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RESEARCH ARTICLE

FORECASTING THE CONSUMPTION OF ELECTRICAL ENERGY ON THE CEB ELECTRICAL NETWORK IN LOMÉ IN TOGO BY APPROACHES: SIMPLE LINEAR REGRESSION, RECURRENT NEURAL NETWORKS AND GENETIC ALGORITHMS

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Abstract

Forecasting the electrical power to be consumed requires planning production on several levels. In this work we used data from the Electric Community of Benin. Temperature, relative humidity, wind speed, normal direct irradiance, precipitation and diffuse radiation are the meteorological variables that made it possible to analyze the forecasts. The objective is to do learning with genetic algorithms, LSTM recurrent neural networks and simple linear regression after a characterization and a correlation study and then to submit the results to performance evaluation criteria. The results of the characterization made it possible to understand that certain variables are significant and influence the consumption of electrical energy. The study of the correlation gives 94% between direct normal irradiance and diffuse irradiance. Both give with the temperature 67% for one and 68% for the other. Regarding modeling, the results are bad with genetic algorithms if we take into account the correlation coefficient (R^2 = 28.84%), good with simple linear regression (R^2 = 69.08%) and very interesting for networks of recurrent neurons where we find: MAE = 0.11; MSE = 0.02; MAPE = 18.50%; RMSE = 13.09%; RRMSE = 18.25% and R^2 = 96.11%. Given these results, we deduce that short- and long-term memory recurrent neural networks (LSTM) are very well suited to predicting the electrical power consumed on the CEB electrical network.

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Introduction:-

The information and communication techniques that revolutionized the world were only possible thanks to the development of the electricity sector. The latter is now present in all areas of activity. Electricity coverage is part of the criteria for classifying countries in terms of their development in the world as well as on an industrial level, [1-3]. Primary energy sources (fossil, renewable) capable of being transformed into electrical energy, to power industries, exist today everywhere and in several forms, [4-9]. Considering that fossil sources contribute enormously to the destruction of nature, international conferences are focusing on the subject by advising the production of electrical energy based on renewable sources, [11, 12]. This is to reduce greenhouse gases, [13,14], which create climate disruption, [15-16], such as heatwaves, melting glaciers, unexpected floods, etc., [17-19].

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However, comfort and the search for ease in daily activities mean that the demand for electrical energy continues to grow exponentially, [20-21], but the storage of electricity is insignificant. The important observation that the quantity of electricity produced throughout the world cannot be stored for later use deserves our serious attention. To do this, it must be consumed as it is produced. It will then be necessary to find a balance between production and consumption in order to avoid waste of available primary energy sources.

Considering all this, energy production companies do everything to provide only the instantaneous electricity necessary for consumption, [22-23]. Knowing that electricity consumption is very uncertain from one region to another and from household to household, the work has provided short- and long-term solutions, [24-25]. From there, many studies around the world have focused on the subject [26-31]. The results of this research have contributed to the reliability of electricity networks by eliminating energy waste by adapting production to consumption. It is time to seek to apply it here (in Togo), particularly in our electrical networks. Togo, a country in humid and coastal West Africa, also has visions of major electrification projects. In the country, energy transport is provided by the Community Electricity of Benin (CEB), [32], and distribution by the Compagnie d'Energie Electrique du Togo (CEET), [33]. Thus, to see the national development plan of the country, [34], drawn up by the government, with regard to electricity coverage, it is necessary that the same solutions are also applied for the adequacy between production and consumption taking into account energy poverty. Which becomes a complex problem to solve.

Solving complex problems today involves systems modeling [35-40]. Among the means of modeling, Artificial Intelligence has become the best following statistical and stochastic methods, [39], [41-42]. Through its algorithms (Artificial Neural Network, [25], |40], Neuro-fuzzy Inference System, [40], Vast Margin Separator, [40], Autoregressive Integrated Moving Average, [24], [43], etc. .), it finds almost real models starting from random or concrete phenomena with even a few sometimes insignificant errors, [25], [40], [43], [44], [45]. Given that weather forecasts have become more and more precise, it would be wise to use them in forecasting electrical energy needs in order to monitor their similarity.

The objective of this work is to exploit certain meteorological variables such as temperature, wind speed, relative humidity, normal direct irradiance, precipitation and diffuse radiation as input variables then the power consumed on certain CEB sites in Lomé to predict its need for electrical energy. The meteorological variables will be extracted from the site https://open-meteo.com, an API (Industrial Programmable Logic Controller) which is an open source weather forecast and offers free access for non-commercial use. We will then exploit simple linear regression, Genetic Algorithms and Recurrent Neural Networks to learn the models. The goal of this work is to submit the results to the performance evaluation criteria most used in the literature in order to observe the behavior of the models to check whether they are favorable or not. Among these criteria, we will use here the mean absolute error (MAE), the mean square error (MSE), the mean absolute error in percentage (MAPE), the square root of the mean absolute error (RMSE), the square root of the relative root mean square error (RRMSE) and the Correlation Coefficient R^2. At the end of the work, the conclusions will allow us to confirm or refute, if the algorithms are well chosen or from the comparisons, which are adapted to the chosen variables a good forecast.

Materials and Methods:-

To develop this work, we will use CEB operating data. The powers consumed during the years from 2019 to 2021, and from January to December will be used. Generally, this data is recorded automatically on the network through an Excel file, the appearance of which is shown in Figure 1. Given that the power consumed data is not recorded over and over with the meteorological variables and that this power consumed is not recorded for a single location but in a space (Lomé), we will look for the meteorological variables on the site https://open-meteo.com. This is an Open-Meteo, an open source weather API that provides free access for non-commercial use. On this site, only the following variables will be used among others:

1. daily gridded dates: YEARS months and days of datatime type;
2. temperature: T (°C) of float type;
3. relative humidity: H (%) of float type;
4. wind speed: V (km/h) of type int64;
5. normal direct irradiance: DNI (W/m²) of float type;
6. precipitation: P (mm) of float type;
7. diffuse radiation: RD (W/m²) type int64.

First a graphical characterization will be carried out on all the variables. Parameters such as: annual mean, mode, median, standard deviation, maximum, minimum, asymmetry coefficient and flattening coefficient will be calculated for each variable in order to judge their correlation. This part will be materialized graphically by a heat map of correlation between all the variables. Then, we will use Simple Linear Regression, Genetic Algorithms and Recurrent Neural Networks to perform the learning. The forecast results will be subject to performance evaluation metrics.

