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Virtual Instrumentation Applied to Identifying Parameters of Solar Radiation and Ambient Temperature Using Autoregressive Modeling with Exogenous Inputs

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Abstract: *This work describes a mathematical model developed to identify solar radiation and ambient temperature patterns in Bogota, Colombia, using autoregressive modeling with exogenous inputs (ARX). The solar radiation data and temperature used in the model were taken from the meteorological stations of Universidad de Bogotá Jorge Tadeo Lozano and Instituto de Hidrología, Meteorología y Estudios Ambientales – IDEAM from Colombia; for a period of 5 years (2011-2015). The model (ARX) was implemented using the LabVIEW graphical programming language, and allow identification of solar radiation parameters using techniques MSE. After applying the ARX model, the results showed that the correlation between the solar radiation measured by the monitoring station and evaluated by the algorithm was 86.64%; while for the temperature was 76.15% for the same period. This type of parameter identification is for application in the field of photovoltaic solar energy as it might be possible to identify future capabilities of generating electricity with solar panels.*
Keywords: *Virtual instrumentation, ARX model, radiation and temperature.*

I. Introduction

Extended research is devoted to estimate the photovoltaic infield conversion efficiency as a prerequisite for accurate design of feasible and affordable systems; literature outlines that the main factors affecting the conversion efficiency are: the PV type/materials, the amount of incident solar irradiance and the operating temperature [1,2]. These factors are further depending on specific features of the implementation location (geographical coordinates, climatic profile) and on parameters such as the ambient and PV module temperature, variation with wind, etc [3].

The energy and environment issues have become increasingly serious with the development of society, solar energy, as a kind of renewable energy, has a good application prospect. However, solar power generation has still some problems as follows: the conversion efficiency of solar cells is lower, and the output power of photovoltaic (PV) array has great relationship with irradiation and temperature [4,5,6].

Many studies have been devoted to develop different non-linear electric models used to describe the characteristics of the PV modules and the effect on module performance of temperature, radiation intensity and other parameters under non-standard conditions [7-22].

Time series models have been obtained from econometric advances, which is a science that grows from the statistics of data obtained [23]. These models are applicable to a diversity of cases in which information is arranged accordingly to analyze the information system's behaviour.

This paper describes and applies a regression ARX model to the database of solar radiation and ambient temperature data recorded in the city of Bogotá, from 2011 to 2015.

II. Theoretical Analysis

2.1. Application of ARX and MSE Models to Irradiance and Temperature Patterns

2.1.1 Model ARX

The models presented in this paper follow the structure of model ARX (autoregressive with exogenous inputs) modified for application of time series [24,25,26]. This model is built with (Input-output measured system data) data measured of input and output of a system, in which the behaviour of the system can be represented through two vectors called input regression size n + 1 and output regression size n. The coefficients aj and bj are parameters to be estimated applying any kind of numeric analysis technique, for example least squares. The term e(k) is associated to disturbances of the systems, not represented by the behaviour of an equation but by a numerical value [24,25].

$$y(k) = \sum_{j=1}^{n} a_j y(k-j) + \sum_{j=0}^{n} b_j u(k-j) + e(k) \qquad (1)$$

Now, as this is a model with exogenous inputs, we take from (1) and join the terms of the second series (bj with its respective regression) to reduce it to a constant γ, retaining its structure to represent mathematically time series as shown in (2). In this way, the new model is called model AR, since it will just depend on an output regression vector plus a constant. [24,26].

$$y(k) = \sum_{j=1}^{n} a_j y(k-j) + \gamma \qquad (2)$$

In order to be able to do one or several predictions with this model, we should shift in (2). For this shift, it is required to define the number of predictions required i, being i = 1,2,3,…N, where N is the maximum number of predictions required to obtain the expression that represents the model of prediction y(k+i). After doing this shifting, in a general manner, it remains as it is shown in (3).

$$y(k+i) = \sum_{j=1}^{n} a_j y(k-j+i) + \gamma \quad i = 1,2,\dots,N \qquad (3)$$

