sinc(i) Research Center for Signals, Systems and Computational Intelligence (fich.unl.edu.ar/sinc)
C. R. Sánchez Reinoso, M. Cutrera, D. H. Battioni & R. H. Buitrago; "Photovoltaic generation model as a function of weather variables using artificial intelligence techniques"
International Journal of Hydrogen Energy, 2012.

PHOTOVOLTAIC GENERATION MODEL AS A FUNCTION OF WEATHER VARIABLES USING ARTIFICIAL INTELLIGENCE TECHNIQUES

Sánchez Reinoso C.R.(1)(2)(3), Cutrera M.(3), Battioni M.(3), Milone D.H.(2), Buitrago R.H.(3)

(1) Research Center for Signals, Systems and Computational Intelligence (SINC), Faculty of Engineering and Water Sciences UNL-CONICET, Ciudad Universitaria, (3000) Santa Fe, Argentine - csanchezreinoso@fich.unl.edu.ar, csanchezreinoso@santafe-conicet.gov.ar
(2) Institute of Technological Development for the Chemical Industry (INTEC) UNL-CONICET, Guemes 3450, (3000) Santa Fe, Argentine.
(3) Center for Design and Optimisation of Systems (DOS), Faculty of Engineering and Applied Sciences, National University of Catamarca, Maximio Victoria 55, (4700) Catamarca, Argentine.

ABSTRACT

The optimisation of photovoltaic systems of electricity generation involve the necesity of real data of the different variables as well as determination of their relationships. In the field of photovoltaic solar energy there is interest to predict the energy generation in terms of solar radiation and climatic parameters. For this purpose, it is needed a good sensing and measurement of these parameters.
In this paper, we propose a method based on artificial intelligence techniques for obtaining the generated energy under climatic conditions during a year. In addition, we propose a model that relates short-circuit current with radiation, considering the true nonlinear behavior of the relationship between variables.
The results of the proposed method using real data show its validity and usefulness in predicting the generated energy by photovoltaic modules and the search for alternative methods of measuring global radiation at low cost and reasonable error.

Keywords: Photovoltaic energy, measurements, generation prediction, artificial intelligence.

1. INTRODUCTION

When planning an installation project for photovoltaic power generation, it is essential to know the availability of solar resource and meteorological parameters information. It is allowed to estimate the available energy for installation throughout the year or at any given time. Furthermore, to achieve this purpose it is necessary a correct measurement of the variables involved, and determine what is most important.
Due to the importance of measuring the available solar energy in a particular location, it is frequently used mathematical models, some of then complex [1-3]. However, some studies use models of neural networks. They are able to find relations between various data and to be useful in determining the parameters of solar modules [4-5], in the estimation of the incident radiation [6 -11] and simulation of electric energy generation systems [12-13]. One of the characteristics of neural models is that they are black box models and therefore, do not provide an explicit function of the physical variables involved.
It is presented the first results of relationship between global radiation and short-circuit current, also considering the weather parameters. Then, it is obtained the dependence of the electrical energy generated by the modules of the climatic variables. In both cases the idea is to obtain explicit functions that allow an alternative model of the phenomena under study.Conclusions are summarized in the last section.

sinc(*i*) Research Center for Signals, Systems and Computational Intelligence (fich.unl.edu.ar/sinc)
C. R. Sánchez Reinoso, M. Cutrera, D. H. Battioni & R. H. Buitrago; "Photovoltaic generation model as a function of weather variables using artificial intelligence techniques"
International Journal of Hydrogen Energy, 2012.

2. MEASUREMENTS

On a rack located on the campus of the National University of Litoral in Santa Fe, Argentine, whose latitude is 31 º 42 'S, mounted 4 modules SOLARTEC of 42 Wp with the following angles to the horizontal plane: 0, 24, 36 and 58 degrees. The modules were installed on vegetation ground level, oriented in a northerly direction, at any time receiving shadows from trees or buildings. Data were obtained from temperature and relative humidity. These data are from the meteorological station installed on the campus of the Meteorological Research Center from the Faculty of Engineering and Water Sciences of the UNL. A data acquisition system designed in our laboratory at the Institute of Technological Development for the Chemical Industry (INTEC) was used to measure the short circuit current Isc, the open circuit voltage V_{oc}, the temperature of the modules, all of then every 5 minutes, and I-V curves at 10, 14 and 16 hours. These measurements were carried out uninterruptedly for a quarter, from January to April 2011. Simultaneously, we used two Kipp & Zonen CM 6 solarimeters to measure the horizontal global solar radiation and diffuse radiation. In the latter case, we used a ring provided by Kipp & Zonen. It was mounted to shade the detector, whose position is corrected according to a weekly shift of the angle of the sun with respect to the horizon. It is corrected the diffuse radiation, as indicated in the solarimeters manual for CM 11/121 shadow ring.
The energy generated by the modules in Wh was calculated using the following equation:

