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Analysis of the Solar Potential and Realization of the Atlas of the Solar Irradiation of Togo for the Production of Photovoltaic Energy

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Abstract

Knowledge of the variability of the solar resource in a geographical area of a photovoltaic energy production project is essential. At the time of decentralization, knowledge of data at the local level becomes critical for new projects of electrical autonomy based on photovoltaic energy in municipalities. Given that the density of the meteorological network in Togo is limited and only covers a small number of rural areas, the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) method was used in this work to predict solar radiation across the entire territory, with the aim of providing a solar radiation data base for each municipality. The method employed exhibited high accuracy with the coefficient of determination (R^2) higher than 98%, mean bias error (MBE) equal to -0.241 and root mean square error (RMSE) equal to 0.045355. Therefore, the data generated from the established models were used to realize solar irradiation Atlas with the Quantum Geographic Information System (QGIS) software to offer a geographical and spatial resource distribution. Therefore, hourly average irradiation maps of the annual and each of the twelve months have been prepared. The results show that Togo has a solar potential favorable for photovoltaic energy production. The sunniest months are January, February, March, April, October, November and December with the north of the country richer in solar potential than the south.

Keywords: ANFIS, Matlab, Photovoltaic energy, QGIS, Solar Atlas, solar irradiation

1. Introduction

One of the new Sustainable Development Goals (SDGs) for 2030, namely SDG 7, aims to ensure access to reliable, sustainable and modern energy services for all at an affordable cost. To this end, several countries and actors have set targets for the use of renewable energy to provide electricity to all and to achieve inclusive development while fighting global warming [1]. This is the case in Togo, which aims to provide access to electricity for all Togolese by 2030 in its National Development Plan (NDP) launched in March 2019, based on several initiatives including off-grid technologies (mini-grids and solar kits) in rural areas [2]. The success of this ambitious project requires knowledge and mastery of the solar resources at the national level. Some works in the past have been interested in the evaluation of the solar energy potential in Togo. This is the case of [3,4] who used artificial intelligence techniques such as artificial neural networks and the vector support machine for predicting solar irradiation because of its intermittent nature. The authors [5,6] have realized in 2010, the first Togo solar Atlas which is an important step in the history of the evaluation of Togo solar resource and be still used today by several researchers and entrepreneurs in the field of photovoltaic energy.

However, this Atlas in use today is more than ten (10) years old and needs to be updated to take into account the climate change observed in recent years. Moreover, in the context of decentralization, knowledge of the solar potential at the local level will allow each municipality to have reliable data for decentralized production projects of electrical energy based on photovoltaic energy to ensure their energy autonomy and improve the provision of telecommunications services [7].

This work provides an answer to these concerns by making available a solar irradiation database for each district and a new version of solar Atlas which will show the spatial distribution and temporal variability of Togo solar energy potential. It is organized in six (6) sections, the second section talks about the social context and the objectives of the project, and the third section discusses the tools and methodology used. Section 4 is devoted to the results of the prediction and section 5 to the realization of the Atlas. Section 6 presents the conclusion and perspectives.

2. Social context and objective

The national electricity network is managed by the Compagnie d'Energie Electrique du Togo (CEET) which is a company that distributes and sells electricity throughout the national territory. It operates on Medium Voltage (MV) and Low Voltage (LV). To fulfill its mission, it has nine (09) MV/LV substations distributed mainly in some major cities, including three (3) in Lomé because of its demand which represents 80% of the national peak. These substations also called dispatching stations, are served by external production

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sources and also in some places by CEET's own emergency power stations. Indeed, some places located far from the distribution network are supplied by power plants equipped with diesel generators as part of the rural electrification projects initiated by the State. In 2020, there were eighteen (18) localities that are supplied by these isolated electrical systems and which total an installed and available power of nearly 2.56 MW, including 0.6 MW in four localities supplied by solar photovoltaic mini-grids.