2.1.2 Model MSE

This is a numerical analysis technique developed by Karl Friedrich Gauss [27], which serves to optimise the square error E(k)2 among the data observed and the data estimated. The summation represented in (4) represents all the square errors to model for in the data k = 1,2,...N $k = 1,2,\dots,N$. This function will help us to calculate the coefficients of the polynomials of a transfer function that better represents the data observed [24,27].

$$J(N) = \sum_{k=1}^{N} e(k)^2 \qquad (4)$$

Taking from (2) and replacing in (4) we obtain the expression (5).

$$J(N) = \sum_{k=1}^{N} \left(\hat{y}(k) - \left(\sum_{j=1}^{n} a_j y(k-j) + \gamma \right) \right)^2 \qquad (5)$$

In order to solve (5) we should do the partial derivatives with respect to all coefficients of the transfer function to obtain a lineal equations system, which, in this case, it is represented by the multiplication of regression vectors c(n+1),1 y f(n+2),1 in (6), obtaining an equations matrix for each model in an instant k (7), then, at the end there is a summation of equation matrices given by (8) which represents the system with a transfer function of order n.

$$c(k,n) = \begin{bmatrix} y(k-1) \\ y(k-2) \\ \vdots \\ y(k-n) \\ -1 \end{bmatrix} \qquad f(k,n) = [y(k-1) \quad y(k-2) \quad \cdots \quad y(k-n) \quad -1 \quad -y(k)] \qquad (6)$$

$$M_{n+1,n+2}(k,n) = c(k,n) * f(k,n) \qquad (7)$$

$$MT_n = \sum_{k=n}^{N} M(k,n) \qquad (8)$$

Now with the total matrix of linear equations, it is necessary to apply a method of reduction to find the coefficients, in this case, we use the Gauss-Jordan method and the result of the coefficients is given by (9), where r1, r2,,...rn+1 are the result of the reduction.

$$MT_n = \left[\begin{array}{ccccc|c} a_1 & 0 & \cdots & 0 & 0 & r_1 \\ 0 & a_2 & \cdots & 0 & 0 & r_2 \\ \vdots & & \ddots & \vdots & & \vdots \\ 0 & 0 & \cdots & a_n & 0 & r_n \\ 0 & 0 & \cdots & 0 & \gamma & r_{n+1} \end{array}\right] \qquad (9)$$

Once the coefficients of the polynomial regression and the constant are obtained the model can be evaluated or make predictions with (3).

2.2 Monitoring System

The measurement system was implemented by Aristizábal et al. (2008, 2011) and extensively described in other articles [28,29]. This is installed at Universidad de Bogotá Jorge Tadeo Lozano.

The monitoring system was developed using the Virtual Instrumentation concept [30]. Thus, compact DAQ devices of National Instruments Company were used as hardware and the LabVIEW (Laboratory Virtual Instrument Engineering Workbench) package [31] was used as software. The system includes sensors and transducers for measuring the parameters required to measure the solar radiation and ambient temperature. Technical specifications of the sensors and acquisition system are as follow:

- Solar Irradiance sensor: Piranometer Kipp & Zonen SP-LITE (Response Time <1s, Sensitivity of 72µV/W/m2, spectral range 0.4-1.1 µm, stability <±2% /year, non linearity <1% up to 1000W/m2).
- Temperature sensor: 10k Thermistor (Time Constant of 2.5s, dissipation Constant of 8 mW/ºC, tolerance 0-70ºC)
- Acquisition System: NI cDAQ-9174 system with the following conditioning input modules:
- NI 9205: 32-Ch ±200 mV to ±10 V, 16-Bit, 250 kS/s Analog Input Module.
- NI 9225: 300 Vrms, Simultaneous Analog Input, 50 kS/s, 3 Ch Module.

2.3 Virtual Instruments

The signal measuring and the acquisition, processing, storing and reporting of the whole data, were achieved through a virtual instrument (VI) developed with the help of the LabVIEW package. The data were stored in the computer hard disk in a universal format, allowing their subsequent processing with LabVIEW or any other known electronic spreadsheet.

