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RESEARCH ARTICLE

PREDICTION OF ELECTRICAL ENERGY DEMAND USING THE MULTIPLE LINEAR REGRESSION METHOD: CASE STUDY OF THE CITY OF N'DJAMENA

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Abstract

The need of electrical energy has been increasing lately in developing countries. However, several methods for predicting the electric charge exist: such as statistics, artificial intelligence and hybrid approaches. This work focuses on the modeling of electrical energy demand by the multiple linear regression method in the case of the National Electricity Society (NES) of the city of N'Djamena. The estimates obtained are based on statistical analyses carried out on 5 exogenous variables. The results of the analyses gave very good meanings through the values of the standard errors associated with the regression coefficients. The two configurations developed all have average absolute MAPE errors of less than 2%. In the first configuration, we obtained an adjusted R^2 coefficient of determination of 0.975, a standard error of 30.395 GWh and an RMSE of 10.1 GWh. While the second configuration gave an R^2 (adjusted) equal to 0.974, with a standard error of 31.092 GWh and an RMSE of 10.28 GWh. The latter is made up of (3) parameters validated by the statistical indicators of the step-by-step downward regression. All of our results have shown that with this method, we can estimate an adequacy of 951 GWh to meet electricity need by 2035. The purpose of this study is to recommend a simple and efficient model for the prediction of the electric charge.

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Introduction:-

Chad located in the heart of Africa covers an area of 1,284,000 km², it has a population of 17,414,717 inhabitants in 2023 [1], [2]. The annual growth rate of this population is estimated at 3.6%, while its density is 12.9inhabitants/km². The country has no electricity interconnection between cities and Current electricity production is largely dependent on fossil fuels (thermal power plants). While Chad has a high potential for renewable energy, it records an average annual sunshine of 2850 hours in the south and 3750 hours in the north, with a very good intensity of solar radiation of between 4.5 and 6.5 KWh/m²/day [3]. However, the rate of access to electricity (grid, solar or group) by households is 11.0%. The source from the electricity grid is used by 6.2% of households throughout the country. A significant segment of households uses solar panels or generators for lighting that means 4.9% nationally. It also appears that 4.7% of households have access to the electricity distribution network (provided by individuals for the benefit of households). The highest level of access to electricity is in N'Djamena (72.3%) [4]. In addition, the national GDP is estimated at 12.7 billion US dollars in 2023 and 28% of the GDP has come from the sale of crude oil since 2003. The average GDP per capita growth rate is 2.9% this places Chad as the 4th largest

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economy in Central Africa after Cameroon, Gabon and Congo according to the World Bank [5]. This work on the electrical load of the city of N'Djamena seems to be well suited because of its better equipped electrical system than in other cities in the country. Unfortunately, the population suffers cruellythe lack of electricity due to the load shedding observed on a daily basis that disrupts socio-economic life Indeed, explanatory parameters such as GDP per capita, population, energy prices and housing rate are widely used in statistical methods. This statistical approach most often includes methods from linear regression, nonlinear regression, autoregressive models (ARMA), etc. Multiple linear regression has been the subject of several studies [6]. It is for these reasons that the multiple linear regression approach is preferred. [7], [8].

The main purpose of this study is to design statistical models with several variables by looking for the most relevant ones in order to predict the demand for electrical energy. In the end, we will interpret the results of the statistical indicators involved in the equations of the models obtained.

Materials and Methods:-

Presentation of the study area

The city of N'Djamena is located between 12°7' north latitude and 15°3' east longitude. It concentrates 40% of the total urban population of Chad with an annual growth rate of 3.9% on average. The city now extends according to the municipality of N'Djamena over a radius of about 25 km with an area of 395 km² and Its population is estimated at 1.6 million in 2023, it has 10 boroughsincluding 64 districts [9]. Many neighborhoods in peripheral areas are not urbanized. The current electricity production capacity does not cover the entire city, 2/3 of the city has remained uncovered.

Figure 1:- 90 kV loop transmission and distribution network (NES 2018 Dispatching).

Modeling Data Sources

The data from the electrical load modeling are collected and processed annually over a period from 2000 to 2023 that means 24 samples. It should be noted that in order to harmonize the analysis, five (5) series of exogenous variables were used to characterize the evolution of the production and demand of electrical energy subscribers to the electricity network of the NES of N'Djamena. Data on GDP per capita and population can be found in the database of the World Bank (WB), the International Monetary Fund (IMF) and INSEED (Chad). Historical electricity consumption data is provided by the NES commercial department, while meteorological parameters such as temperature (in degrees Celsius) and relative humidity (%) are taken from the NASA database, measured at two (2) meters above the ground. Excel has made it possible to obtain curves and tables.

To make a forecast, it is important to control the behavior of the maximum loads, the peak power of the production is observed over a day or beyond a day during which the load demand is maximum. Its study is very important because it plays a key role in the proper functioning of electrical transmission and distribution equipment. To do this, it is necessary to produce graphs of the peaks of demand for the reference day, month and year [10]. Below are the annual peak powers of the city of N'Djamena, reaching the peak of 103.25 MW in May 2023. In Figure 2, we can see a very remarkable evolution in electricity production between 2015 and 2023 thanks to the new installations and the contribution of private producers to the electricity system of the N'Djamena NES. This production is not stable with the departure of the private partner Aggrecko in May 2018, electricity production has fallen, giving the appearance of a decreasing curve caused by load shedding sometimes due to lack of maintenance and fuel defects. The largest quantity in terms of maximum loads, called peak power or simply maximum peak recorded is observed in 2023 and is worth 103.25 MW, for 557 GWh of annual energy delivered corresponding to a period of good electricity production.

