Revue des Energies Renouvelables Vol. 14 N°2 (2011) 329 – 342
DOI: https://doi.org/10.54966/jreen.v14i2.263

Using multilayered neural networks for determining global solar radiation upon tilted surface in Fianarantsoa Madagascar

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(reçu le 24 Février 2011 – accepté le 28 Juin 2011)

Abstract - *The knowledge of the local solar radiation characteristics is indispensable in the survey of any system exploiting solar energy in any location. The author is particularly interested by the global solar radiance upon tilted surface per time unit to help operators using solar energy in their work. The target is, among others, helping solar drying operators that need while tuning drying system the knowledge of the global solar radiation that could be received on inclined solar captors in implantation site. The aim of this paper is to use neural network method to search for solar radiation upon a tilted surface. Multilayered neural networks (MNN) trained by gradient back-propagation are used to determine numeric values of monthly means and hourly variations of the global solar radiation upon a titled surface per time unit. The numerical calculations are made with the geographical and meteorological parameters (latitude, longitude and clearness index) of the location of Fianarantsoa, Madagascar.*

Résumé - *La connaissance des caractéristiques locales du rayonnement solaire est indispensable dans l'étude de tout système exploitant l'énergie solaire. Ce travail traite en particulier le rayonnement solaire global sur une surface inclinée par unité du temps pour aider des opérateurs exploitant l'énergie solaire dans leur travail. Les cibles sont entre autres les opérateurs du traitement de séchage solaire qui ont besoin, lors de la mise au point de leur système, la connaissance de la puissance solaire qui pourrait être reçue sur leurs capteurs solaires inclinés conformément au site d'implantation. Le but de ce travail est d'utiliser la méthode des réseaux de neurones pour calculer la puissance solaire sur une surface inclinée. Des réseaux neuraux multicouches (MNN) ont été formés. Leur apprentissage a été fait par la rétro-propagation du gradient. Leurs simulations ont permis de déterminer des valeurs numériques en moyennes mensuelles et les variations horaires de la puissance solaire sur une surface inclinée. Les calculs numériques sont faits avec les paramètres géographiques et météorologiques (latitude, longitude et indice de clarté journalier) du site de Fianarantsoa, Madagascar.*

Key words: Neural network - Back-propagation - Simulation - Global solar radiation.

INTRODUCTION

The preservation of the environment requires more researches concerning the different energy resources indispensables to human life. One of these resources currently developed is the renewable energy in which solar energy take an important place. In solar energy exploitation like solar drying with flat-plate heaters, electricity production with photovoltaic cells or other applications, the knowledge of the solar

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radiation parameters corresponding to the location is indispensable to forecast the system performance.

Studies prove that in most cases, solar irradiance captors are inclined. So, the author is particularly interested by the global solar radiation upon a tilted surface which contains direct, diffuse and reflected components [1]. Its value will be calculated per time unit so that it could be named global solar radiance power upon a tilted surface, expressed in W/m^2.

Many works of research are already appeared concerning the methods used in the calculation of the solar radiance. One of the oldest methods is the statistic theory of Liu and Jordan, [1] which studies the interrelationship and characteristic distribution of direct, diffuse and total solar radiation. In that theory, the calculations are complicated because of the interdependence of the parameters.

Recently, artificial neural network models have been used successfully in estimating monthly mean solar radiation by many researchers as Mohandes *et al.* [2], Mihalakakou *et al.* [3], Yu *et al.* [4], Dorvloa *et al.* [5], Reddy *et al.* [6], Elminir *et al.* [7], Iqdour *et al.* [8], Boscha *et al.* [9], Moustrisa *et al.* [10], Mubiru *et al.* [11], Zervas *et al.* [12], Rehmana *et al.* [13], Jiang [14], Mubiru [15], Behrang *et al.* [16], Rahimikhoob *et al.* [17].

Among others, Zervas *et al.* [12] have developed a prediction of daily gobal solar irradiance on horizontal surfaces based on neural-network techniques.

This paper uses multilayered neural networks (MNN) to predict the global solar radiation upon a tilted surface. Data are taken in the location of Fianarantsoa (21,27° South and 47,06° East) in Madagascar. The results are compared with the global solar radiation power upon a tilted surface calculated by Liu and Jordan statistic theory [1].

The following parts are presented successively in this paper: characteristics of the artificial neuron that has been used, creation of the neural networks, the equations for calculations, neural network training, results presentation and discussion on numerical values compared to those calculated by other method.

2. STRUCTURES AND CHARACTERISTICS

2.1 Artificial neuron

The artificial neuron feature is represented on figure 1.