The monitoring of the whole system was performed with several sub-VI´s which are integrated to the main VI through the source code contained in the block diagram. The numerical data and graphics generated with each sub-VI can be visualized in the computer screen by activating a window displayed in the upper side of the frontal panel of the main VI [31].

Fig. 1 shows the front panel of the VI displaying numerical values of solar radiation and ambient temperature.

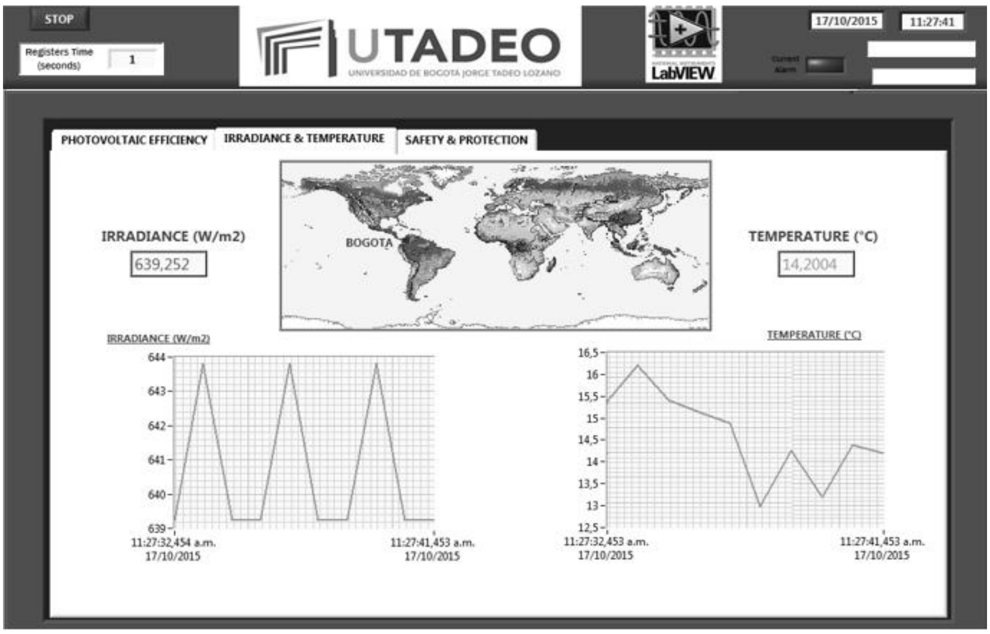

Fig. 1. Front panel of the VI developed for monitoring the solar radiation and ambient temperature.

III. Results and discussion

Solar Radiation and ambient temperature data were obtained from the meteorological station at Universidad de Bogotá Jorge Tadeo Lozano for 2015 and from IDEAM database for 2011 – 2014.

3.1 Autoregressive model implemented in LabVIEW

The algorithm with exogenous inputs (ARX) was implemented in LabVIEW and the operating process is as follows [24]:

Data to be entered by the user are: Vector of input data, vector of output data, and numbers of models to verify.

Step 1: All the local variables are initiated and the size or number of input and output vector data is calculated.
Step 2: Two vectors with entry and output data corresponding to the current order are organized, one size (n + 1) and the other (n +2), the same way as the partial derivatives are represented to identify, through MSE, a system of one entry and one output (SISO) (ec. (6)). These two vectors are multiplied to obtain a matrix of ([n+1]x[n+2]) that are added up to the matrix of the previous iteration. This step is repeated until all entry and output data are shifted.
Step 3: From the resulting matrix of the previous step, we proceed to make a reduction through the GAUSS-JORDAN method. Obtaining the coefficients of a difference equation, we can represent them as polynomials of a transfer function corresponding to the estimated model (ec. 9).
Step 4: With the coefficients of the difference equation, we move on evaluate the model with input data to obtain an estimated response. This response is compared to the real data through a correlation.
Step 5: Evaluating the correlation obtained, the order of the model that is closest to a correlation of 100% is stored. After evaluating the correlation, the order is increased and we repeat step 2, to evaluate another model of a higher order. This is done until all the orders proposed by the user, at the beginning, are checked.
Step 6: Once all the models have been evaluated, the order that has the best correlation can be obtained. We re-evaluate the coefficients for this order and in this way, find the transfer function that best represents the data.
The structure of the model used was the following [10]:

