (1), expresses the linear relationship between the dependent variable and the independent variables:

$$P_p = \beta_1 + \beta_2 X_2 + \ldots + \beta_k X_K + \varepsilon \tag{1}$$

where:

P_p = The power to predict which is the dependent variable
$X_1,\ldots,X_k$ = The different independent variables used
$\beta_1,\ldots,\beta_k$ = Constitute the regression coefficients corresponding to the variables $X_1,\ldots,X_k$
ε = Random error

Indeed, multiple linear regression is used to predict the values of a dependent variable from explanatory or

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independent variables. Multiple linear regressions are used to find the most satisfactory linear relationship and predict the dependent value that produces the smallest standard error. In such a model, each independent variable is weighted so that the value of the regression coefficients maximizes the influence of each variable in the final equation. It is possible to manipulate several independent variables from multiple linear regressions, but only one dependent variable, (Tso and Yau, 2007).

After multiple linear regression modeling, it is necessary to evaluate the models obtained. In most cases, performance evaluation criteria are used. For this study, the evaluation criteria considered are The Mean Absolute Error (MAE), the Mean Square Error (MSE), the square root of the Mean Square Error (RMSE), and the correlation coefficient (R^2). They are calculated respectively from the formulas (2-5), (Apaloo-Bara, 2020; Pierre *et al*., 2023):

$$MAE = \frac{1}{N}\sum_{j=1}^{N}\left|p_{p_i} - p_{m_i}\right| \quad (2)$$

$$MSE = \frac{1}{N}\sum_{j=1}^{N}\left(p_{p_i} - p_{m_i}\right)^2 \quad (3)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(p_{p_i} - p_{m_i}\right)^2} \quad (4)$$

$$R^2 = \frac{\sum_{j=1}^{N}\left(p_{p_i} - p_{m_p}\right)*\left(p_{m_i} - p_{m_m}\right)}{\sqrt{\left[\sum_{j=1}^{N}\left(p_{p_i} - p_{m_p}\right)^2\right]*\left[\sum_{j=1}^{N}\left(p_{m_i} - p_{m_m}\right)^2\right]}} \quad (5)$$

where:

p_{p_i} = The predicted power
p_{m_i} = The measured power
p_{m_p} = The predicted average power
p_{m_m} = The average power measured
N = The number of points sampled

Results

The work carried out in this study began with the characterization of input and output parameters based on statistical variables such as mean, median, standard deviation, minimum, maximum, skewness coefficient, and kurtosis. Tables from 2-8 group together the results obtained through the characterization.

Table 2: Summary of temperature characterization results

Balance sheet dates	Mean	Median	STD	Min	Max	Skewness	Kurtosis
2019-01-31	29.11000	29.20	0.504709	28.2	29.9	-0.523510	-0.61896995
2019-02-28	29.56786	29.60	0.576743	28.6	30.5	-0.199600	-1.15729255
2019-03-31	29.41290	29.70	0.952450	26.4	30.7	-1.253500	1.94555400
2019-04-30	29.55000	29.70	0.887752	27.7	30.8	-0.684540	-0.61566372
2019-05-31	28.16774	28.20	0.799745	26.4	29.6	-0.533330	0.08740416
2019-06-30	26.82667	26.90	0.864205	24.4	28.1	-0.742390	0.83785252
2019-07-31	26.28710	26.20	0.484934	25.7	27.3	0.727142	-0.35422028
2019-08-31	26.13871	26.10	0.364854	25.5	26.9	0.226282	-0.39955202
2019-09-30	26.48667	26.40	0.566132	25.4	27.7	0.164085	-0.24613912
2019-10-31	26.64839	26.70	0.686960	25.1	27.7	-0.529300	-0.42662047
2019-11-30	28.12000	28.60	1.275877	24.9	29.6	-1.331370	1.09437002
2019-12-31	28.94516	29.00	0.679136	26.8	30.3	-1.170260	2.65188326
2020-01-31	28.11613	28.90	1.389028	25.3	29.7	-0.789280	-0.84147383
2020-02-29	29.66552	29.80	0.666159	27.6	30.6	-1.039560	1.71712022
2020-03-31	29.34839	29.40	0.947935	26.8	30.6	-1.053230	1.28933939
2020-04-30	29.00000	29.30	1.156988	25.8	30.7	-0.928910	0.60890704
2020-05-31	28.49677	28.60	1.135924	25.4	29.9	-0.673700	0.18034087
2020-06-30	27.21667	27.30	0.977359	24.7	29.1	-0.375160	0.70426482
2020-07-31	25.93548	25.90	0.450591	24.9	26.9	-0.085210	0.17028190
2020-08-31	25.54839	25.60	0.444875	24.8	26.3	-0.089190	-1.07578763
2020-09-30	26.20333	26.35	0.575046	24.5	27.1	-1.137570	1.36460065
2020-10-31	27.26129	27.30	0.732884	25.2	28.6	-0.820000	0.99098179
2020-11-30	28.66333	28.60	0.446815	27.8	29.6	0.006354	-0.35203061
2020-12-31	28.80000	28.80	0.447958	27.1	29.3	-1.802810	5.65064963
2021-01-31	28.78387	28.80	0.643996	26.9	29.7	-0.892100	1.30811343
2021-02-28	29.33571	29.45	0.790787	27.1	30.7	-1.481370	3.20909085
2021-03-31	29.32581	29.60	1.071438	26.7	31.3	-0.729880	0.35156986
2021-04-30	29.30333	29.70	0.829825	26.8	30.1	-1.412900	1.61913014
2021-05-31	28.70000	28.90	0.869099	26.1	29.8	-1.304010	1.67771974
2021-06-30	27.44333	27.15	1.225781	24.3	29.6	-0.172270	0.08468080
2021-07-31	26.26129	26.20	0.570776	25.4	27.6	0.393744	-0.50059553
2021-08-31	26.32581	26.30	0.425807	25.3	27.2	-0.082910	0.12923703
2021-09-30	26.49333	26.50	0.687290	25.3	27.7	-0.154770	-0.77153805
2021-10-31	27.50968	27.80	0.775609	26.0	28.8	-0.260640	-0.98470383
2021-11-30	28.25333	28.50	1.018022	25.1	29.7	-1.249010	1.74502692
2021-12-31	28.80000	29.10	0.859457	25.5	29.7	-2.205110	6.26046459

