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Estimation of tilted solar irradiation using Artificial Neural Networks

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Abstract

Calculation of solar global irradiation on tilted planes from only horizontal global one is particularly difficult when the time step is small. We used an Artificial Neural Network (ANN) to realize this conversion at an hourly and 10-min time step. The ANN is developed and optimized using five years of solar data. The accuracy is respectively for hourly and 10-min data of 6% and 9% for the RMSE and 3.5% and 5.5% for the RMAE i.e. similar or slightly lower than the errors obtained with conventional empirical correlations for hourly data.

Keywords: Solar radiation; Articial neural network; Model; Tilted planes; Global solar radiation.

1. Introduction

If monthly average values allow to realize a preliminary sizing, daily values and even better hourly values are required if we want to perform a more correct and precise sizing particularly when an energy storage mean or an electrical power buffer is in the system. In commercial software for solar systems, the inclination of collectors is requested, the software "inclines" the horizontal global irradiation contained in the database with generally a low accuracy. It is useless to develop precise physical models if the input data are too approximated.

As said by Behr [1], three main reasons make it impossible to develop a simple model for converting horizontal global solar radiation into tilted radiation:

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- the radiations incident on tilted planes include the radiation reflected by the environment;
- when the plane is tilted, only a portion of the sky is "seen" and the sky diffuse component depends on the inclination and orientation of the collector, on the sun elevation and azimuth but also on the sky conditions rarely uniform. This induces complex anisotropic effects. There are two main problems for this sky anisotropy: the circumsolar brightness due to solar radiation diffusion by aerosols (around the sun) and the horizon brightness near the horizon.
- at last, these data are relatively rare.

2. Solar radiation components

When solar radiation enters the earth's atmosphere, the incident energy is removed by scattering and absorption. The scattered radiation is the diffuse radiation. A part goes back to the space and another one reaches the ground directly in line from the sun, the beam radiation. The solar radiation on a tilted collector has a beam component, two diffuse ones from the sky and from the ground (Fig. 1).

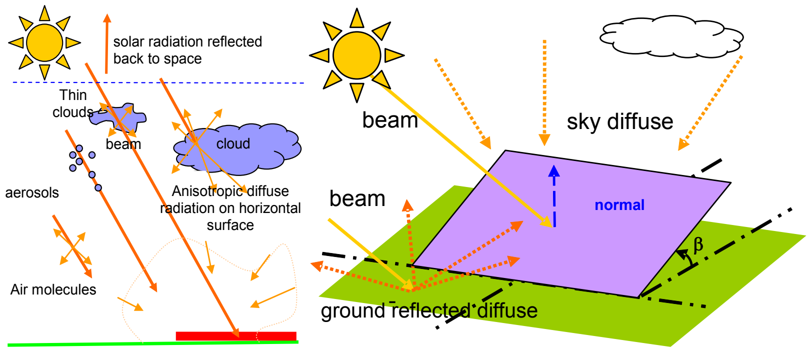

Fig. 1. Solar radiation on an horizontal and tilted surface.

3. The experimental data and validation tests

Measures are realized in our laboratory in the gulf of Ajaccio (41°55' N; long: 8°55' E) at about 200 m from the sea at an altitude of 70 m (Fig. 2) with an insular Mediterranean climate. The data are measured each minute. For the normal beam irradiance, a pyrheliometer Kipp & Zonen at normal incidence is mounted on an automatic Solar Tracker SMT-3. Every two days, the pyrheliometer is cleaned and its alignment verified. The global irradiance on 0°, 45° and 60° tilted surfaces is measured by three Kipp & Zonen (CM11) pyranometers. The experimental data were collected since January 2006. We have 5 years of minute data of horizontal global irradiance, normal beam irradiance and 45° and 60° inclined global irradiance. Four calculated parameters are added: horizontal extraterrestrial and diffuse irradiance, solar declination and the zenith angle [2].