$$y(k) = \zeta - (a_1 y(k-1) + a_2 y(k-2) + \cdots + a_n y(k-n)) \qquad (10)$$

3.1.2 Solar Radiation

To obtain the most appropriate model, we entered the 60 irradiance data of Bogotá city, which are equivalent to five years (one data per month), and through MSE, we found the order 32 and the coefficients are represented in the Table 1. With $\zeta = 1.6712$, the correlation obtained was 86.64%.

a1	0,2456	a2	0,1230	a3	-0,0276	a4	0,3421	a5	0,3315
a6	0,2634	a7	-0,1982	a8	-0,1741	a9	0,4231	a10	-0,3564
a11	0,0103	a12	-0,1122	a13	0,0212	a14	-0,3657	a15	-0,2454
a16	0,0890	a17	-0,1783	a18	0,2867	a19	-0,0871	a20	0,4287
a21	-0,3177	a22	0,1163	a23	-0,4128	a24	-0,3769	a25	0,3241
a26	0,0370	a27	0,1321	a28	-0,4166	a29	0,3862	a30	0,2169
a31	-0,0132	a32	0,3538						

Table 1. Coefficients obtained for the model of solar radiation of order 32.

3.1.3 Temperature

To obtain the most appropriate model, we entered the 60 irradiance data of Bogotá city, which are equivalent to five years, and through MSE, we found the model.
The model obtained was of order 12 and the coefficients are represented in Table 2.
With $\zeta = 18.5423$, the correlation obtained was 76.15%.

a1	0,6743	a2	-0,4321	a3	0,1187	a4	-0,0046	a5	0,5341
a6	0,3731	a7	-0,1589	a8	0,1351	a9	-0,5482	a10	0,0865
a11	-0,4231	a12	-0,2461						

Table 2. Coefficients obtained for the temperature model of order 12.

In Figs. 2 and 3 we can observe the results of models that were applied for the solar radiation as well as for the temperature using the algorithm in LabVIEW.

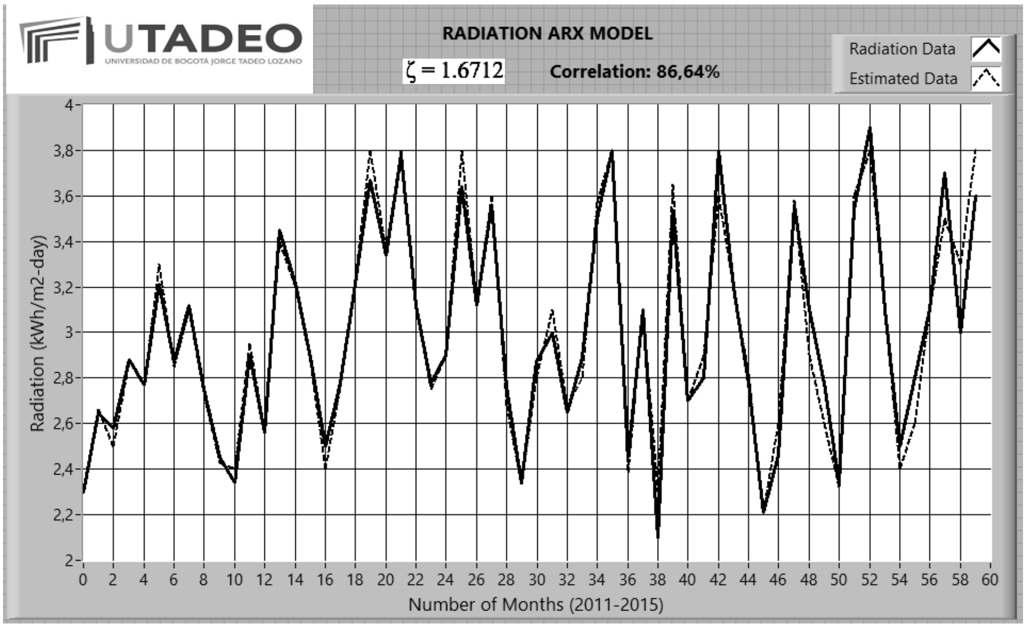

Fig. 2. Behavior for real radiation and the model estimated.