$$E = FF\ I_{CC}\ V_{OC}\ t \quad (1)$$

where FF is the fill factor of modules calculated daily from the I-V curve measurements, I_{sc} is the short circuit current, V_{oc} is the open circuit voltage and t is the time interval between measurements, 5 minutes in this case.

3. EVOLUTIONARY MODEL

Having a set of climate parameters and measurements of energy generated by the modules, we searched for relationships to estimate the energy generated by a photovoltaic system in Santa Fe city, using meteorological data. In general the data are not linearly related and besides it shows some dispersion. Therefore, there is an alternative to use neural networks. This technique only allows black box models.
Other study carried out is referred to the behavior of the global radiation as function of short circuit current and climatic variables. The aim is to obtain an explicit model of the variables so as to employ methods of genetic programming.

3.1 Evolutionary computation

Evolutionary Computation (EC) is based on the paradigm of Neo-Darwinism and the evolutionary process intended to simulate on a computer [14]. To achieve its objective, it is required the following elements [15]:

-A representation for potential solutions to the problem.
-One way to create an initial population of these potential solutions.
-An evaluation function that plays the role of the environment, comparing the solutions in terms of their ability.
-Genetic operators that alter the composition of the offspring.
-Values for the technique parameters (population size, probabilities of applying genetic operators, etc.).

The EC has been applied in search problems, optimisation and machine learning, where solutions are hard to find through conventional techniques, because the search spaces are extremely large, complex and often difficult to meet with restrictions.

sinc(*i*) Research Center for Signals, Systems and Computational Intelligence (fich.unl.edu.ar/sinc)
C. R. Sánchez Reinoso, M. Cutrera, D. H. Battioni & R. H. Buitrago; "Photovoltaic generation model as a function of weather variables using artificial intelligence techniques"
International Journal of Hydrogen Energy, 2012.

The algorithms used in the EC manipulate a set of potential solutions, which implies a high degree of parallelism because they explore various regions of the search space at once. Their operators are probabilistic, not deterministic, which prevent an easy entrapment in local optima.
In artificial intelligence the EC is considered as a set of sub-symbolic heuristics, because they represent the knowledge of numerical and non-symbolic (as opposed to expert systems that use symbolic representation).

3.2 Genetic programming

One of the main variants of the evolutionary techniques is the Genetic Programming (GP). It was proposed independently by N. L. Cramer and John Koza. They suggested a tree structure to represent a program in a genome [16]. Koza's work differs from Cramer, he succeeds in automating the fitness function, which is the main reason why this proposal has been popularized.
Individuals in the PG are hierarchically structured computer programs.
Individuals are formed by sets of terms and functions, which act as underlying primitive for the construction of programs. The set of terms consists of the variables and constants that are used as arguments to functions. The terms are considered as leaves in the tree structure. The functions set is composed of arithmetic operators while the binary operators or functions of specific domain, and the tree are called nodes of type function [16, 17, 18].

The basic algorithm for PG [19, 16, 17, 18] is shown below:
• Initialize the population.
• Evaluate existing programs in the population and assign a fitness value to each individual.
• Until the new population is complete:
- Select one or more individuals in the population using a selection process.
- Run the genetic operators or individuals in the selected population.
- Insert the new individuals in new population.
• Replace the existing population by a new one to meet the criteria for termination.
• Present the best individual in the population.
The used selection methods are proportional selection, selection by tournament and selection of uniform state.
To implement the crossing operator must follow the following steps
• Select two individuals as parents.
• Randomly select a subtree or segment of instructions.
• Swap the subtrees or segments of code between the two parents.
• Avoid substitutions terminal node at the root node.
In PG, there are four operators (which are applied in a low percentage of the population) [16, 17, 18]:
1. Mutation. A node is selected at random and the subtree is changed by a new randomly generated.
2. Permutation. A node is selected at random and rearranged the arguments of the subtree.
3. Edition. It is choosen a random point and decreases according to a set of rules.
4. Encapsulation. Are identified potentially reusable subtrees.

