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Machine Learning techniques for estimation of BIPV production

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TOPIC: Energy efficiency and sustainability in buildings and industry

1. Introduction

In the last decades, an increase in the global warming has been registered which is causing real global climate change. To mitigate the causes and their effects, the European Commission has stablished the European Green Deal [1], in which climate neutrality is promoted by 2050. To achieve this objective, the efficient use of resources is encouraged. In addition, to reduce the energy dependence and greenhouse gas emissions, the use of renewable energy sources are proposed [2, 3].

The cost of electricity generated from utility-scale solar Photovoltaic (PV) installations has been notably reduced since 2010 and, nowadays, is getting closer to be a real competitive alternative to conventional electricity sources [4]. Building Integrated PV facilities (BIPV) highlights in the technology market due to their potential saving in costs and relatively good efficiency. In addition to the energy performance benefits, BIPV also offers to architects alternatives to conventional construction materials that can be used to modify the visual appearance of a building facade [5]. Nevertheless, BIPV production is highly dependent on weather conditions [6] and the building surrounding area, especially when PV modules are installed in vertical position.

Contrary to sloped and horizontal surfaces, vertical PV panel receive less solar radiation, aspect that is increased in the summer months, when the sun reaches the highest solar altitude. In large cities with high building density, the amount of solar radiation that a PV panel receives is even lower [7]. However, this can be compensated since these installations can cover large extensions of the façades.

Another relevant aspect regarding the amount of energy that can be generated by BIPV on the facade is its orientation, being able to obtain several generation peaks distributed throughout the day. This aspect helps to homogenate the total energy production [8]. In addition, those facades located with a north orientation will have lower production, because the Sun's position rarely is in the North quadrant of the northern hemisphere.

The performance of PV panels is also affected by outdoor weather conditions such as Vertical Solar global irradiance (RaGV), air temperature (T), wind speed (WS), wind direction (WD), and relative humidity (RH) [6]. Accurate meteorological data is crucial for any building energy simulation model [9].

This study proposed a model based on Artificial Neural Networks (ANN) to predict the electricity generated by a BIPV system, using different meteorological variables as input. The model was applied to a vertical PV installation placed in Astudillo (Castilla y León, Spain) that has an annual mean daily energy of 16.04 MJ/M^2. Figure 1 shows the location of the experimental facility and the annual mean daily global irradiance (MJ/m^2)

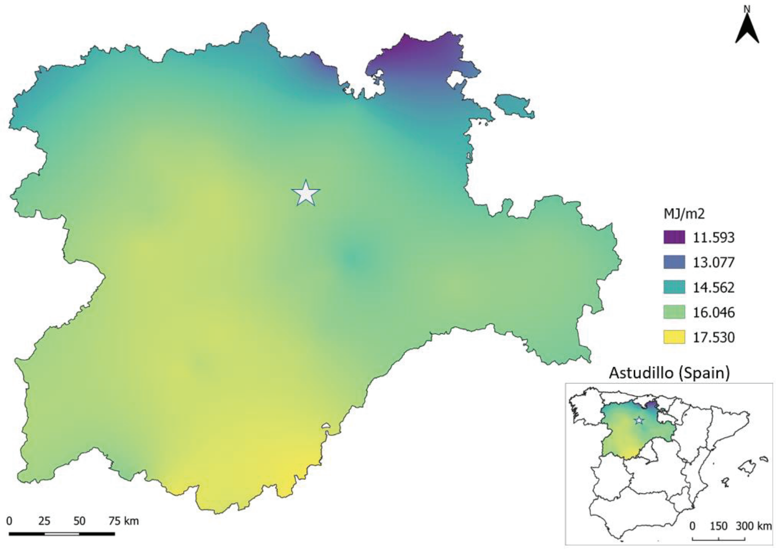

Figure 1. Average distribution of the energy in Castilla y Leon (own source).

2. Materials and method

The experimental data for the study was recorded in the experimental facility located in Astudillo, (Palencia) and shown in Figure 2-A. The following variables are recorded: temperature, T, wind speed and direction, WS and WD, relative humidity, RH, and RaGV on four vertical planes facing north (RaGVN), south (RaGVS), east (RaGVE) and west (RaGVW). The PV production on facades was obtained from the measurement of the electrical output of four vertical PV panels facing the four cardinal points (Figure 2-B). The experimental campaign ran from April 1st to December 31th, 2016 and data was registered every 10 minutes.