Simple linear regression [25], [46]

We only introduce here the notion of linear model through its most basic expression.After having explained the necessary hypotheses and the terms of the model, we will present the notions of estimates of the model parameters and forecasting using the confidence interval.Finally, particular attention will be paid to influential values. In modeling if we note *Y*, the real random variable to be explained (endogenous, dependent or response variable) and *X*, the explanatory variable or fixed effect (exogenous);the model amounts to assuming that, on average, *E(Y)*, is an affine function of *X*. Writing the model implicitly assumes a prior notion of causality in the sense that *Y* depends onsymmetrical.Relations (1) or (2) can be considered.

$$E(Y) = f(X) = \beta_0 + \beta_1 X \qquad (1)$$

Where

$$Y = \beta_0 + \beta_1 X + \varepsilon \qquad (2)$$

We will assume for simplicity that *X* is deterministic. Otherwise, if *X* is random, the model is then written conditionally on the observations of relation (3) and leads to the same estimates.

$$X : E(Y / X = x) = \beta_0 + \beta_1 x \qquad (3)$$

The assumptions relating to this model are as follows:

1. the error distribution ε is independent of X where X is fixed,
2. the error is centered and of constant variance (homoscedasticity): $\forall i = 1,...,n$ $E(\varepsilon_i) = 0$, $Var(\varepsilon_i) = \sigma^2$,
3. β_0 and β_1 are constant, no break in the model,
4. Additional hypothesis for inferences: $\varepsilon \sim N(0, \sigma^2)$

The estimation of the parameters β_0, β_1 and σ^2 are obtained by maximizing the likelihood, under the hypothesis that the errors are Gaussian, or by minimizing the sum of the squares of the differences between observations and model (least squares). The two approaches lead to the same estimates while maximum likelihood leads to better properties of the estimators. For a sequence of observations $f(x_i, y_i)$, $\{(x_i, y_i) i = 1,...,n\}$, the least squares criterion is written by the expression of the relation (4):

$$\underset{\beta_0,\beta_1}{Min} \sum_{i=1}^{n} \left(y_i - \beta_0 - \beta_1 x_i \right)^2 \qquad (4)$$

We pose:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \;; \qquad \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \;;$$

$$s_x^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2 \;; \qquad s_y^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2$$

$$s_{xy} = \frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right) \;; \qquad r = \frac{S_{xy}}{S_x S_y}$$

Least squares are minimized by relations (5) and (6):

$b_1 = \frac{S_{xy}}{S_x^2}$ (5)

$b_0 = \overline{y} - b_1 \overline{x}$ (6)

Which are the realizations of the estimators β_0 and β_1. We show that these estimators are unbiased and have minimum variance among the linear function estimators y_i (resp. among all the estimators in the Gaussian case). Each value of X corresponds to the estimated or adjusted value of Y: $y_i = b_0 + b_1 x_i$ The calculated or estimated residuals are presented by the relation (7) and the variance σ^2 is estimated by the residual variation (8):

$e_i = y_i - \overline{y_i}$ (7)

$\sigma^2 = \frac{1}{n-2} \sum_{i=1}^{n} e_i^2$ (8)

Genetic algorithms [47-50]

Genetic algorithms are based on the idea of biological evolution and use the concept of genetics to solve optimization problems. Figure 1 illustrates the operating principle of the genetic algorithm. In order to take full advantage of the potential of a genetic algorithm, we followed each step of its flowchart methodically and efficiently.

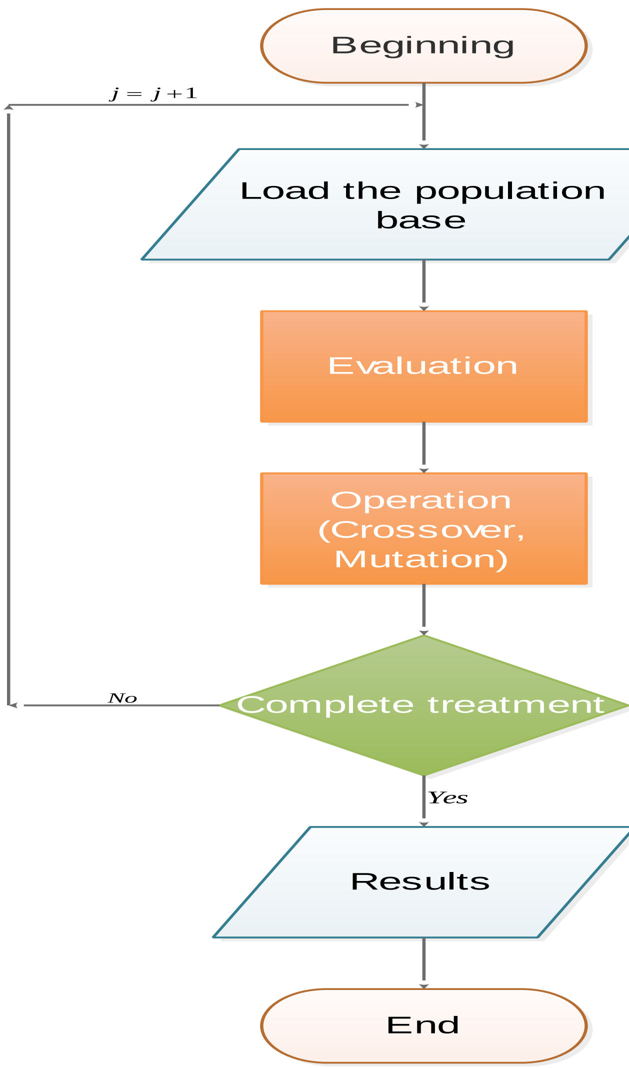


Figure 1:- Functional flowchart of the genetic algorithm.

Genetic algorithm flowchart:
The main formula used in genetic algorithms is the fitness function which measures the quality of each candidate solution. Indeed, AGs work on the maximization of an objective function. In many problems, the objective is to minimize a given function. We thus transform this objective function into an adaptation function defined by relation (9).

$$f_a(x) = f_{\max}(x) - f(x) \qquad (9)$$

Where : $f_{\max}(x) = \max(f(x))$

In the case where the objective function to be maximized takes negative values, relation (9) is replaced by relation (10).

$$f_a(x) = f(x) - f_{\min}(x) \qquad (10)$$

where : $f_{\min}(x) = \min(f(x))$.

The adaptation function has intrinsic characteristics that must be exploited to best effect when adapting to the relevant research domain. This allowed us to take into account the evaluation strategy, the selection method, and the type of operation which takes into account mutation and crossing. Because of this characteristic we adapt it here to the forecasting problem despite it being an optimization algorithm. The operation of the genetic algorithm also arises from its flowchart structure, as is the case for any algorithm.