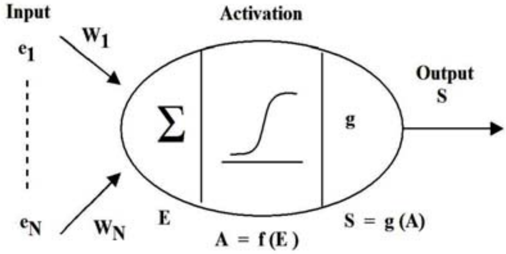


Fig. 1: Artificial neuron scheme

Neural characteristics used in this paper are:

Input nature: real

$$\left(e_1, \ldots, e_n \right)$$

Total input function: linear

$$E = h \times \left(e_1, \ldots, e_n \right) = \sum_{i=1,n} W_i \times e_i$$

Activation functions: sigmoid or linear

$$f(x) = th(x) = \frac{1 - e^{-2x}}{1 + e^{-2x}}$$

$$f(x) = Id(x) = x$$

Activation

$$A = f(E)$$

Output function: the identity

$$g(x) = x$$

Output nature: real

$$S = g(A) = A$$

2.2 Neural network structure

Among so many others, the model of neural network used in this paper is the multilayered neural network [18]. Two multilayered neural networks were created. The first multilayered neural network ('MNN1', Fig. 2), intended to determine monthly mean from 6 to 18 o'clock of the global solar radiation power upon a tilted surface, is constituted by two layers containing respectively four sigmoid neurons and a single linear neuron.

Every neuron of the first layer is connected to the neurons of the following layer by a connection whose weights are variable. 'MNN1' takes in input the following parameters: the daily clearness index (K_T), the location latitude (φ), the location longitude (L) and the surface slant (β). It returns in output the global solar radiation power (I_T) that should be received on the titled surface, in monthly mean from 6 to 18 o'clock, for each month.

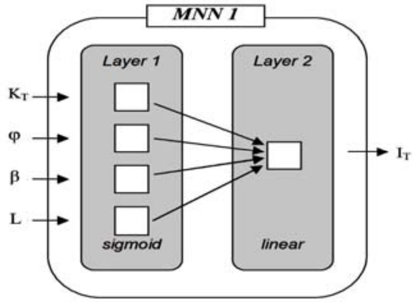


Fig. 2: Multilayered neural network for determining monthly mean of global solar radiation power on tilted surface

The second one ('MNN2', Fig. 3), intended to itemize the hourly variation of the global solar radiation power upon a tilted surface during the characteristic day of each month [19], contains also two layers with two sigmoid neurons in the first layer and thirteen linear neurons in the second.

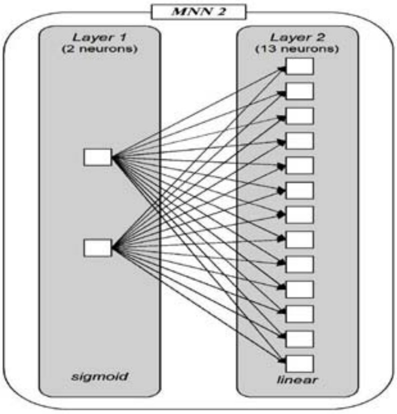


Fig. 3: Multilayered neural network for determining hourly variation of solar radiation power on tilted surface

MNN2 takes in input the characteristic day number (N_T) of the month [3] and the daily clearness index (N_T) of the month. It returns in output the hourly values of the global solar radiation power that should be received on the titled surface, for each month, from 1 to 24 o'clock.

2.3 Equations

The input weighted sum is firstly calculated from the input vector $X(x1,\ldots,xE)$ and the weight/bias (P, B_1), for every neuron of the first layer. Then every sum is introduced in the corresponding neuron to generate its activity $a1_j$ by applying sigmoid activation function.

The weighted sum of these activities $a1_j$ is calculated again for every neuron of the second layer with the weight/bias (P, B_2) to determine the activity $a2_j$ by applying the linear activation function. The last activities will be the components of the neural network effective output $Y(y1,\ldots,yE)$.

Calculations follow the neural network functioning illustrated on figure 4.

Vectors and matrix calculated are:
Input vector

$$X = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_E \end{pmatrix}$$

Weights

$$P = \begin{pmatrix} p_{11} & p_{11} & \cdots & p_{1E} \\ p_{21} & p_{22} & \cdots & p_{2E} \\ \vdots & \vdots & & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NE} \end{pmatrix} \qquad Q = \begin{pmatrix} q_{11} & q_{12} & \cdots & q_{1N} \\ p_{21} & p_{22} & \cdots & q_{2N} \\ \vdots & \vdots & & \vdots \\ q_{M1} & q_{M2} & \cdots & q_{MN} \end{pmatrix}$$