With this production capacity, electrification rate at the national level has increased by 2.7% between 2019 and 2020 (from 50.3% to 53%). This increase is attributed to the continued investment in the extension of the distribution network, which has increased the population's access to the electricity network. Figure 1 shows the evolution of Togo electricity access rate from 2018 to 2020 [8].

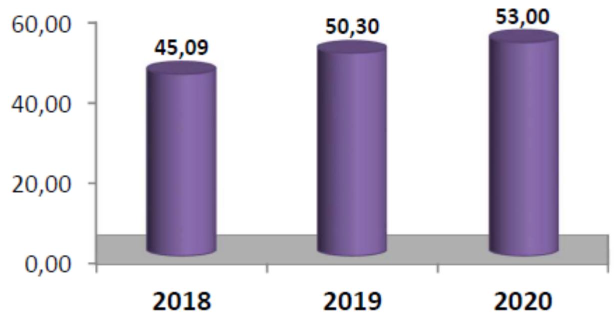

Fig. 1. Evolution of the electricity access rate from 2018 to 2020 [8].

This low growth in the rate of access to electricity shows that the extension of the existing network alone will not be able to achieve the objectives of SDG 7. Moreover, electricity coverage by the existing network is unevenly distributed throughout the country. The network is denser in maritime region, but less developed in other regions, often because of lack of financial resources and difficulties in accessing certain localities. Figure 2 shows a breakdown of electricity access rate by region [8].

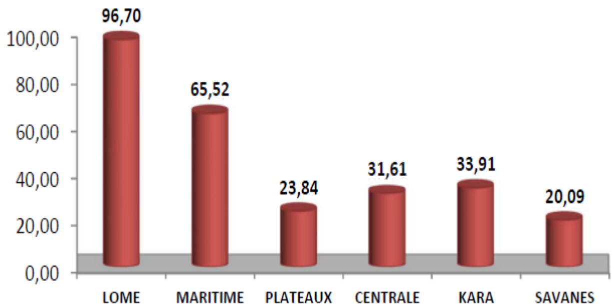

Fig. 2. Rate of access to electricity by region in percentage (%) in 2020 [8].

It is important to note that within a given locality, the network is randomly extended and shows discontinuous progress. This disparity becomes more glaring when one considers the huge differences between urban and rural areas. It follows that the priority of the moment is to emphasizes the localities farthest from the national electricity network to increase the rate of access to electricity. This is why Togo's ambition is to ensure universal access to energy services for all Togolese by 2030. This objective will be achieved with the introduction of renewable energy sources in to electric energy production park as well as the development of off-grid electrification technologies through microgrid projects [9, 10, 11] and distribution of solar kits.

Introduction of photovoltaic electric energy in to energy mix requires a mastery of the solar potential. This is why this work aims at extending the research on the evaluation of the solar energy potential in the whole country in order to facilitate the optimal choices of production sites.

3. Materials and Methodology

This section is devoted to the methodology used to evaluate the data collected from the two sources and the tools used in this work. Indeed, a time series is a succession of observations (or measurements) of parameters or characteristics of a phenomenon over time. In this manuscript, the phenomenon studied is the solar irradiation whose time unit of the observations is constant and the modalities of data acquisition are identical for whole period of observation.

3.1. Data collection

The data used in this work were obtained from two different sources, namely:

- ground data from the General Direction of National Meteorology (DGMN) of Togo, an overview of the dataset is presented in Figure 3;
- Satellite data available on the NASA website [12].

Hourly data of solar irradiation, ambient temperature, pressure, precipitation, wind speed, wind direction, relative humidity, etc. were collected from both sources, from January 2010 to December 2020, with a resolution step of 1h.

3.2. Methodology

The methodology used is based on the analysis, processing and calculation of the quantities to be determined in the following two steps [13]:

- the preparatory analysis consisted of a comparative study of the two data sources in order to identify the most reliable data to be used for constituting a robust database;
- the determination of the rules and calculation criteria to be implemented in the computer code queries to determine the monthly and annual hourly averages.