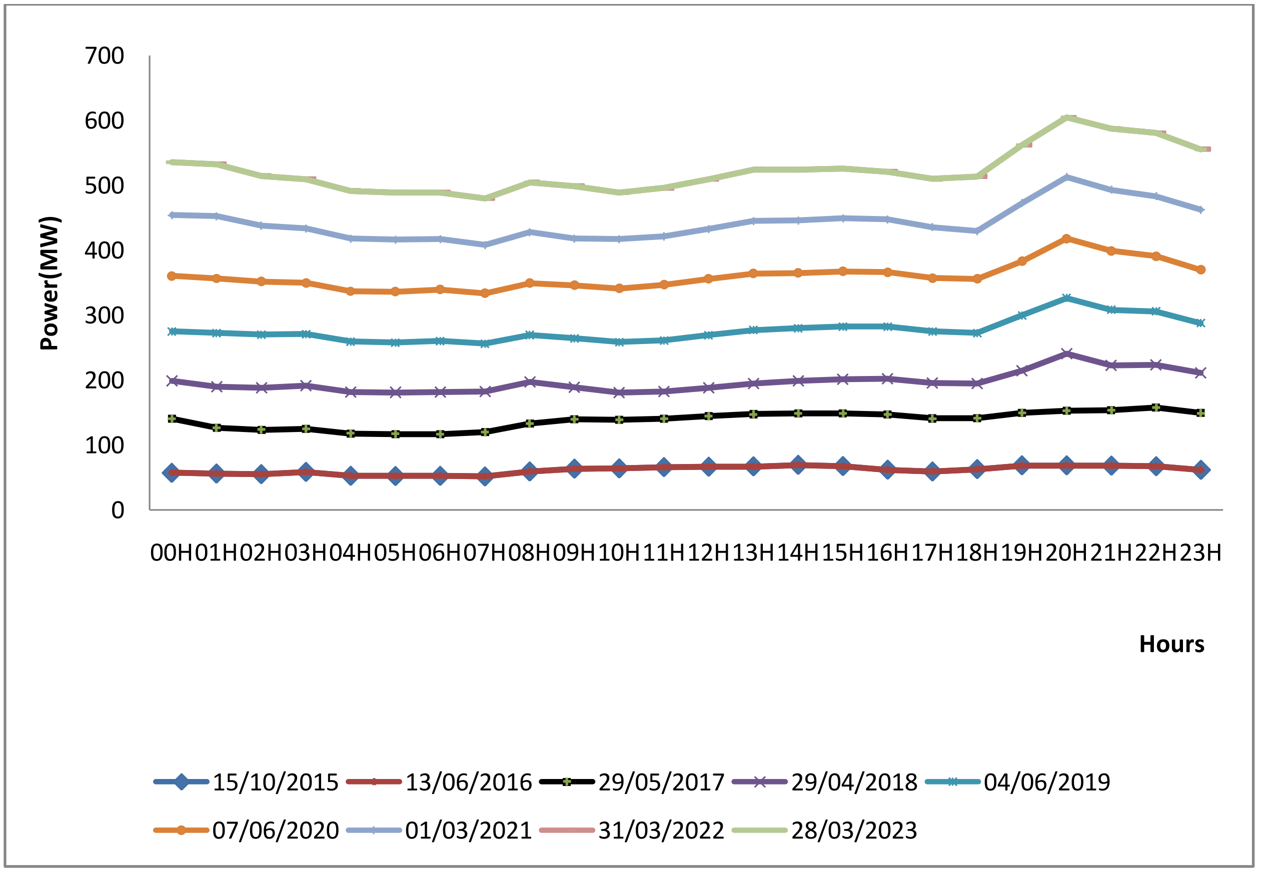

Figure 2:- 2015-2023 peak power curve N'Djamena.

The Modeling Process

The Multiple linear regressionis a statistical method extension of simple linear regression to describe changes in an endogenous variable associated with changes in multiple exogenous variables [11]. This technique is applied in physics to characterize a controlled evolution of a variable magnitude for which a history has been collected. However, this method presupposes that the relationship between the different intervention variables will remain unchanged in the future. Before carrying out this model, it is first necessary to analyze the continuous quantitative variables, initially correlated with each other two by two [12]. This analysis makes it possible to identify the factors influencing the electricity demand and to define new variables by graphical or visual representations.

The interpretation of the results of the regression analysis is carried out on the eigenvalues of the correlation matrix, the analysis of variance called ANOVA and, on the estimators, of course.

Identification of quantitative regression variables

The purpose of our analysis is above all to identify and explain a fundamental parameter called "electrical energy demand in N'Djamena". This applied method is a mathematical concept, which aims to analyze statistical series at p-dimensions and allows establishing relationships between one of the variables and all the other variables, it is presented as follows (equation 1) [12], [13], [14], [15].

$$\mathbf{Y_t = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 (1)}$$

In our case study, the equation of electrical energy demand is as a function of macroeconomic and meteorological parameters.

- Y_t: Explained variable is represented by (DEM (GWh) or electrical energy demand);
- β_0: A constant; this is a vector of residuals or random disturbances;
- X_i : Explanatory variables such as: X_1 (NSE's delivered production represented by PBL (KWh)); X_2 and X_3 represent respectively (gross domestic product per capita GDPPH (€) and population of the city of N'Djamena per POP); X_4 and X_5 represent respectively (relative humidity at 2 meters from the ground % and temperature T°C Degree Celsius.
- And (β_i) are the weighting coefficients for the variablesX_i. This is a vector of parameters or regression coefficients to be estimated.