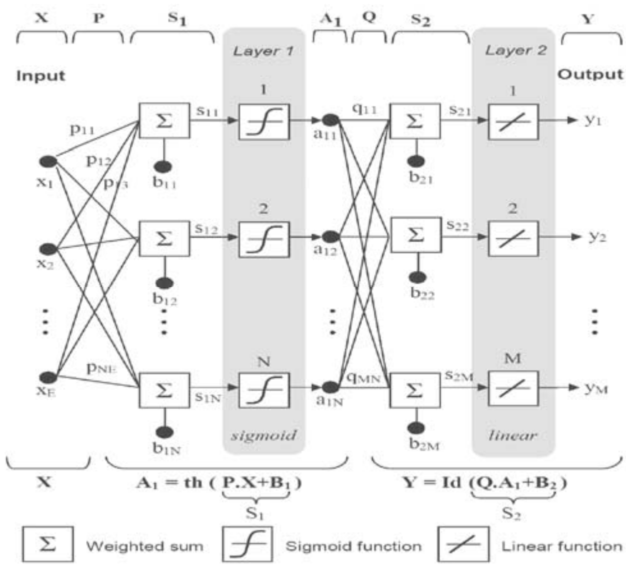


Fig. 4: Neural network functioning for MNN with two layers

Biases

$$B_1 = \begin{pmatrix} b_{11} \\ b_{12} \\ \vdots \\ b_{1N} \end{pmatrix} \qquad B_2 = \begin{pmatrix} b_{21} \\ b_{22} \\ \vdots \\ b_{2M} \end{pmatrix}$$

Weighted sum

$$S_1 = \begin{pmatrix} S_{11} \\ S_{12} \\ \vdots \\ S_{1N} \end{pmatrix} \qquad S_2 = \begin{pmatrix} S_{21} \\ S_{22} \\ \vdots \\ S_{2M} \end{pmatrix}$$

Activations

$$A_1 = \begin{pmatrix} a_{11} \\ a_{12} \\ \vdots \\ a_{1N} \end{pmatrix} \qquad A_2 = \begin{pmatrix} a_{21} \\ a_{22} \\ \vdots \\ a_{2M} \end{pmatrix}$$

Effective output

$$Y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{pmatrix} = \begin{pmatrix} a_{21} \\ a_{22} \\ \vdots \\ a_{2M} \end{pmatrix} = A_2$$

The equations joining vector components or matrix elements of the model, from the input to the output, are:

Input weighted sum

$$\begin{cases} S_{11} = p_{11}\,x_1 + p_{12}\,x_2 + \cdots + p_{1N}\,x_E + b_{11} \\ S_{12} = p_{21}\,x_1 + p_{22}\,x_2 + \cdots + p_{2N}\,x_E + b_{12} \\ \quad\vdots \\ S_{1N} = p_{N1}\,x_1 + p_{N2}\,x_2 + \cdots + p_{NE}\,x_E + b_{1N} \end{cases}$$

First layer's neuron activations

$$\begin{cases} a_{11} = \mathrm{th}(S_{11}) = \mathrm{th}(p_{11}\,x_1 + p_{12}\,x_2 + \cdots + p_{1N}\,x_E + b_{11}) \\ a_{12} = \mathrm{th}(S_{12}) = \mathrm{th}(p_{21}\,x_1 + p_{22}\,x_2 + \cdots + p_{2N}\,x_E + b_{12}) \\ \quad\vdots \\ a_{1N} = \mathrm{th}(S_{1N}) = \mathrm{th}(p_{N1}\,x_1 + p_{N2}\,x_2 + \cdots + p_{NE}\,x_E + b_{1N} \end{cases}$$

Weighted sums of first layer's neuron activations

$$\begin{cases} S_{21} = q_{11}\,a_{11} + q_{12}\,a_{12} + \cdots + q_{1N}\,a_{1N} + b_{21} \\ S_{22} = q_{21}\,a_{11} + q_{22}\,a_{12} + \cdots + q_{2N}\,a_{1N} + b_{22} \\ \quad\vdots \\ S_{2M} = q_{M1}\,a_{11} + q_{M2}\,a_{12} + \cdots + q_{MN}\,a_{1N} + b_{2N} \end{cases}$$

Second layer's neuron activations

$$\begin{cases} a_{21} = \mathrm{id}(S_{21}) = S_{21} \\ a_{22} = \mathrm{id}(S_{22}) = S_{22} \\ \quad\vdots \\ a_{1M} = \mathrm{id}(S_{1M}) = S_{2M} \end{cases}$$

$$\begin{cases} a_{21} = S_{21} = q_{11}\,a_{11} + q_{12}\,a_{12} + \cdots + q_{1N}\,a_{1N} + b_{21} \\ a_{22} = S_{22} = q_{21}\,a_{11} + q_{22}\,a_{12} + \cdots + q_{2N}\,a_{1N} + b_{22} \\ \quad\vdots \\ a_{2M} = S_{2M} = q_{M1}\,a_{11} + q_{M2}\,a_{12} + \cdots + q_{MN}\,a_{1N} + b_{2N} \end{cases}$$