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Table 3: Summary of wind speed characterization

Balance sheet dates	Mean	Median	STD	Min	Max	Skewness	Kurtosis
2019-01-31	13.78065	13.50	3.412958	7.4	19.4	-0.113250	-1.448850
2019-02-28	14.09643	13.30	3.841728	9.8	23.0	0.909457	-0.006880
2019-03-31	14.88710	15.60	3.012833	8.7	19.3	-0.245390	-1.146650
2019-04-30	15.63000	15.30	3.698849	7.4	23.0	-0.144610	0.019781
2019-05-31	11.19355	11.30	1.977698	7.8	14.8	0.048925	-0.912900
2019-06-30	14.63000	14.90	3.163493	6.7	19.8	-0.579180	0.578952
2019-07-31	17.85161	17.40	2.025483	14.8	22.4	0.461659	-0.457440
2019-08-31	20.57097	19.80	2.672601	15.4	25.7	0.247003	-0.849220
2019-09-30	15.49000	15.65	2.954640	9.8	21.5	0.026980	-0.829090
2019-10-31	11.89032	11.10	3.500415	5.9	19.1	0.366428	-0.718270
2019-11-30	9.96000	10.80	3.021372	2.6	14.6	-0.895150	0.605856
2019-12-31	10.03548	9.10	2.346281	6.1	16.5	0.651897	0.169617
2020-01-31	10.30968	10.00	2.509629	6.3	16.1	0.730603	-0.037480
2020-02-29	12.30000	11.50	3.170061	8.1	18.7	0.383448	-1.206840
2020-03-31	16.99355	17.40	3.498089	9.3	24.6	-0.201410	0.162340
2020-04-30	14.82333	15.10	3.783329	8.5	20.9	0.180901	-1.135920
2020-05-31	12.29032	12.60	3.118371	7.6	18.7	0.217885	-0.935010
2020-06-30	13.90333	13.60	3.360571	6.3	20.0	-0.046860	-0.088410
2020-07-31	17.94839	17.80	2.549624	11.5	22.0	-0.318220	-0.238670
2020-08-31	19.05161	18.70	2.987180	13.1	25.6	0.244498	-0.377830
2020-09-30	17.09667	17.90	3.038544	9.8	22.6	-0.594360	-0.160670
2020-10-31	12.95161	13.10	2.507438	7.4	18.1	-0.159340	-0.101330
2020-11-30	11.20667	11.05	2.049715	7.2	14.6	-0.071320	-0.962750
2020-12-31	12.42903	12.80	2.042579	8.7	15.6	-0.383120	-1.063260
2021-01-31	13.35484	14.10	2.645353	7.4	17.8	-0.747200	-0.100500
2021-02-28	13.67500	13.60	2.213364	9.8	19.1	0.296481	0.194178
2021-03-31	15.79032	15.90	3.548836	9.3	22.6	0.022538	-0.796160
2021-04-30	13.98667	13.70	2.598373	9.6	18.9	0.118016	-0.842920
2021-05-31	14.42258	14.80	3.023983	8.5	18.7	-0.378980	-0.916740
2021-06-30	11.90333	11.60	2.636152	6.9	18.1	0.422736	0.019480
2021-07-31	16.40323	16.90	2.275739	11.1	20.2	-0.414310	-0.426870
2021-08-31	16.46129	16.10	2.064571	11.1	20.4	-0.414920	0.489518
2021-09-30	12.64000	12.50	2.556344	8.1	17.0	0.003337	-0.629440
2021-10-31	11.97097	12.20	2.582272	6.7	16.9	-0.037390	-0.381230
2021-11-30	10.76667	11.00	2.207563	7.2	17.2	0.543132	0.933195
2021-12-31	10.83871	11.70	2.131772	5.7	15.2	-0.399330	-0.284110