Short and long-term memory (LSTM) recurrent neural network [51]
Recurrent Neural Networks (RNN) are powerful machine learning models that allow you to analyze sequences of data, such as text, speech or time series. These networks allow machines to "remember" past information and use it to make real-time decisions. In this article we will discover how RNNs work. RNNs sometimes fail to resolve certain problems; For this they need to have a stronger memory. We do this by making the neurons more complex. In particular, we use LSTM (Long Short-Term Memory).

Long Short-
Term Memory (LSTM), more explicitly a recurrent neural network with short-term and long-term memory, is a particular type of recurrent neural network (RNN). In an RNN, each neuron or processing unit is capable of maintaining the internal state or memory of retaining information associated with the previous input. This feature is particularly important in many time series applications. The main idea behind this type of neural network architecture is the consideration of time. The name of this neural network is derived from the fact that these types of networks operate recursively. An operation is performed for each element of a sequence whose output depends on the current input and previous operations. This is accomplished by reusing an output from the network at time t with the network input at time t + 1 (i.e. the output from the previous step is combined with the new input in the new floor). These cycles allow the existence of information from one stage to the next.

LSTM is considered the most suitable model for forecasting stochastic and noisy data such as time-dependent consumption data. This use is consistent with the ability to deduce peaks and oscillations from consumption curves as a function of time.

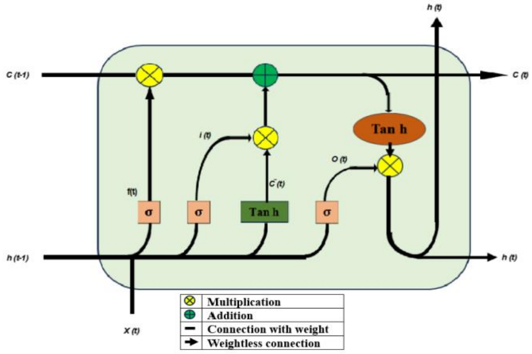


Figure 2:- Internal architecture of a unit of the LSTM short-term and long-term memory recurrent neural network [51].

Performance evaluation criteria [24], [25], [40], [45]

Statistical measurements that represent key performance indicators provide information on the performance and behavior of a given model. Among these measures, we will use the mean absolute error (MAE), the mean square error (MSE), the root mean square error (RMSE), the Normalized root mean square error (NRMSE), the mean error absolute percentage (MAPE), the correlation coefficient (R^2). RMSE is the most widely used metric for comparing different classification models, giving a simple and transparent quantitative measure of the difference between the input and the target [24], [35], [40]. MAPE is one of the most used metrics to compare forecast models. The NRMSE [40] is calculated as the RMSE divided by the range of the observed values, expressed as a percentage. The range of the observed values is the difference between the maximum and minimum values of the observed data. R^2 studies the correlation between two random (or statistical) variables; that is to say the intensity of the connection that can exist between these variables. The connection sought is an affine relation. It is best when it is close to 100%. The mathematical representations of these different indicators are given by equations (11), (12), (13), (14), (15), (16):

$$MAE = \frac{1}{N}\sum_{j=1}^{N}\left|p_{p_i} - p_{m_i}\right| \qquad (11)$$

$$MSE = \frac{1}{N}\sum_{j=1}^{N}\left(p_{p_i} - p_{m_i}\right)^2 \qquad (12)$$

$$MAPE = \frac{1}{N}\sum_{j=1}^{N}\left|\frac{p_{p_i} - p_{p_{m_i}}}{p_{p_i}}\right| \times 100 \qquad (13)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(p_{p_i} - p_{m_i}\right)^2} \qquad (14)$$

$$RRMSE = \frac{\sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(p_{p_i} - p_{m_i}\right)^2}}{\sum_{j=1}^{N} p_{m_i}} \qquad (15)$$

$$R^2 = \frac{\sum_{j=1}^{N}\left(p_{p_i} - p_{m_p}\right)*\left(p_{m_i} - p_{m_m}\right)}{\sqrt{\left[\sum_{j=1}^{N}\left(p_{p_i} - p_{m_p}\right)^2\right]*\left[\sum_{j=1}^{N}\left(p_{m_i} - p_{m_m}\right)^2\right]}} \qquad (16)$$

Where:

- ✓ p_{p_i} is the predicted power;
- ✓ p_{m_i} is the measured power;
- ✓ p_{m_p} is the predicted average power;
- ✓ p_{m_m} is the average power measured;
- ✓ N is the number of points sampled.

Results:-

The results of the characterization are presented as follows: Table 1 summarizes the statistical variables of each parameter by year and the figures going from 3 to 10 show a graphical view of the evolution of each variable during the study period.

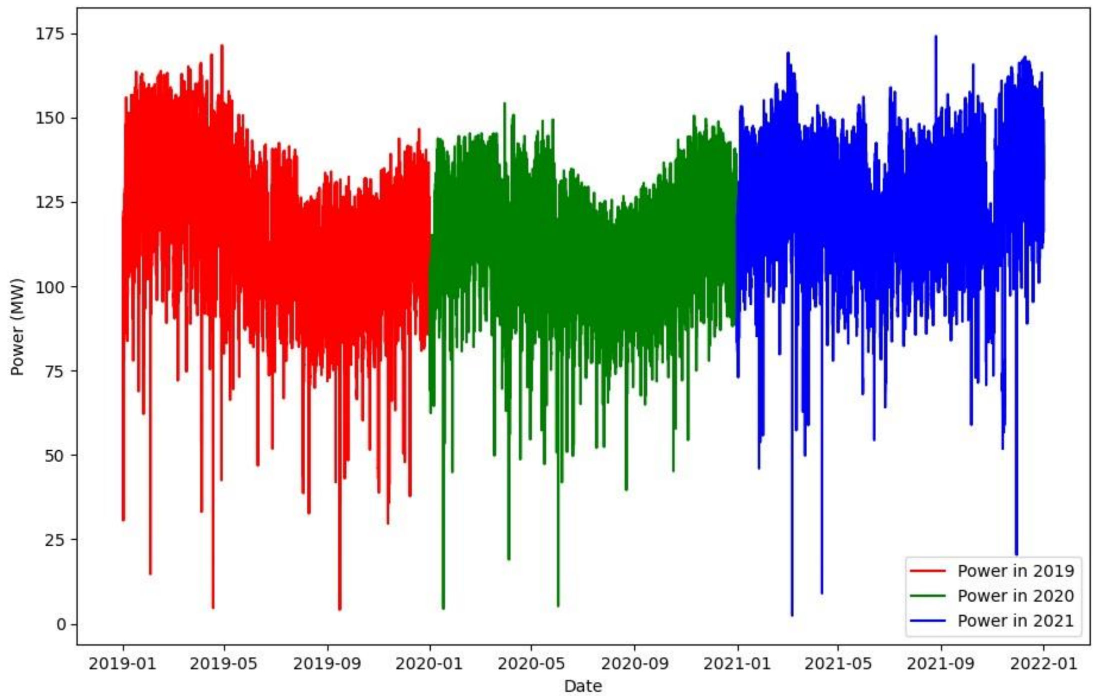


Figure 3:- Energy production from 2019 to 2021 on an hourly basis.