Effective outputs returned by the neural network which are the second layer's neuron activations

$$\begin{cases} y_1 = q_{11}\, a_{11} + q_{12}\, a_{12} + \cdots + q_{1N}\, a_{1N} + b_{21} \\ y_2 = q_{21}\, a_{11} + q_{22}\, a_{12} + \cdots + q_{2N}\, a_{1N} + b_{22} \\ \vdots \\ y_M = q_{M1}\, a_{11} + q_{M2}\, a_{12} + \cdots + q_{MN}\, a_{1N} + b_{2N} \end{cases}$$

These equations can be condensed in the following matrix equations:
Input weighted sum

$$S_1 = P \times X + B_1$$

First layer's neuron actications

$$A_1 = th(S_1)$$

$$A_1 = th(P \times X + B_1)$$

Weighted sums of first layer's neuron activations

$$S_1 = Q \times A_1 + B_2$$

$$S_2 = Q \times th(P \times X + B_1) + B_2$$

Second layer's neuron activations

$$A_2 = id(S_2) = S_2$$

Effective output

$$Y = A_1 + B_2$$

$$Y = Q \times A_1 + B_2$$

$$Y = Q \times th(P \times X + B_1) + B_2$$

Therefore, for MNN1 and MNN2, the expression of the solar power radiance deceived on a tilted surface can be determined by the neuronal formula.

$$I_T = Q \times th(P \times X + B_1) + B_2$$

in which th is the hyperbolic tangent function.

Weights and biases P, Q, B_1 and B_2 are matrix whose elements are arbitrarily initialized. Their values will be modified and adjusted during the neural network training or learning.

2.4 The data processing

The computer processing of all this work has been done with Matlab software. It followed the processing chart shown on figure 5.

2.5 Neural network training

The neural network training is the stage during which the weights and the bias of each neuron of the MNN are adjusted to minimize the error between effective outputs and targets (values given by the learning samples). It has been accomplished according to the gradient back-propagation algorithm [2].

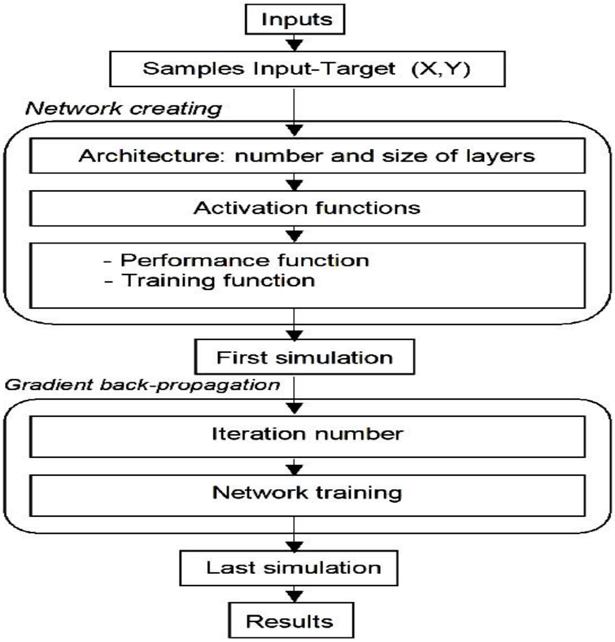


Fig. 5: Processing chart of data computing

3. RESULTS

Data used are those of the site of Fianarantsoa, Madagascar whose geographical and meteorological parameters are:

- latitude: 21,27°South; - longitude : 47,06°East;
- surface slant (inclination angle): 30°;
- monthly mean of daily clearness index, from January to December: 0,491; 0,485; 0,468; 0,495; 0,502; 0,488; 0,481; 0,507; 0,529; 0,528; 0,518 and 0,494.

These data have been first treated to form the input-target couples which would be presented to the MNN during its training.

The first results, those restored by MNN1, are the monthly mean from 6 to 18 o'clock of the global solar radiation power on tilted surface I_T in the site of Fianarantsoa, Madagascar.

They are represented on figure 6 and their numeric values are shown on **Table 1**.

Table 1: Monthly mean values of global solar radiation power upon a titled surface restored by multilayered neural network (W/m²) Inclination angle: 30°; Site: Fianarantsoa, Madagascar

Month	Q				B_2	$I_T = Q \times A_1 + B_2$
January	[83,5668	83,7904	-83,9137	83,4879]	82,2112	415,97
February	[73,9168	74,1404	-73.2637	73,8379]	72,5612	367,72
March	[59,5848	59,8084	-58,9317	59,5059]	58,2292	296,06

April	[46,6688	46,8924	-46,0157	46,5899]	45,3132	231,48
May	[33,6948	33,9184	-33,0417	33,6159]	32,3392	166,61
June	[27,2508	27,4744	-26,5977	27,1719]	25,8952	134,39
July	[29,5028	29,7264	-28,8497	29,4239]	28,1472	145,65
August	[41,3188	41,5424	-40,6657	41,2399]	39,9632	204,73
September	[58,9508	59,1744	-58,2977	58,8719]	57,5952	292,89
October	[75,5048	75,7284	-74,8517	75,4259]	74,1792	375,66
November	[85,6728	85,8964	-85,0197	85,5939]	84,3172	425,50
December	[86,0748	86,2984	-85,4217	85,9959]	84,7192	428,51

