A PHOTOVOLTAIC PRODUCTION ESTIMATOR BASED ON ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The ability to forecast the expected power production from renewable sources nowadays is increasingly critical because of the reliability expected from them. For instance improving the reliability of photovoltaic production forecasts in a small/medium microgrid permits to save money to supply its own loads and also to plan the participation to the ongoing services the smart distribution grid will require. In this paper we propose a method to predict photovoltaic production based on a statistical model. This type of models, compared to other ones, are easily configurable, cope well with heterogeneous plants, with different ageing devices and are able to consider diverse exogenous, well known and accidental, drawbacks. Such models is daily updated with the data arising from the monitoring until 5 days before and include the relevant variables for the photovoltaic forecasting function.

INTRODUCTION

In Italy the most abundant renewable energy source is solar energy which can be harnessed for commercial uses through solar plants, and which is predicted by numerous analyses to become the mostly used energy resource in the next future. For the time period 2030–2050, The European Photovoltaic Industry Association (EPIA) together with the European Renewable Energy Council (EREC) has shown the high potential of PV within the RE-thinking 2050 scenario [2]. PV is expected to become a mainstream power source in Europe by 2020 and a major power source in 2050 with an approximation of 962 GW of installed capacity. This is especially true due to the installation of grid connected PV systems [3]. As a result, new challenges have arisen in the PV industry over the past years such as: identifying and quantifying the impact of PV power on the electrical distribution grid; minimizing the influence of its fluctuations; managing uncertainties in order to guarantee a secure and reliable electrical power services; and the PV systems performance prediction.

The performance of a photovoltaic (PV) installation is related to factors including the electrical parameters of its components, such as PV panels and inverters, the characteristics of the installation (tilt angle, orientation, etc.) and the meteorological conditions. The power produced by a (PV) field depends mainly on the absorbed solar irradiance. In fact, a correlation exists between the PV modules' maximum power and the solar irradiance. Solar irradiance on a panel varies with geographic location, time, the orientation of the panel relative to the sun and weather conditions. This explains the variable, chaotic and intermittent behaviour of generated solar power. To ensure an efficient exploitation and a large penetration for such a power source, it is important to predict the amount of energy that a PV installation can generate.

Once fully exploited during the PV installations' design stage, PV production forecasting is, nowadays, a must to ensure an effective management system for the electrical distribution grid. Several studies were conducted to ensure this task [4][5].

The literature presents numerous models for PV modules which can be used to quantify the expected produced electric power [6]. Also a significant number of studies on solar irradiation modelling and forecasting have been undertaken, offering a wide range of possibilities gleaned from diverse areas of knowledge such as atmospheric physics, solar instrumentation, machine learning, forecasting theory and remote sensing in its quest for better predictive skills [7].

This paper presents a part of the research in progress that seeks to estimate and forecast PV installations' production one day ahead for the RSE distributed generation microgrid. RSE microgrid is equipped with a PV field, an engine to produce electricity and heat, and a number of energy storage systems. The microgrid can be operated in connected or in islanded mode with respect to the distribution grid. Microgrid operation is conducted according to a daily plan production that exploit renewable power sources as far as possible to supply loads. The plan is elaborated taking into account forecasts of load requests and PV production supply. PV production supply forecast is computed by means of weather forecast and it is crucial to ensure the reliability of the PV field production. The methodology proposed here adopts artificial neural networks (ANNs) modelling techniques for the PV renewable sources. The methodology we are proposing set an estimator which given a daily weather forecast leads to define the microgrid PV power production. This estimator is articulated into three different ANNs: the first one estimates the Global Tilted Irradiance (GTI), the second one estimates the PV panel temperature and the last one estimates the PV power production.

The rest of the paper is organized as follows: first it is proposed an overview of the problem addressed by the paper, than a brief introduction to neural networks is given and next experimental results gained on the RSE microgrid plant are reported.