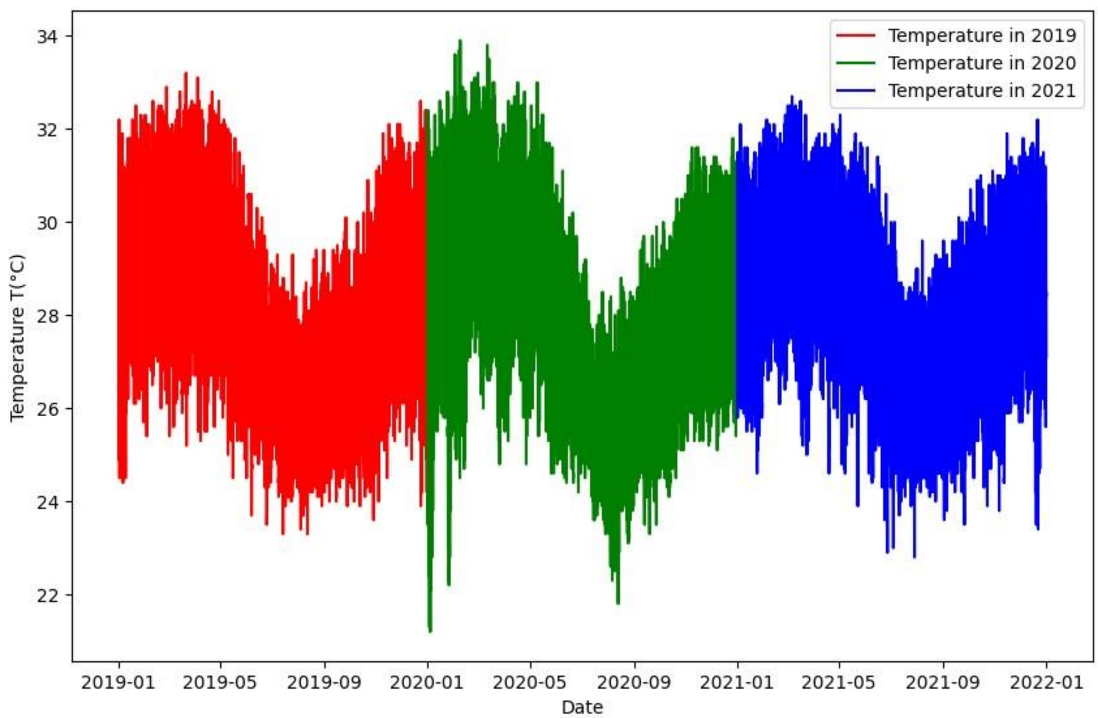


Figure 4:- Temperature variation from 2019 to 2021 on an hourly basis.

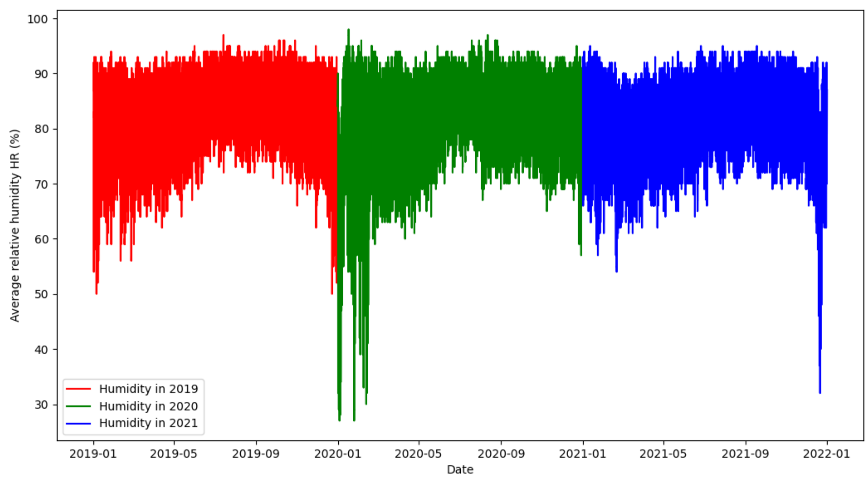


Figure 5:- Variation in relative humidity from 2019 to 2021 on an hourly basis.

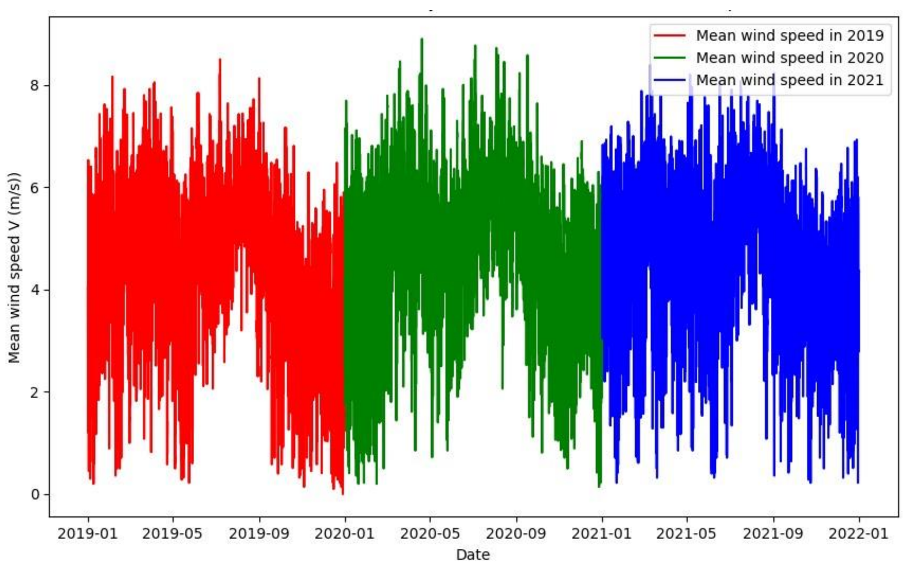


Figure 6:- Variation in wind speed from 2019 to 2021 on an hourly basis.