Table 4: Summary table of relative humidity characterization

Balance sheet dates	Mean	Median	STD	Min	Max	Skewness	Kurtosis
2019-01-31	75.03226	78.0	8.553689	51	85	-1.573550	1.550249
2019-02-28	78.78571	78.5	2.833100	73	85	0.097509	-0.191790
2019-03-31	79.80645	80.0	2.600248	75	86	0.470208	-0.031000
2019-04-30	79.53333	79.0	2.459792	76	85	0.433679	-0.429650
2019-05-31	83.09677	83.0	3.477114	76	91	0.299766	0.035096
2019-06-30	85.80000	86.0	3.284236	79	94	0.302371	0.395848
2019-07-31	85.41935	86.0	1.962553	82	89	-0.182210	-0.582940
2019-08-31	83.29032	84.0	2.132191	79	87	0.056803	-0.598520
2019-09-30	86.00000	86.0	2.197177	81	91	-0.083600	0.019023
2019-10-31	86.03226	860.0	3.229901	80	92	-0.024630	-0.697630
2019-11-30	82.63333	81.0	4.131321	79	92	1.456055	0.824818
2019-12-31	76.16129	78.0	6.408831	57	91	-1.191120	2.968723
2020-01-31	69.22581	77.0	14.655400	36	82	-1.119290	-0.148300
2020-02-29	70.58621	77.0	11.681850	41	81	-1.330000	0.573354
2020-03-31	77.19355	77.0	2.468729	71	82	-0.436670	0.434859
2020-04-30	78.83333	78.0	3.085934	75	88	1.842081	3.682626
2020-05-31	81.38710	81.0	3.574702	76	91	0.886930	0.561859
2020-06-30	83.16667	83.0	3.163186	75	90	-0.387810	0.611675
2020-07-31	83.32258	83.0	2.286002	79	88	0.057395	-0.389070
2020-08-31	81.48387	82.0	2.743124	76	88	0.210255	0.077033

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Table 4: Continue

2020-09-30	83.40000	83.0	2.283373	79	88	0.064054	-0.002490
2020-10-31	82.45161	82.0	2.778953	77	88	0.254463	-0.399660
2020-11-30	78.13333	78.5	1.925032	73	81	-0.761620	0.539208
2020-12-31	78.54839	78.0	2.218689	72	82	-1.145360	2.055646
2021-01-31	78.06452	78.0	3.424767	67	88	-0.500400	4.822558
2021-02-28	77.50000	77.0	3.085210	71	83	-0.150760	0.117514
2021-03-31	76.29032	76.0	2.253790	72	83	0.863758	1.421414
2021-04-30	77.93333	78.0	2.362543	73	83	0.152364	-0.259870
2021-05-31	78.48387	78.0	2.249014	74	85	0.661600	1.741831
2021-06-30	80.36667	80.5	4.004164	75	91	0.715929	0.283848
2021-07-31	83.25806	83.0	2.516184	77	89	-0.178000	0.435973
2021-08-31	83.12903	83.0	2.704834	79	89	0.243032	-0.378990
2021-09-30	84.46667	84.0	2.713101	80	90	0.399777	-0.243130
2021-10-31	82.61290	82.0	2.603554	79	89	0.553117	-0.162310
2021-11-30	79.53333	79.0	2.596195	74	87	0.782669	1.761844
2021-12-31	73.35484	77.0	10.011820	47	89	-1.595410	1.688207

Table 5: Summary table of the characterization of normal direct irradiance

Balance sheet dates	Mean	Median	STD	Min	Max	Skewness	Kurtosis
2019-01-31	254.0128	0.00	310.4290	0	865.0	0.635900	-1.316340
2019-02-28	213.3369	0.10	269.7804	0	809.4	0.766283	-1.022440
2019-03-31	218.1824	0.00	267.4669	0	828.5	0.688987	-1.119520
2019-04-30	220.0640	0.00	264.8683	0	854.5	0.674427	-1.121260
2019-05-31	180.4823	0.20	233.4953	0	759.4	0.888611	-0.743960
2019-06-30	145.3542	2.55	197.3861	0	698.4	1.084914	-0.162560
2019-07-31	152.7613	8.15	197.0403	0	690.0	0.913119	-0.606660
2019-08-31	153.5790	0.55	205.5602	0	725.5	1.015147	-0.351500
2019-09-30	156.0526	0.00	209.4597	0	816.5	1.136929	0.103788
2019-10-31	193.0379	0.00	247.3889	0	835.5	0.892411	-0.676370
2019-11-30	217.0742	0.00	265.0880	0	852.4	0.725874	-1.064320
2019-12-31	238.4649	0.00	291.9373	0	835.7	0.645876	-1.276210
2020-01-31	233.6739	0.00	285.3307	0	815.3	0.672362	-1.189020
2020-02-29	215.0167	0.00	267.3921	0	806.3	0.731624	-1.085680
2020-03-31	237.7216	0.10	281.9705	0	811.0	0.578233	-1.316750
2020-04-30	214.9389	0.00	265.5526	0	859.3	0.755055	-0.997050
2020-05-31	170.0972	0.65	227.5742	0	843.9	1.134570	0.072566
2020-06-30	148.1640	4.80	199.7221	0	729.3	1.094688	-0.131640
2020-07-31	152.8212	6.75	206.5040	0	779.7	1.066969	-0.214680
2020-08-31	181.2781	2.65	223.4359	0	768.9	0.751092	-0.957730
2020-09-30	139.2063	0.00	190.2462	0	777.5	1.152644	0.074000
2020-10-31	138.2720	0.00	209.2276	0	828.5	1.372255	0.642153
2020-11-30	215.7482	0.00	272.6932	0	879.1	0.784947	-1.008570
2020-12-31	237.0375	0.00	291.0261	0	853.5	0.674483	-1.195230
2021-01-31	275.3446	0.00	330.1855	0	887.9	0.578198	-1.401890
2021-02-28	262.6942	0.15	315.9834	0	860.5	0.596758	-1.346990
2021-03-31	224.8831	0.00	281.2791	0	859.0	0.778903	-0.912680
2021-04-30	232.6107	0.00	284.7164	0	873.9	0.735752	-1.029750
2021-05-31	206.3210	4.40	256.4345	0	870.3	0.836647	-0.738170
2021-06-30	132.9010	1.65	192.9614	0	759.9	1.328333	0.630933
2021-07-31	120.1509	5.60	172.2667	0	672.7	1.304456	0.461802
2021-08-31	179.8876	2.25	224.9285	0	902.9	0.882152	-0.435710
2021-09-30	159.6008	0.00	218.1735	0	858.2	1.174100	0.165677
2021-10-31	190.7276	0.15	249.8582	0	838.3	0.957431	-0.574120
2021-11-30	222.0557	0.00	265.8036	0	818.2	0.657077	-1.182720
2021-12-31	227.1272	0.00	277.2345	0	841.3	0.649717	-1.245800