PROBLEM OVERVIEW

To obtain a high quality weather and irradiance data is one of the most important steps in PV performance modeling, since the uncertainty in the irradiance data usually accounts a large amount of the total uncertainty. Historical data, concerning irradiance, power production and also weather variables, plays a fundamental role. However, when the results of the model are being used for large

investment decisions, additional data is usually used (e.g., satellite data and site specific ground measurements). The PV source system is composed of many panels, with fix or variable inclination/orientation. Panels enclosed in the RSE microgrid have orientation and inclination fixed but in general different one from the other. further, each panel can differ from the other by provider, technology, power peak production, aging, etc.

A model of the PV power production process is composed of a number of different factors that influence the production of electrical power. These include:

1. the *intensity of the solar irradiation* depends on the angle of incidence of the light beam;

2. solar irradiation is reduced when go through the earth atmosphere because of many and different causes:

   a. *air mass*, it expresses the effect of atmosphere on the solar beam;

   b. *weather conditions*: clouds, humidity, wind can reduce and in general modify the effect of irradiation;

   c. *geomorphology* of the territory where plants are installed introduces other modification reflecting the solar beam like mountains, waterways/basins, trees, buildings, etc..

   d. *exogenous factors*, human activities can affect the intensity of irradiance hitting the panel; for instance the unexpected presence of obstacles temporary or permanently posed between the beam and the panel (like soiling, shading etc.)

   e. *installation*: panel can be installed with a tracker, to follow the sun trajectory in one or two direction, or fixing inclination and orientation one and for all, and may happen that panels in a field are installed with different inclination and orientation

3. *technical characteristics* and aging of the PV panels: each panel technology and product behaves differently with respect to the same irradiation and weather conditions;

In order to build a model of the PV panel system taking into all these factors, a model for each one of the mentioned characteristics should be designed. Many of them can be mathematically expressed achieving a physical model, but for the others this is a complicated, or even impossible, task. In any case each model should be continuously updated in order to adhere to the dynamics of these characteristics. The maintenance of a deterministic mathematical model can be hard without a deep analysis phase. Another issue discouraging the choice to adopt a physical model of the PV system field concerns the number of components, often distributed over the territory, and the difficulty to build a correct and reliable mathematical model for many of them.

Given this picture, we propose a statistical model where the PV system is thought as a set of input to produce specific output. In this case the model consists of a function configured according to the relationship between input and output ruled out from data analyzed. Model identification supports this methodology: a model is built through the analysis of the relationship between a set of input and the corresponding output. It is performed considering the system as a *black box*: what is known is the relationship between the inputs and system response (output). The model of the system completely abstract from the structure of the physical system, but completely adhere to the system behavior. System validation consists to show the model explains the system behavior. The methodology proposes by statistical model shows a high level of reliability as it is able to formulate a forecast even in case of data degradation.

It is generally widely recognized the quasi-linear dependence between solar global irradiance (G) and PV power production, thus the adoption of a linear (or semi-linear) statistical model based on this variable seems a natural mean to get a PV power production estimator. Then the statistical model can be integrated with extra-variables in order to improve the forecast precision. These variables can include: *wind*, direction (WD) and intensity (WI), environment *temperature* (T), *humidity* (H), *pressure* (P), PV *panel temperature* (Tmod). The model integrated with all these variables takes the following shape (regressive model):

$$PV(t) = f(B^0, B^1, ..B^k, G(t), T(t), WI(t), WD(t), H(t), P(t), \underline{Tmod}(t)) \qquad (1)$$

The model identification step will set the different vectors of parameters B^i. According to the data characteristics a first detail of the model proposed must be introduced. This concerns the global irradiance, the main responsible of photovoltaic power production. There is the global radiation that heat the panel, named "Global Tilted Irradiance" (GTI), and the Global Horizontal Irradiance (GHI) which is the global radiation forecasted by weather predictions. This type of irradiance is coupled with the Diffuse Horizontal Irradiance (DHI) and the Direct Normal Irradiance (DNI).