Figure 4 shows a time series of hourly solar irradiance for the year 2019.

3.3. Tools used

For data processing, statistical and programming software were used, in particular, Excel, Python, Matlab, etc. The results of this processing were used to make predictions using a learning algorithm in order to obtain the data for all districts to realize the sunshine map with the geographic information system QGIS.

3.3.1- Choice of the prediction model

There are several machine learning techniques for solar irradiance estimation such as artificial neural networks (ANN), support vector machines (SVM), Markov chain, etc. Research is ongoing to find prediction methods that minimize the mean square error between predictions and actual data. Recently, the Adaptive Neuro-fuzzy Inference System (ANFIS) has gained prominence because of its ability to interpret and analyze information (numerical, linguistic and logical) and improve the quality of prediction. Current developments in nonlinear time series prediction problems have shown that the performance of ANFIS exceeds that of other methods both in accuracy of results and learning efficiency [14]. Moreover, the rules of ANFIS are transparent allowing its validation, its manipulation by an expert [15] and is promising in cases where the available data are limited [16].

Date	Temp mini (	Temp maxi ('	Temp moyen	Durée gel (H	Humid mini ('	Humid maxi (	Hum moyenr	Pluie (mm)	Pluie max (m	Rayon globa	Vitesse moy	Direction pré	Vent maxi (n	Dir maxi (De	Pression min	Pression ma:	Pression mo	Durée d'inso	Humid >80%	(H
02/04/2020	23,60	35,50	29,33	0,00	43,00	80,00	58,71	0,00	0,00	2291,40	2,87	270,00	13,60	140,00	948,80	952,60	950,48	7,20	0,43	
01/04/2020	23,40	34,60	28,51	0,00	48,00	75,00	65,42	0,00	0,00	1675,90	3,64	270,00	15,60	200,00	948,10	953,50	950,70	2,35	0,00	
31/03/2020	27,00	37,00	30,99	0,00	43,00	74,00	59,63	0,00	0,00	2102,50	3,38	180,00	12,20	270,00	948,10	952,00	949,64	7,10	0,00	
30/03/2020	26,00	36,30	30,77	0,00	43,00	77,00	58,79	0,00	0,00	2275,90	3,29	270,00	14,20	190,00	946,80	951,70	949,10	7,85	0,00	
29/03/2020	27,20	36,70	31,38	0,00	38,00	70,00	53,83	0,00	0,00	2417,20	3,43	270,00	13,40	200,00	948,00	951,90	950,08	10,25	0,00	
28/03/2020	26,30	37,80	31,14	0,00	35,00	77,00	54,13	0,00	0,00	2322,00	3,33	270,00	10,80	260,00	948,70	953,10	951,05	9,10	0,00	
27/03/2020	26,10	37,30	31,15	0,00	30,00	70,00	47,00	0,00	0,00	2365,10	2,37	135,00	11,70	220,00	948,50	952,90	950,70	9,40	0,00	