4. RESULTS

4.1 Variables related to global radiation

In the first stage of the experiments, there are two objectives. One is to find the relationship between the short circuit current and global radiation. First, this involves to study most relevant variables of the problem, then find an explicit function that determines the value of global radiation.
Experiments were conducted to train the genetic program with data from short-circuit current, temperature, cell temperature, relative humidity, diffuse radiation, direct radiation and global

sinc(i) Research Center for Signals, Systems and Computational Intelligence (fich.unl.edu.ar/sinc)
C. R. Sánchez Reinoso, M. Cutrera, D. H. Battioni & R. H. Buitrago; "Photovoltaic generation model as a function of weather variables using artificial intelligence techniques"
International Journal of Hydrogen Energy, 2012.

radiation. The latter was thought as predicted variable and the others as predictors. The data set was partitioned into training and testing. After performing a series of training, the solution was selected with the lowest test error. This solution was obtained with the following parameters: population size = 65, probability of cross = 0.5, mutation probability = 0.02.
As the error criterion used was a mean absolute error and a criterion of complexity the number of nodes in the tree representation of the solution. It is obtained a solution that fulfilled the requirement of minor error in the first place and less complexity in second place. This equation is

$$y = 0.805\,x_2 + 8.15e3\,x_1 + 27.8\ sen\left(\frac{23.5 + x_3}{4.49 + 74.9\,x_2}\right) \quad (2)$$

where x_1 is the short circuit current in A; x_2 is the module temperature in ° C; x_3 is the diffuse radiation in W/m^2, y is the global radiation in W/m^2. The solution selected is the least error, but having others with the same error, we chose the one that consisted of fewer terms. The correlation coefficient between the measured value and the calculated value by the model expression is 0.997, indicating an excellent fit to the data.
It is important to clarify that it was also considered to initialize the genetic program, other variables such as cell temperature, relative humidity, and direct radiation. During the evolutionary process, it was found solutions that did not require these variables to get a good fit of the data. Therefore, it can be said that it is not necessary to measure these variables to get a good correlation between Icc and global radiation. This behavior also indicates that a good correlation should incorporate the module temperature and diffuse radiation. If the short-circuit current is only used at the expense of an increase in the error, its relationship with global radiation is nonlinear.

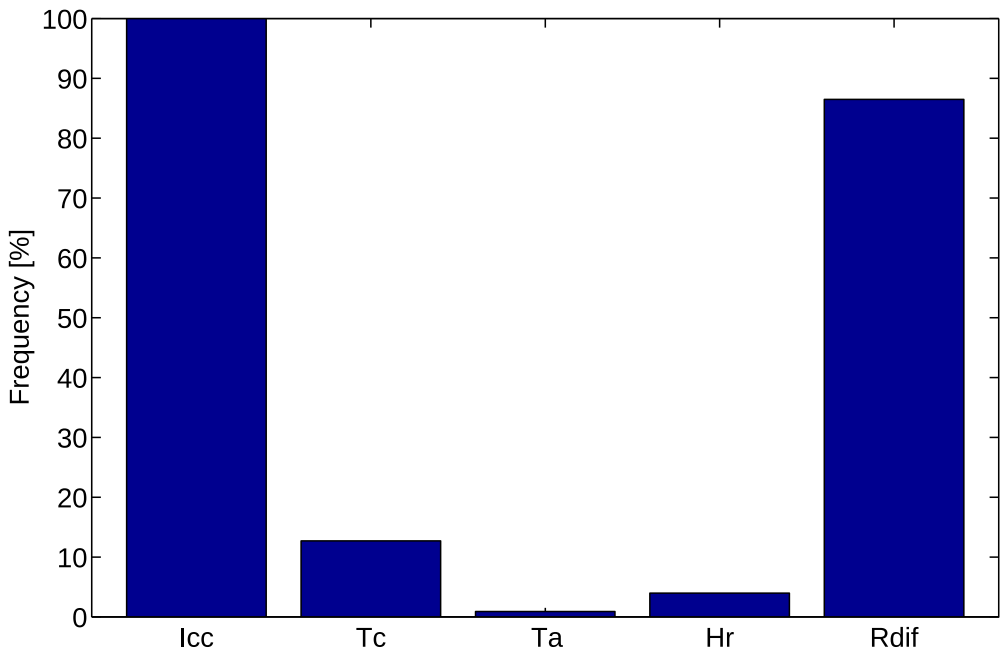

Figura 1. Frequency of variables measured on the best solutions.