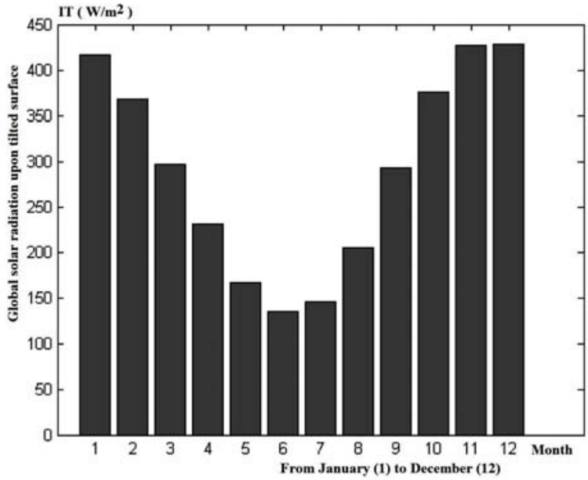


Fig. 6: Monthly mean from 6 to 18 o'clock of global solar radiation power upon a titled surface. Surface slant: 30°, Site: Fianarantsoa

Remark on I_T numerical calculation:

For each month, the numerical value of $\text{th}(P \times X + B_1)$ is:

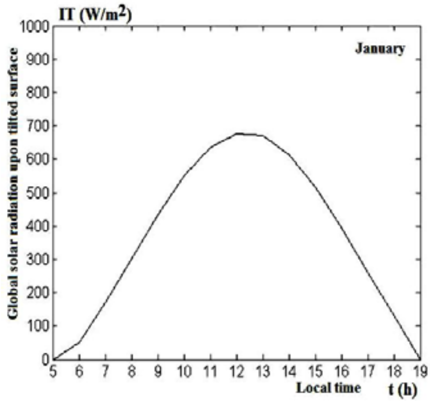
$$A_1 = \begin{pmatrix} 1 \\ 1 \\ -1 \\ 1 \end{pmatrix}$$

So I_T has been calculated by $I_T = Q \times A_1 + B_2$.

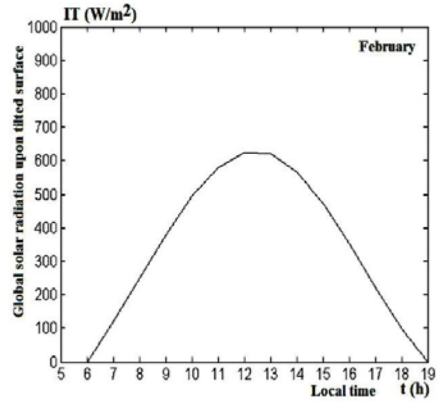
The second results series, provided by MNN2, are the hourly variation of the global solar radiation power on tilted surface at the same site during the day characteristic of the month according to Klein concept.

Numerical values are presented on **Table 2**.

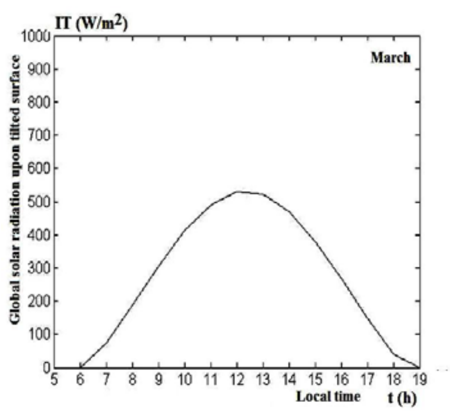
The 12 following graphes grouped on figure 7 shows the hourly variation of global solar radiation power upon a surface inclinated (inclination: 30°); Site: Fianarantsoa (latitude: 21,27° South; longitude: 47,06° East); Month: January to December.