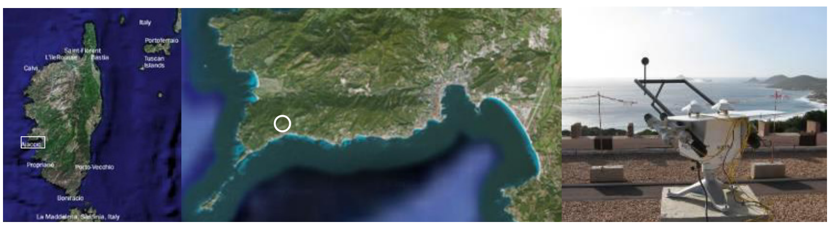

Fig. 2. Position of the Meteorological site and the solar measuring station

Some quality control tests are imposed on these minute data in order to extract outlier or missing data [3-4]. Then the 10-min and hourly values are calculated (we allowed 10% of missing data over the given period). A second quality control [5] is applied to the 10-min and hourly data, and all data that do not comply with the following conditions are not used. Very often, the sunset and the sunrise induce some problems in the correlations, because of the mask effect of the environment and due to the bad response of pyranometers when the zenith angle is high (cosine effect) [5]. Thus, we extracted these sunset and sunrise periods. After these verifications, over the 5 years, we have 18 615 validated hourly data (1.5% of missing data) and 101140 validated 10-min data (6.46% of missing data). Thus, we have monthly files for 10-min and hourly data containing : day, hour, declination, zenith angle, horizontal global irradiation, normal beam irradiation, extraterrestrial irradiation, global irradiations on a 45° and 60° tilted plane.

4. Artificial Neural Networks (ANN)

An ANN is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain process information. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. The goal of this network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. An ANN has a parallel-distributed structure and consists in a set of processing elements called neurons. The ANN structure consists in:

- an input layer which receives data;
- an output layer to send computed information;
- one or several hidden layers lying the input and output layers.

According to the architecture, all or a part of the neurons in a layer are connected with all or a part of the neurons of the previous and next layer. The number of hidden layers and of neurons of each layer depends on the specific model, convergence speed, generalization capability, physical process and the training data that the network will simulate [6]. A typical artificial neuron and the modeling of a multi-layered neural network are shown in Fig. 3. The signal flow from inputs $x_{k,1}$, $x_{k,2}$,…, $x_{k,p}$ of a layer k is considered here as unidirectional (feed forward). The output signal O to the j^{th} neuron of the following layer (k+1) is given by [7]:

$$O = f(net) = f\left(w^T x_k\right) = f\left(\sum_{j=1}^{p} w_{k,j} x_{k,j}\right) \qquad (1)$$

where $w_{k,j}$ is the synaptic weights (k is the layer index, j is the neuron index) and $f(net)$ is referred to as an activation or transfer function. The variable net is the scalar product of the weight and input vectors. T is the transpose of a matrix. The result of this sum, net, is then transformed by a transfer function f which produces the output O of a neuron if this sum exceeds a certain threshold. The output is then distributed to other neurons as inputs.

There are two main problems concerning the ANN implementation: specifying the network size (number of layers in the network and number of nodes in each layer) and finding the optimal values for the connection weights. An insufficient number of hidden nodes may be the cause of difficulties in learning data whereas an excessive number of hidden nodes might lead to unnecessary training time with marginal improvement as well as make the estimation for a suitable set of interconnection weights more difficult [8]. To determine the optimal number of hidden nodes; the common method used is trial and error based on a total error criterion. This method starts with a small number of nodes, gradually increasing the network size until the desired accuracy is achieved.

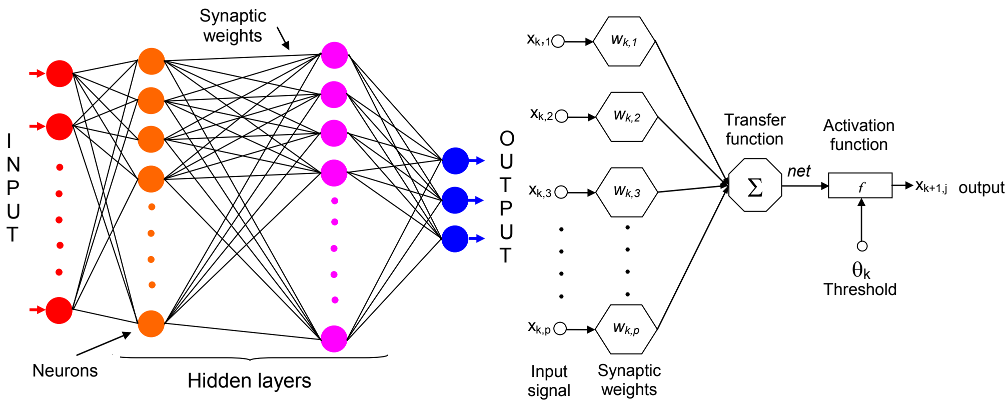

Fig. 3. Architecture of an artificial neuron and a multilayered neural network.