Figure 1 shows a statistical analysis to determine the most relevant explanatory variables for the problem. It shows how often the explanatory variables are the solutions that have a mean absolute error of less than 0.07. Clearly the variables that contribute most to the reduction of error are the short circuit current and diffuse radiation. The maximum temperature of the module also contributes to, but less.

sinc(*i*) Research Center for Signals, Systems and Computational Intelligence (fich.unl.edu.ar/sinc)
C. R. Sánchez Reinoso, M. Cutrera, D. H. Battioni & R. H. Buitrago; "Photovoltaic generation model as a function of weather variables using artificial intelligence techniques"
International Journal of Hydrogen Energy, 2012.

The temperature and relative humidity improves the solution in a few occasions. Therefore they are not necessary if the other variables are available.

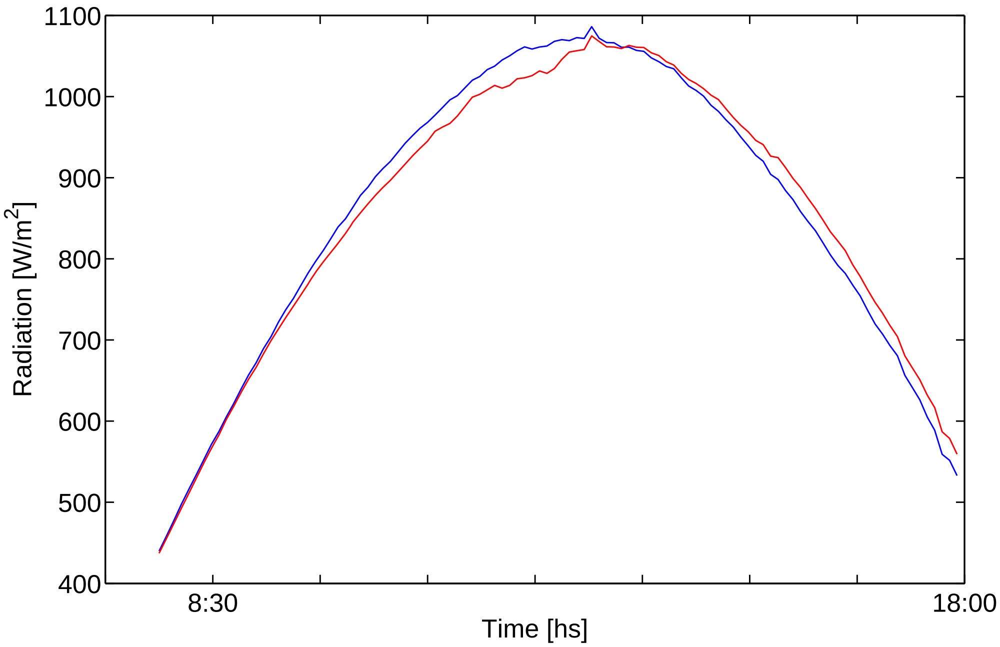

Figura 2. Global radiation as a function of climatic variables for different times of day.

Figure 2 shows the behavior of global radiation as function of the variables: short-circuit current, temperature of the module and diffuse radiation for different times of the day, for the period between January and April 2011.
The results plotted correspond to the measured data and the ones delivered by the selected model. Clearly there is a good fit of the solution found.
The expression found is useful for determining the global radiation as function of the short circuit current and weather parameters.