Another issue regards PV panel temperature for which there is no forecast. Though, this can be computed according to the GTI, temperature and wind speed (as specified by Sandia [1]). The regressive model proposed in (1) can be detailed into a more specialized version. The next section will propose how neural networks code the previous model.

NEURAL NETWORK MODEL

Artificial Neural Network (ANN) is a suitable tool to code the estimator for the PV power production. ANN presents strong features of flexibility and reliability. Previously the PV power production has been formalized by a regressive model where a multi-dimensional polynomial computes the PV value according to the different terms identifying

parameters and weather variables . The goal of this section is to show how a neural network can code this polynomial.

The PV power estimator is daily set. It is composed of three different neural networks to model, respectively: global tilted irradiance, panel module temperature and PV production. The next Figure shows this architecture.
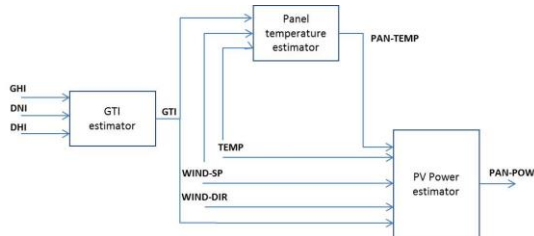

Fig. 1 – PV production estimator architecture

Each neural network has one hidden layer and one output layer. The number of inputs changes for each network, and it is equal to the number of input variables defined for the estimator; the number of output is just one. Each ANN is *trained* with a set of, at most, 5 days data with 1 minute sampling time. Training process is conducted with respect to many different networks each one distinguished for: the number of data consistency (5 days or 3 days measures), the complexity of the hidden layer (5 – 10 – 15 – 20 neurons), and the training algorithm adopted (10 different algorithms).

Thus, 80 neural networks will be defined and trained for each network. After the training phase each neural network is subject to a *verification phase*. All the estimators are verified with respect to the day after the last day of the training set. Among the different estimators the one selected presents the minimum *mean square error* (MSE). The process to train and test the best PV production estimator involves 180 networks and require about 10 minutes on a standard pc. Though, this methodology ensures to gain the best estimator each time.

The Global Tilted Irradiance estimator

The estimator of global irradiance hitting the PV system (PV-GTIe), in brief GTI (Global Tilted Irradiance) is expressed by means of the irradiance: global, diffuse and direct taken on the horizontal plane, respectively, GHI, DHI and DNI (Direct Normal Irradiance). This estimator is aimed at setting the relationship between the irradiance on the horizontal plan, this is the type of irradiance forecasted by the RSE weather service, and the irradiance hitting the panel, the GTI.

The relationship between the two radiations is time dependent according to the sun/earth position changes and inclination and orientation of panels. Global, direct and diffuse irradiance measured on the horizontal plan are taken as input to the estimator, and the global irradiance measured on the panel plan (tilted plan), is taken as output of the estimator. The training session set the best

relationship between input and output in order to get the best model estimation of the following type:

$$\text{GTI}(t)= \sum_i f_1((B_i^1)^T \bullet [\text{GHI}(t)\ \text{DHI}(t)\ \text{DNI}(t)]^T + a_{i0}^1)$$

Where a_{i0}^1 belongs to $\underline{a}_0$ (the bias vector), B_i^1 is a parameter vector with i ranging the dimension of the ANN hidden layer. The training phase sets these parameters to get the best mean square error with respect to the target set values. The network is then verified with respect to a day not included in those considered for the training phase. The error computed during that phase is expressed by the mean square error value MSE.

$$\text{MSEPV-GTIe}=(\text{GTI} – \underline{\text{GTI}})^2/n$$

where $\underline{\text{GTI}}$ is the target value and GTI is the estimation computed by the network, and n is the cardinality of the set of values considered.