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Table 6: Summary table of the characterization of diffuse radiation

Balance sheet dates	Mean	Median	STD	Min	Max	Skewness	Kurtosis
2019-01-31	175.15320	1.5	244.8471	0	748	1.02816720	-0.5525378
2019-02-28	154.59230	0.0	224.1194	0	785	1.19598998	-0.0157365
2019-03-31	164.81050	1.5	232.5850	0	823	1.16553619	-0.0389528
2019-04-30	164.93890	0.0	231.3323	0	825	1.16577273	-0.0051193
2019-05-31	130.90590	0.0	196.6962	0	777	1.36949960	0.5937998
2019-06-30	104.14310	0.0	162.4238	0	659	1.55282912	1.3917962
2019-07-31	111.25940	0.0	166.3127	0	660	1.40399391	0.8476925
2019-08-31	114.01750	0.0	172.8049	0	766	1.46456733	1.0963753
2019-09-30	117.03330	0.0	181.8976	0	827	1.60607705	1.7021324
2019-10-31	141.87500	0.0	211.0167	0	800	1.32908362	0.4805571
2019-11-30	148.94030	0.0	212.3827	0	763	1.17804685	-0.0211257
2019-12-31	160.54970	1.5	224.9501	0	717	1.06524231	-0.4113400
2020-01-31	160.01480	0.5	225.3180	0	726	1.09709948	-0.3207844
2020-02-29	157.46260	2.0	225.2834	0	755	1.14900974	-0.1758388
2020-03-31	179.21640	2.0	245.5837	0	824	1.05382651	-0.3895509
2020-04-30	161.77920	0.0	231.8557	0	854	1.21463182	0.0983050
2020-05-31	123.55380	1.0	191.3568	0	823	1.62616088	1.7724382
2020-06-30	106.85140	0.0	165.9880	0	691	1.56151790	1.3894992
2020-07-31	111.47180	0.0	172.8531	0	728	1.52871048	1.2814925
2020-08-31	134.44220	0.5	189.3303	0	768	1.20955102	0.1946996
2020-09-30	103.59310	0.0	163.1012	0	747	1.63362209	1.8201454
2020-10-31	100.80650	0.0	174.1793	0	773	1.80332525	2.2923587
2020-11-30	149.15420	0.0	218.7537	0	814	1.22924497	0.0846043
2020-12-31	158.27150	1.0	222.3688	0	734	1.09665970	-0.2980292
2021-01-31	188.00940	3.5	259.7329	0	797	1.01065023	-0.5797170
2021-02-28	190.22320	0.0	262.7607	0	805	1.02199626	-0.5316008
2021-03-31	169.22580	0.5	243.7144	0	853	1.26125197	0.2742345
2021-04-30	173.61810	0.0	247.2905	0	868	1.20999855	0.0774992
2021-05-31	149.53360	1.0	216.1904	0	856	1.32529708	0.5938147
2021-06-30	95.08611	0.0	158.6560	0	701	1.81138385	2.5009610
2021-07-31	85.88575	0.0	140.1914	0	632	1.75017966	2.1291651
2021-08-31	132.67340	0.0	187.2811	0	874	1.31357134	0.8450685
2021-09-30	120.32360	0.0	190.6189	0	866	1.63317710	1.7077809
2021-10-31	137.51210	0.5	209.3624	0	799	1.41007656	0.7065357
2021-11-30	150.96810	1.0	211.0158	0	776	1.13165816	-0.1014435
2021-12-31	152.32660	2.5	213.5093	0	723	1.08455731	-0.3424213

