Conference Proceedings

EuroSun 2016
Palma de Mallorca (Spain), 11 – 14 October 2016

Estimation of Global Solar Radiation from Air Temperature using Artificial Neural Networks based on Reservoir Computing

Miquel L. Alomar[1], Vincent Canals[1], Josep L. Rosselló[1] and Víctor Martínez-Moll[1]

[1] University of Balearic Islands, Palma de Mallorca (Spain)

Abstract

Solar radiation data are crucial for the design and evaluation of solar energy systems. For locations where measurements are not available, models to estimate solar radiation from more readily available data are required. In this paper, we introduce the use of the reservoir computing (RC) technique to model daily global solar radiation (GSR) as a function of air temperature. RC is a type of artificial neural network (ANN) with closed loops (recurrent neural network, RNN) particularly suited to process time-dependent information. The novelty of this work is the use of a recurrent network for modeling solar radiation, which allows including temporal correlations between the input and output variables. The proposed approach is used to estimate GSR using weather data from a location in Almeria, Spain. The results show higher accuracy than those obtained with conventional regression models.

Keywords: *Global solar radiation, modeling, artificial neural networks, reservoir computing*

1. Introduction

Reliable knowledge of solar radiation availability and variability is essential for the efficient and economical development and implementation of solar energy applications such as photovoltaic, solar thermal and passive solar systems. Long-term real measurements at the site of the proposed solar system are the ideal database for the simulations required to evaluate the performance of such application. However, solar radiation measurements are made at few locations due to the high cost of the equipment. This makes necessary the use of accurate models for locations where measured values are not available.

A number of empirical formulas have been developed to estimate solar radiation from more commonly available data at weather stations. A review of such models for global, beam and diffuse radiation is presented in Wong and Chow (2001). In the present paper, we focus on the estimation of daily global solar radiation (GSR) on the horizontal surface. Several methods for decomposing direct and diffuse irradiance from GSR can be found in the literature (Lam and Li, 1996).

The empirical models for the assessment of GSR use historical weather data of the location under study. The meteorological observations typically employed are sunshine, cloud and temperature. As cloud is routinely detected by satellites and strongly influences solar radiation, numerous accurate models have been proposed to estimate GSR through satellite images (Janjai et al., 2009). Nonetheless, sunshine and satellite-based cloud observations are not readily available in most locations. On the other hand, air temperature is measured (usually along with humidity and precipitation) in any weather station worldwide and has been shown to be an important meteorological parameter for the modeling of GSR (Almorox et al., 2011). This motivates the research to find precise models for GSR based only on the geographical location and in commonly available temperature measurements, such as maximum and minimum temperature registers.

Apart from standard regression models (see Almorox et al., 2011 for a review of empirical temperature-based GSR models), artificial neural networks (ANNs) have also been employed in recent years for the estimation of GSR from other available meteorological parameters (Rehman and Mohandes, 2008; Behrang

doi:10.18086/eurosun.2016.09.13 Available at http://proceedings.ises.org

et al., 2010). Conventional regression models are based on the use of empirical equations that define a relationship between the desired output function (daily GSR, H) and some input variables (for example, the extraterrestrial GSR, H_0, and the daily maximum, T_{max}, and minimum temperature, T_{min}). Some empirical coefficients in these equations need to be calibrated for the site under study with available measurements by means of a mathematical regression. On the contrary, ANNs represent a methodology that allows fitting an output function without a predefined structure (black box modeling). In this approach, a network of so-called artificial neurons with configurable connections is used to learn from data the desired nonlinear output function.

ANNs can be essentially classified into feed-forward neural networks (FFNNs) and recurrent neural networks (RNNs). A FFNN has its neurons organized in layers with no feedback or lateral connections. The input signal propagates through the network in a forward direction, on a layer-by-layer basis. On the other hand, RNNs present loops, feedback connections between neurons. Thus, information can propagate forward and backwards. The major advantage of RNNs over FFNNs is that they can implicitly learn temporal tasks. That is to say, an output function can be learnt such that it does not only depend on the current value of the input signal but also on the input history. In other words, RNNs are appropriate for processing time series.