One of the properties of ANNs is their ability to learn from their environment and to improve their performance through a learning process called also training process. Learning results in a change in the weights value $w_{k,j}$ connecting the neurons from one layer to another. The goal is to achieve equality between the actual output and simulated output. It is therefore necessary first to choose the learning algorithm and to define the part of the data used for learning in relation to the total amount of data available. The various steps in the implementation of an optimized ANN consist in selecting:

- ANN structure;
- transfer function type;
- ANN size (number of layers and number of neurons per layer);
- learning algorithm;
- training/test set;
- input data

5. ANN Implementation

From a bibliography review [9], we chose for the ANN implementation :

1. Structure: a MultiLayer Perceptron (MLP) using feed-forward back-propagation;
2. Transfer function : the combination of a sigmoid and a linear transfer functions allows a good approximation of several types of functions.
3. Learning algorithm: the Levenberg–Marquardt algorithm (LM) is an approximation to the Newton method used during the training;
4. Training/test set : among the available data, we must use a percentage for the training and the rest for the testing. As proposed by Dreyfus [10] we must use more than 50% of data for the training phase. Thus, we decided to take 3 whole years of data for training (60%) and 2 whole years (40%) for testing;
5. ANN size: whatever the number of inputs, the ANN has to be as simple as possible. These configurations give the best results with a small error. The compromise between the number of hidden layers and the number of neurons in each layer allows to obtain a fast and robust network giving the best results. A large sized architecture requires more data and easily becomes over-trained, i.e unable to generalize efficiently. There is no mathematical method allowing the optimal sizing of the ANN; the choice of the optimal structure is done only after testing different configurations and estimating their performance.

6. Input data: the declination represents the position of the Earth from the Sun and depends on the day number. The sun position influences the quantity and the quality of the sun radiation: when the sun is high in the sky (low zenith angle), the solar radiation is maximal (in clear skies) and as the optical path is minimal, therefore the incident radiation is less absorbed. This position is characterized by the zenith angle. Depending on the season and sky conditions, several values of inclined solar irradiation correspond to the same horizontal irradiation. In diffuse radiation models, the clearness or the diffuse index are used to take account of sky condition which is an important parameter in the repartition of diffuse and beam radiations. The higher the clearness index is, the clearer the sky is and the more is global radiation composed of beam radiation. The extraterrestrial irradiation is used as reference and is useful as an input parameter. Thus, the input parameters will be: i) the declination, ii) the zenith angle, iii) the horizontal global and iv) the extraterrestrial horizontal solar irradiation. We developed three ANNs for hourly and 10-min time step (Fig. 4):

- the first one for the estimation of global horizontal on a 45° tilted plane;
- the second one for the estimation of global horizontal on a 60° tilted plane;
- the third one for the estimation of global horizontal on a 45° or 60° tilted plane;

In case 3, the number of input data is doubled because each value of hourly global horizontal irradiation is entered twice, with β=45° and with β=60°.

We use a two hidden layers model and we optimize it in varying the number of neurons in each hidden layer. We varied the number of neurons in the first hidden layer from 15 to 50 and in the second one from 5 to 50; we limited the number of hidden layers to two because the ANN must be as simple as possible.

