PREDICTION OF GLOBAL SOLAR IRRADIATIONS ON INCLINED PLANES BY LIU & JORDAN MODELS AND THE ARTIFICIAL NEURAL NETWORK (RNA). APPLICATION SITE MAHAJANGA

DONA Victorien Bruno[1], MAXWELL Djaffard[2], RATIARISON Adolphe Andriamanga[3]

1Doctor, Department of physics, Laboratory of Applied Physics and Renewable Energies, Mahajanga, University
2 Doctor, Department of physics, Laboratory of Applied Physics and Renewable Energies, Mahajanga, University
3 Emeritus Professor, Department of physics, Laboratory of Atmospheric, Climate and Ocean Dynamics, University of Antananarivo

ABSTRACT

The design and sizing of solar energy systems (photovoltaic solar panel, thermal solar panel, parabolic solar concentrators, aerovoltaic system, solar tower chimney, etc.) requires precise knowledge of the solar field at the site where the system will be installed. One of the major factors in the evaluation of the solar field at a given site is the availability of consistent and accurate global inclined irradiation data. This paper proposes the Liu and Jordan models and the artificial network for estimating global solar irradiations in an inclined plane, based on a single meteorological data, the monthly average daily global radiation striking a horizontal plane. The latter is determined from frequently measured meteorological data, solar insolation. These two models lead to almost similar results, confirming the ability of neural networks to accurately predict solar irradiation.
Keywords: Sunstroke duration, solar field, Liu and Jordan models, global solar irradiation, estimation; artificial neural networks.

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1-INTRODUCTION

The solar field is the set of data describing the evolution of solar radiation at a given location and over a given period of time. Any exploitation of solar energy at a given site requires a complete knowledge of the site's solar deposit beforehand. The average values (hourly, daily, monthly) of the global solar irradiation on a horizontal and inclined surface are among the important data for predicting the performance of solar conversion systems. However, in the majority of cases, there are no local measurements of sunshine and solar flux at several sites.
This problem is also encountered in several regions in Madagascar, in particular, the city of Mahajanga which has interesting solar deposits (average insolation rate 75%) but the local meteorological station can only provide solar

insolation measurements. To overcome this problem, recourse to the use of approximate mathematical methods to predict the different components of global solar radiation is necessary. This study aims to use two models to estimate global irradiations on an inclined plane in the Mahajanga site from a single meteorological data: the monthly average daily global radiation striking a horizontal plane. For this purpose, the Liu and Jordan empirical model and the artificial network are adopted.

2-MATHEMATICAL MODELLING

2.1-Isotropic model of LIU &JORDAN

The empirical model of Liu and Jordan[1] makes it possible to determine the hourly and daily monthly mean values of the components of solar radiation on an inclined plane from a single meteorological data: the monthly mean daily global radiation striking a horizontal plane. The method also states that there is a day in the so-called characteristic average day month, for which the values of the radiation components are equal to their monthly average values. The advantage of this model over others is that it allows to generate the solar irradiation received on the ground for different sky conditions and different surface inclinations.

Figure 1: Input and output parameters of the LIU &JORDAN model

2.1.1-General process to be followed.

(1) Correlations between the duration of sunshine and horizontal global solar radiation

The Glover & McCulloch model[2] allows to overcome the local dependence of the Angström & Prescott model by using a latitude-dependent coefficient, the cosine of geographical latitude. The term cosine corrects, in a way, the local dependence on the constant coefficient. The values of a and b for this model are 2.09 and 0.52 respectively. This model imposes a constant coefficient, b, for the latitude spectrum analyzed (0° - 60°N). The time angle of sunrise in degrees; $\omega s \approx 90°$ for the months of February, March,
April, August, September and October, $\omega s \approx 100°$ for the months of May, June and July and $\omega s \approx 80°$
for the months of November, December and January.

(2) Correlations between global and horizontal diffuse radiation

These correlations show the relationship between the sky brightness index (global radiation/ global radiation out of atmosphere) and the ratio of diffuse radiation (diffuse radiation/ global radiation)[3].

(3) Correlations between daily and inclined hourly radiation

The regression model of Collares-Pereira and Rabl[3] is used to obtain the average values of the hourly global radiation from the daily global radiation and the Liu & Jordan model allows to obtain the hourly diffuse radiation from the daily diffuse radiation.
Figures 2 and 3 present the general process flow diagram of the simplified methods for obtaining the monthly average of the global hourly radiation on an inclined plane.

Meteorological data: Monthly average of daily insolation Sm
Monthly average of daily global radiation Hm striking a horizontal plane Glover & McCulloch model

$$H_m = H_0\left[a\cos\varphi + b\left(S_m / S_{0,m}\right)\right] \qquad (1)$$

Diffuse component of daily horizontal irradiation Model of Collares-Pereira and Rabl:

$$\frac{H_{d,m}}{H_m} = 0{,}775 + 0{,}347\left(\frac{\pi}{180}\right)(\omega_S - 90) - \left[0{,}505 + 0{,}261\left(\frac{\pi}{180}\right)(\omega_S - 90)\right]\times cos\left[2(K_T - 0{,}9)\right] \quad (2)$$

Angle horaire du lever du soleil: ω_S □ 90° *pour les mois de Février,Mars, Avril,Août,Septembre et Octobre*
ω_S □ 100° *pour les mois de Mai, Juin et Juillet;* ω_S □ 80° *pour les mois de Novembre, Décembre et Janvier*