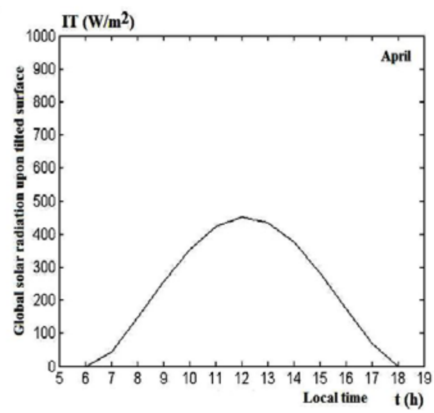
a- January



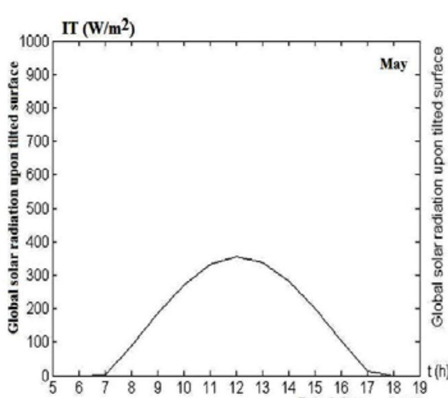
b- February



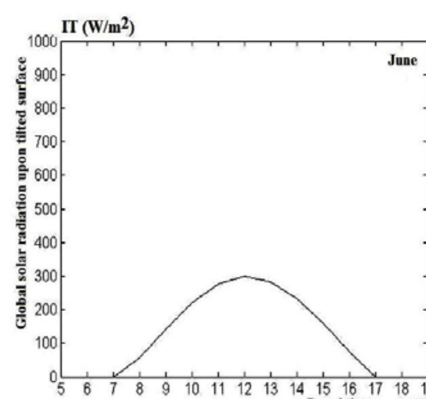
c- March



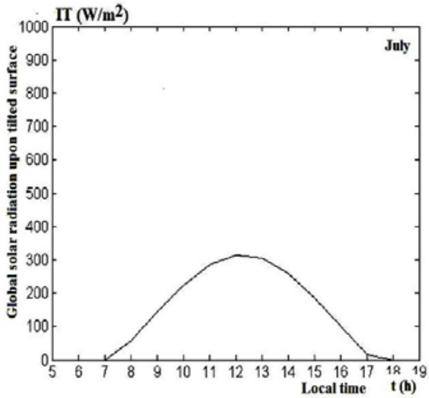
d- April



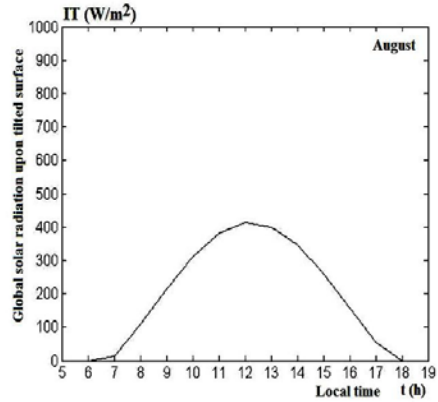
e- May



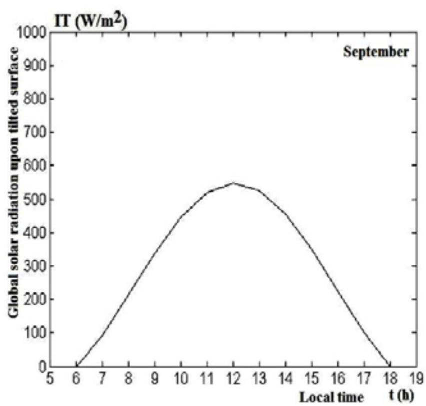
f- June



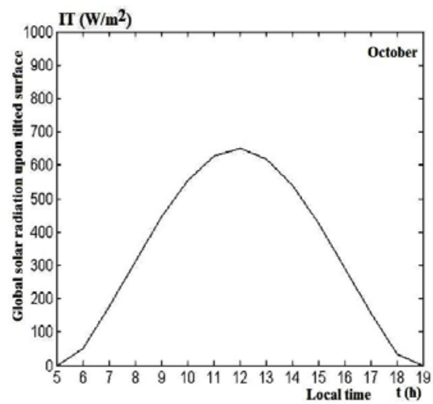
g- July



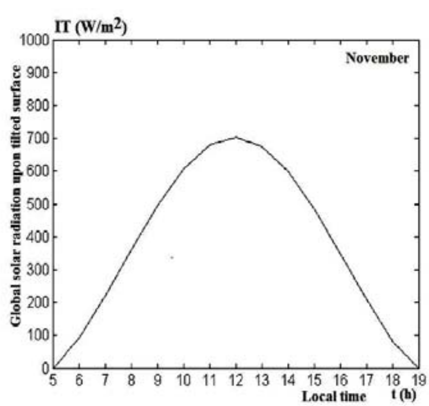
h- August



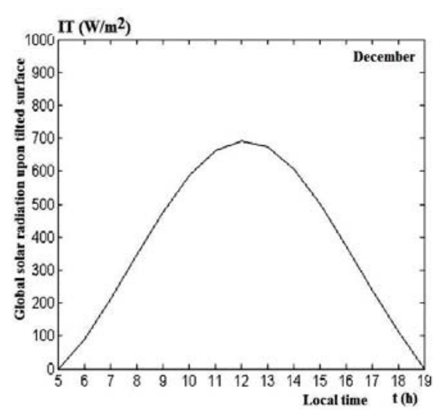
i- September



j- October



k- November



l- December

Fig. 7: Hourly variation of global solar radiation upon a surface inclinated (inclination: 30°); Site: Fianarantsoa; Month: January to December