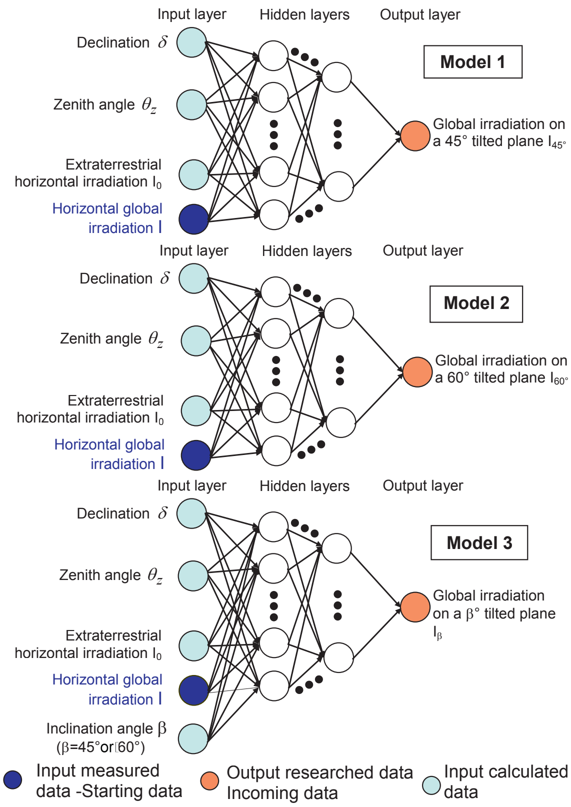

Fig. 4. The three ANN models.

We tested various configurations of monolayer and double layer ANN for the three models presented above and the best configurations are shown in Table 1. The decision criteria are applied to the whole data (training set and test set) using the RRMSE, the RMAE and the CC values defined by equation (2). The models being nonlinear, the training results depend on the initial values of the model inputs. Thus, each configuration has been tested 6 times.

$$\mathrm{RMAE} = \sum_{i=1}^{N} \left| y_i - x_i \right| \Big/ N\bar{x} \quad \mathrm{RRMSE} = \left[\sqrt{\left(y_i - x_i \right)^2 / N} \right] \Big/ \bar{x}$$

$$\mathrm{CC} = \left[\sum_{i=1}^{N} \left(y_i - \bar{y} \right)\left(x_i - \bar{x} \right) \right] \Big/ \left\{ \left[\sum_{i=1}^{N} \left(y_i - \bar{y} \right)^2 \right] \left[\sum_{i=1}^{N} \left(x_i - \bar{x} \right)^2 \right] \right\}^{1/2} \qquad (2)$$

y_i and x_i are the estimated and measured values and the respective average values are given by $\bar{x} = \sum_{i=1}^{N} x_i$ and $\bar{y} = \sum_{i=1}^{N} y_i$ where N is the data number.

Table 1. Best configurations for the ANN and adequacy parameters

Model number	Inclination β	Neurons per layer		RRMSE %	RMAE %	CC
Hourly data						
1	45°	25	15	5.28	2.79	0.998
2	60°	30	20	6.24	3.42	0.998
3	45°/60°	25	20	6.62	3.93	0.997
10-min data						
1	45°	12	0	8.10	5.02	0.996
2	60°	24	0	10.11	5.75	0.994
3	45°/60°	12	0	9.46	6.01	0.995

Several remarks can be made:

- The optimal structures are not the same for hourly and 10-min data;
- For the 10-min data, the best results are obtained for a monolayer ANN composed of 12 neurons in its hidden layer for model 1 and 3 and with 24 neurons for model 2 with an RRMSE between 8.10% and 10.11% and a RMAE between 5.02% and 6.01%;
- For hourly data, the best results are obtained for a double-layer ANN with an RRMSE between 5.28% and 6.62% and a RMAE between 2.79% and 3.93%;
- The errors are higher for 60° than 45° and in the literature, this observation is also realized for empirical model and is due to the greater influence of the sky anisotropy on the diffuse radiation when the inclination angle is high;
- The model 3 proposing to generalize the first two models, gives the worst results.

To illustrate the good reliability of the developed models, we show in Figs. 5 to 6 the estimated data versus the experimental data for the model 1 for hourly data and the model 2 for 10-min data. We randomly selected periods of days for which we plotted the experimental and calculated data (Figs. 7-8).