Estimation of parameters

The estimation of parameters in a statistical model is one of the most fundamental steps in multiple linear regressions. This regression estimates the vector β_i as the least-squares solution [13], [14], [15]. The relationship linking the six (6) variables of the model is written:

$$\mathbf{Y = X\beta + \varepsilon} \quad \mathbf{(2)}$$

Where X is a $n \times (p+1)$ matrix of random variables (including an all-and-always 1 first column), and ε is an n × 1 matrix of noise variables. [15]

By the modeling assumptions,

$$\mathbf{E\,[\varepsilon\,|X] = 0} \qquad \mathbf{(3)}$$

While, $\mathbf{Var\,[\varepsilon|X] = \sigma^2 I.}$ **(4)**

Matrix :

$$\mathbf{Y} = \begin{pmatrix} \mathbf{Y_1} \\ \mathbf{Y_2} \\ \vdots \\ \mathbf{Y_{24}} \end{pmatrix};\ \mathbf{X} = \begin{pmatrix} \mathbf{1} & \mathbf{X_{11} \dots X_{15}} \\ \mathbf{1} & \mathbf{X_{21} \dots X_{25}} \\ \vdots & \vdots \quad \vdots \\ \mathbf{1} & \mathbf{X_{241} \dots X_{235}} \end{pmatrix};\ \boldsymbol{\beta} = \begin{pmatrix} \boldsymbol{\beta_0} \\ \boldsymbol{\beta_1} \\ \vdots \\ \boldsymbol{\beta_5} \end{pmatrix};\ \boldsymbol{\varepsilon} = \begin{pmatrix} \boldsymbol{\varepsilon_0} \\ \boldsymbol{\varepsilon_1} \\ \vdots \\ \boldsymbol{\varepsilon_{24}} \end{pmatrix} \mathbf{(5)}$$

- Y: denotes the vector to be explained of size 24 (corresponding to the number of observations),
- X: the explanatory matrix of size 24 × (6),
- Ɛ: the error vector of size 24. With β the parameters to be estimated

The solution to the problem is:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X^T X})^{-1}\mathbf{X^T Y (6)}$$

Subject to $X^T X$ being invertible, consequently $\hat{\beta}$is an estimator of the coefficients $\beta_i$with X^T the transpose of X

Parameter estimates of a statistical model are the most fundamental steps in linear regression [18]. Multiple linear regression helps us deal with the collinearity of variables by choosing those that are iterative with the highest explanatory value. Estimating involves making choices to establish a calibration strategy. To carry out this test, we can also look at the probable value "p-value", also known as the level of significance of the test: if p-value $\leq \alpha$, we reject the null hypothesis [19].Regression is said to be ascending, if it starts with no variable, or a subset of the available variables, and adds the most significant variable (the one with the lowest probability value, associated with estimated F statistics) at each step of the model. Whereas a downward step regression starts with all available variables and removes the least important variable at each step [20].

Validation of the model by regression analysis

In our study, the top-down form of multiple regressions was used. There are many estimation methods and this is due to the variety and nature of the parameters [21]. However, no generally satisfactory estimation method has been chosen [22]. Strategies are focused on the performance of the desired model. The estimate is made automatically using weights for the selected variables. Adjusted numerical values are assigned to the model parameters to better reproduce the observed response. The standard error is used to measure the variability of the regression coefficient based on the analysis. Since the results are presented in terms of regression coefficients, the standard error associated with this analysis is nothing more than a statistical indicator equated with the standard deviation. In fact, the standard error is related to the regression coefficient, whereas the standard deviation is the mean of a variable [23].

Model validation

The main role of a specific indicator is to translate the variance explained by the model. The least squares criterion is used to estimate the parameters by minimizing the sum of squares of the deviations between the observations and the model predictions. This step is performed once the model has been calibrated, and can then be used to make predictions [24], [25]. The indicators used are:

- The coefficient of determination R^2
- The average predictor of Y is $\overline{Y}$
- Errors (MSE: Mean Square Error) or (RMSE: Root Mean Square Error)
- MAPE: Percentage Average Absolute Error

The proportion of variability is explained by the model. The advantage of adjusted R^2 over R^2 is that it takes into account the number of predictors [26]. The percentage of variability Y explained by the model is denoted: R^2

$$0 \leq R^2 \leq 1 \quad (7)$$

If R^2 is equal to 1, the prediction is perfect in the best case, the sum of the residual squares is equal to 0, the model predicts exactly all the Y values from the X values. In the worst case, the sum of the squares of the explained regression is equal to 0; the best predictor of Y is its mean is denoted :$\overline{Y}$

The fundamental property measures the fit of the model by the coefficient of determination

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \overline{Y})^2} \quad (8)$$

It is necessary to evaluate the models obtained by error studies [27], [28], [29], [30] [31]. Performance evaluation criteria are used with the root mean square error (MSE), which represents the arithmetic mean of the squared deviations between the predictions and the observations of the model.

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\hat{Y} - Y_i)^2}{24}} \quad (9)$$

$$RMSE = \sqrt{MSE} \quad (10)$$

$$MAPE = \frac{1}{24}\sum_{i=1}^{n}\left|\frac{\hat{Y} - Y_i}{Y_i}\right| \times 100 \quad (11)$$

Where:

- $\hat{Y}$= predicted energy
- Y_i= measured energy
- $\overline{Y}$= the average predictor of Y
- N = 24 is the number of points sampled

Results and Discussion:-

Results of the identification of explanatory variables

In terms of results to the problem posed, is a vector of observed values of electrical energy demand or need which is expressed in KWh or GWh. The results of the Regression Analysis of the various components are presented in the form of tables or graphs for comment. However, there is a link between all the variables taken in pairs and the correlation coefficients between these different variables are given by the correlation matrix (Table 1).