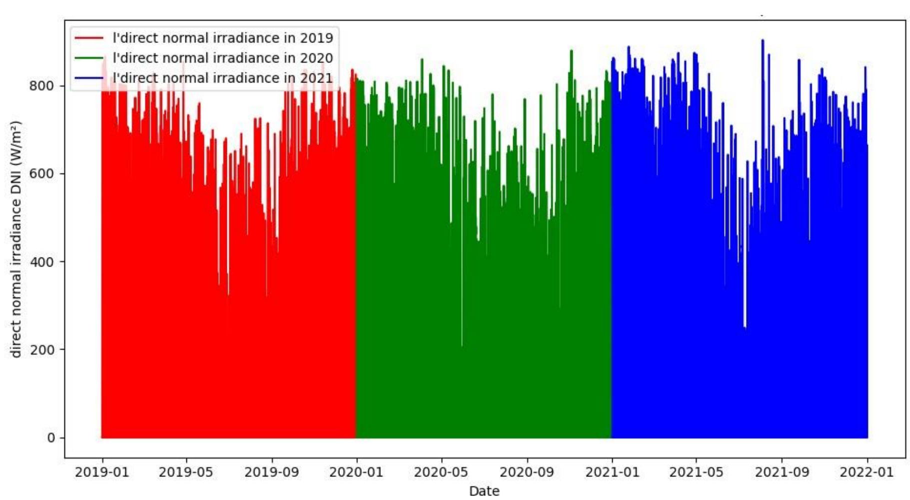


Figure 7:- Variation in direct irradiance from 2019 to 2021 on an hourly basis.

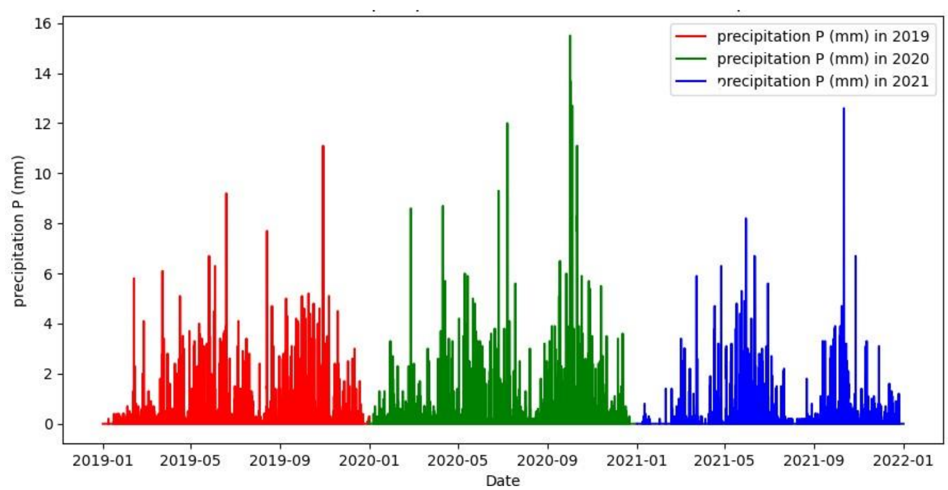


Figure 8:- Variation in precipitation from 2019 to 2021 on an hourly basis.

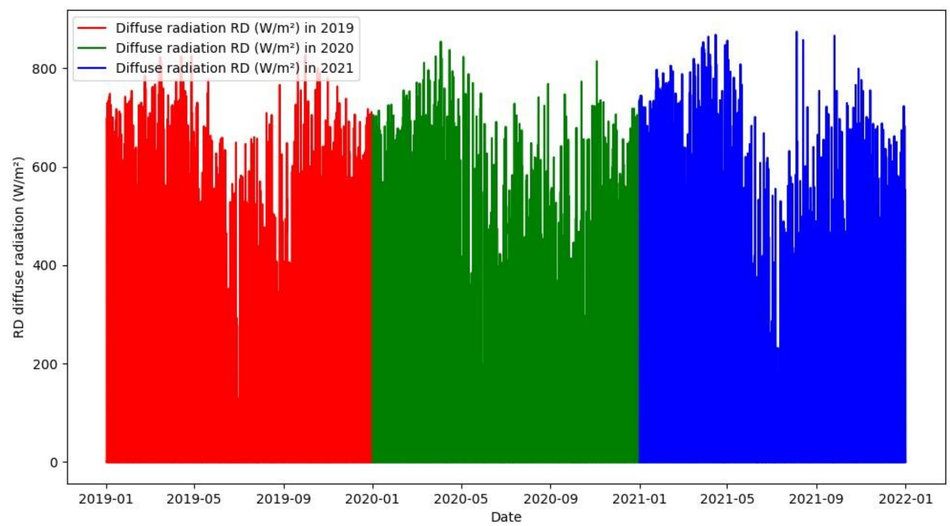


Figure 9:- Variation in diffuse radiation from 2019 to 2021 on an hourly basis.

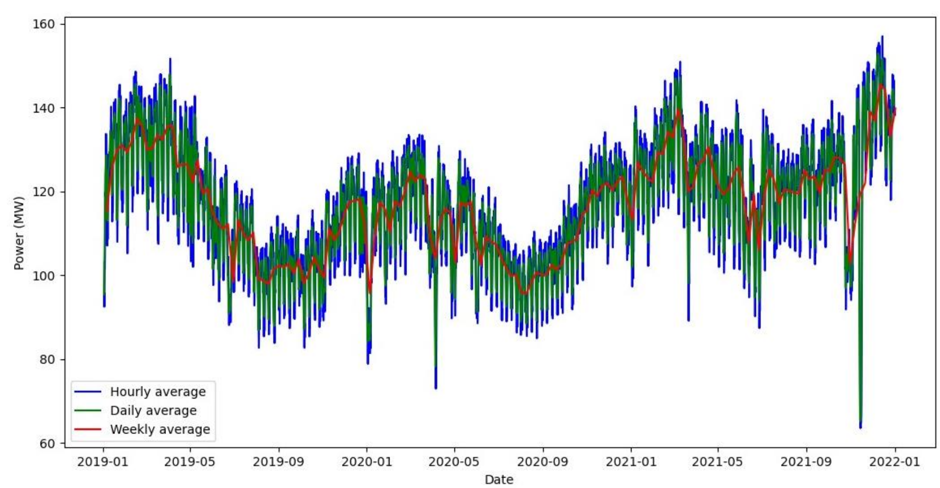


Figure 10:- Hourly, daily and weekly power averages from 2019 to 2021.