Table 7: Summary table of the characterization of precipitation

Balance sheet dates	Mean	Median	STD	Min	Max	Skewness	Kurtosis
2019-01-31	0	0.041369	0	0.4	7.743548	63.81766	0
2019-02-28	0	0.333206	0	5.8	11.735270	169.98810	0
2019-03-31	0	0.386407	0	6.1	10.895640	140.28640	0
2019-04-30	0	0.391306	0	5.1	7.840350	71.29707	0
2019-05-31	0	0.599079	0	6.7	5.017173	31.86830	0
2019-06-30	0	0.771966	0	9.2	6.584076	54.08686	0
2019-07-31	0	0.400116	0	4.1	5.765703	39.68671	0
2019-08-31	0	0.499050	0	7.7	8.825944	104.54260	0
2019-09-30	0	0.635463	0	5.1	4.458013	22.72155	0
2019-10-31	0	0.837937	0	11.1	7.368133	69.23888	0
2019-11-30	0	0.387570	0	5.1	8.151805	80.82236	0
2019-12-31	0	0.252082	0	3.0	7.988550	72.57779	0
2020-01-31	0	0.158156	0	3.3	14.194420	261.52920	0
2020-02-29	0	0.465374	0	8.6	11.388660	176.17310	0
2020-03-31	0	0.247256	0	3.0	7.940753	75.69181	0
2020-04-30	0	0.539613	0	8.7	9.109414	112.33570	0
2020-05-31	0	0.625779	0	6.0	5.412855	35.46822	0
2020-06-30	0	0.670699	0	9.3	7.650188	81.04109	0
2020-07-31	0	0.866064	0	12.0	8.260138	82.56415	0
2020-08-31	0	0.270378	0	3.2	7.230364	63.43301	0

Table 7: Continue

2020-09-30	0	0.669892	0	6.5	5.178185	32.47256000	0
2020-10-31	0	1.727360	0	15.5	5.081458	29.65039000	0
2020-11-30	0	0.392744	0	5.5	7.323385	70.12483000	0
2020-12-31	0	0.228822	0	3.6	10.882060	147.44840000	0
2021-01-31	0	0.047147	0	0.8	12.674170	183.29100000	0
2021-02-28	0	0.108857	0	1.4	9.818283	106.44000000	0
2021-03-31	0	0.385993	0	5.9	8.737419	95.62069000	0
2021-04-30	0	0.417676	0	6.3	9.388481	107.91020000	0
2021-05-31	0	0.614877	0	8.2	7.017224	62.66132000	0
2021-06-30	0	0.768622	0	6.7	4.906655	27.57180000	0
2021-07-31	0	0.293703	0	2.7	5.603354	34.92699000	0
2021-08-31	0	0.084494	0	1.8	14.423650	279.16050000	0
2021-09-30	0	0.371871	0	3.9	7.320442	61.10329000	0
2021-10-31	0	0.993491	0	12.6	7.964209	78.47912000	0
2021-11-30	0	0.267783	0	3.3	7.948161	79.79891000	0
2021-12-31	152.3266	2.500000	213.5093	0.0	723.000000	1.08455731	-0.3424213

Table 8: Summary table of the characterization of the consumed power

Balance sheet dates	Mean	Median	STD	Min	Max	Skewness	Kurtosis
2019-01-31	196.5019	203.86460	18.696560	156.18330	219.7917	-0.623860	-0.80881
2019-02-28	205.5684	212.52600	16.557040	165.75210	224.2667	-1.079210	0.031642
2019-03-31	201.8801	208.61040	19.622800	157.82290	225.2188	-0.521580	-0.94752
2019-04-30	200.8512	205.97600	17.856180	161.55630	232.6875	-0.350160	-0.55892
2019-05-31	185.6368	186.98540	16.533100	158.05000	218.6583	0.093658	-0.70666
2019-06-30	164.3238	158.75630	15.622220	136.20210	189.0146	0.112502	-1.45516
2019-07-31	164.2012	168.12710	12.659130	139.86040	181.9271	-0.514220	-0.92738
2019-08-31	153.5124	158.90420	13.258060	126.14170	172.0375	-0.863130	-0.61801
2019-09-30	155.8745	161.18230	10.937180	134.05420	172.2854	-0.668580	-0.88131
2019-10-31	154.3784	156.42710	12.535450	127.25630	171.6188	-0.734740	-0.43249
2019-11-30	169.7319	170.87080	15.387530	133.37500	191.1813	-0.644620	-0.30527
2019-12-31	179.4753	185.96040	15.895630	150.42290	197.4292	-0.655910	-1.15133
2020-01-31	111.2833	112.53750	17.171360	81.40833	166.8771	0.605278	2.568004
2020-02-29	119.3022	123.50000	9.663162	101.71250	130.9792	-0.666010	-1.00783
2020-03-31	118.9148	121.30420	10.249130	96.50417	131.1625	-0.449710	-0.95701
2020-04-30	110.9561	111.83540	12.632290	77.66667	128.3708	-1.031010	1.090603
2020-05-31	113.9616	113.67500	8.784519	89.08333	128.2458	-0.643940	0.758717
2020-06-30	105.9339	108.48130	8.833575	88.10833	119.5375	-0.381730	-1.08806
2020-07-31	101.2226	103.21250	5.848761	90.21250	109.7083	-0.514110	-1.09867
2020-08-31	97.9961	97.57917	6.237270	87.65000	106.7500	-0.203590	-1.47527
2020-09-30	102.0157	103.87080	6.397329	87.33750	113.3083	-0.592500	-0.41833
2020-10-31	111,8798	113,1875	9,237277	94,55833	136,2417	0,174226	0,399535
2020-11-30	119,9911	122,2229	7,921597	102,8208	132,2208	-0,55299	-0,6429
2020-12-31	120,6871	122,2083	6,468197	107,1708	128,7958	-0,64176	-0,70101
2021-01-31	122,7879	126,125	10,00985	101,5042	137,35	-0,56478	-0,75384
2021-02-28	131,1844	133,7313	8,734357	115,0875	144,125	-0,36491	-0,91356
2021-03-31	128,2032	126,0917	12,44503	98,80417	148,7833	-0,13184	-0,33048
2021-04-30	127,0689	128,7083	9,201381	109,9458	139,5375	-0,42608	-1,04039
2021-05-31	121,5095	124,5958	11,7648	94,00417	139,6125	-0,41365	-0,67265
2021-06-30	113,5514	113,8125	11,6309	93,4625	135,9042	0,022735	-0,88337
2021-07-31	122,2966	123,8458	9,392457	104,125	134,5875	-0,41439	-1,21032
2021-08-31	120,4777	121,9167	7,80705	106,8125	134,5417	-0,36802	-0,94976
2021-09-30	122,8357	124,5396	8,348134	106,3833	133,2167	-0,49126	-1,04366
2021-10-31	122,2718	125,7083	12,89069	91,20833	138,0917	-1,01164	0,076422
2021-11-30	123,0386	132,8458	24,83562	64,74167	151,3	-1,13644	0,43797
2021-12-31	140,1776	138,7792	9,350538	120,5833	156,9375	-0,06073	-0,6812