Monthly average daily clarity index over a horizontal area: $K_{T,m} = H_m / H_o$

Moyenne mensuelle du rayonnement global journalier sur un plan incliné G_m

$$R_{b,m} = \frac{\cos(\phi-\beta).\cos\delta.\sin\omega_{s\beta} + \frac{\pi}{180}.\omega_{s\beta}.\sin(\phi-\beta).\sin\delta}{\cos\phi.\cos\delta.\sin\omega_s + \frac{\pi}{180}.\omega_s.\sin\phi.\sin\delta}$$

$$\frac{G_m}{H_m} = \left(1 - \frac{H_{d,m}}{H_m}\right)R_{b,m} + \frac{H_{d,m}}{H_m}\left(\frac{1+\cos\beta}{2}\right) + \rho\left(\frac{1-\cos\beta}{2}\right) \qquad (3)$$

Figure 2: Algorithm for calculating the monthly average of the daily global radiation on an inclined plane

Hourly diffuse radiation as a monthly average in a horizontal plane Liu and Jordan's model

$$r_d = \frac{I_{d,m}}{H_{d,m}} = \frac{\pi}{24}.\frac{\cos\omega - \cos\omega_s}{\sin\omega_s - \frac{\pi}{180}.\omega_s.\cos\omega_s} \quad \text{et} \quad I_{d,m} = r_d.H_{d,m} \qquad (4)$$

Overall hourly radiation as a monthly average in a horizontal plane Im Collares-Pereira & Rabl model

$$a = 0,4090 + 0,5016.\sin(\omega_s - 60) \text{ et } b = 0,6609 - 0,4767.\sin(\omega_s - 60)$$

$$r_t = (a + b.\cos\omega)\times r_d \quad \text{et} \quad I_m = r_t.H_m \qquad (5)$$

Overall hourly radiation on an inclined plane for the average day of the month

$$R_{b,m} = \frac{\cos(\phi-\beta).\cos\delta.\cos\omega + \sin(\phi-\beta).\sin\delta}{\cos\phi.\cos\delta.\cos\omega + \sin\phi.\sin\delta}$$

$$I_{\beta,m} = \left(I_m - I_{d,m}\right)R_{b,m} + I_{d,m}\left(\frac{1+\cos\beta}{2}\right) + I_m\,\rho\left(\frac{1-\cos\beta}{2}\right) \qquad (6)$$

Figure 3: Algorithm for calculating the monthly average of the hourly global radiation on an inclined plane

2.2- Perceptron Multilayer Artificial Neural Network Model

Artificial neural networks (ANS) are mathematical models inspired by the structure and behaviour of biological neurons. They are composed of interconnected units called formal or artificial neurons capable of performing specific and very specific functions. Figure 4 shows the biological neuron model that forms the basis of artificial neural networks.

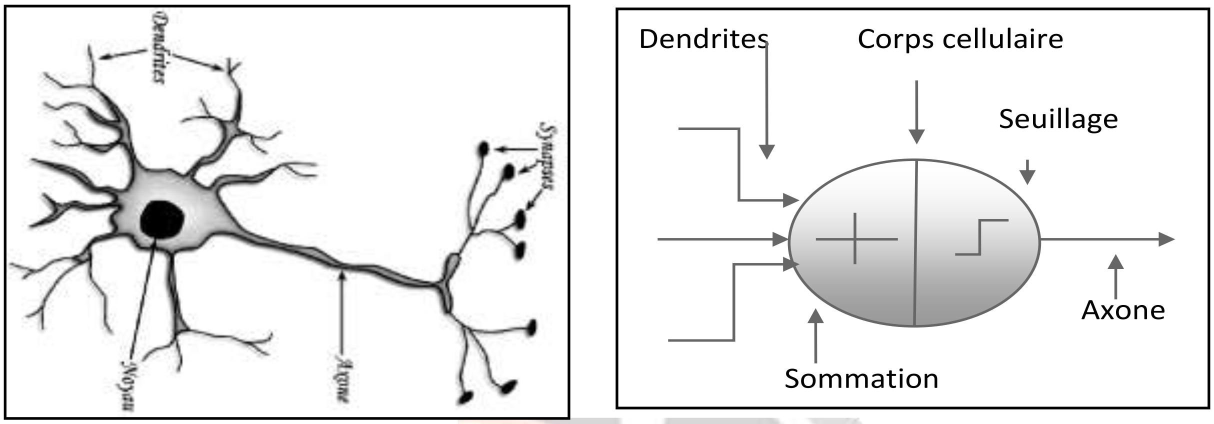
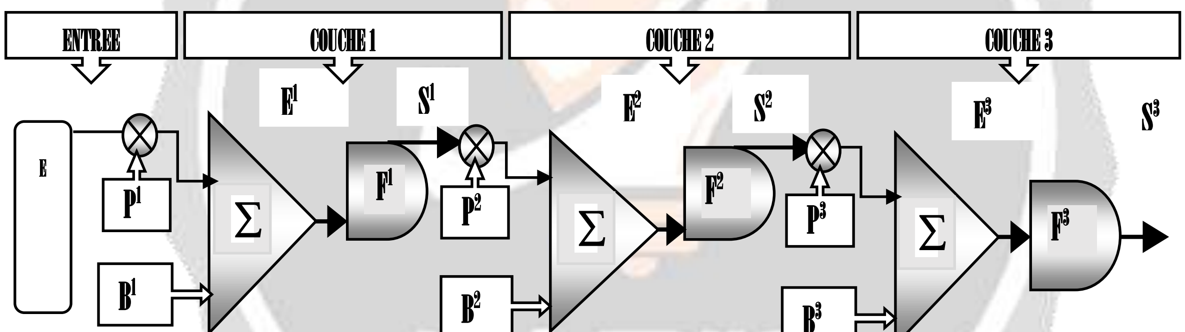