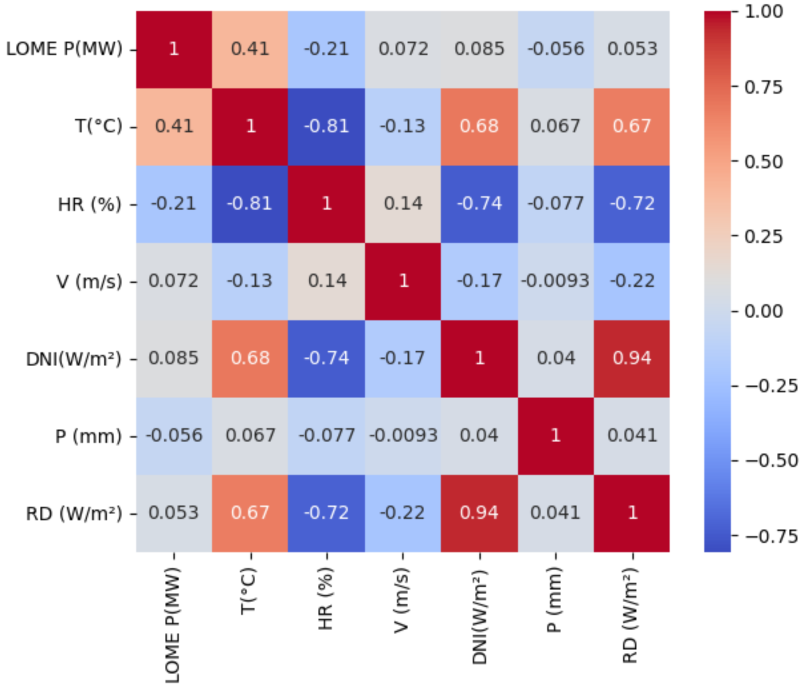


Figure 11:- Correlation table between the study variables.

The results of the statistical characterization are summarized in Table 1 and Table 2 shows the summary of the performances obtained by the algorithms

Table 1:- Summary of the characterization of the study variables.

Years	Variables	Mean	Mode	Std	Median	Min	Max	Skewness	Kurtosis
2019	Power : (MW)	115.579	88.77	20.549	115.285	4.14	171.37	-0.096	-0.099
	Temperature : T (°C)	27.624	27.7	27.4	2.120	23.3	33.2	0.393	-0.638
	Relative humidity : (%)	83.514	91	8.035	86.0	50	97	-0.890	0.273
	Wind speed : (km/h)	s	4.88	1.425	4.6	0.0	8.5	-0.381	-0.153
	Normal direct irradiance : (W/m²)	195.166	0.0	251.656	0.0	0.0	865.0	0.894	-0.677
	Precipitation : (mm)	0.1258	0	0.514	0.0	0	11.1	8.400	98.196
	Diffuse radiation: (W/m²)	140.646	0	208.040	0.0	0	827	1.322	0.455
2020	Power : (MW)	110.987	104.2	7.531	111.3	4.4	154.2	-0.2798	-0.141
	Temperature : T (°C)	27.481	27.2	2.258	27.3	21.2	33.9	0.304	-0.426
	Relative humidity : (%)	82.422	91	9.962	85.0	27	98	-1.734	4.713
	Wind speed : (km/h)	4.717	5.02	1.430	4.85	0.14	8.9	-0.384	-0.017
	Normal direct irradiance : (W/m²)	190.314	0.0	248.746	0.0	0.0	879.1	0.932	-0.598
	Precipitation : (mm)	0.162	0	0.718	0.0	0	15.5	10.016	135.165
	Diffuse radiation: (W/m²)	137.182	0	205.545	0.0	0	854	1.366	0.597
2021	Power : (MW)	124.640	130.0	19.334	126.8	2.4	174.1	-0.564	0.663
	Temperature : T (°C)	27.726	27.9	1.985	27.5	22.8	32.7	0.273	-0.696
	Relative humidity : (%)	82.308	88	8.129	84.0	32	95	-0.972	1.342
	Wind speed : (km/h)	4.580	4.88	1.388	4.71	0.22	8.39	-0.393	-0.118
	Normal direct irradiance : (W/m²)	202.542	0.0	263.322	0.0	0.0	902.9	0.928	-0.592
	Precipitation : (mm)	0.095	0	0.4756	0.0	0	12.6	11.211	183.569
	Diffuse radiation: (W/m²)	145.195	0	216.739	0.0	0	874	1.375	0.662

The learning results across the performance criteria are gathered in Table 2 and the graphical evolution of the test results in relation to learning are observed through the figures ranging from 12, 13 and 14.

Table 2:- Learning results obtained by performance criteria.

Algorithms Used	Performance evaluation criteria					
	MAE	MSE	MAPE (en %)	RMSE (en %)	RRMSE (en %)	R^2 (en %)
Simple Linear Regression	12.01	233.74	17.45	20.14	17.21	69.08
Genetic Algorithms	27.98	141668.92	17.45	20.14	17.21	68.08
Recurrent Neural Networks	0.11	0.02	18.50	13.09	18.25	96.11

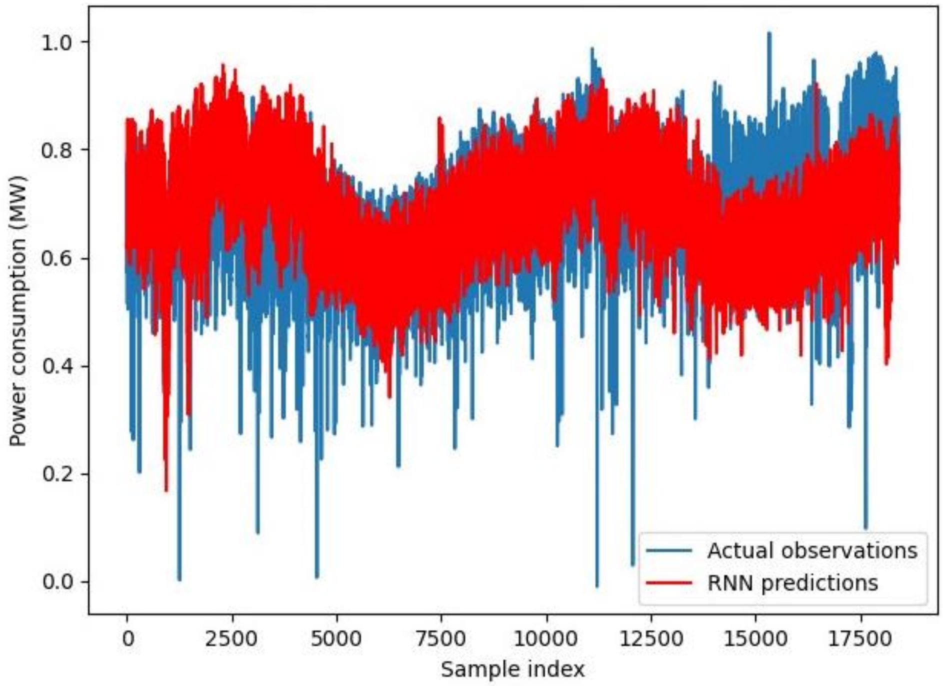


Figure 12:- State consumption prediction with the recurrent neural network.