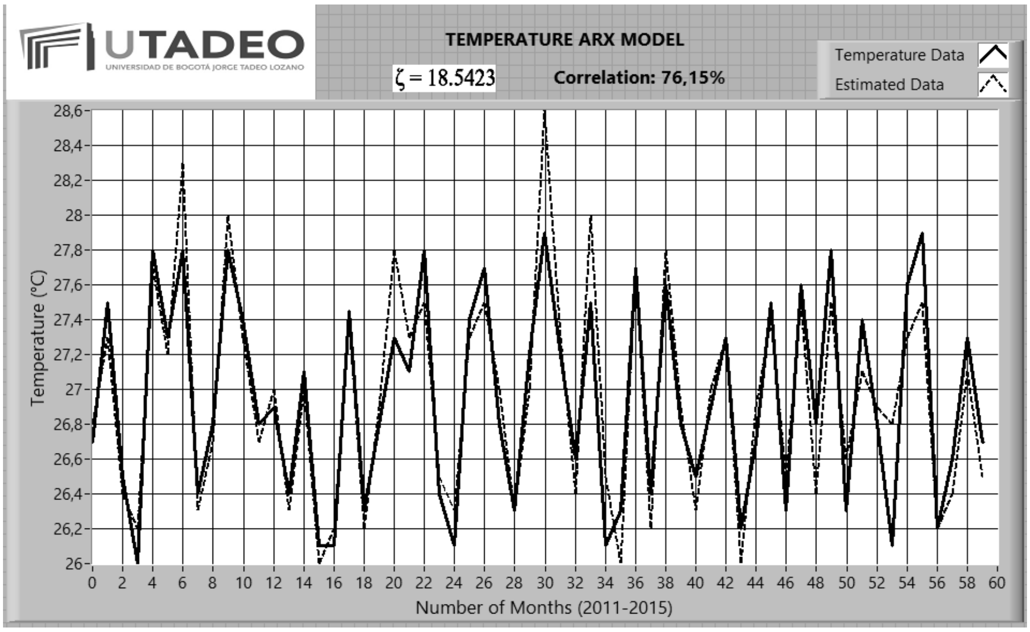

Fig. 3. Behavior for real temperature and the model estimated.

As these models need a regression vector of past data to calculate a new data, as for predicting or evaluating the model with the current data, it is necessary to know, at least, a number of data equal to the order of the model. The correlation obtained was calculated from the sample, in the same position of the order of the model, to the end of the data because just in this space it is possible to observe the behaviour of the model. This was also taken into account when drawing the graph and therefore, it is observed that the results of the graph are the same from the beginning until the data in the position of the order [24].

The results indicate the possible order of the resulting model that represents the data and the possible order of the real system. As the order increases, the program generates models unstable in their behaviour with respect to the real, causing the correlation to change significantly with respect to the previous model.

IV. Conclusion

This paper presents a descriptive analysis of the variables of solar radiation and ambient temperature for the city of Bogotá. The results obtained show the typical characteristics for these tropical regions.

The application of the autoregressive model with exogenous input allows us to obtain a polynomial for the behaviour of the solar radiation with a correlation above 86%, showing the applicability of the algorithm implemented in LabVIEW. The model obtained for temperature was of order 12 with ζ = 18.5423, the correlation obtained was 76.15%. The models applied as well as the behaviours and correlations obtained for the patterns of solar radiation and ambient temperature represent a reliable source of information that could be used to interpret the environmental variables.

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