Figure 4: Modelling a biological neuron [4]

Multilayer perceptron RNAs allow to approach non linear at significant degrees of complexity. Figure 5 illustrates the architecture of a 3-layer perceptron network formed by 3 neurons per layer.



$$S^1 = F^1\left(P^1.E + B^1\right) \qquad S^2 = F^2\left(P^2.S^1 + B^2\right) \qquad S^3 = F^3\left(P^3.S^2 + B^3\right)$$

Figure 5: Matrix representation of 3-layer perceptron[5]

The final simulation consists in calculating the final value of the actual output of the network, using the actual output returned by the network S3 with the values of P1, P2, P3, B1, B2 and B3 set at the end of the learning process.

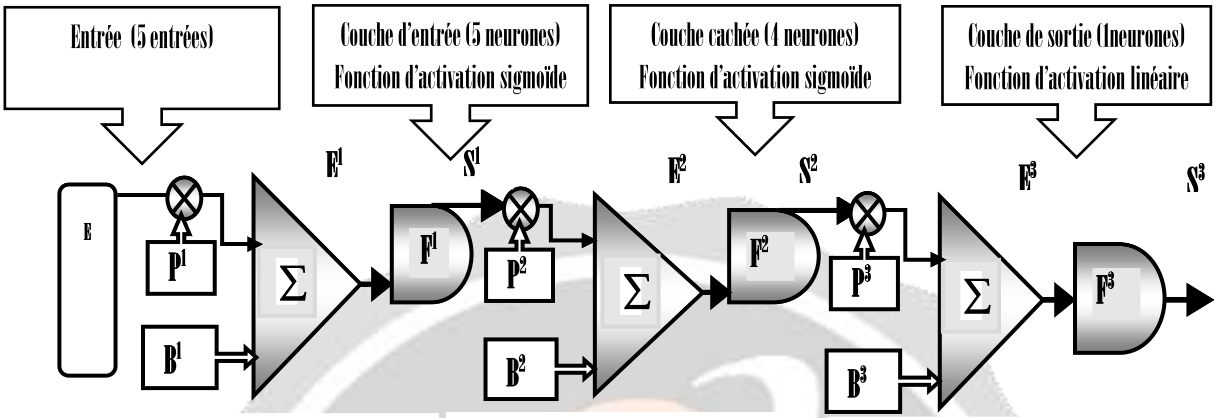
$$S^3 = F^3(E^3) = F^3\left[P^3 F^2\left[P^2 F^1\left(P^1.E + B^1\right) + B^2\right] + B^3\right] \qquad (7)$$

$$E = \begin{bmatrix} e_1 & e_2 & e_3 \end{bmatrix}^T \;;\; B^1 = \begin{bmatrix} b^1_{1,1} & b^1_{1,2} & b^1_{1,3} \end{bmatrix}^T \;;\; B^2 = \begin{bmatrix} b^2_{2,1} & b^2_{2,2} & b^2_{2,3} \end{bmatrix}^T \;;\; B^3 = \begin{bmatrix} b^3_{3,1} & b^3_{3,2} & b^3_{3,3} \end{bmatrix}^T$$

$$P^1 = \begin{bmatrix} p^1_{1,1} & p^1_{1,2} & p^1_{1,3} \\ p^1_{2,1} & p^1_{2,2} & p^1_{2,3} \\ p^1_{3,1} & p^1_{3,2} & p^1_{3,3} \end{bmatrix} ; P^2 = \begin{bmatrix} p^2_{1,1} & p^2_{1,2} & p^2_{1,3} \\ p^2_{2,1} & p^2_{2,2} & p^2_{2,3} \\ p^2_{3,1} & p^2_{3,2} & p^2_{3,3} \end{bmatrix} ; P^3 = \begin{bmatrix} p^3_{1,1} & p^3_{1,2} & p^3_{1,3} \\ p^3_{2,1} & p^3_{2,2} & p^3_{2,3} \\ p^3_{3,1} & p^3_{3,2} & p^3_{3,3} \end{bmatrix} ; S = \begin{bmatrix} S^1 & S^2 & S^3 \end{bmatrix}^T$$

2.2.1- Architecture of the selected PMC

Figure 6 shows the architecture of the selected PMC, to predict the monthly average values of 6 to 18 hours of solar irradiation received on an inclined plane for each month. The three-layer perceptron array takes as input parameters, insolation (S), daily brightness indices (KT), latitude (φ), longitude (L) and angle of inclination (β) of the capture plane.



$$S^1 = \mathrm{th}\left(P^1.E + B^1\right) \qquad S^2 = \mathrm{th}\left(P^2.S^1 + B^2\right) \qquad S^3 = \mathrm{Id}\left(P^3.S^2 + B^3\right)$$