Indeed, electricity demand shows a very strong correlation with the production of energy delivered by the NES (0.979), followed by (0.57) with population and (0.47) with gross domestic product per capita. Then negative correlations of (-0.57) with temperature and (-0.009) with relative humidity.

These results reflect a major influence of the energy production delivered by the NES, population growth and temperature (explanatory variables) on the demand for electrical energy in the city of N'Djamena (variable explained). Simple linear regression curves were used to assess the quality of the correlations between electricity demand and the relevant parameters i.e. energy production delivered, population and temperature.

In addition, the values of the correlation coefficient between electricity demand and meteorological factors are very low for long-term forecasts.

	PBL (KWh)	PIBPH (€)	POP	HR (%)	T°C	DEM (GWh)
PBL (KWh)	**1**					
PIBPH (€)	**0,48**	**1**				
POP	**0,68**	**0,52**	**1**			
HR (%)	**-0,01**	**0,34**	**-0,17**	**1**		
T°C	**-0,62**	**-0,36**	**-0,43**	**-0,5**	**1**	
DEM (GWh)	**0,98**	**0,47**	**0,57**	**-0,009**	**-0,57**	**1**

Table 1:- Matrix of correlations between different variables.

We have the following tables: the correlations between the explanatory and explained variables two by two.

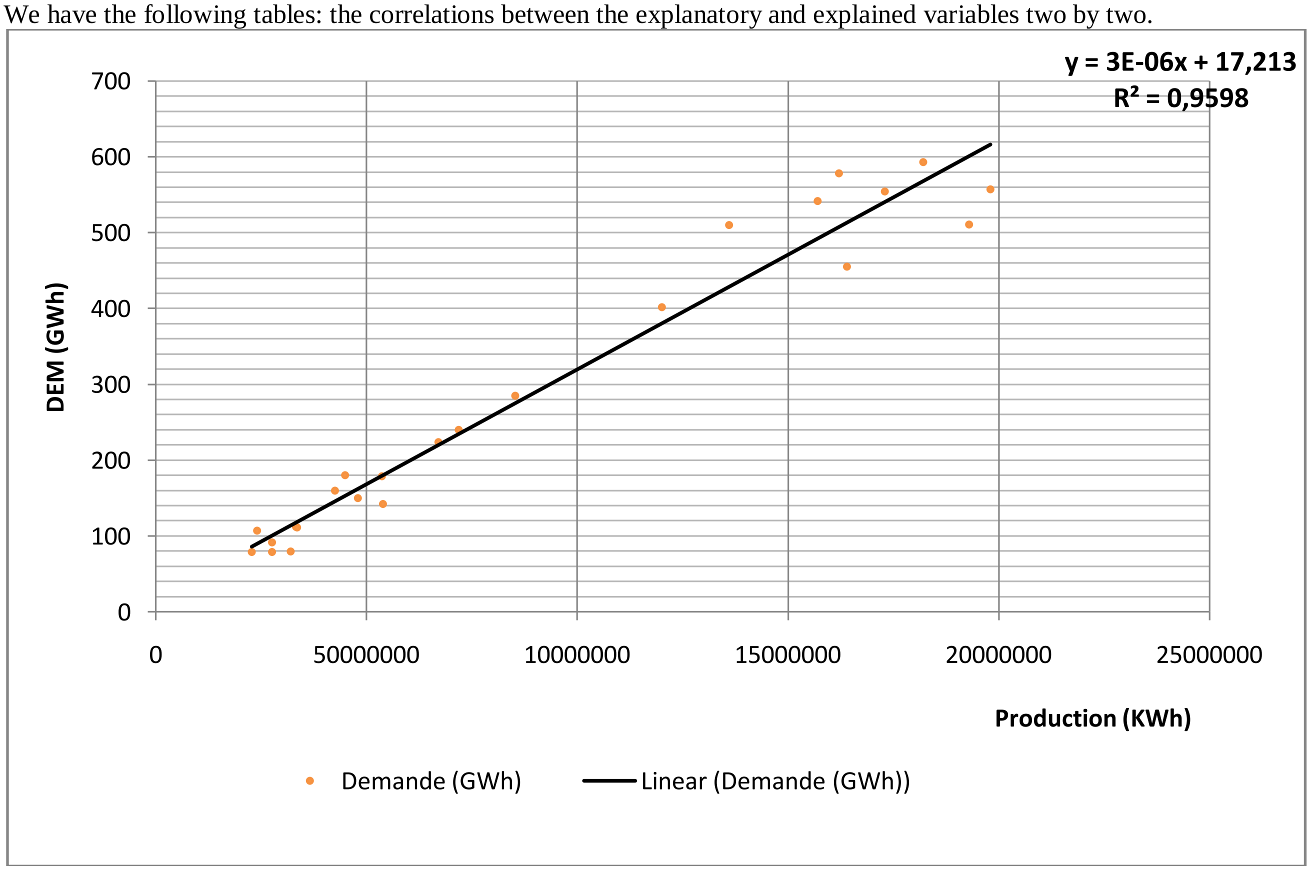

Figure 3:- Electricity demand as a function of NES's delivered output.