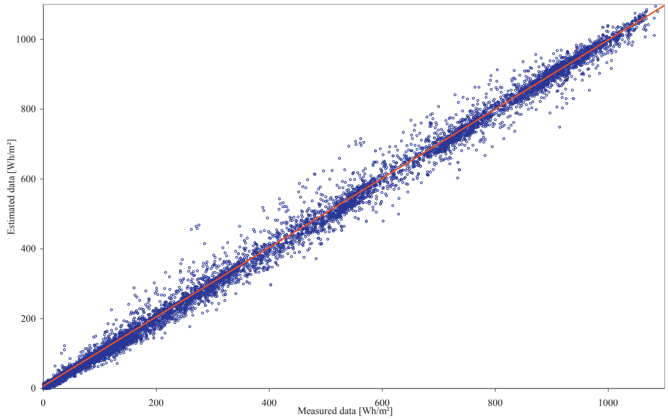

Fig. 5. Validation of model 1: estimation of hourly global irradiation on a 45° tilted plane.

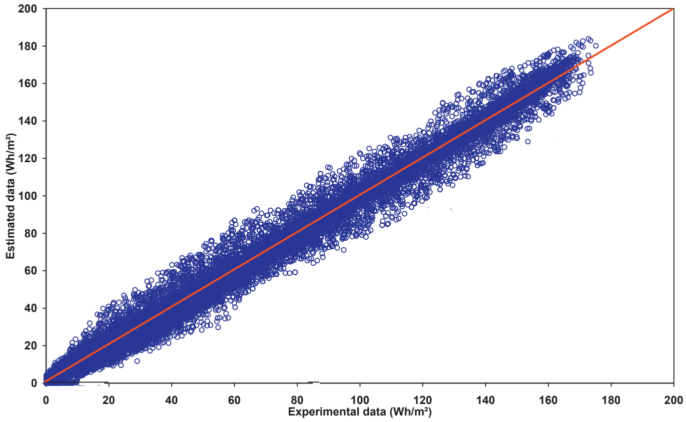

Fig. 6. Validation of model 2: estimation of 10-min global irradiation on a 60° tilted plane.

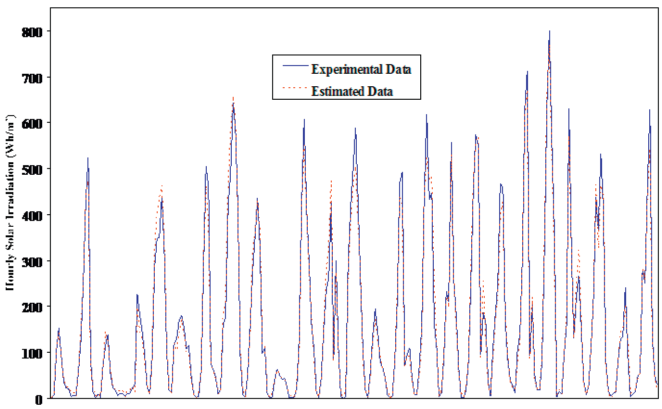

Fig. 7. Validation of the model 1 over few days for hourly data.

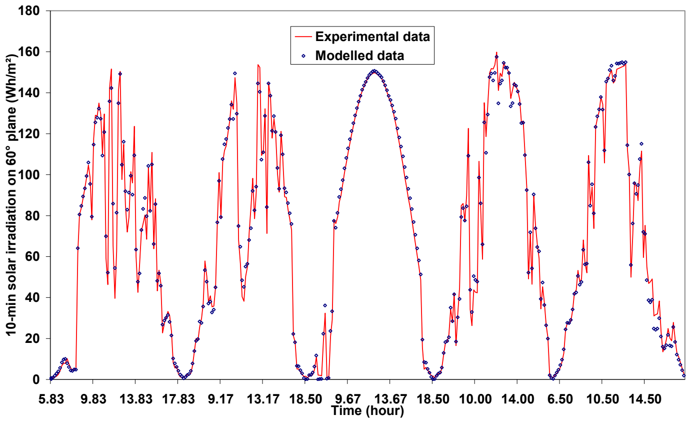

Fig. 8. Validation of the model 2 over few days for 10-min data.

6. Comparison with models of the literature

There are a number of models available to estimate global radiation on inclined surface from horizontal radiation. But, these models require information at the same time on the global and the beam or diffuse radiation on a horizontal surface. Olmo et al [11] developed a model only requiring the global radiation, the sun'azimuth and elevation. Another method consists in coupling two types of models as illustrated on Fig. 9: model for the estimation of horizontal diffuse solar radiation from the horizontal global one and model for computing the global solar radiation on tilted planes from horizontal global and diffuse radiations.