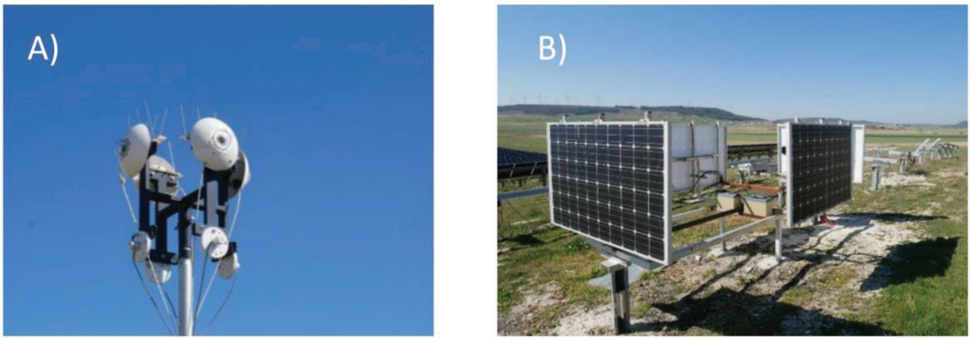

Figure 2. Pyranometers and commercial vertical PV panels available in the weather station (Astudillo) facing to cardinal orientations.

This research proposes a model to predict the power production of BIPV systems from meteorological data for the south orientation. The technique implemented in this procedure was an Artificial Neural Network (ANN). ANN techniques split the dataset into three subsets: training, validation, and test. The training set serves to tune the weighted matrix (W^1 and W^2), throughout the Levenberg-Marquardt algorithm [10], that was implemented in this study following a prior publication [11]. The validation set is used to evaluate the performance of the model proposed by the training process. This tuning process involves the training set and the validation set by an interanion process, that it is over when the performance of the ANN reaches the desired quality. The dataset was randomly splitted, according to the following ratios: training set (70%), validation set (15%), and testing set (15%). Besides, the architecture of the ANN has one single hidden layer and one single output, as shown in Figure 3.

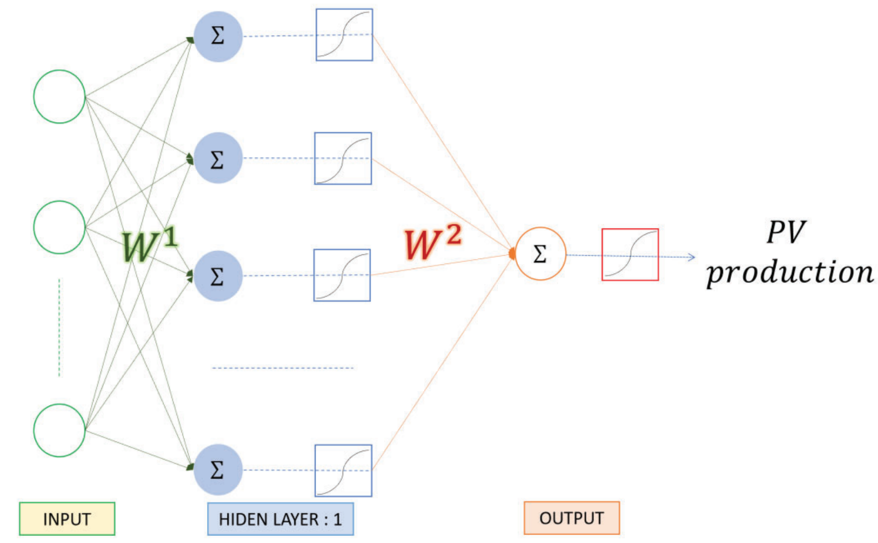

Figure 3. Architecture of the ANN. (W^1, W^2) are the matrix of weights, and the circles represents the neurons.

The design of the ANN must be adapted to the process to be modeled. But, so far, there is no standardized procedure to establish the most effective number of neurons [12]. Therefore it is compulsory to carry out an iterative process. Nine ANNs were programmed (ANN1 to ANN9). In the input layer, each neuron is a meteorological variable (T, WS, WD, RH, or Ra). For each ANN, the best number of neurons in the hidden layer is unknown, but it is generally accepted that the number of neurons should not exceed the number of neurons of the previous layer [13]. So, if the input has three meteorological variables and, consequently, three neurons, the number of neurons of the hidden layer can be one, two, or three. If the layer input has two meteorological variables, the hidden layer can have one or two neurons, and so on. Finally, the number of neurons of each ANN corresponds to the hit performance over the testing set, *i.e.*, the part of the dataset which is unused during the training process.