Table 9: Coding table for model variables

Input variables used	Associated codes
Relative humidity (HR in %)	H
Direct Normal Irradiance (DNI in W/m^2)	I
Precipitation (P in mm)	P
Temperature (T in °C)	T
Wind Speed (V in m/s)	V

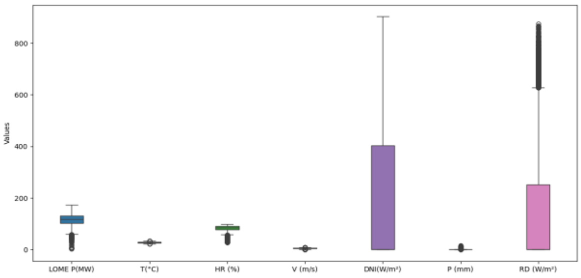
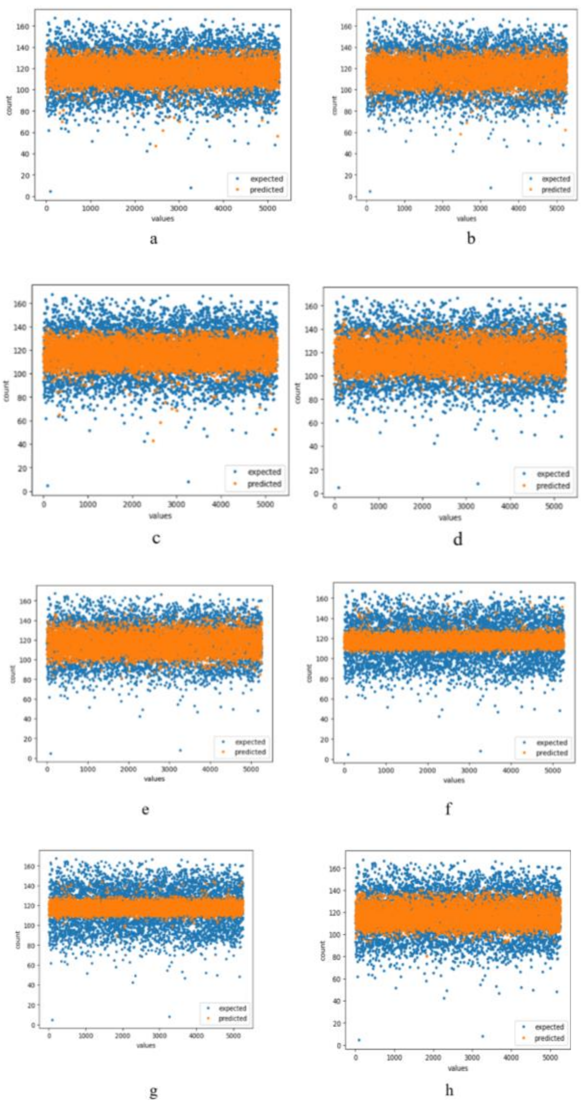