Table 2: Hourly variation of the global solar radiation upon a tilted surface (W/m^2) restored by multilayered neural network. Inclination: 30°; Site: Fianarantsoa, Madagascar; Period: the day characteristic of each month according to Klein concept

	17Ja	1Feb	16Ma	15Ap	15Ma	11Ju	17Ju	16Au	15Se	15Oc	14No	17De
1-5	0	0	0	0	0	0	0	0	0	0	0	0
6	51,68	0	0	0	0	0	0	0		51,1	92,29	88,64
7	169,81	122,45	75,71	42,17	0,43	0	0	13,37	92,03	175,56	221,3	212,23
8	301,82	248,67	188,86	146,84	89,01	58,01	57,06	110,56	214,31	311,87	360,5	346,28
9	434,26	378,34	306,48	256,3	184,2	142,8	143,8	215,2	338,25	444,5	494,4	476,56
10	555,1	494,76	412,55	353,75	270,1	220,37	225,1	310,74	445,65	555,3	605,6	587
11	636,47	581,55	491,03	422,86	330,75	275,9	285,8	380,76	519,3	627,7	678,5	662,63
12	678,3	625,7	529,36	451,48	354,73	298,46	314,2	412,5	546,8	650,34	702,4	692,66
13	670,3	620,4	521,22	434,47	337,35	283,4	304,7	400,2	523,45	619,6	673,6	672,7
14	613,7	566,47	467,9	374,9	281,9	233,8	259,1	346,04	453,27	540,51	596,52	605,65
15	516,9	472,2	378,3	283,3	199,25	159,5	189,49	259,99	348,08	425,22	482,47	501,3
16	393,4	351,6	266,37	175,3	104,4	74,93	100,55	157,28	224,8	290,83	347,38	373,63
17	289,41	221,27	148,6	67,9	13,74	0	16,69	54,89	101,74	155,49	208,5	239,1
18	130,52	97,26	40,18	0	0	0	0	0	0	34,79	81,1	112,4
19-24	0	0	0	0	0	0	0	0	0	0	0	0

4. DISCUSSION

The results kept with MNN1 were compared in figure 8 with those by the statistical theory of Liu and Jordan.

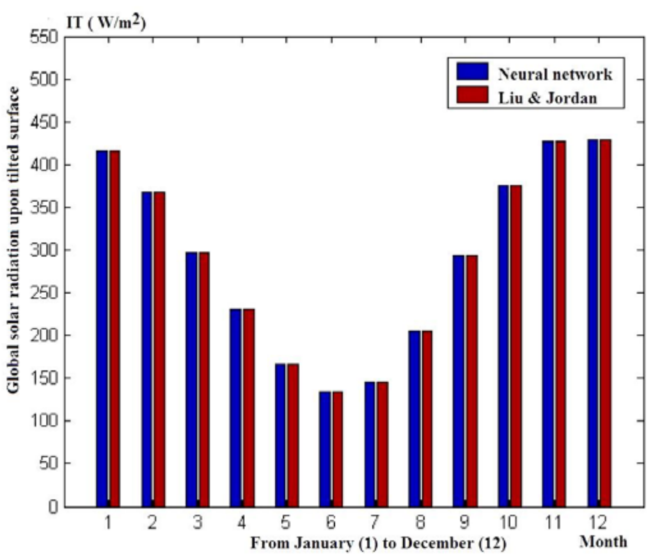


Fig. 8: Comparison of the multilayered neural network prediction of the monthly means from 6 to 18 o'clock of global solar radiation power upon a surface with those calculated by Liu and Jordan statistic theory

The results are not the same from an essay to another. This phenomenon is due to the fuzzy logic which characterizes the neural network functioning.The errors released by the neural network during its simulation are, for each month, less than 10^{-12}. So, numerical values of monthly means from 6 to 18 o'clock of global solar radiation power upon a titled surface predicted by Multilayer Neural Network are as reliable as numerical values calculated by Liu and Jordan theory.

5. CONCLUSION

This survey has shown the success of the use of the neural network method for the simplification of the results exploitation while keeping their reliability.

The monthly average values of the global solar radiations parameters and in particular the global solar radiation power on an inclined surface is recovered with this method.

The use of the model in layers requires a lot of program execution tests because the result quality and the calculation time depend on the choice of the architecture of the network: the number of layers created and the number of formal neurons in every layer, as well as the choice of the functions used and the iteration number during neural network training.

One of the perspectives is the use of the neural network in the simulation of a partially solar heating drying system.

NOMENCLATURE

I_T : Global solar radiation upon a tilted surface per time unit (W/m^2)

K_T : Daily clearness index

L : Longitude of the location (degree)

φ : Latitude of the location (degree)

β : Surface slant (degree)

MNN: Multilayered neural network

REFERENCES

[1] B.Y.H. Liu and R.C. Jordan, '*The Interrelationship and Characteristic Distribution of Direct, Diffuse and Total Solar Radiation*', Solar Energy, Vol. 4, N°3, pp. 1 - 19, 1960.