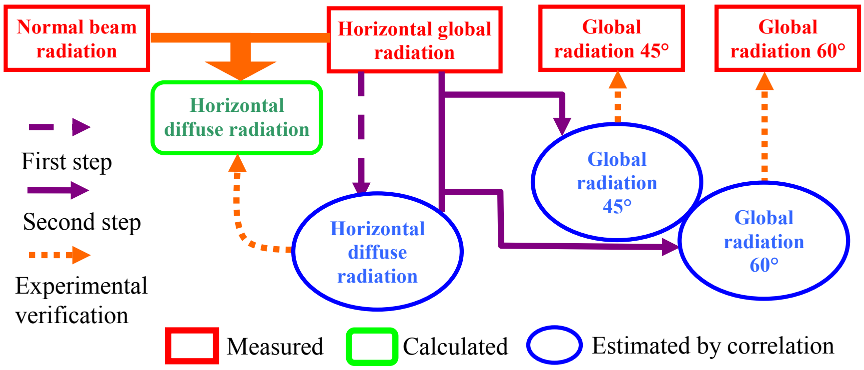

Fig. 9. Conventional method in two steps.

94 combinations were tested in Ajaccio by Notton et al [12] using 7 horizontal diffuse solar irradiation models [13] and 15 tilted diffuse solar irradiation models [14]. The RRMSE obtained with these combinations are around 10% and the best combination conduces to a RRMSE of 8.11% for 45° and 10.71% for 60° [12]. With the Olmo method [11], RRMSE was only 12.14% for 45° and 17.01% for 60°. A comparison between our ANN methods with conventional one is shown in Fig. 10.

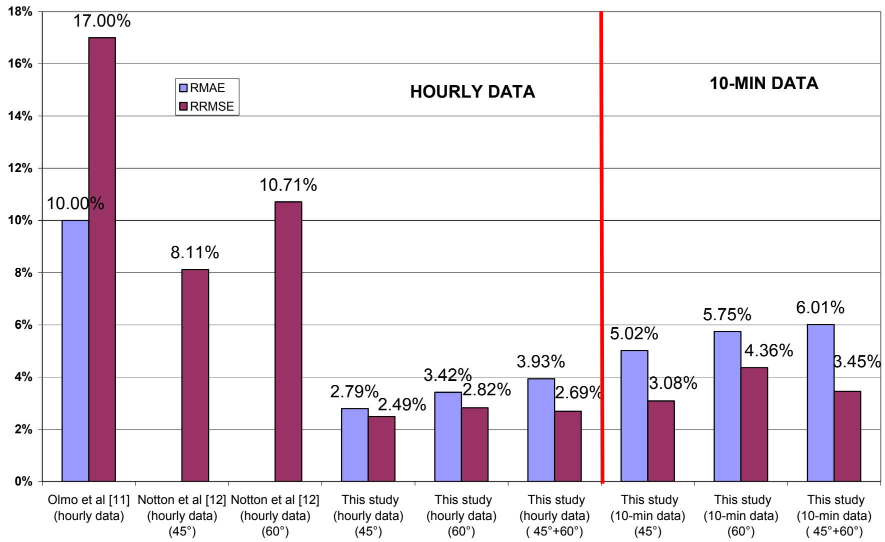

Fig. 10. Comparison of the adequacy of conventional methods with ANN methods.

7. Conclusion

We developed three models of solar global irradiation on tilted plane from horizontal ones using Artificial Neural Networks successively for hourly and 10-min data. This study was performed by using five years of 10-min solar and hourly radiation data collected in the Mediterranean site of Ajaccio, France. The choice of the ANN type and transfer functions were realized from a bibliographical study. Using a sensitivity analysis, we optimized the ANN architecture. 4 input parameters were used in these models (5 for the third model).

The adequacy of the ANN models is very satisfying, better than that obtained with empirical models for hourly time-step. For 10-min data estimation, the ANN methodology shows a good adequacy. This ANN approach out-performs the traditional methods for this type of estimation.

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