Figure 6: Selected PMC architecture

After learning the gradient back-propagation algorithm, the PMC retransmits the following information at its output:
-the values of the elements of the weight-matrixes and the biases-vectors, the column vector formed by the weighted sums of the inputs arriving on each neuron of the first layer, the column vector formed by the activities of the neurons of the first layer, the value of the real output (that of the quantity to be determined) emitted by the network and the error defined as the difference between the value found by the neural network and the value determined using the Liu & Jordan model.

$$B^1 = \begin{bmatrix} b^1_{1,1} & b^1_{1,2} & b^1_{1,3} & b^1_{1,4} & b^1_{1,5} \end{bmatrix}^T \quad ; \quad B^2 = \begin{bmatrix} b^2_{1,1} & b^2_{1,2} & b^2_{1,3} & b^2_{1,4} & b^2_{1,5} \end{bmatrix}^T \quad ; \quad B^3 = \begin{bmatrix} b^3 \end{bmatrix}$$

$$P^1 = \begin{bmatrix} p^1_{1,1} & p^1_{1,2} & p^1_{1,3} & p^1_{1,4} & p^1_{1,5} \\ p^1_{2,1} & p^1_{2,2} & p^1_{2,3} & p^1_{2,4} & p^1_{2,5} \\ p^1_{3,1} & p^1_{3,2} & p^1_{3,3} & p^1_{3,4} & p^1_{3,5} \end{bmatrix} ; P^2 = \begin{bmatrix} p^2_{1,1} & p^2_{1,2} & p^2_{1,3} & p^2_{1,4} & p^2_{1,5} \\ p^2_{2,1} & p^2_{2,2} & p^2_{2,3} & p^2_{2,4} & p^2_{2,5} \\ p^2_{3,1} & p^2_{3,2} & p^2_{3,3} & p^2_{3,4} & p^2_{3,5} \end{bmatrix} ; P^3 = \begin{bmatrix} p^3_{1,1} & p^3_{1,2} & p^3_{1,3} & p^3_{1,4} & p^3_{1,5} \end{bmatrix}$$

$$E^3 = P^3.S^2 + B^3 = P^3\,\mathrm{th}\left[P^2\mathrm{th}\left(P^1.E + B^1\right) + B^2\right] + B^3$$

$$S^3 = F^3(E^3) = \mathrm{Id}\left[P^3\,\mathrm{th}\left[P^2\mathrm{th}\left(P^1.E + B^1\right) + B^2\right] + B^3\right] \qquad (\mathbf{8})$$

3-RESULTS AND INTERPRETATIONS

3.1-Description of the MAHAJANGA site

Table 1: Mahajanga Site Geographic Data

Latitude (°)	Longitude (°)	Altitude (m)	Reference meridian (°)	Soil albedo	DEL
15°40'Sud	46°21'Est	22m	40°	0 ,35	0 ,9h

3.2- Insulation, insolation fraction and site clarity index

Figure 7 shows the average monthly distributions of the maximum, average and minimum exposure duration during the year 2010 to 2017 in Mahajanga.

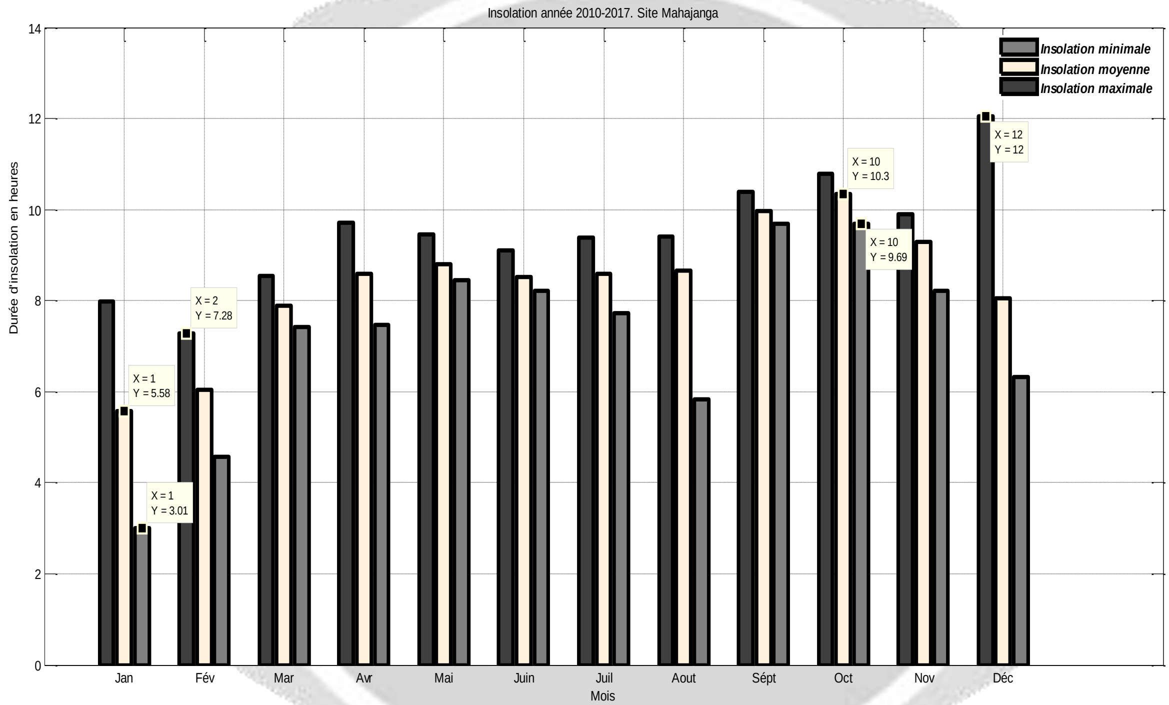


Figure 7: Distribution by month of maximum, average and minimum insolations from 2010 to 2017. Mahajanga website

The monthly average of the sunstroke duration during the year from 2010 to 2017 is significant in October; it is about 10.33 hours of sunstroke per day.