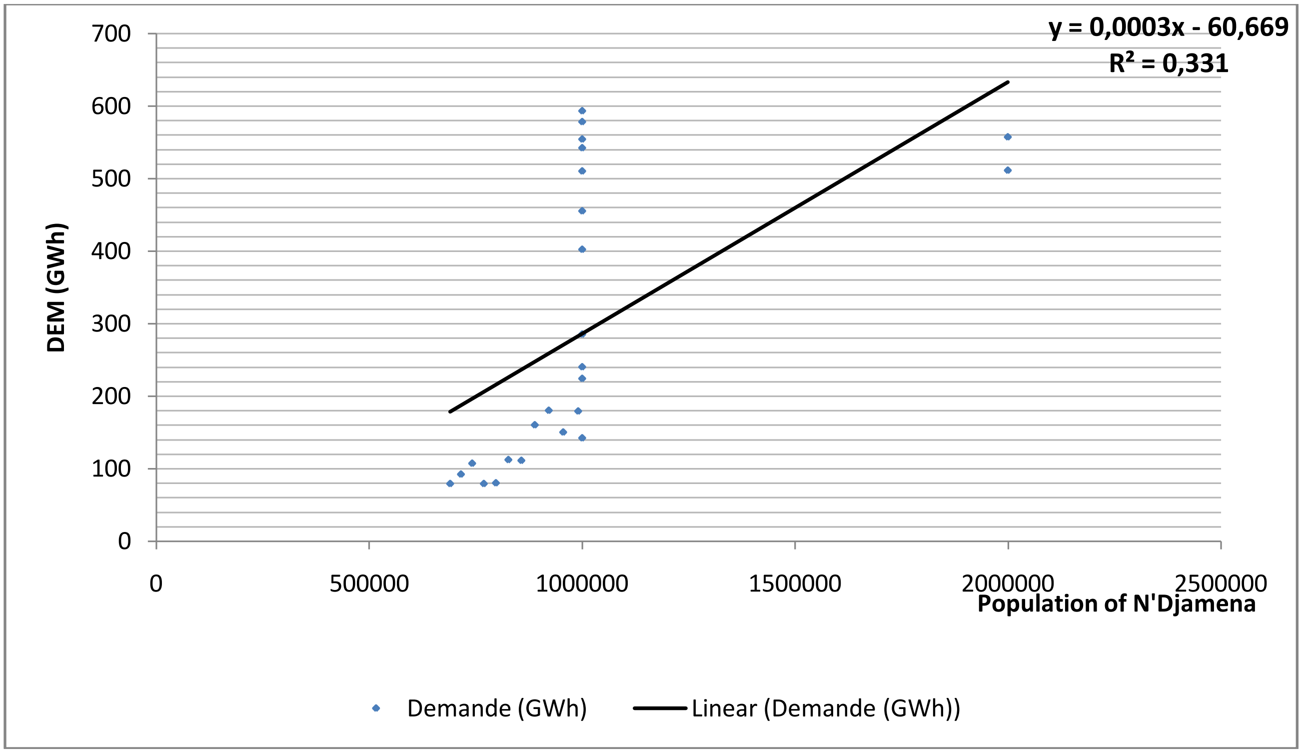

Figure 4:- Electrical energy demand as a function of population growth in N'Djamena.