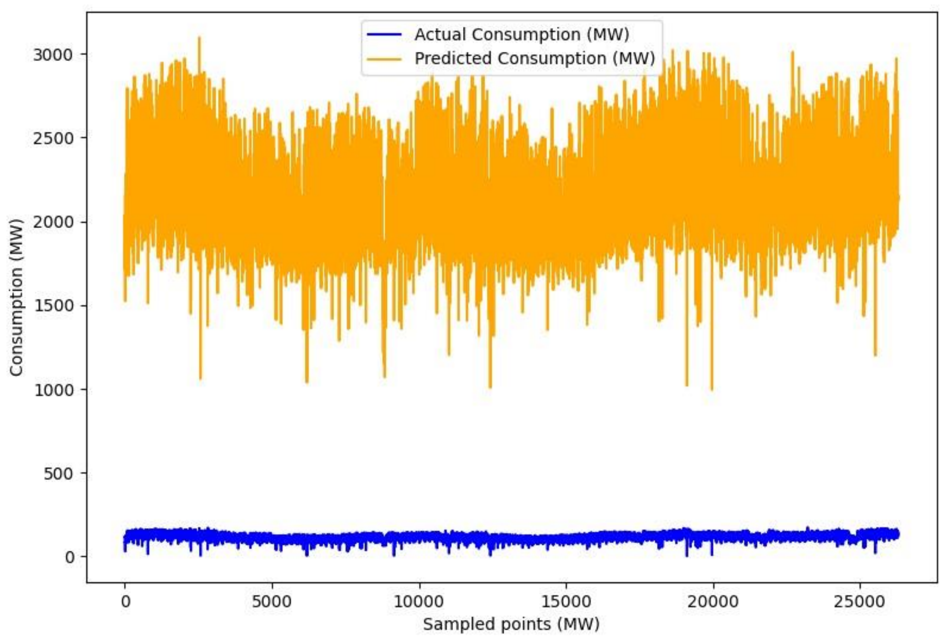


Figure 13:- State of prediction of electricity consumption by genetic algorithms.

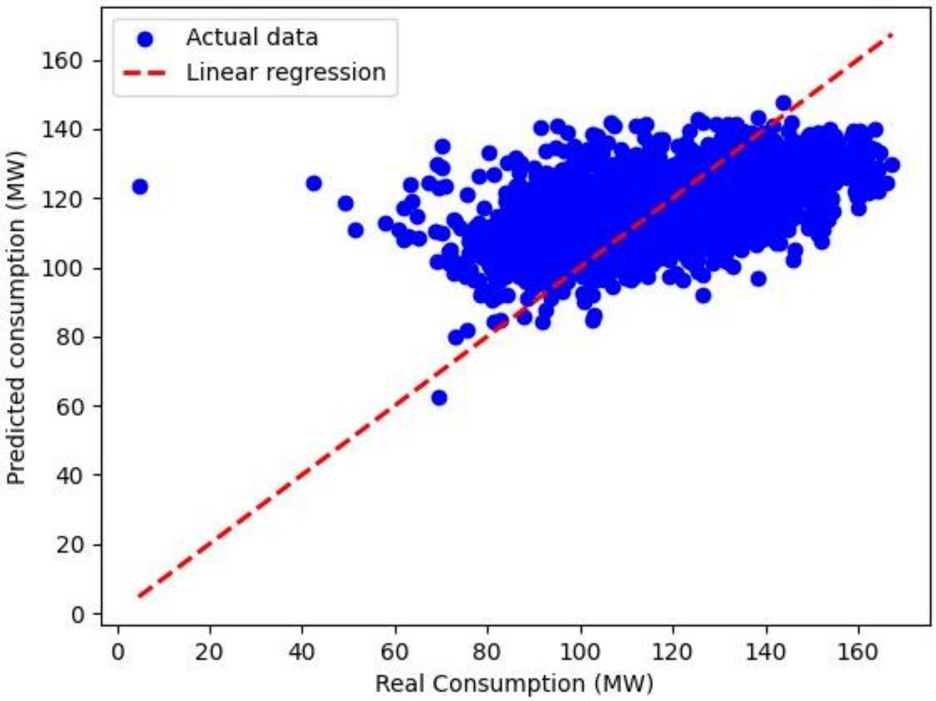


Figure 14:- Data prediction by simple linear regression.

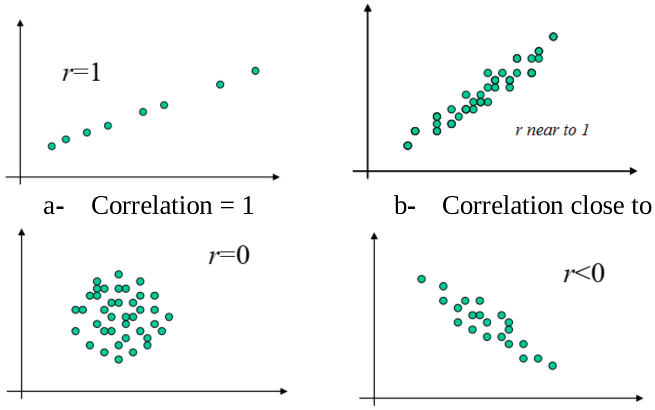
Analysis and Discussions:-

The “Energy Futures 2050” describe possible paths to transform the electricity system with a view to achieving carbon neutrality. Over the time horizons considered, the evolution of the electricity mix and the climate reinforce dependence from the balance of the system to climatic hazards and constitutes a crucial element to take into account in planning the energy system. Of all meteorological variables, this work takes into account temperature, relative humidity, wind speed, normal direct irradiance and precipitation to predict the active power to be consumed in a one-hour interval. The variables in the study are observed over a period of three years from 2019 to 2021. We observe that the highest temperature is 33.9°. The distribution of its values is stable and Figure 4 shows us that it is almost uniform each year. Observation confirmed through table XX where its average value is 27.624° in 2019; 27.481° in 2020 and 27.726° in 2021 then reinforced by the asymmetry coefficients which remains around 0. Through its statistical behavior, we can declare it well chosen for predicting the power to consume. The same observation can be made regarding relative humidity (figure 5). However, if we observe this figure correctly, we find extremely low values occasionally. This is 27% in 2020 and 32% in 2021 while the minimum in 2019 is 50%. Also its average is 83.514% in 2019; 82.422% in 2020 and 82.308 in 2021 showing its stability on a statistical level and capable of being considered for the prediction of electricity consumption; but the minimum values observed mean that an algorithm is needed to properly carry out the study of the forecast. Likewise, the wind speed also responds to the observations made in relation to the forecast of the power to be consumed because its statistical values are as follows: average 08 km/h in 2019; 4,717 km/h and 4,580 km/h. The minimum values are: zero in 2019; 0.14 km/h in 2020 and 0.22 in km/h. The skewness is almost around zero, a normalized value showing the validity of the observation. On the other hand, climate change, the reality of which is no longer in doubt today and which is likely to continue over the coming decades, we must question the resilience of the electricity system's infrastructure to its effects. In order to propose robust electricity mix options in the face of the effects of climate change, the prospective of the energy system must therefore necessarily integrate these effects into the study of the functioning of the system in the long term. We can mention normal direct irradiance, precipitation and relative humidity. For direct normal irradiance, we have: 195.166 w/m² in 2019; 190,314 w/m² in 2020 and 202,542 w/m² as average. The values are zero in mode, median and minimum showing its very random statistical nature. Precipitation is sometimes zero in mode, median and minimum observable in Table 1 in 2020 against maximums which go up to 15.5 mm in 2020; 11.1 mm in 2019 and 12.6 mm in 2021. We also find the observed skewness: 10.016 in 2020 shows the unequal statistical distribution not leading to a conclusion for a forecast based on statistics. Observations also made on diffuse radiation where the averages are: 140.646 w/m² in 2019; 137.182 w/m² in 2020 and 145.195 w/m² against the zero mode, median and minimum in 2021. It is the same for the years 2019 and 2020.