A number of works have already proposed the use of FFNNs to model GSR (Mohandes et al., 1998; Rehman and Mohandes, 2008; Benghanem et al., 2009; Behrang et al., 2010). Here, however, we propose the use of a RNN for that purpose. More specifically, we make use of reservoir computing (RC, Lukosevicius and Jaeger, 2009), a particular approach for building and training RNNs that presents a conveniently simple learning algorithm. As records of GSR represent time-series values, we hypothesize that the RNN's capability of learning temporal features from the data may improve the accuracy of the GSR estimations. This idea was already suggested by the empirical model of Bristow and Campbell (Bristow and Campbell, 1984) where the estimated radiation at current time does not only depend on the current temperature value, but also on that at a different time step.

2. Methods

2.1. Empirical models

Among the existing methods that use empirical relationships to estimate GSR, two of them have been chosen as representative for comparing the accuracy of our RC-based proposed model with conventional regression ones. Namely, the Hargreaves model (Hargreaves and Samani, 1982) and the Bristow-Campbell model (Bristow and Campbell, 1984).

Daily total extraterrestrial radiation (H_0) is included in both models together with maximum (T_{max}) and minimum temperature (T_{min}) or other quantities derived from them. H_0 can be calculated using standard geometric procedures as described in Almorox et al. (2011). The only inputs required to calculate this value is the day of the year and the latitude of the location.

The equation to estimate daily GSR according to the Hargreaves model can be expressed as follows:

$$H = H_0 \cdot [A_{HG}(T_{max} - T_{min})^{\frac{1}{2}}] \qquad \text{(eq. 1)}$$

where A_{HG} is an empirical coefficient that usually ranges between 0.16 and 0.17, but must be derived for the particular site using the available data.

The Bristow-Campbell model is based on a function (ΔT) of the maximum and minimum temperatures and on three empirical parameters (A, B and C):

$$H = H_0 \cdot A \cdot [1 - \exp(-B \cdot \Delta T^{C})] \qquad \text{(eq. 2)}$$

where ΔT is defined as the next function (i corresponds to the current day and $i+1$ to the next day):

$$\Delta T = T_{max,i} - (T_{min,i} + T_{min,i+1})/2 \qquad \text{(eq. 3)}$$

Typical values for the empirical coefficients are $A=0.7$, $B=0.004\text{-}0.001$ and $C=2.4$, but they can be determined using solar radiation data.

2.2. Reservoir computing approach

Artificial neural networks (ANNs) are a computational tool inspired by the way our brain seems to process information. Basically, an ANN is an interconnected group of processing nodes (neurons) that can be used to estimate or approximate functions that depend on a number of inputs. As in biological neural networks, ANNs can learn from experience adjusting the strength of the connections (weight values). That is, they learn from examples (data) constructing an input-output mapping without explicit derivation of the model equation. ANNs can be used for many different applications, such as pattern recognition (in speech, handwriting, etc.), optimization problems, prediction and control among others.

Reservoir computing (RC) is a particular type of ANN characterized by a recurrent network architecture with a high number of interconnected nodes as illustrated in Fig.1 (a). Contrary to conventional RNNs, where all connections need to be adapted, all connection weights in an RC system are randomly chosen and kept fixed except for a linear output layer, which is the only configurable part of the network. This design reduces the complex RNN training to a simple linear regression problem, which facilitates the practical application of RNNs.