4.2 Energy generated as a function of climatic variables

Using real data, it is obtained explicit relationships that link the energy generated with radiation and climatic variables.
Experiments were conducted using evolutionary computation with different settings, with data partitioned into training and testing.
The tradeoff between test error and complexity it is used as a criterion for model selection. The parameters used in the search for the best solution were a
population size = 300, cross probability = 0.5, mutation probability = 0.3.
The equation obtained for the best individual was

$$y = x_2 + \frac{8.34e6}{12.7x_4 + \frac{1.42e7}{x_4} + x_1^{\;2}} - x_2 x_3^{\;0.185} \quad (2)$$

where x_1 is the day, x_2 is the module temperature in ° C, x_3 is the diffuse radiation in W/m^2, x_4 is the global radiation in W/m^2, y is the energy generated in Wh. The final solution was selected because it has fewer terms than other ones with very similar error.
Most of the solutions obtained by the algorithm include the explanatory variables of (2).

sinc(*i*) Research Center for Signals, Systems and Computational Intelligence (fich.unl.edu.ar/sinc)
C. R. Sánchez Reinoso, M. Cutrera, D. H. Battioni & R. H. Buitrago; "Photovoltaic generation model as a function of weather variables using artificial intelligence techniques"
International Journal of Hydrogen Energy, 2012.

The relationship between the predicted variable and the value calculated measure give a correlation coefficient of 0.96, indicating good performance of the function found.

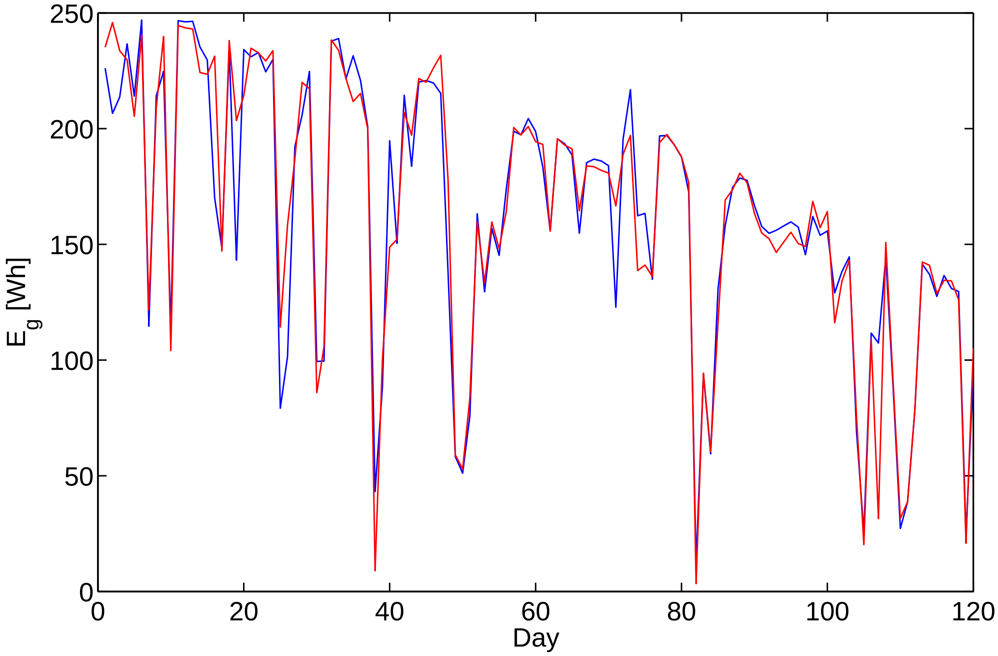

Figura 3. Energy generated as function of climatic variables and short circuit current for the different days of the year. The number of the days corresponds to data taken from January to April.

A graph of the energy generated as a function of x_1, x_2, x_3, and x_4 (Fig. 3) allows to observe a proper behavior of the model. In this graph it is shows the results for the model and measured real data. The resulting model allows an adequate prediction of the energy.

5. CONCLUSIONS

In a first stage, it was found a useful expression for determining the global radiation as function of the short circuit current and weather parameters. In the future, it will be worked to find a function whose independent variables are those that allow the use of a photovoltaic cell as a measure of global radiation with good feasibility.
Then, the generated energy function was obtained with real data from climatic variables as independent ones. The equation obtained allow to quantify the effect of changes in climatic variables and the day in the photovoltaic modules power generation. Then, the generated energy function was obtained with real data climatic variables as independent ones. The obtained equation allows to quantify the effect of changes in climatic variables and the day in the power generation of photovoltaic modules. When there are a greater amount of measured data, it will be reconsider the equations for the prediction in a year.