26/03/2020	25,30	36,50	30,30	0,00	25,00	78,00	51,43	0,00	0,00	2108,30	2,00	45,00	10,80	290,00	948,30	953,00	950,52	6,50	0,00	
25/03/2020	22,90	32,50	27,20	0,00	50,00	90,00	70,63	0,00	0,00	2334,10	3,71	225,00	11,50	250,00	949,50	953,80	951,51	7,87	9,18	
24/03/2020	22,10	30,10	25,16	0,00	58,00	98,00	81,25	4,20	1,60	1649,10	4,82	270,00	23,20	120,00	949,50	954,80	952,05	2,87	15,87	
23/03/2020	24,40	34,00	27,83	0,00	51,00	93,00	68,08	1,80	0,20	2020,20	3,61	270,00	20,80	160,00	948,20	953,40	950,83	6,53	3,48	
22/03/2020	26,00	36,90	30,14	0,00	34,00	72,00	57,13	0,00	0,00	2173,20	4,15	180,00	12,30	150,00	947,70	952,60	949,97	6,70	0,00	
21/03/2020	25,70	34,90	29,03	0,00	45,00	81,00	65,50	0,20	0,20	1697,10	3,13	180,00	13,10	240,00	947,60	952,60	950,40	4,17	0,83	
20/03/2020	23,70	33,40	28,35	0,00	54,00	83,00	66,96	0,00	0,00	1815,10	3,72	225,00	14,70	240,00	948,30	953,00	950,81	4,20	2,12	
19/03/2020	26,70	36,40	29,63	0,00	45,00	90,00	61,58	0,80	0,40	2044,50	4,69	225,00	16,90	220,00	947,70	953,00	950,64	7,12	1,05	
18/03/2020	26,80	36,80	31,33	0,00	36,00	77,00	53,42	0,00	0,00	1996,30	3,64	225,00	12,90	230,00	947,90	953,00	950,35	5,28	0,00	
17/03/2020	26,60	38,60	32,18	0,00	19,00	62,00	40,00	0,00	0,00	2338,70	2,77	225,00	10,20	240,00	947,60	952,40	949,93	9,43	0,00	
16/03/2020	26,00	37,90	31,73	0,00	27,00	69,00	41,54	0,00	0,00	2244,60	2,10	270,00	10,40	230,00	947,00	952,00	949,80	9,03	0,00	
15/03/2020	25,90	37,70	31,71	0,00	24,00	76,00	45,29	0,00	0,00	2311,20	2,03	135,00	9,20	160,00	947,80	952,40	950,34	8,75	0,00	
14/03/2020	24,90	34,10	28,88	0,00	41,00	81,00	60,54	0,00	0,00	1573,50	2,30	180,00	11,00	200,00	949,20	953,90	951,46	3,12	1,70	
13/03/2020	25,00	38,20	30,73	0,00	33,00	81,00	54,21	0,00	0,00	2246,00	3,13	135,00	13,40	170,00	947,60	952,60	950,20	9,13	0,50	
12/03/2020	26,10	38,50	32,40	0,00	14,00	61,00	34,92	0,00	0,00	2478,40	2,41	270,00	11,70	140,00	947,30	951,70	949,50	10,03	0,00	
11/03/2020	26,50	38,10	31,78	0,00	14,00	71,00	42,08	0,00	0,00	2183,10	2,50	270,00	10,00	40,00	947,40	952,00	950,06	8,23	0,00	
10/03/2020	25,00	37,50	30,30	0,00	36,00	78,00	56,38	0,00	0,00	2121,00	3,17	270,00	12,30	210,00	947,30	952,20	949,80	7,52	0,00	
09/03/2020	27,40	38,30	31,13	0,00	29,00	60,00	48,38	0,00	0,00	1854,90	3,15	180,00	18,00	340,00	946,90	953,20	950,24	5,37	0,00	
08/03/2020	24,90	37,90	31,29	0,00	32,00	72,00	48,67	0,00	0,00	2327,20	2,58	180,00	11,40	180,00	948,60	953,90	951,00	10,20	0,00	

Fig. 3. Data collected at the DGMN

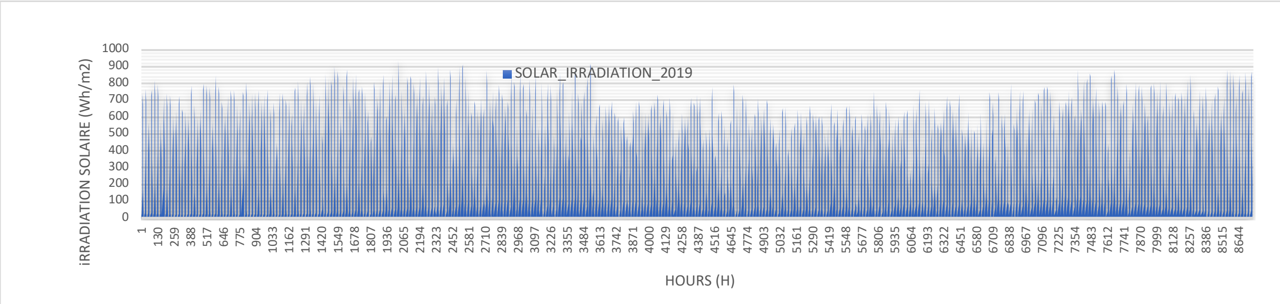

Fig. 4. Time series of solar irradiance.