According to Figure 2, in Mahajanga, the insolation fraction takes high values between 0.4 and 0.9 almost all year round. Days with 0.6 to 0.8 sunshine are the majority (57%). These variations and characteristics of the insolation fraction are similar to those of the brightness index, which corresponds to the ratio of the amount of global radiation received to the amount of solar energy available outside the atmosphere. The proportion of days with a high brightness index (from 0.7 to 0.8) is higher, most periods are very sunny, with 75% of days having a brightness index above 0.6.

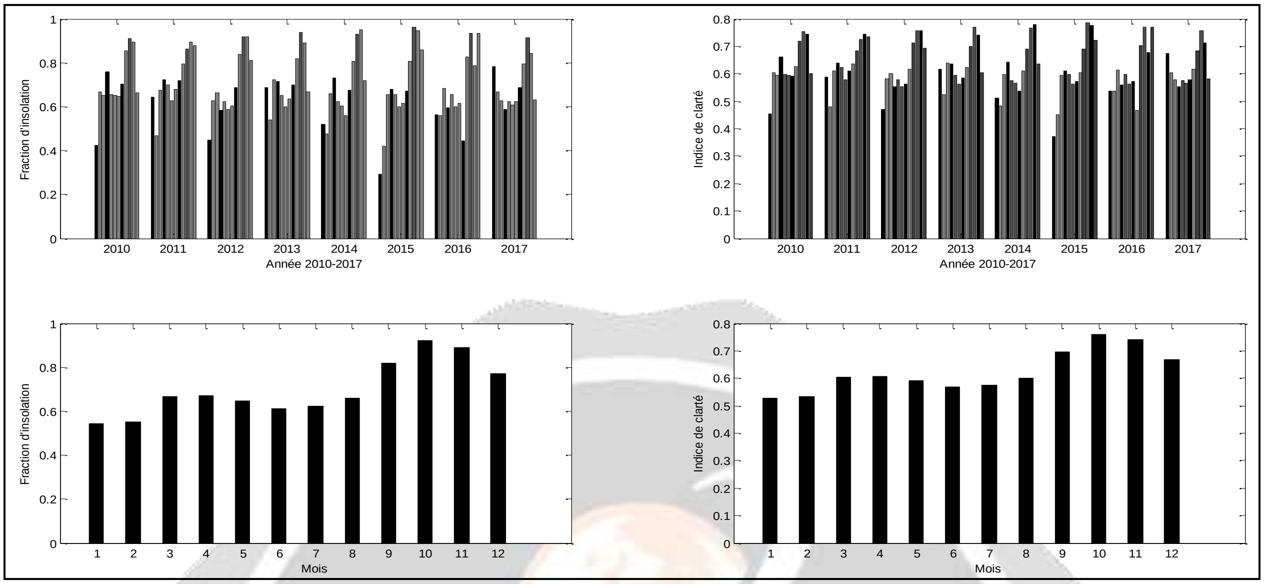


Figure 8: Monthly and average monthly distributions of sunstroke fractions and clarity indices - Mahajanga site

3.3- Analysis of solar irradiations on a horizontal plane

The monthly average global solar radiation over a horizontal area of the Mahajanga site was estimated using the Angstrom-Prescott-type linear regression method.