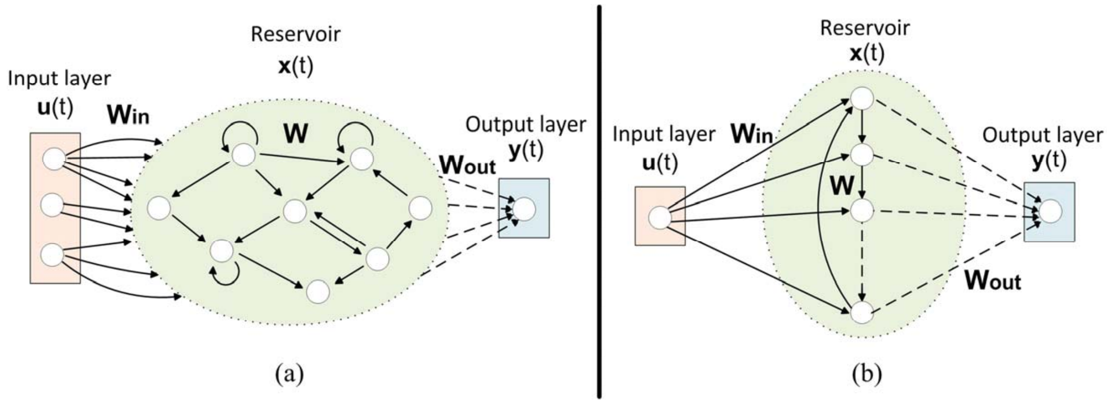

Fig. 1: (a) General architecture of an RC system. All connections are randomly chosen and kept fixed except the ones coupling the reservoir on the output layer (dashed arrows). (b) Particular RC architecture where the reservoir units are organized in a cycle.

An RC system consists of two clearly differentiated parts (apart from the input signals):

- The reservoir, a recurrent network that is randomly generated and remains unchanged.
- The output layer, a simple linear combination of the reservoir states. The weights of such combination are obtained through linear regression using a training set of data.

The general expression to estimate the neuron states in the reservoir at current time, $\boldsymbol{x}(t)$, as a function of the (multidimensional) input signal, $\boldsymbol{u}(t)$, and of the reservoir states at the previous time step, $\boldsymbol{x}(t-1)$, is given by eq. 4:

$$\boldsymbol{x}(t) = \boldsymbol{f}[\boldsymbol{W_{in}} \cdot \boldsymbol{u}(t) + \boldsymbol{W} \cdot \boldsymbol{x}(t-1)] \qquad \text{(eq. 4)}$$

where ***Win*** refers to the strength of the connections coupling the input signals with the reservoir and ***W*** corresponds to the reservoir internal weights (both matrixes of weight values are, in general, randomly generated). ***f*** denotes the nonlinear transfer function employed for the neurons. When a sigmoidal function is used for ***f***, such as the hyperbolic tangent function (it is the case of the present work), the reservoir is called an echo state network (ESN).

The output layer units ($\boldsymbol{y}$) in RC (readouts) are computed as a simple linear combination of the reservoir states ($\boldsymbol{x}$):

$$\boldsymbol{y}(t) = \boldsymbol{W_{out}} \cdot \boldsymbol{x}(t) \qquad \text{(eq. 5)}$$

where ***Wout*** corresponds to the matrix of output connection weights.

The recent study of Rodan and Tino (2011) shows that a simple reservoir where the neurons are organized in a cycle as illustrated in Fig.1 (b) is practically equivalent to the original reservoir structure with random connections of Fig.1 (a). The connections between internal units in the reservoir have the same weight value r. The input layer is fully connected to the reservoir with a connection weight that is positive or negative with equal probability and with the same absolute value for the weight (v). Parameters r and v must be scanned in order to find the best performing weight configuration. This conveniently simple RC topology, known as the simple cycle reservoir (SCR) is the one employed in the present article. For more details about this approach, see the work by Rodan and Tino (2011) or that by Alomar et al. (2016).

RC can be viewed as an expansion (or kernel) method similar to the support vector machine (SVM) approach (Burges, 1998) where the input signal is projected to a higher dimensional state space through the nonlinear dynamics of the reservoir recurrent network. The expanded feature vector ($\boldsymbol{x}$) composed of the reservoir states can be finally readout with a linear method to get an estimation ($\boldsymbol{y}$) of the desired output function. However, it must be noted that apart from producing a nonlinear transformation of the input signals, RNNs (unlike SVMs or FFNNs) have the capability to learn a temporal task. That is, to set a relationship between the desired output value and the input history.

2.3. Data description

A 5-year recording (from 1 July 2007 to 30 June 2012) of GSR and temperature values derived from satellite data for a location in Almeria has been used for training and testing the different models (conventional regression models and RC networks). These data are freely available on the internet (SolarGis, 2016). The original data provided with a 15-minute time basis have been integrated to obtain daily values. The resulting time-series are shown in Fig. 2 and Fig. 3. All input signals (T_{max}, T_{min}, H_o) have been normalized to the [0, 1] range before being processed by the RC network. The first 4 years of data have been used as training set for calibrating the models while the last year has been employed for testing them.