Fig. 4: Graphical view of all model input variables



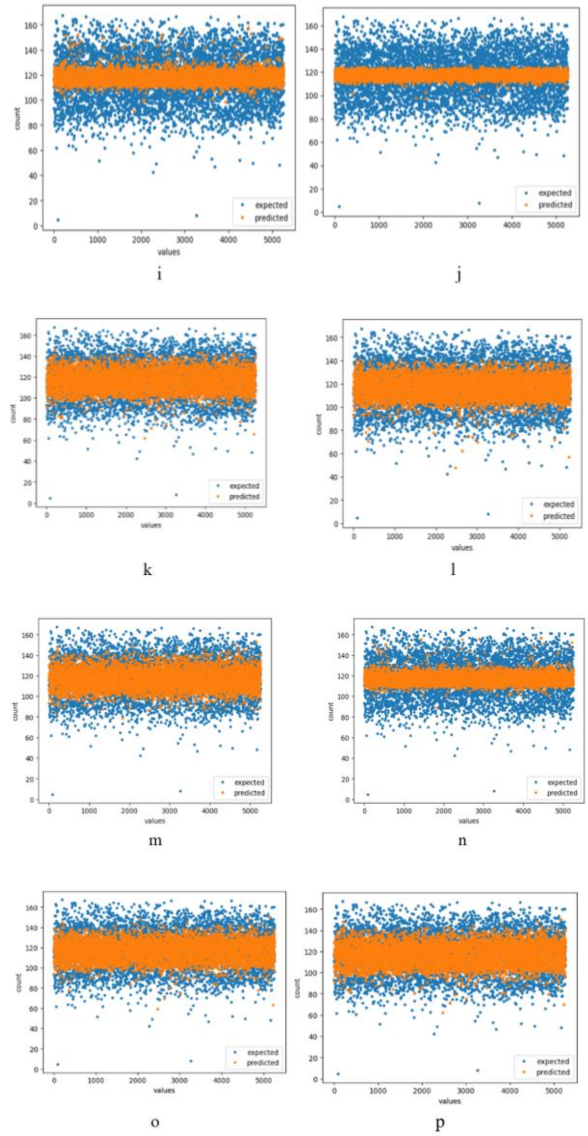


Fig. 5: Configurations of models: A-HTV; b-HIT; c-HPT, d-ITV; e-IPT; f-HIV; g-HPV; h-PTV; i-HIP; j-IPV; k-HITV; l-HPTV; m-IPTV; n-HIPV; o-HIPV; p-HIPTV

Table 10 summarizes the results obtained by performance evaluation metrics per explored model. To make the results easier to read, modifications are made and summarized in Table 9. The graphical view of the characterization is observed in Fig. 4. Those obtained by configuring the models from learning are presented by the different graphs in Fig. 5.

Discussion

Analysis of the results shows a large disparity between the variables. It is then evident that different sets of variables display distinct prediction performances.

Table 1 shows significant values of temperature. Temperatures vary between 24.4°C (2019-06-30) and 31.3°C (2021-03-31). This observation helps us to confirm that there must be a strong connection between the electrical power consumed to be predicted with it. On this same date, we observed that the average electrical power consumed is 122.2718 MW, for a minimum of 91.20833 MW and a maximum of 138.0917 MW. The same observation can be made in Table 2 if we refer to the wind speed. It varies between 2.6 m/s observed on 2019-11-30 and 25.7 m/s on 2019-08-31. However, in this table, we notice that the wind speed is not zero. Therefore, the three random variables (Temperature, wind speed, and Electrical power consumed) are linked. However, if we only consider these three variables as meteorological to study the forecast of the electrical power to be consumed, the answer would be trivial. The use of artificial intelligence requires the presence of complex situations to be resolved. The complexity of this study is found more clearly in Tables 3-6. There we find zero values and even very large ones for the same dimensions over the study period. Concerning relative humidity (Table 3), it is not very complicated. That is to say that either the minimum is zero and at the same time the maximum is very high (854%) as of 2020-04-30. The cases become more and more complicated if we take direct normal irradiance. Almost all averages are very far from the medians. Which shows a very poor statistical distribution (Veysseyre, 2006). As of 2021-01-31, we find an average of 275.3446 W/m^2; a median of 0 W/m^2 as well as the minimum, with a maximum of 887.9 W/m^2. The same phenomenon is observed for diffuse irradiation. By observing the asymmetry and flattening coefficients we can conclude on the irregularity of the statistical distribution of the variables studied. In fact, skewness is a measure of asymmetry, which corresponds to the study of the regularity (or not) with which observations are distributed around the central value. Its normalized value is equal to 0 (Veysseyre, 2006). They are observed correctly in all tables except in Table 7 which shows outliers. Empirical kurtosis, theoretically equal to 3, is a measure of kurtosis of the distribution, compared to the kurtosis of a normal distribution. It was not found in any of the summary tables of the variables during the characterizations. Thus, there arises the need to use algorithms in order to purify the study and predict the prediction error rate from the metrics.