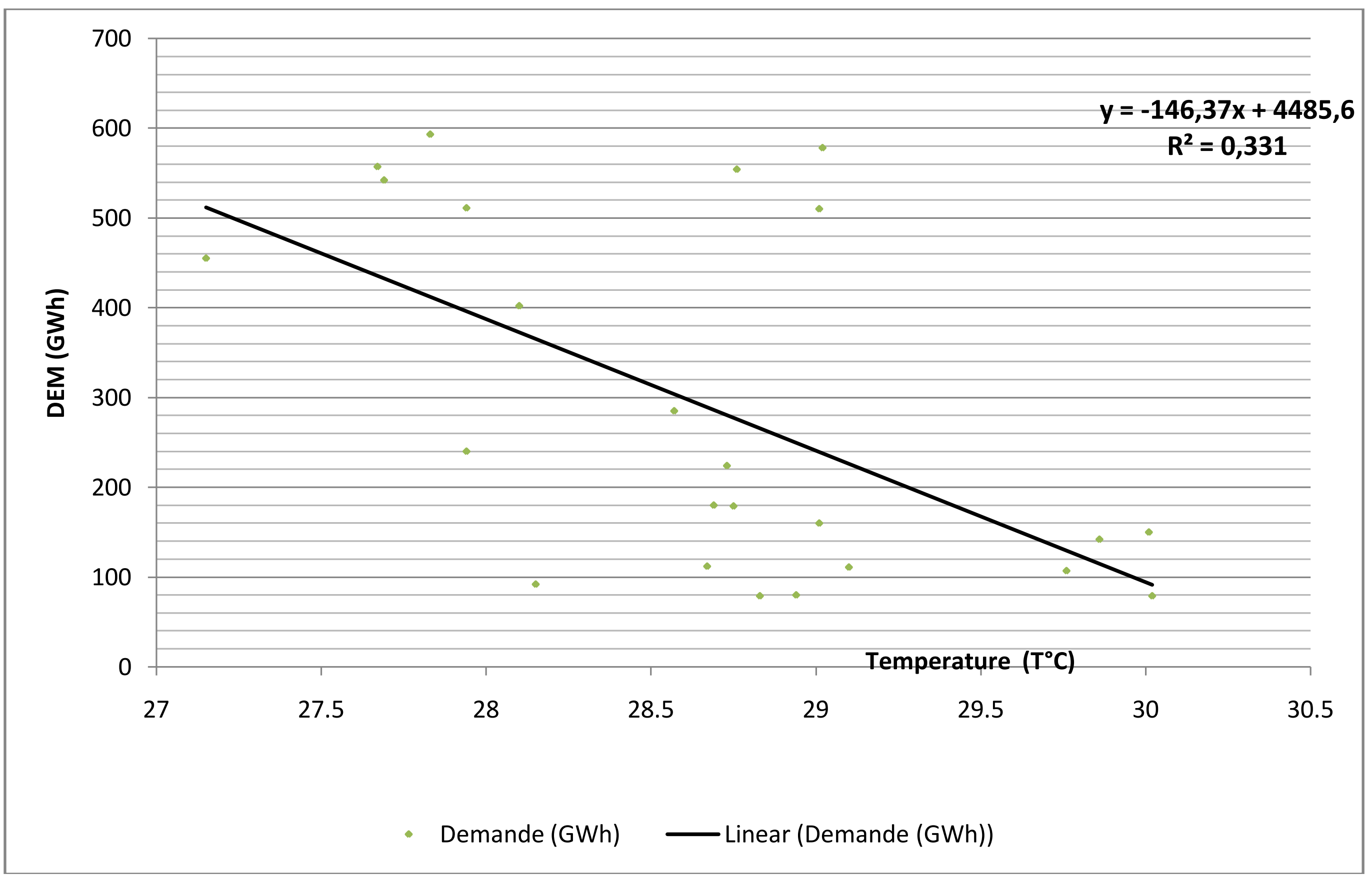

Figure 5:- Electricity demand as a function of annual temperature in N'Djamena.

Results of multiple linear regression variance analysis

The ANOVA table above indicates that the model, as a whole, is a significant fit to the data, so electrical energy demand are given directly by the regression analysis of variance. [15], [30], [32], [33]

Table 2:- ANOVA (analysis of variance).

	df	SS	MS	F	Significance F
Regression	**5**	**859840,6**	**171968,1**	**198,2**	**4,4E-15**
Residual	**18**	**15617,3**	**867,6**		
Total	**23**	**875457,8**			

Df: degrees of freedom, SS: sum of squares, Fisher (F) and MS: mean square

Electricity demand modeling is performed by a regression analysis consisting of the five (5) explanatory variables. The following tables identify all the estimators with the coefficients of the multiple linear regression, the standard errors on the different coefficients, the different statistical tests and the probable values of the model.

The energy production delivered by the NES (PBL), GDP per capita, temperature (T°C) and the constant have coefficients of equal positive values (3.4E-06), (0.9), (6.4) and (370.1). As for the values of the constant, the population (POPs) of the city of N'Djamena and those of the relative humidity are negative coefficients (-0.00013) and (-11.22) respectively. The standard errors associated with the various explanatory variables remain relatively small (1.7E-07 - 14.9), for the constant is very high (943.2).

The statistical tests are positive for the variables PBL, PIBPH and T°C respectively (20.3), (1.7), (0.4), population and relative humidity (-4,2) and (-0,9).

The significance level of the P-value test ≤ α, depending on the assumption that the regression validation is top-down, the confidence interval is set α = 5%. [30]. However, all variables with a p-value greater than 0.05 after the first analysis have been discarded, for this purpose; we are left with only two (2) explanatory variables, namely the PBL and the POP.

While the probable values called P-value, three parameters have a P-value > 5%, namely the GDPPH, RH and the T°C with the respective probable values >of (0.09), (0.4) and (0.7)

Table 3:- Regression coefficients, model standard errors, statistical test, and probable model values.

	Coefficients	Standard Error	t Stat	P-value
Intercept	**370,1**	**943,2**	**0,4**	**0,7**
PBL	**3,4E-06**	**1,7E-07**	**20,3**	**7,7E-14**
PIBPH	**0,9**	**0,5**	**1,7**	**0,09**
POP	**-0,00013**	**3,2E-05**	**-4,2**	**0,0005**
HR	**-11,22**	**13,2**	**-0,9**	**0,4**
T°C	**6,4**	**14,9**	**0,4**	**0,7**

Table 3: Regression coefficients and model standard errors

These results reflect homogeneity of the regression coefficients relative to the model and show the relevance of the different variables in the modeling of electrical energy demand.

The equation for the first configuration is as follows (equation 10):

$$\boldsymbol{DEM_t = 3,4.10^{-06} \times PBL_t + 0,9 \times PIBPH_t - (1,3.10^{-04} \times POP_t + 11,22 \times HR_t) + 6,38 \times T°C_t + 370,1} \qquad \textbf{(12)}$$

- DEM: Electricity demand in the city of N'Djamena simulated (GWh);
- PBL: Gross production delivered annually for consumption in (KWh)
- GDPPH: Gross Domestic Product per capita of the city of N'Djamena in Euro (€)
- POPs: Number of annual population living in the city of N'Djamena
- HR: Annual mean relative humidity at 2 meters from the soil of N'Djamena in (%)

- T°C: Average annual temperature at 2 meters from the ground in N'Djamena in (°C)
- With "t" in the year

The coefficient for the production of electrical energy PBL is very low (3.4 E-06) and that for the POP population is negative (-0.00011), these coefficients do not vary in the same order of magnitude and are of opposite signs. The constant has appositive coefficient of (91.921) and the standard errors obtained are (141E-07) for PBL, (2.7E-05) for POP and the (22) for the constant remains the most important compared to the others. The statistical tests give us results such that the constant and the PBL are positive (4.16) and (24.2) respectively, but the POP has a negative value of (-3.9) and the P-values have values below 0.05.