The authors of [17, 18] tested the performance of the ANFIS model and compared the results with other models in case studies. Statistical performance parameters such as root mean square error (RMSE), mean bias error (MBE) and coefficient of determination (R^2) showed that the predictions made with ANFIS are better than those made using other models. Authors further proved the ability of ANFIS to make predictions for any geographical area with changing weather conditions.

In this manuscript, ANFIS was chosen for the prediction of hourly solar irradiance with Matlab software.

3.3.2- Mapping tools

The mapping tool used in our work is the geographic information system QGIS. As the best open-source desktop GIS software, QGIS is a professional GIS application built on open-source bricks, compatible with Linux, Unix, Mac OS X, Windows and Android and integrates many vectors, raster, database formats and features. QGIS offers an ever-increasing number of possibilities through its internal functions and extensions. You can visualize, manage, edit, analyze data and compose maps for printing. You can perform spatial data analysis of vectors, resampling tools, geometry management and databases. All these processes are performed in the background, allowing work to continue in parallel. The graphical modeler allows combining functions to realize a complete process, with an intuitive graphical interface [19].

4. Results

In this work, the ANFIS model in MATLAB software version 9.5.0.3402 (R2018) was used.

The results of the prediction were used to produce the Solar Irradiance Atlas of Togo. The different steps followed to obtain the qualitative, quantitative and graphical results are presented in this section.

4.1. Normalization of data

The data obtained are numerical but the variables are measured in different units and are therefore incompatible in their raw state. Thus, before applying the ANFIS model to these data whose scales and units are variable, data were normalized using the formula in Equation 1 to bring all values between 0 and 1, while maintaining the distances between values.

$$X_{NORM} = \frac{X - X_{MIN}}{X_{MAX} - X_{MIN}} \epsilon [0, 1] \quad (1)$$

where:

- X_{NORM} is the normalized or transformed data set;
- X is the original data set;
- X_{MAX} et X_{MIN} are respectively the maximum and minimum of the data set.
-

4.2. Data distribution

The database used in this study consists of data from 2010 to 2020. Figure 5 gives an overview of an extract of the studied parameters namely: horizontal solar irradiation, mean temperature, relative humidity, surface pressure, mean wind speed and wind direction.

This database was subdivided into two parts, namely:

- a first part consisting of data from 2010 to 2018 for model training and generation of the general rule for the model;
- a second part consisting of data from 2019 to 2020 for the evaluation of the model.

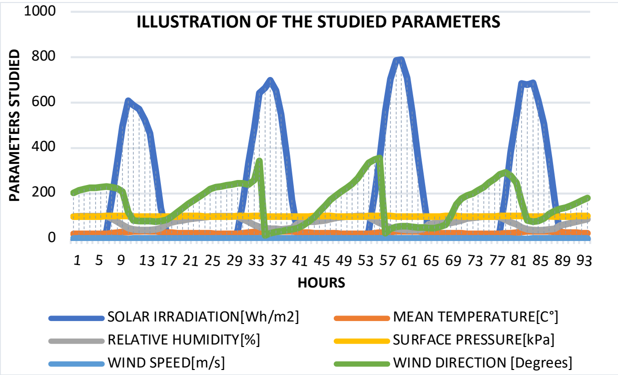

Fig. 5. Extract of input and output data used in ANFIS.

4.3 Solar irradiation prediction

The data used in ANFIS are organized as follows:

- as inputs: mean temperature, relative humidity, surface pressure, mean wind speed and wind direction;
- as output: solar irradiance.