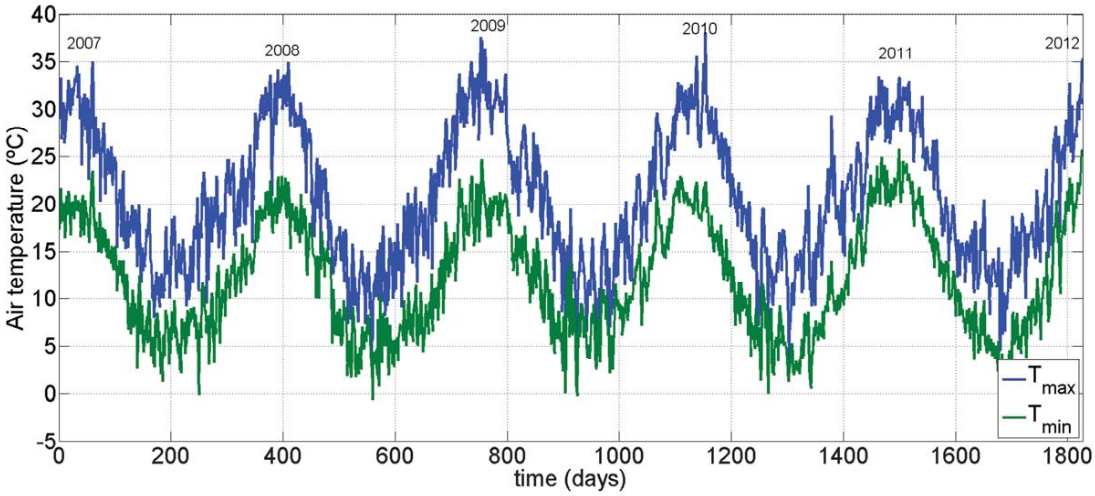

Fig. 2: Daily maximum and minimum temperature values employed as input data to estimate the GSR.

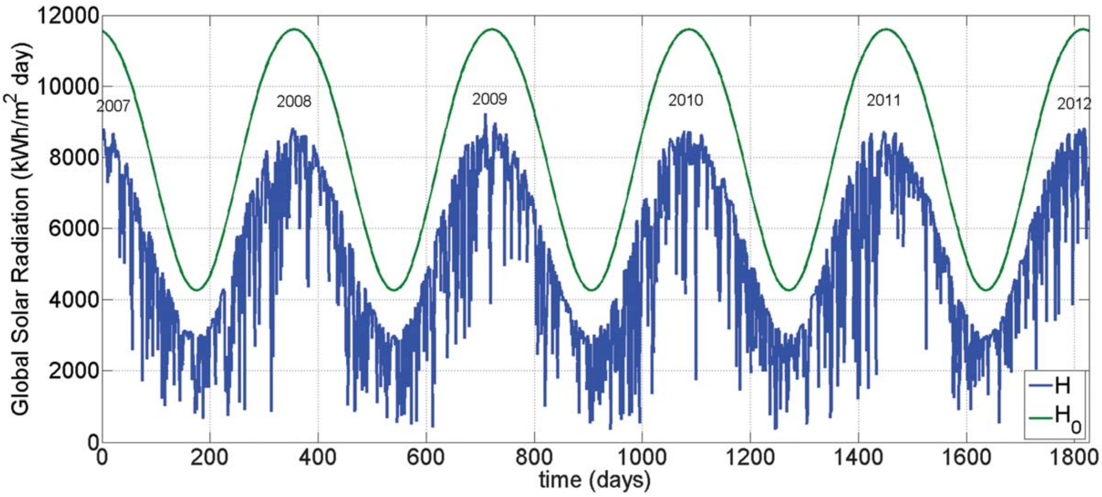

Fig. 3: Observed daily GSR (*H*) along with the daily total extraterrestrial radiation (*H_0*) calculated using standard geometric procedures from the latitude of the location.