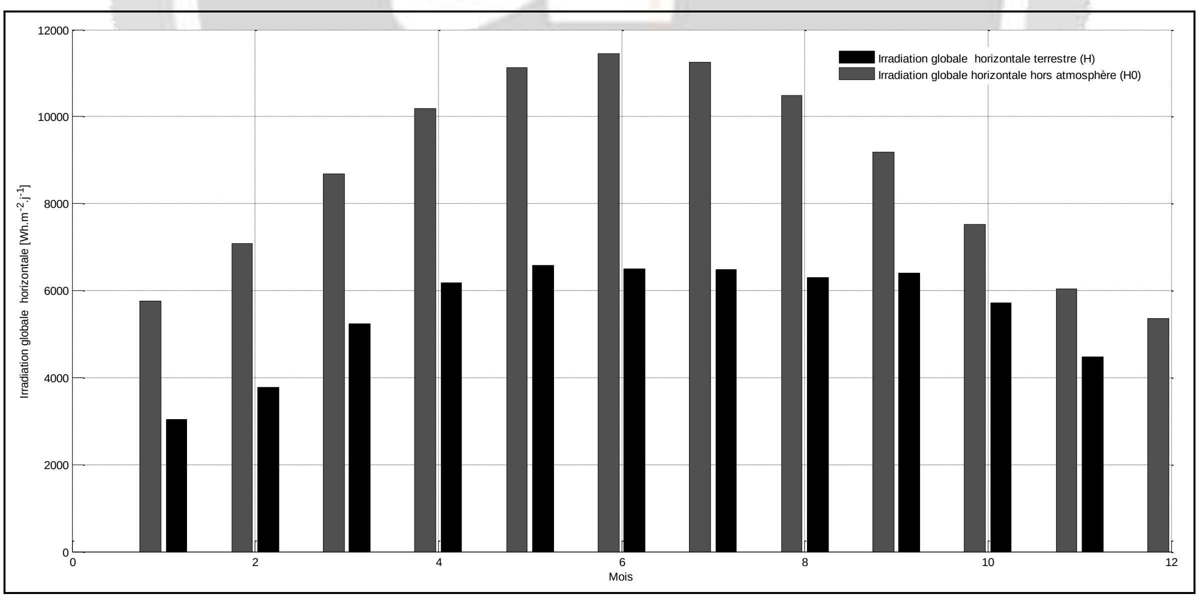


Figure 9: Daily global irradiation monthly outside the atmosphere and on land over a horizontal surface. Mahajanga site (2010-2017)

3.4- Analysis of solar irradiations on the inclined plane

Figure 7 shows the evolution of global hourly radiation as a function of true solar time (TSV) for the different months of the year.

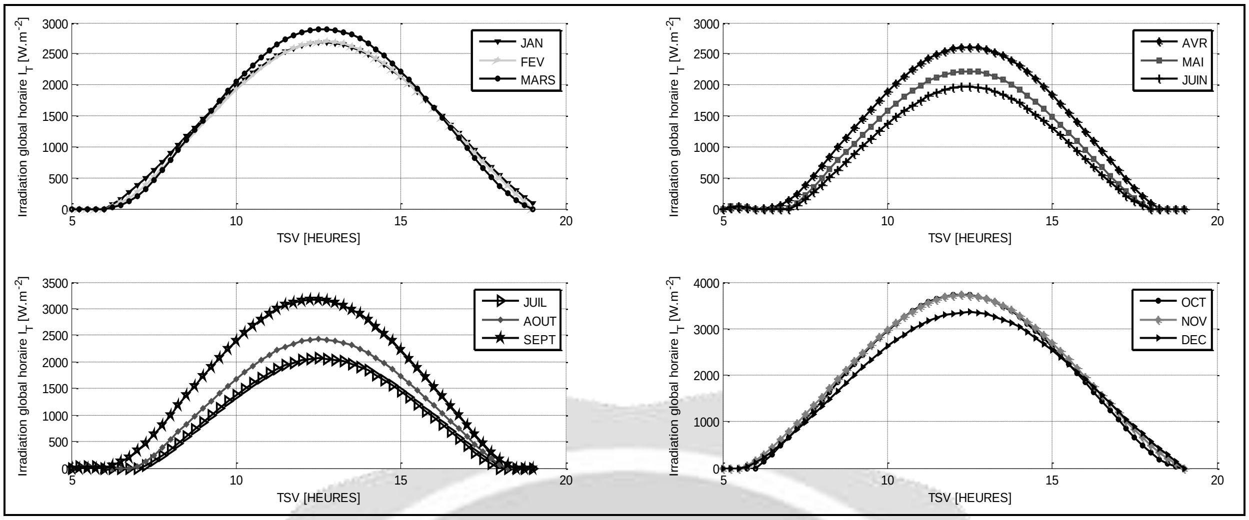


Figure 10: Overall hourly irradiation per month for an inclination equal to the latitude of the Mahajanga site - Lui & Jordan Model

The solar irradiation received by an inclined surface varies in the form of a Gauss curve during an undisturbed day: zero at night, it increases from daybreak to reach a maximum at noon before decreasing again until it is cancelled out at nightfall.Figure 11 also shows the most favourable and worst months at the Mahajanga site..

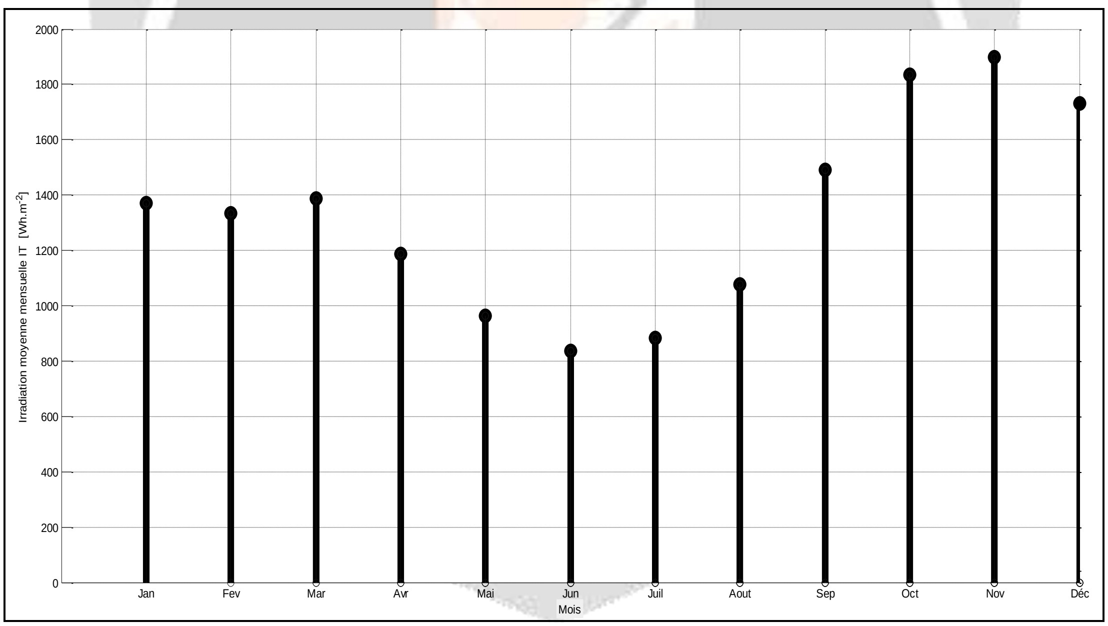


Figure 11: Monthly average of the global hourly irradiation for an inclination equal to latitude.