	Coefficients	Standard Error	t Stat	P-value
Intercept	**91,92**	**22**	**4,17**	**0,0004**
PBL	**3,4E-06**	**1,41E-07**	**24,2**	**8,16E-17**
POP	**-0,00011**	**2,75E-05**	**-3,9**	**0,0007**

Table 4:- Regression results for the suggested models.

The second simulation gave us a second configuration whose equation below

(13) $$DEM_t = 3,4.10^{-06} \times PBL_t - 1,1.10^{-04} \times POP_t + 91,92$$

- DEM: Electricity demand in the city of N'Djamena simulated (GWh);
- PBL: Gross production delivered annually for consumption in (KWh)
- POPs: Number of annual population living in the city of N'Djamena
- With "t" in the year

Both of our configurations from the forecast modeling fit well, with identical determination coefficients 0.97 close to 1 means that the demand forecast based on the two simulated regression analyses is nearly perfect. The standard errors between the 24 observations did not vary significantly.The figure below is a comparison of the actual values of electrical energy demand with those predicted from the two models obtained. As the evolution of load demand is annual, the two configurations have identical trends. The predicted values are similar to those of the actual value of electrical demand with standard deviations identified through maximum and minimum values. Briefly, the three curves show a general trend of growth in the energy demand of the population of N'Djamena, with a margin of uncertainty represented by confidence intervals. The upward trend in the upper and lower confidence intervals around the green curve indicates that this demand may fluctuate but remain on an upward trajectory overall. This anticipated growth in energy demand may require measures to adjust energy supply or promote demand management initiatives to meet future needs.

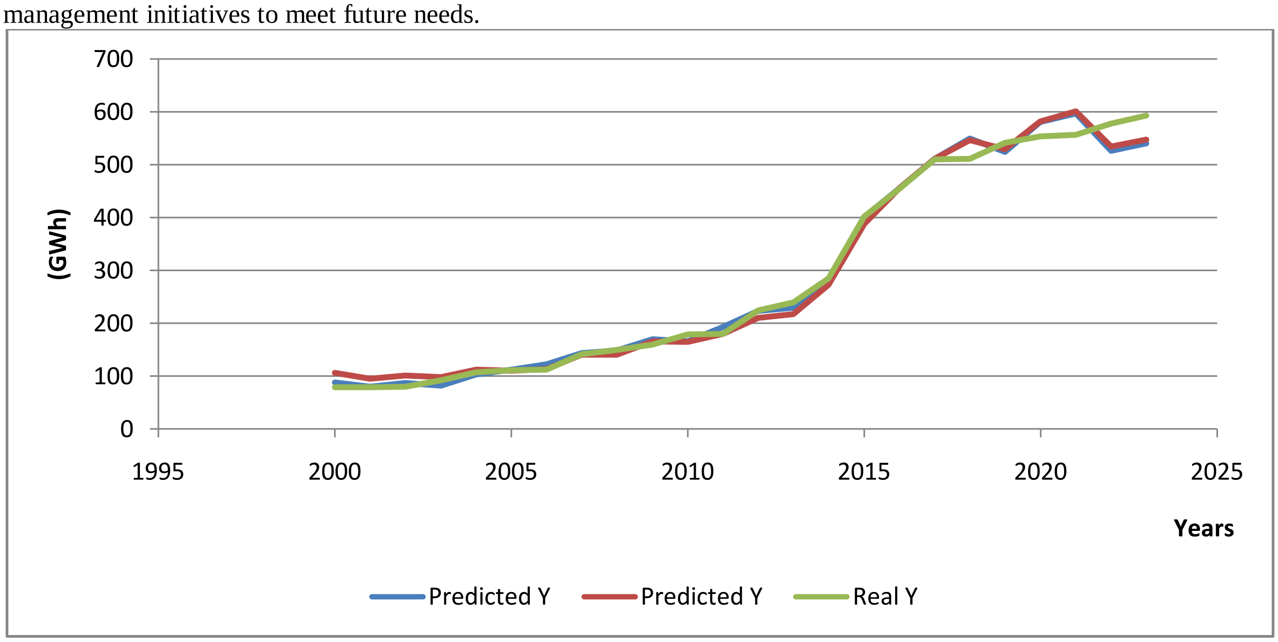

Figure 6:- Comparison of predicted and actual values.

The higher values R² and the smaller values of RMSE indicate that the calculated results describe better the observed results [34]. The values of R² are around 1 and those of RMSE and MAPE are mostly very close to 0. This verifies the efficiency of the model used. In both configurations, we got the following MAPE and MSRE errors in the table.

The mean absolute error MAPE and the mean square error MSRE for the years 2021-2023 have minimal values compared to the other years. The statistical values indicators for first and second configuration are shown in the table below.Note that the value of R² varies between 0 and 1.

Configurations	R Multiple	R^2	$R^2 ajusted$	Standards-errors(GWh)	MAPE	MSRE (GWh)
1	0,99	0,98	0,97	29,455	1,517%	10,10
2	0,98	0,97	0,97	31,092	6,77%	15,02

Table 5:- Statistical indicators of regression.

We can easily do our electricity demand forecasting test by using our model to estimate its future value. The graph below shows the estimated values in terms of energy expected over a period from 2024 to 2035. It shows the model's performance over the long term. This estimate of electricity demand is made at the level of net energy injected into the grid, transmission, distribution and commercial losses are not included. The starting point of the forecast is therefore 557 GWh of net electricity injected in 2023. Calculate at the rates of 75% and 125% respectively for the low and high scenarios, respecting the annual average annual electricity production delivery rate of 5.47%, the growth rate of the population of the city of N'Djamena with an annual average of 3.6% using the function of the finite growth rates.