3. Results

A number of network combinations using different parameters as inputs (T_{max}, T_{min}, T_{mean}, δT=T_{max},- T_{min}, H_0) and different numbers of units (30, 50, 70 and 100 neurons) have been tested. The performance of the various models has been assessed according to various statistical errors: normalized mean-square error (NMSE), normalized root mean-square error (NRMSE), coefficient of determination R-squared (R^2), root mean-square error (RMSE), mean-square error (MSE), mean absolute error (MAE) and mean bias error (MBE).

Two network configurations have been found to perform the best, both using 50 neurons. The first model (which we call "RC-1") employs a single input (δT) to estimate the ratio H/H_0 (desired output). That is, a linear dependence between H and H_0 is assumed. The second model ("RC-2") utilizes two input signals (δT and H_0) for modeling H as output function. Any other combination of variables used as input signals have resulted in less accurate estimations. The test error results of both RC-based models compared to those of the standard regression methods are presented in Tab.1 where "Regress1" corresponds to the Hargreaves model and "Regress2" to the Bristow-Campbell model. It can be appreciated that both RC-based models are practically equivalent, which indicates that assuming that H is directly proportional to H_0 seems adequate.

On the other hand, it can be observed that, as expected, the proposed RC-based models exhibit a higher accuracy than the conventional regression-based empirical methods. Only for the case of the MBE one of the conventional models provides a lower error than the RC-based models. However, it must be mentioned that the MBE is not a good indicator of the estimations' accuracy but just of the error bias.

The function fitting performed by one of the proposed models ("RC-1") is finally illustrated for the test set (one year of data) in Fig.4.

Tab. 1: Statistical evaluation of the conventional (regression-based) and proposed (RC-based) models for the test data set.

Model	NMSE	NRMSE	R^2	RMSE ($Wh/m^2 \cdot day$)	MSE ($(Wh/m^2 \cdot day)^2$)	MAE ($Wh/m^2 \cdot day$)	MBE ($Wh/m^2 \cdot day$)
Regress1	0.2467	0.4967	0.7533	1053.90	$1.18 \cdot 10^6$	836.82	237.61
Regress2	0.2201	0.4691	0.7799	995.35	$9.93 \cdot 10^5$	823.73	535.26
RC-1	0.1940	0.4404	0.8060	934.49	$8.76 \cdot 10^5$	745.03	407.08
RC-2	0.1940	0.4404	0.8060	934.48	$8.76 \cdot 10^5$	771.49	426.06

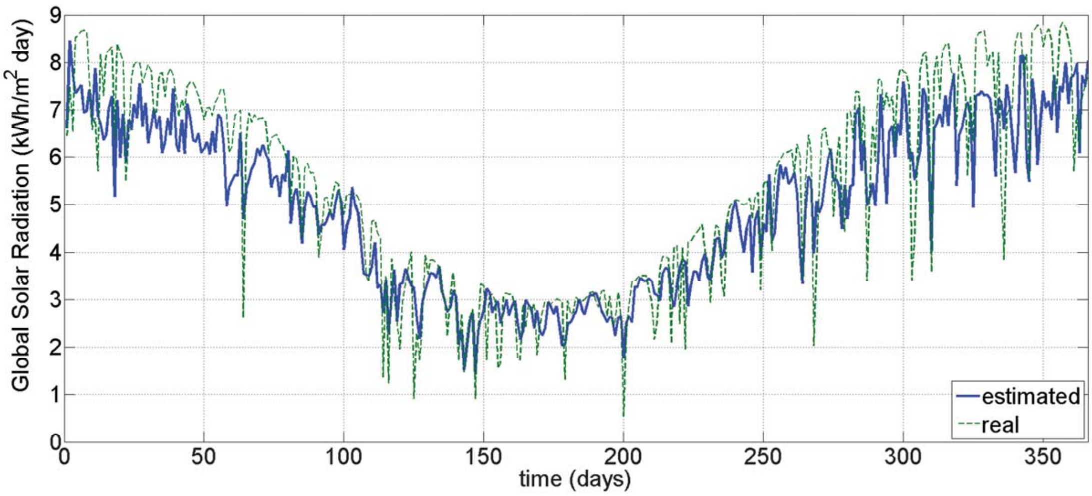

Fig. 4: Estimated and observed GSR for the test data set using an RC-based model that employs Tmax-Tmin as input signal.