The overall monthly hourly irradiation rate varies according to the month considered, it is highest in November and lowest in June. The use of solar energy is therefore well suited to applications whose needs coincide with the hours and months of maximum sunshine.

Figure 12 shows the monthly average values of the global daily irradiation for an inclination equal to the latitude of the Mahajanga site, the irradiation has a minimum value in June and July and in November the value is high.

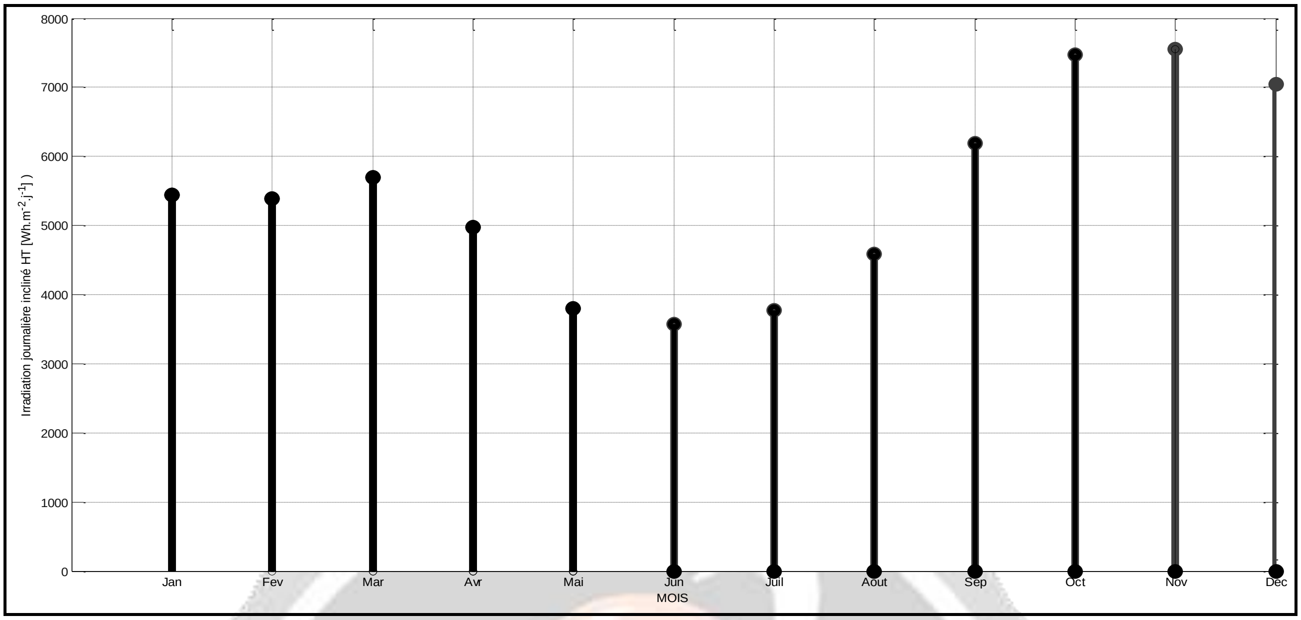


Figure 12: Mean monthly values of the global daily irradiation on the inclined plane - Lui & Jordan model

3.5- Prediction of global inclined irradiations by the Artificial Neural Network method.

Finally, based on meteorological data accumulated from 2010 to 2017, the established 3-layer Perceptron Neural Network model can predict the average monthly hourly and daily irradiations received on an inclined plane (Figures 13 and 14).

It is clear that the Liu & Jordan and PMC Neural Network models give practically the same upward curves in the most favourable (higher radiation) and least favourable (low radiation) months. It should also be noted that sigmoid activation functions (generally present on the hidden layer(s)) are the main elements that allow PMCs to be qualified as non-linear models. If these sigmoid activation functions are replaced by linear functions, the PMC is transformed into a linear regression. The combination of these two models would certainly allow a better approximation of the actual size.