6. REFERENCES

[1] W.F. Philips, Harmonic analysis of climatic data, Solar Energy 32 (1984), pp. 319-328.
[2] A.C. Herrero, Harmonic analysis of monthly solar radiation data in Spain, Ambient Energy 14 (1993), pp. 35-40.
[3] A. Dorvlo and B. Ampratwum, Modeling of weather data for Oman, Renewable Energy 17 (1999), pp. 421-428.

sinc(*i*) Research Center for Signals, Systems and Computational Intelligence (fich.unl.edu.ar/sinc)
C. R. Sánchez Reinoso, M. Cutrera, D. H. Battioni & R. H. Buitrago; "Photovoltaic generation model as a function of weather variables using artificial intelligence techniques"
International Journal of Hydrogen Energy, 2012.

[4] E. Karatepe, M. Boztepe and M. Colak, Estimation of equivalent circuit parameters of PV module using neural network, IJCI Proceedings 1 (2003), pp. 76-78.

[5] G. Tamizh, L. Ji, Y. Tang, L. Petacci and C. Osterwald, Photovoltaic module thermal/wind performance, NCPV and Solar Program Review Meeting NREL 520-33586 (2003).

[6] K.H. Elminir, J. Alamjam, U.R. Ali and V. Benda, Estimation of Solar Radiations Incident on a Photovoltaic Solar Module using Neural networks, XXVI ASR Seminar, Instruments and Control, Ostrava, April (2001).

[7] F.S. Tymvios, C. Jacovides, S.C. Michaelides and C. Scouteli, Comparative study of Angström's and artificial neural networks methodologies in estimating global solar radiation, Solar Energy 78 (2005), pp. 752-762.

[8] G. López, F. Batles and J. Tovar, Selection of input parameters to model direct solar irradiance by using artificial neural networks, Energy 30 (2005), pp. 1675-1684.

[9] A. Serrano, P. Lucio, A. Silva and S. Leite, Meteorological Time Series Reconstruction via Artificial Neural Network, Geophysical Research 8 (2006), 00879.

[10] A. Mellit, M. Benghanem, A. Hadj and A. Guessoum, A simplified model for generating sequences of global solar radiation data for isolated sites: Using artificial neural network and a library of Markov transition matrices approach, Solar Energy 79 (2005), pp. 469-482.

[11] L. Hontoria, J. Aguilera and P. Zufiria, A new approach for sizing stand alone photovoltaic systems based in neural networks, Solar Energy 78 (2005), 313-319.

[12] C.R. Sánchez Reinoso, D.H. Milone and R.H. Buitrago, Efficiency study of different photovoltaic plant eficiency connection schems under dynamic shading, International Journal of Hydrogen Energy 35 (2011), pp. 5838-5843.

[13] C.R. Sánchez Reinoso, D.H. Milone and R.H. Buitrago, Desarrollo de un modelo para estudio de centrales fotovoltaicas bajo diferentes configuraciones, Eighth Latin-American Congress on Electricity Generation and Transmission (2009), pp. 1-8.

[14] L.J. Fogel. Artificial Intelligence through Simulated Evolution. John Wiley, New York; 1966, pp. 170.

[15] Z. Michalewicz. Genetic Algorithms + Data Structures = Evolution Programs. Springer–Verlag, New York, USA, third edition; 1996, pp. 387.

[16] J.R. Koza. Genetic Programing. On the Programming of Computers by Means of Natural Selection. MIT Press, Cambridge, Massachusetts; 1992, pp. 835.

[17] J.R. Koza. Genetic Programing II. Automatic Discovery of Reusable Programs. MIT Press, Cambridge, Massachusetts; 1998, pp. 768.

[18] J.R. Koza and F.H. Benett. Genetic Programing III. Darwinian Invention and Problem Solving. Morgan Kaufmann Publishers, San Francisco, California, USA; 1999, pp. 1115.

[19] W. Banzhaf, Peter Nordin, Robert E. Keller and Frank D. Francone. Genetic programming an introduction. In On the Automatic Evolution of Computer Programs and Its Applications. Morgan Kaufmann Publishers, San Francisco, California, USA; 1998, pp. 451.