These data are structured so that the first columns are the input parameters and the last column the output parameter. For this study, the following parameters were chosen:

- Generate FIS: the membership functions of type "Gaussmf" for each input and a function of type "linear" for the output variable.
- Train FIS: the optimization method (hybrid), the tolerance (error = 0) and the number of iterations (100);

Validation of these choices allowed to generate the structural model of Figure 6.

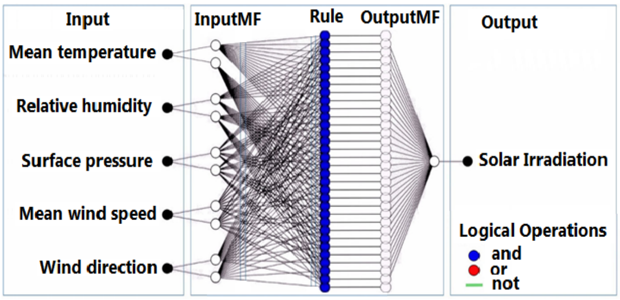

Fig 6. Main architecture of the ANFIS model

4.4 Model validation

Validation allows to judge the reliability of the model and its ability to reproduce the modeled variables. Several criteria used for validation exist but only the three criteria namely: the coefficient of determination (R^2), the mean square error (RMSE) and the biased mean (MBE) were used in this work. These are the most popular indicators used in similar studies. A good model should have a very low RMSE. In contrast to the RMSE, a reliable fit occurs when R^2 is close to 1; this shows the robustness of the correlation between the estimated and actual data [20]. The above statistical indicators and their corresponding equations are presented as follows.

4.4.1 Coefficient of determination (R^2)

Coefficient of determination R^2 is a statistical measure that indicates how the regression line fits the actual data. A value of R^2 close to 1 indicates that the regression line fits the data well. This indicator ranges from 0 to 1. A value of 1 indicates perfect agreement between the measure and the model, while a value of 0 indicates complete disagreement. This coefficient is determined by the following Equation 2:

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{N}\left(I_M(i)-I_E(i)\right)^2}{\sum_{i=1}^{N}\left(I_M(i)\right)^2}\right] \qquad (2)$$

with:

- N: Number of examples used in the training or validation base.
- $I_M(i)$: Measured solar irradiation;
- $I_E(i)$: Solar irradiation estimated by the model.

4.4.2 Mean Bias Error (MBE)

MBE is the mean bias error which gives an indication of the average deviation of the predicted values from the corresponding measured values. A positive value indicates an overestimation in the predicted global irradiation and a negative value indicates an underestimation. It is determined by Equation 3.

$$MBE = \frac{1}{N}\sum_{i=1}^{N}\left(I_M(i) - I_E(i)\right) \qquad (3)$$

4.4.3 Root Mean Square Error (RMSE)

RMSE criterion is the Root Mean Square Error and indicates deviations by giving information on the magnitude of these deviations. It is expressed by Equation 4.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I_M(i) - I_E(i)\right)^2} \qquad (4)$$

RMSE is a measure of the variation of predicted values around measured values. The model is better in terms of accuracy if the value of the RMSE criteria is close to zero.

4.5 Validation results

A comparison of the measured and predicted data was made and illustrated in Figure 7.

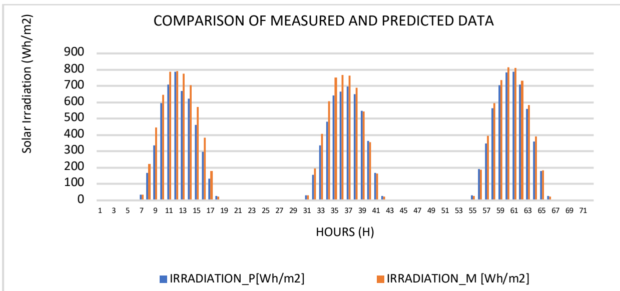

Fig. 7. Comparison of measured and predicted data

Performance of the model is obtained by minimizing the training error, also called learning error, whose evolution is illustrated in Figure 8

The previous statistical performance parameters have been calculated and recorded in the following Table 1:

Table 1. Statistical parameters of model validation

Parameters	**RMSE**	R^2	**MBE**
Value	0.045355	0.9896	-0,241

In order to appreciate the results of the proposed model, a comparative study is made with the results of other studies conducted in the past.

