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Forecasting short-term solar irradiance based on artificial neural networks and data from neighboring meteorological stations

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Abstract

The study focused on the use of Artificial Neural Networks (ANN) in short-term prediction of Global Solar Irradiance (GSI). It introduces a new methodology based on observations made in parallel by neighboring sensors and values for different variables (temperature, humidity, pressure, wind and other estimates), using up to 900 inputs (higher dimensions). Experiments were carried out using ANN with different architectures and parameters in order to determine which of these generated the best GSI predictions for the various time frames studied (between 1 and 6 h). The results of the study allowed us to generate ANN models that predict short-term GSI with error rates less than 20% nRMSE. In addition, using observations from neighboring stations within a 55 km as a reference radius reduced error rates in predictions for time frames between 1 and 3 h, while the best predictions for time frames between 4 and 6 h were generated by ANNs that used only initial data from the station for which the prediction was being made.
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1. Introduction

Enriching our understanding of Solar Radiation at Earth's surface and predicting it is of particular interest for Renewable Energies such as Solar Energy and the various industrial and ecological applications of Renewable Energies. Understanding and predicting solar radiation values plays an important role in developing and exploiting Renewable Energy systems that rely on Solar Energy, such as solar thermal and photovoltaic plants (Mellit and Pavan, 2010). These Solar Energy systems require Solar Radiation data throughout all stages, from selecting the ideal locations for their construction, to the design stage and, finally, during operation, when this data is used to predict energy production (Perpiñán, 2008: pg. 21; Almeida et al., 2015). Solar radiation data and prediction for different time frames are especially useful during the production stage, when these data are used by both electrical generators and electrical system operators in order to plan and manage energy (Voyant et al., 2014). These needs have generated and increased demand for short-term solar energy production forecasts, which has increased the demand for more accurate Solar Radiation forecasts in order to help plan and manage electricity generation and distribution (Martins et al., 2012).

The methods for forecasting the GSI on different intraday time frames can be grouped as follow: statistical,

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machine learning, image based and numerical weather prediction. Forecasting based on satellite images have proven to be a powerful method (Hammer et al., 1999; Perez et al., 2010; Nonnenmacher and Coimbra, 2014) however it presents some issues such as the satellite image availability, real time processing of images, albedo correction, resolution, among others (Nonnenmacher and Coimbra, 2014). Forecasting systems based on numerical methods can provide realistic estimates of atmospheric dynamics guaranteeing their stability through data assimilation processes, nevertheless these kind of systems are inadequate when used within limited space and time frames (small spatio-temporal scale) as they tend to reduce the impact of local phenomenon in favor of overall coherence (Kretzschmar et al., 2004). Furthermore, GSI is affected by nonlinear characteristics that are amplified by variations in the weather as well as by the presence of clouds, gasses and other atmospheric particles such as dust (Badescu, 2008; Wang et al., 2012). These conditions present non-linear relations that further complicate short-term GSI prediction. ANNs as one of the machine learning approaches have proven to be useful in researching models for estimating processes associated with non-linear functions, as is the case with short-term GSI prediction. ANNs are encompassed within the field of Artificial Intelligence (AI), emulating human beings' capacity to learn, memorize and identify both linear and non-linear relationships. ANNs attempt to reproduce the behavior of biological neural networks in a simplified manner (Hagan et al., 1996). ANNs are useful tools for various scientific fields thanks to their ability to learn non-linear relations and their capacity to model complex systems with unknown behavioral rules (Reed and Marks, 1998; Paoli et al., 2010; Yadav and Chandel, 2012).

Working under the hypothesis that it is possible to improve short-term GSI prediction (intra-day forecasts) with ANN models using the spatial component (location of neighboring stations) and other input variables, this study aimed to investigate GSI prediction in time frames between 1 and 6 h by modeling ANNs that include data from neighboring stations. To this end, the following research questions were posed: Is it possible to outperform error rates for short-term GSI predictions using a greater number of inputs in the ANN models? What is the relationship between spatial limits and time frames in GSI predictions using ANN?

The structure of the article is: Section 2 presents the related works identified in the literature. Section 3 describes the geographical context and data used for the experiments. Section 4 specifies the methodology implemented. Section 5 presents the main results reached at this research work. Section 6 presents some concluding remarks. Finally, Section 7 indicates the future works.

2. Related work

This study used a type of ANN architecture known as *Multi Layer Perceptron* (MLP) in order to experiment with short-term GSI prediction. MLP is the most popular ANN architecture used to solve scientific problems (Tymvios et al., 2008) and therefore is the most widely used in related studies for GSI prediction (Voyant et al., 2014, 2011; Yadav and Chandel, 2012; Wang et al., 2012; Koca et al., 2011; Linares-Rodríguez et al., 2011; Mellit and Pavan, 2010; Paoli et al., 2010; Bosch et al., 2008; Mellit, 2008; Mellit and Kalogirou, 2008; Mubiru, 2008; Mubiru and Banda, 2008; Mellit et al., 2006; Hontoria et al., 2002; Mohandes et al., 1998). MLP is also known as the universal approximator, because of its proven capacity to approximate nonlinear relationships between inputs and outputs with any degree of accuracy (Reed and Marks, 1998: pg. 37).

ANNs with MLP architecture have at least one layer of hidden neurons, distributed in such a way that each layer is connected in a feed-forward way to each neuron in the next layer. Fig. 1 illustrates an MLP with n input values, a hidden layer with Ni artificial neurons and a single "o" neuron in the output layer. The figure also indicates the weights (w) associated with each connection. The information acquired by ANNs is stored in the weights of the connections between neurons. The superscripts $L1$ and $L2$ indicate which layer the weight belongs to. The first superscript indicates the input, or the neuron from which the connection stems, while the second superscript indicates the target neuron for the connection. The MLP output "o" in this figure corresponds to the system of Eqs. (1) and (2).

$$o = f\left(\sum_{i=1}^{i=i}(y_i) * \left(w_{Ni,o}^{L2}\right)\right) \tag{1}$$

$$y_i = g\left(\sum_{j=1}^{n}(x_j) * \left(w_{j,Ni}^{L1}\right)\right) \tag{2}$$

ANNs have been widely used in models for predicting Solar Irradiance with different time frames and in different parts of the world, for instance: Spain (Hontoria et al., 2002; Bosch et al., 2008; Linares-Rodríguez et al., 2011), Italy (Mellit and Pavan, 2010), the Island of Corsica in France (Paoli et al., 2010; Voyant et al., 2011, 2014), Turkey (Koca et al., 2011), Saudi Arabia (Mohandes

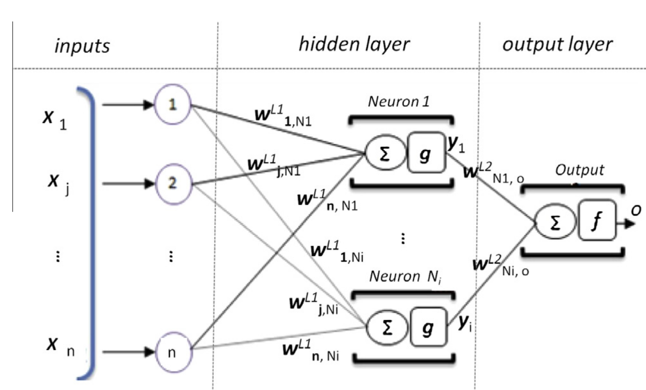

Fig. 1. MLP ANN with n inputs, i neurons in the hidden layer and one "o" neuron in the output layer. Figure adapted from Voyant et al. (2014).

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