4. Conclusions and future work

In this paper, we have proposed a convenient model for estimating daily global solar radiation (GSR) using temperature measurements commonly available at weather stations. The model is based on reservoir computing (RC), a particular type of recurrent neural network (RNN), which allows implicitly learning from time-series data the relation between the input and output signal. We have shown that the proposed neural approach outperforms other conventional empirical methods. The RC-based model can be calibrated for any particular desired location, which makes it useful for the simulation of solar energy systems.

Nevertheless, it is worth highlighting that the validity of the proposed approach has been tested using meteorological data derived from satellite observations assuming that such values present a similar complexity to those that might be obtained from direct physical measurements at a weather station. Therefore, it would be of high interest to further validate the proposed methodology with measured data.

Furthermore, although the presented RC models have been compared with standard methodologies (adjustable empirical equations), they have not yet been demonstrated to outperform other simpler kernel approaches, such as feed-forward neural networks (FFNNs). Finally, it could be an interesting step for the future analyzing whether GSR estimations can be improved by including other input parameters different from temperature, such as humidity and precipitation, which are also often available at most weather stations.

5. References

Almorox, J., Hontoria, H., Benito, M., 2011. Models for obtaining daily global solar radiation with measured air temperature data in Madrid (Spain). Applied Energy 88, 1703-1709.

Alomar, M. L., Canals, V., Perez-Mora, N., Martínez-Moll, V., Rosselló J. L., 2016. FPGA-based stochastic echo state networks for time-series forecasting. Computational Intelligence and Neuroscience 2016, 1-14.

Behrang, M. A., Assareh, E., Ghanbarzadeh, A., Noghrehabadi, A. R., 2010. The potential of different artificial neural network (ANN) techniques in daily global solar radiation modeling based on meteorological data. Solar Energy 84, 1468-1480.

Benghanem, M., Mellit, A., Alamri, S. N., 2009. ANN-based modeling and estimation of daily global solar radiation data: A case study. Energy Conversion and Management 50, 1644-1655.

Bristow, K. L., Campbell, G. S., 1984. On the relationship between incoming solar radiation and daily maximum and minimum temperature. Agricultural and Forest Meteorology 31, 59-166.

Burges, C. J. C., 1998. A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery 2, 121-167.

Hargreaves, G. H., Samani, Z. A., 1982. Estimating potential evapotranspiration. Journal of Irrigation and Drainage Engineering 108(IR3), 223-230.

Janjai, S., Pankaew, P., Laksanaboonsong, J., 2009. A model for calculating hourly global solar radiation from satellite data in the tropics. Applied Energy 86, 1450-1457.

Lam, J. C., Li, D. H. W., 1996. Correlation between global solar-radiation and its direct and diffuse components. Building and Environment 31(6), 527-535.

Lukosevicius M., Jaeger, H., 2009. Reservoir computing approaches to recurrent neural network training. Computer Science Review 3, 127-149.

Mohandes, M., Rehman, S., Halawani, T. O., 1998. Estimation of global solar radiation using artificial neural networks. Renewable Energy 14(1-4), 179-184.

Rehman, S., Mohandes, M., 2008. Artificial neural network estimation of global solar radiation using air temperature and relative humidity. Energy Policy 36, 571-576.

Rodan, A., Tino, P., 2011. Minimum Complexity Echo State Network. Trans. Neural Netw. 22(1), 131-144.

SolarGis web-page, last accessed Apr. 2016. http://solargis.info/doc/climdata-samples.

Wong, L. T., Chow, W. K., 2001. Solar radiation model. Applied Energy 69, 191-224.

6. Ackowledgements

This work has been supported by the Spanish Ministry of Economy and Competitiveness (MINECO) under Grant Contract TEC2014-56244-R, and a fellowship (FPI/1513/2012) financed by the European Social Fund (ESF) and the Govern de les Illes Balears (Conselleria d'Educació, Cultura i Universitats).