Through the metrics used in this study, the observations become clearer. We find that the parameters considered for the prediction are suitable because Table 10 exhibits average absolute errors that are not exorbitant. Indeed, the MAE (mean absolute error) measures the average differences between the predicted values and the actual values (Amusa *et al.*, 2019). The closer the MAE value is to 0, the better. The lowest values are the best. For our case study, the highest is 16.066 for the IPV configuration and the lowest (13.214) is obtained for the (HIPTV) configuration. Mean squared error, or MSE, is a popular error measure for regression problems. It is also an important loss function for algorithms tuned or optimized using the least squares framing of a regression problem. The MSE is calculated as the average of the squared differences between the predicted and expected target values in a data set. Which shows their very values in the results. The RMSE metric on the other hand is the measurement of the breakdown of these residuals. In other words, it indicates the concentration of data around the line of best fit. Figures 5 graphically show their observations. In Table 10, they vary between 19.643 for the IPV configuration where the correlation coefficient (21.021%) is very low, and 13.137 for the HPV configuration. Furthermore, we will base ourselves on the correlation coefficient which studies the intensity of the link which can exist between these random variables. The connection sought is an affine relation. The lowest as obtained by the IPV configuration shows that the direct normal irradiance, precipitation, and temperature combined are not suitable to correctly predict the power to consume. As its greatest value (77.284%) is obtained through the configuration bringing together all the parameters, we conclude that they are all suitable, by combining them, for the prediction of electrical energy consumption. Thus, the best result retained for forecasting electrical energy consumption for some CEB sites in Togo is MAE = 13.214; MSE = 282.199; RMSE = 16.798, and R^2 = 77.284%. As the R^2 is not equal to 1, work must continue through other algorithms to find, with better precision, the means of predicting the consumption of electrical power in the CEB networks.

Table 10: Summary of modeling results by configuration

Model configurations	Results of performance evaluation metrics			
	MAE	MSE	RMSE	R^2 (%)
HVT	13.787	305.394	17.475	63.225
HIT	13.527	294.162	17.151	62.253
HPT	13.812	306.748	17.514	67.221
ITV	13.488	293.251	17.124	73.256
IPT	13.495	292.556	17.104	68.257
HIV	15.400	365.936	19.129	31.071
HPV	15.463	366.224	13.137	32.070
PTV	13.994	312.910	17.689	64.206
HIP	15.391	365.671	19.122	29.072
IPV	16.066	385.847	19.643	21.021
HITV	13.463	290.824	17.053	71.262
HPVT	13.712	301.705	17.369	60.234
IPTV	13.389	289.011	17.000	70.266
HIPV	15.325	362.596	19.041	41.080
HIPT	13.389	289.011	17.000	73.266
HIPTV	13.214	282.199	16.798	77.284

Conclusion

This article presents the results of forecasting consumption in an electrical network by implementing models in order to plan the supply of electrical energy. Given the almost precise nature of weather forecasts, some codified ones were taken into account for the study. These are relative Humidity (H), direct normal Irradiation (I), Precipitation (P), Temperature (T), and wind speed (V). The values of electrical power used (in MW), collected at certain CEB transformation stations (Lomé Aflao, Légbasito, and port of Lomé) for the Lomé site, were used as a basis for carrying out this study. A statistical characterization of each exploited variable is carried out. Parameters such as mean, median, standard deviation, minimum, maximum, kurtosis coefficient, and skewness coefficient are calculated in order to observe their distribution. The characterization results show a good distribution of temperature, relative humidity, and wind speed values. These results are confirmed by their median values which are very close to the means. This is not the case for direct normal irradiation, precipitation, and diffuse radiation. For the latter, we find zero values momentarily and also very high values. This is the same observation for the key statistical parameters (Skewness and Kurtosis) which have values that are not close to the normalized one. In reality, we must find asymmetry coefficients close to 0 against kurtosis coefficients which are around 3. Unfortunately, this is not the case. Which led us to deduce the state of their distribution.

Considering the distribution of variables, we used multiple linear regression as an algorithm to predict the power to consume. The results of the models are subject to certain performance evaluation criteria most used in the literature. These are: Absolute error of means (MAE) which measures the average differences between predicted values and actual values, mean squared error (MSE), a popular error measure for regression problems, the square root of the root mean square error (RMSE) which measures the decomposition of these residuals and the correlation coefficient (R^2) which studies the intensity of the link which may exist between the predicted values and those which were used in the study. The modeling results show that some configurations are better than others. The most unfavorable is the IPV configuration giving MAE = 16.066; MSE = 385.847; RMSE = 19.643 and R^2 = 21.021% because its correlation is closer to 0 instead of 1. Also, its MSE is very high. On the other hand, for this modeling, the best result is obtained by the HIPTV configuration thus bringing together all the parameters considered for the study of the model. It gives: MAE = 13.214; MSE = 282.199; RMSE = 16.798 and R^2 = 77.284%. This will allow monitoring of costs to increase or decrease production and on the contrary to have on short-term consumption in order to supply accordingly. In fact, for a model to be efficient, there must be a strong correlation between the actual values and those predicted and to obtain it, it must be very close to 100%. For this, it is now necessary to explore other algorithms given that the models studied do not give very satisfactory correlation coefficients. Taking into account more sensitive data would also position the company on the evolution of consumption.

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Author's Contributions

Apaloo Bara Komla Kpomonè: Designed the study, wrote the simulation codes, analyzed the data, and then wrote the manuscript.

Palanga Eyouleki Tcheyi Gnadi: Monitored the work, revised the manuscript critically, and provided constructive suggestions for its improvement.

Bokovi Yao: Followed up the work, revised the manuscript critically, and provided constructive suggestions for its improvement.

Kuevidjen Dosseh: Provided the data and tested the results on their electrical network.

Nomenyo Komla: Revised the summary by improving it and then adapting it to the content after his critical contribution as a reviewer and following his series of questions leading to an understanding of the manuscript based on the work carried out.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and that no ethical issues are involved.

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