The analysis was continued further by studying the correlation between the variables. In fact, correlation exclusively measures the more or less linear character of the cloud of points, in other words the quality of the linear relationship or the degree of linear dependence between the variables. Its properties, [53], [54], are as follows:

- ✓ $-1 \leq r \leq 1$ (or $|r| \leq 1$)
- ✓ r is a dimensionless indicator;it is not sensitive to the units of each of the variables
- ✓ $|r| = 1$ is equivalent to the existence of an exact linear relationship
- ✓ If the variables are not independent r = 0, but the converse is not true in general: non-correlation is not necessarily independence, while independence necessarily leads to non-correlation
- ✓ note finally that the correlation is not transitive

Figures 15:-Show the different distributions of the data for assigned values of the correlations.



a- Correlation = 1 b- Correlation close to 1

c- Correlation = 0 d- Correlation < 0

Figure 15:- Different distributions of data depending on correlations.

Figure 16, thermal correlation table shows the different values of the links between the variables. Between direct normal irradiance and diffuse irradiance, it is 94% showing a good correlation between them. Both always have good values with temperature and vary between 67% for one and 68% for the other. It is not at all good between precipitation and normal direct irradiation (04%) then temperature and precipitation (06.7%)

Taking into account observations, to name just a few, led us to explore some algorithms in this work such as genetic algorithms, recurrent neural networks and simple linear regression. The results of the studies, in order to properly judge them, are subject to several performance evaluation criteria. Here, we cite: MAE, MSE, MAPE, RMSE, RRMSE and R^2. We observe in this regard that the results are not at all good for genetic algorithms because the MSE goes up to 141668.92, a very high value for the square of an error. For simple linear regression, it is not as favorable especially since we find that its value 233.74, still large. On the other hand, for recurrent neural networks we find an extremely interesting result because the MSE is only 0.02. Thus, the modeling results are presented as: MAE = 27.98; MSE = 141668.92; MAPE = 12.88%; RMSE = 16.14%; RRMSE = 14.32% and R^2 = 28.84% for genetic algorithms. We have for simple linear regression, MAE = 12.01; MSE = 233.74; MAPE = 17.45%; RMSE = 20.14%; RRMSE = 17.21% and R^2 = 69.08%. Finally, for recurrent neural networks, we find: MAE = 0.11; MSE = 0.02; MAPE = 18.50%; RMSE = 13.09%; RRMSE = 18.25% and R^2 = 96.11%. Given these results, we deduce that short- and long-term memory recurrent neural networks (LSTM) are very well suited to predicting the electrical power consumed on the CEB electrical network.

Conclusion:-

The fight against global warming requires the electrification of energy users and the abandonment of carbon-based production sources. It is therefore necessary that the production and supply of electrical energy be carried out while respecting short-term efficiency constraints, but also by providing reliable signals to guide the investments of producers to balance production with consumption, not only under normal macroeconomic conditions but also by using new forecasting methods in order to find a reliable solution. Today, it is artificial intelligence that provides solutions to complex situations. In the work combined in this manuscript, we used hourly consumption data collected by the CEB over the years 2019 to 2021 to predict the electrical energy needs in the network. To carry out this study, we used meteorological variables whose forecasts have become increasingly precise. These are temperature (T in °C), relative humidity (H in %), wind speed (V in km/h), normal direct irradiance (DNI in W/m²), precipitation (P in mm) and diffuse radiation: (RD in W/m²). As methods, we first carried out a characterization of all the variables by calculating the statistical parameters (mean, mode, standard deviation, median, minimum, maximum, skewness and kurtosis). Then we carried out a correlation study on all the variables in order to monitor their relevance on the electrical energy consumption to be predicted. Genetic algorithms, simple linear regression and LSTM recurrent neural networks made it possible to learn the models. Learning outcomes are subject to performance evaluation criteria such as: MAE, MSE, MAPE, RMSE, RRMSE and R^2.

The results made it possible to understand that certain variables (temperature, wind speed and precipitation) are significant and have a good statistical distribution confirming that they have an influence on the consumption of electrical energy in relation to their statistical characteristics. Which is not the case for the others (relative humidity, direct normal irradiance and diffuse irradiance). The study of the correlation confirmed this behavior of the modeling by its values. Between direct normal irradiance and diffuse irradiance, it is 94%. Both give with the temperature 67% for one and 68% for the other. Contrary, between precipitation and normal direct irradiation we have 04% then between temperature and precipitation we find 06.7%. Furthermore, the results of the modeling are as follows: MAE = 27.98; MSE = 141668.92; MAPE = 12.88%; RMSE = 16.14%; RRMSE = 14.32% and R^2 = 28.84% for genetic algorithms. We have for simple linear regression, MAE = 12.01; MSE = 233.74; MAPE = 17.45%; RMSE = 20.14%; RRMSE = 17.21% and R^2 = 69.08%. Finally, for recurrent neural networks, we find: MAE = 0.11; MSE = 0.02; MAPE = 18.50%; RMSE = 13.09%; RRMSE = 18.25% and R^2 = 96.11%. Given these results, we deduce that short- and long-term memory recurrent neural networks (LSTM) are very well suited to predicting the electrical power consumed on the CEB electrical network. It would be necessary to test these results using data from the years felt (from 2022 to 2023) and explore other algorithms to confirm and/or refute the choice made in this work.

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