To satisfy the demand for electrical energy 100% by 2035, the production to be delivered by the NES must increase annually by 8.33% and reach a maximum peak power equal to 200 MW or 1728 GWh per year. The model forecasts demand in 2035 at 761.13 GWh. While this estimate is higher than the one made in 2014 by the consultant FICHTNER, which forecast 252.60 MWh in 2025 and 308.66 MWh in 2030 in the city of N'Djamena using the consumerist method [35]. The key is to achieve a balance between what NES offers to satisfy the population of N'Djamena in terms of electricity demand.

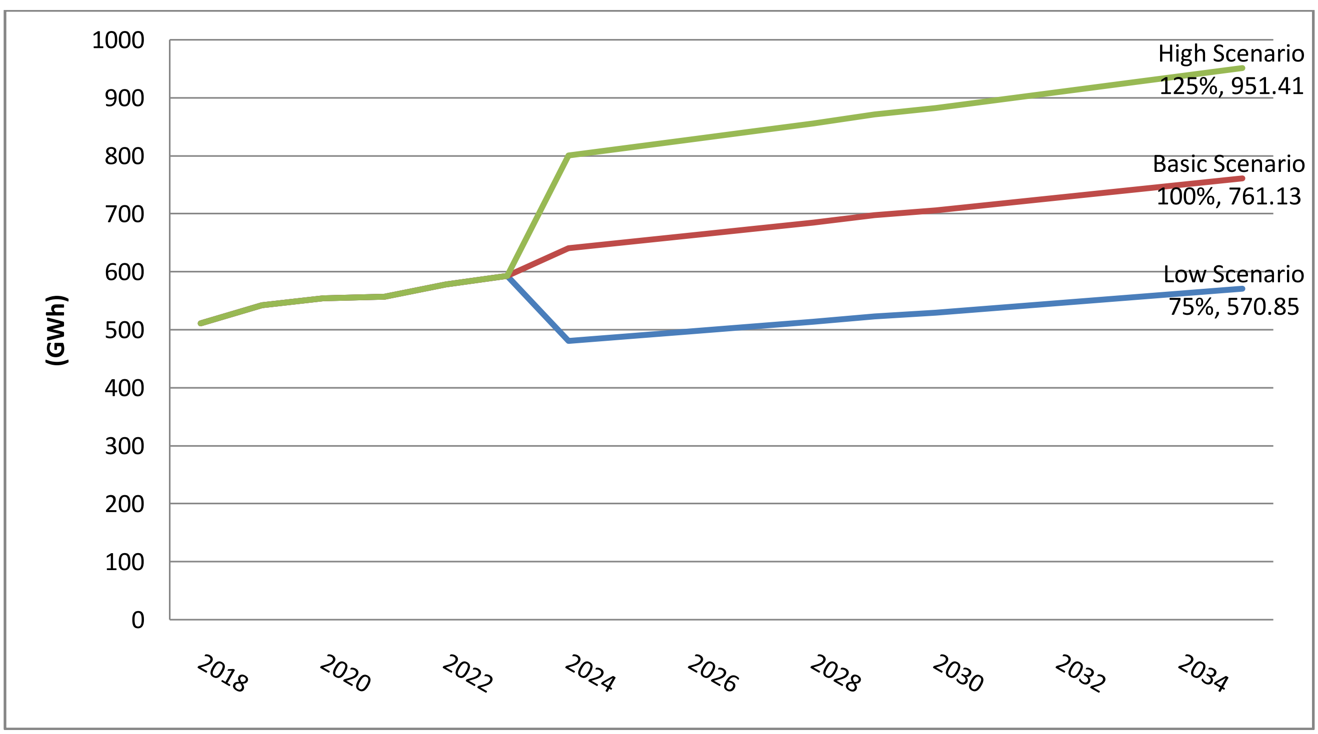

Figure 7:- N'Djamena: Electricity demand forecast GWh from 2018 to 2035.

The model estimates demand in 2035 at 761.13 GWh in the baseline scenario. While this estimate is far above the one dating from 2014 carried out by the consultant FICHTNER, which predicted by the consumerist method: 252.60 MWh in 2025 and 308.66 MWh in 2030 in the city of N'Djamena. The main thing is to achieve a balance between what the NES offers to satisfy the population of N'Djamena in terms of electricity demand.

Conclusion:-

The multiple linear regression method based on observational data; in particular, macroeconomic and meteorological parameters highlighted the relevant variables in the demand for electrical energy. Our results seem to be close to reality. The interest of this work is to identify the relevant predictive variables in the model. Our model is designed using statistical regression indicators and tests. These results explain why our two (2) configurations obtained have a very good meaning through the values of the standard errors associated with the regression coefficients. The most relevant explanatory variables correlated with electrical energy demand are delivered production $R^2=0.979$ followed by population and temperature with an identical correlation coefficient $R^2=0.575$ remain the best estimators. It should be noted that the objective is to propose a simple model allowing the (NES) to estimate the future electricity demand, without going through sophisticated physical models and to identify the most relevant parameters of the models. Multiple linear regression allows to have quite acceptable results, with an average absolute error percentage (MAPE) of less than 2% of the two (2) configurations. Thanks to its simplicity of implementation and speed, the second configuration is the best for the long term. However, in order to ensure a good match between supply and demand for electricity in N'Djamena, an annual contribution in terms of energy production is expected.

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