[2] M. Mohandes, S. Rehman and T.O. Halawani, '*Estimation of Global Solar Radiation using Artificial Neural Networks*', Renewable Energy, Vol. 14, N°1-4, pp.179 - 184, 1998.

[3] G. Mihalakakou, M. Santamouris and D.N. Asimakopoulos, '*The Total Solar Radiation Time Series Simulation in Athens, Using Neural Networks*', Theoretical and Applied Climatology, Vol. 66, N°3-4, pp. 185 – 97, 2000.

[4] X. Yu, O. Efe and O. Kaynak, '*A General Backpropagation Algorithm for Feedforward Neural Networks Learning*', IEEE Transactions Neural Networks, Vol. 13, N°1, pp. 251 – 254, 2002.

[5] A.S.S. Dorvlo, J.A. Jervase and A. Al-Lawati, '*Solar Radiation Estimation Using Artificial Neural Networks*', Applied Energy, Vol. 71, N°4, pp. 307 -319, 2002.

[6] K.S. Reddy and M. Ranjan, '*Solar Resource Estimation Using Artificial Neural Networks and Comparison with Other Correlation Models*', Energy Conversion and Management, Vol. 44, N°15, pp. 2519 - 2530, 2003.

[7] H.K. Elminir, F.F. Areed and T.S. Elsayed, '*Estimation of Solar Radiation Components Incident on Helwan Site using Neural Networks*', Solar Energy, Vol. 79, N°3, pp. 270 – 279, 2005.

[8] R. Iqdour and A. Zeroual, '*The Multilayered Perceptrons Neural Networks for the Prediction of Daily Solar Radiation*', International Journal of Signal Processing, Vol. 3, N°1, pp. 24 - 29, 2006.

[9] J.L. Boscha, G. López and F.J. Batllesa, '*Daily Solar Irradiation Estimation Over a Mountainous Area Using Artificial Neural Networks*', Renewable Energy, Vol. 33, N°7, pp. 1622 – 1628, 2008.

[10] K. Moustris, A.G. Paliatsos, A. Bloutsos, K. Nikolaidis, I. Koronaki and K. Kavadias, '*Use of Neural Networks for the Creation of Hourly Global and Diffuse Solar Irradiance Data at Representative Locations in Greece'*, Renewable Energy, Vol. 33, N°5, pp. 928 - 932, 2008.

[11] J. Mubiru and E.J.K.B. Banda, '*Estimation of Monthly Average Daily Global Solar Irradiation Using Artificial Neural Networks'*, Solar Energy, Vol. 82, N°2, pp. 181 - 187, 2008.

[12] P.L. Zervas, H. Sarimveis, J.A. Palyvos and N.C.G. Markatos, '*Prediction of Daily Global Solar Irradiance on Horizontal Surfaces Based on Neural-Network Techniques*', Renewable Energy 33, N°8, pp.1796 – 1803, 2008.

[13] S. Rehmana and M. Mohandes, '*Artificial Neural Network Estimation of Global Solar Radiation Using Air Temperature and Relative Humidity*', Energy Policy, Vol. 36, N°2, pp. 571 – 576, 2008.

[14] Y. Jiang, '*Prediction of Monthly Mean Daily Diffuse Solar Radiation Using Artificial Neural Networks and Comparison With Other Empirical Models*', Energy Policy, Vol. 36, N°10, pp. 3833 – 3837, 2008.

[15] J. Mubiru, '*Predicting Total Solar Irradiation Values Using Artificial Neural Networks*', Renewable Energy, Vol. 33, N°10, pp. 2329 – 2332, 2008.

[16] M.A. Behrang, E. Assareh, A. Ghanbarzadeh and A.R. Noghrehabadi, '*The Potential of Different Artificial Neural Network (ANN) Techniques in Daily Global Solar Radiation Modeling Based on Meteorological Data*', Solar Energy, Vol. 84, N°8, pp. 1468 – 1480, 2010.

[17] A. Rahimikhoob, '*Estimating Global Solar Radiation using Artificial Neural Network and Air Temperature Data in a Semi-Arid Environment*', Renewable Energy, Vol. 35, N°9, pp. 2131 – 2135, 2010.

[18] E. Davalo et P. Naïm, '*Des Réseaux de Neurones*', 256 p., Editeur Eyrolles, 1992.

[19] S.A. Klein, '*Calculation of Monthly Average Insolation on Titled Surface*', Solar Energy, Vol. 19, N°4, pp. 325 - 329, 1977.

[20] Neural Computing Research, Group NETLAB, *'Neural Network Software'*, Aston University, Birmingham, UK.

[21] B. Kosko, '*Neural Networks and Fuzzy Systems. A Dynamical Systems Approach to Machine Intelligence*', Englewood Cliffs, NJ, Prentice-Hall, 1991.