Indeed, the authors [5,6] used the neural network to predict sunshine in Togo at three sites namely, Lomé, Atakpamé and Mango. The results of the evaluation of their model are shown in Table 2.

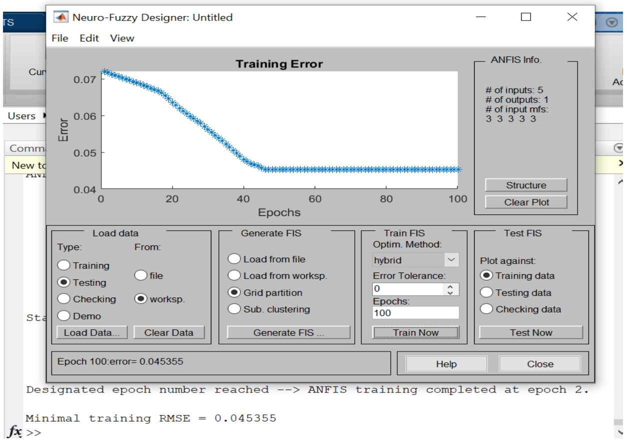

Fig. 8. Evolution of the training error of the model

Table 2. Statistical parameters [5,6]

Parameters	MPE	MBE	RMSE
Lomé	0.8	1.1	42.0
Atakpamé	1.3	-3.4	71.5
Mango	0.6	0.2	41.3

Also, the authors [3,4] proposed a model for estimating solar irradiance values in Togo using an artificial neural network (ANN) based approach using the radial basis function and the multilayer perceptron. The results of their model training step are shown in Table 3.

Table 3. The errors obtained by [3,4]

Multilayer Perceptron (MLP)			Radial Base Function (RBF)		
MAPE (%)	R^2	RMSE	MAPE (%)	R^2	RMSE
3,277	0,933	0,216	4,089	0,912	0,267

From this comparative study, it can be seen that the proposed ANFIS model performs better with an accuracy higher than 98%, a mean square error of 0.04535 and a biased mean error of -0.241. Therefore, the proposed model is an effective technique to predict global solar radiation for practical purposes.

5. Atlas of Togo

5.1 Daily variation of solar irradiation

An analysis of the daily variation of the real data and predicted time series is shown in Figure 9. It can be seen that solar energy is available between 5 am and 6 pm. Thus, to evaluate the daily averages of solar irradiation, the time slot considered is from 7:00 am to 4:00 pm because in general, as can be seen in Figure 9, at these start and end times, the average amount of energy available is greater than 200 Wh.

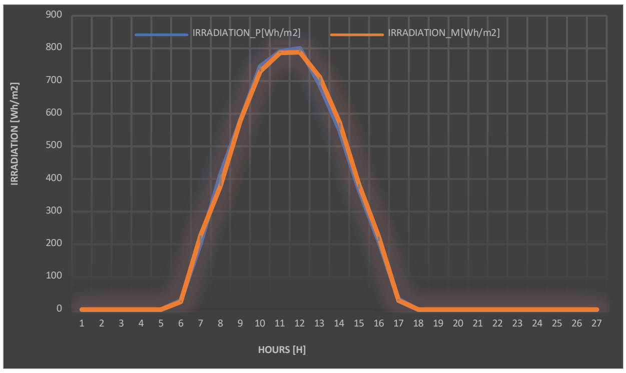

Fig. 9. Comparison of real data and prediction.