The goodness-of-fit analysis was conducted by the Mean Bias Error (MBE) and the Root Mean Square Error (RMSE) [14] [15], defined in Equations (1) and (2), respectively. As previously stated, the 15% of the dataset was used as testing set and the remaining data to train the model. The RMSE grades the performance of the ANNs, as links the deviation of the predicted values versus the experimental data. MBE summarizes the bias of the model that can either over-estimate or under-estimate the prediction.

$$RMSE(\%) = 100\,\frac{\sqrt{\sum \frac{(x_{model}-x_{measured})^2}{N}}}{\frac{\sum x_{measured}}{N}}$$

(1)

$$MBE(\%) = 100\,\frac{1}{N}\frac{\sum x_{predicted}-x_{measured}}{\sum x_{measured}}$$

(2)

3. Results and discussion

This study compared 9 ANNs that differs in the input variables and the number of neurons in the hidden layer, as described in Table 1. It is observed that the RMSE of the ANN varies widely with the input. The best performance was achieved by the ANN6, which depended on RaGVS, T and RH. It does not use the complete set of available meteorological variables. Therefore, introducing more variables does not necessarily imply better estimation quality, as the goodness indices RMSE and MBE calculated by ANN8 and ANN9 show. The ANN1, which was based only on irradiance values, shown an acceptable agreement, with a RMSE of 14%.

Table 1. Performance indices of each programmed Artificial Neural Network.

ANN	**ANN1**	**ANN2**	**ANN3**	**ANN4**	**ANN5**	**ANN6**	**ANN7**	**ANN8**	**ANN9**
INPUTS	RaGVS	RaGVS -T	RaGVS -RH	RaGVS -WS	RaGVS -WD	RaGVS -T-RH	RaGVS -T-WS	RaGVS -T-WD	RaGVS -T-RH-WS
RMSE (%)	13.5	11.2	10.2	13	13	9.9	10.5	11	10.5
MBE (%)	0.3	0.2	0.05	0.2	0.1	-0.01	0.2	0.2	0.1
Number of neurons	1	2	2	2	2	3	3	2	2

The scatter plot shown in Figure 4 compares the PV production values obtained by the best performing model (ANN6) versus the measured ones for the south oriented PV module. The testing set (15% of the dataset) was used for this plot as the ANN predictions are independent of the fitting process. The shape of the plot shreds evidence that the ANN6 had relatively low dispersion as the scattering points fits with the straight line. In consequence, ANN6 prediction is applicable with confidence for the experimental facility in Astudillo, Palencia.

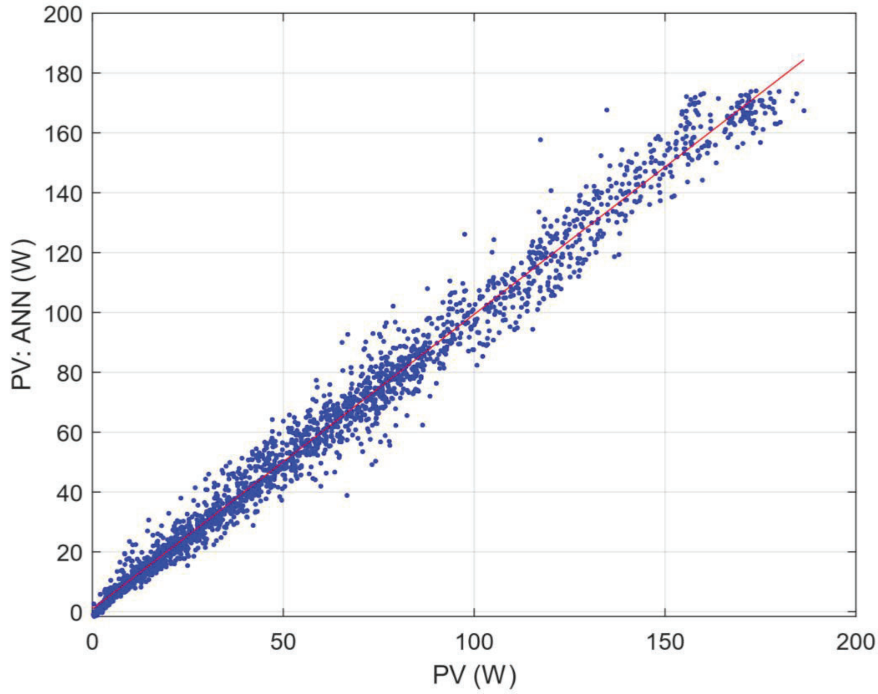

Figure 4: PV production of the south oriented vertical panel predicted by ANN6 model vs. experimental data.

4. Conclusions

This study evaluated the performance of nine ANNs to estimate the electricity production of a BIPV system from meteorological data that are generally accessible from ground-based meteorological stations. Solar irradiance was proved to be the most adequate input variable to predict PV production with a simple ANN. However, the accuracy of this simple model was notably improved with the inclusion of the temperature and relative humidity. Wind speed and direction were less relevant as their statistical indicators highlighted. Indeed, all reviewed ANN structures shown good performance as the $RMSE$ and MBE kept relatively low. Besides, the largest number of neurons does not lead to a better performance.

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