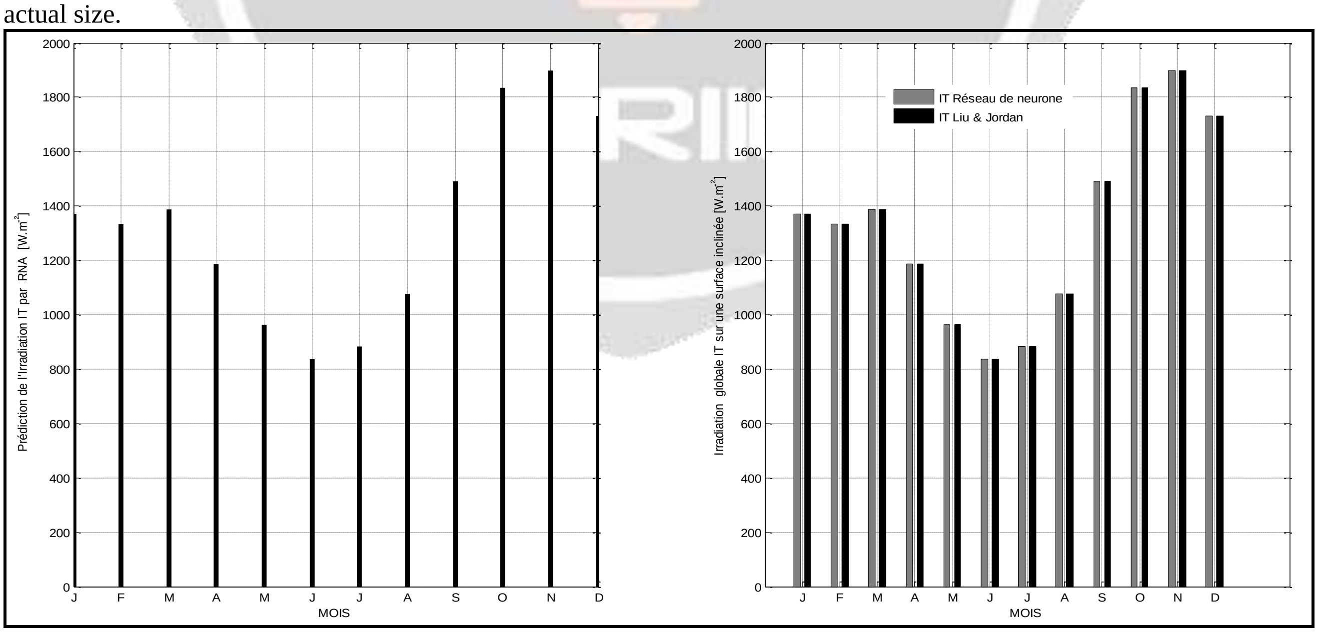


Figure 13 : Moyenne mensuelle de l'irradiation horaire estimée par les modèles de Liu & Jordan et de Réseau de neurone perceptron à 3 couches

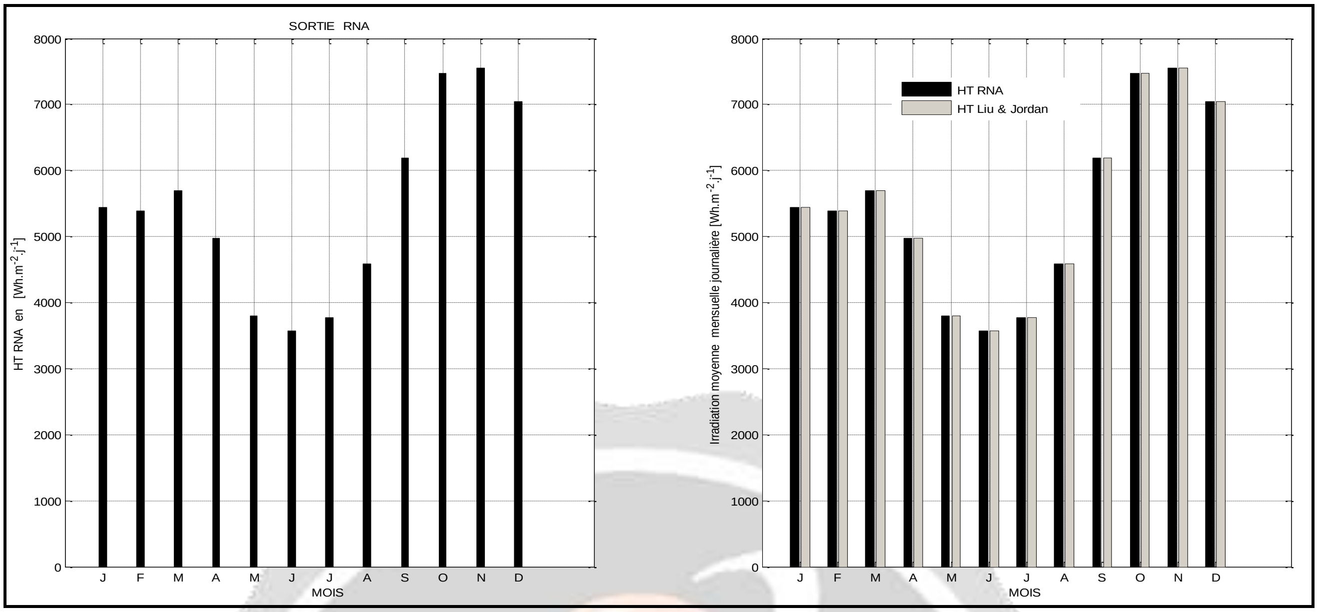


Figure 14: Monthly average of hourly irradiation estimated by Liu & Jordan and 3-layer perceptron neural network models

4-CONCLUSION

LIU JORDAN's model is used to evaluate the component of solar radiation on inclined planes. The great advantage of neural networks is their ability to learn automatically, which allows problems to be solved without the need to write complex rules, while being error-tolerant. In this study, these two models lead to almost similar results, in the prediction of the global irradiation received on an incline. The accuracy of the results obtained justifies the importance of using these two models in the pre-dimensioning calculations of solar systems.

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