5.2 Solar irradiation maps

The evaluation of the hourly irradiation carried out allowed to obtain the maximum and minimum monthly and annual averages data shown in Figure 10.

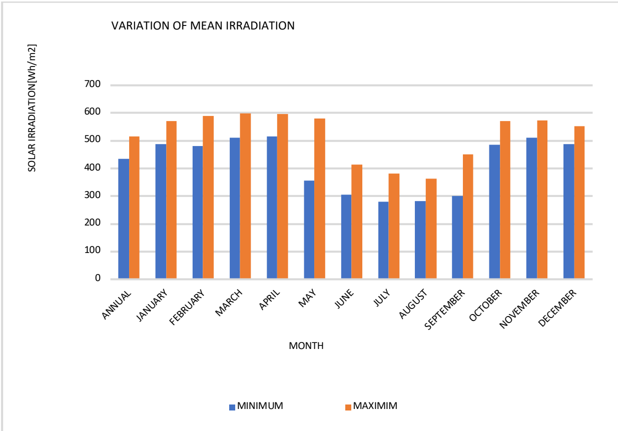

Fig. 10. Variation in annual average hourly global irradiation in Togo

The results obtained were used to produce the second edition of the Atlas of solar irradiation of Togo.

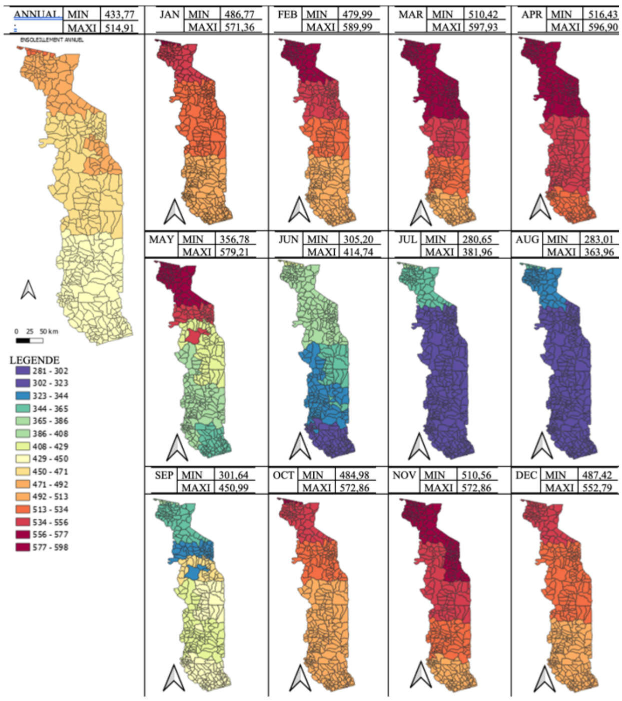

Fig. 11. Atlas of the average hourly solar irradiation in Togo

Thus, Figure 11 shows the monthly and annual maps to illustrate a seasonal distribution of hourly solar irradiance in time and space.

5.3 Results interpretation

It is clear that the months of low sunshine are May, June, July, August and September. These periods correspond to the rainy season and the frequent presence of rain and clouds at this time of year can justify this situation.

The months of January, February, March and April, October, November and December are the sunniest months in Togo.

This edition, in addition to offering the national solar irradiation map, allows the data to be visualized at the level of each canton.

6. Conclusion

In this work, the ANFIS model was used to predict monthly global solar radiation with Matlab R2018 software. The evaluation of the results obtained shows the predictive capability of the model as the values of the performance parameters such as root mean square error (RMSE), coefficient of determination (R^2) and mean bias error (MBE) presented in this study are very satisfactory. This model allowed to generate, for all districts at the national level, data used to produce a new edition of the Togolese solar irradiation Atlas which like the previous edition, is an important contribution in the field of the production of photovoltaic energy.

Further work, will be carried out on evaluating the solar irradiation on an inclined plane, fundamental to correctly dimensioning the generator integrated in the photovoltaic networks and correctly estimating the quantity of energy that can be produce annually.

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