The PV panel temperature estimator

The PV panel temperature greatly influence the efficiency of power production. In particular, the more the temperature increases the more the panel efficiency reduces. A mathematical model to compute the panel temperature value is proposed by Sandia national Labs [1]. In this case the panel temperature depends by the global irradiance, the wind speed, the ambient temperature and other parameters characteristics of the PV panel technology. We started from this model in order to define the PV module temperature estimator (PV-MTe). The next vector expression gives the relationship between input and output for the GTI estimator configured by the network:

$$\text{T-mod}(t) = \sum_i f_2((B_i^2)^T \bullet [\text{GTI}(t)\ \text{T}(t)\ \text{WI}(t)]^T + a_{i0}^2)$$

Where a_{i0}^2 belongs to the bias vector a_0^2, and B_i^2 is a parameter vector, with i ranging the dimension of the hidden layer. The trained network sets the values of a_0^2 and B^2. Forecast values of irradiance on the panel plane, ambient temperature and wind speed are applied to the ANN to get the panel temperature forecast. The error of this estimation is computed with the MSE as follows:

$$\text{MSEPV-TMODe}=(\text{T-mod} – \underline{\text{T-mod}})^2/n$$

where $\underline{\text{T-mod}}$ is the target value and T-mod is the estimation computed by the network.

The PV power production estimator

PV power production estimation takes as input a number of variables: GTI, the wind direction and speed, ambient temperature, humidity, atmospheric pressure measured in the microgrid and the panel temperature. The output computed is the reference (target) PV power production measured on the PV system.

$$\text{PVPROD}(t) = \sum_i f_3((B_i^3)^T \bullet [\text{GTI}(t)\ \text{T}(t)\ \text{WI}(t)\ \text{WD}(t)\ \text{T-mod}(t)\ \text{H}(t)\ \text{P}(t)]^T + a_{i0}^3)$$

Network performance is evaluated according to the MSE:

$$\text{MSEPV-PVPRODe}=(\text{PVPROD} – \underline{\text{PVPROD}})^2/n$$

where $\underline{\text{PVPROD}}$ is the target value and PVPROD is the estimation computed by the network.

EXPERIMENTAL RESULTS

In this chapter a few results of the experimentation conducted to evaluate the behavior of the PV production estimator are proposed. The experimentation concerned the estimator, represented in the architecture of Figure 1, applied to a *test day*: October 4th 2015. The training set included October 3rd and the 4 days before. The time scale considered was the minute one (1440 minutes for each day).

The estimation is performed in three steps, consider first the GTI estimation. To this aim the ANN is supplied with the measures of horizontal irradiations (GHI, DHI and DNI) taken during the test day. The GTI estimation gained is compared with the GTI measures, taken during the test day, in the next figure.
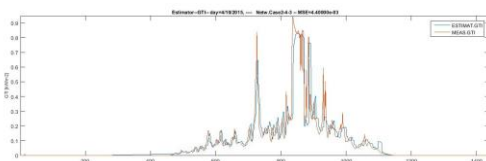
Figure 2 – GTI estimation

The GTI is estimated with respect to the minutes of the day with a great accuracy, as attested by the low value of MSE. The estimator faithfully follows the target value of GTI even in day where GTI has particularly fluctuating values. The GTI estimation gained is collected together with the ambient temperature T and the wind speed WS and are given as input to the ANN to estimates the PV module temperature. In the next figure is shown the behavior of the PV module temperature estimation and the value measured along the test day. Even in this case there is a good agreement between the two.
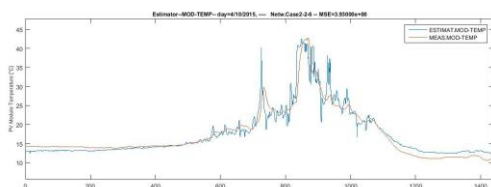
Figure 2 – PV module temperature estimation

As a last step we estimate the PV module production. For this purpose a number of data and measures referring the test day are collected. GTI and PV module temperature estimations are considered together to: temperature T, wind speed WS and direction WD, humidity H and atmospheric pressure P. All these are inputs to the third ANN to estimate the PV power production. Next figure shows the comparison between the estimation computed and the PV power production measured during the minutes of the test day.
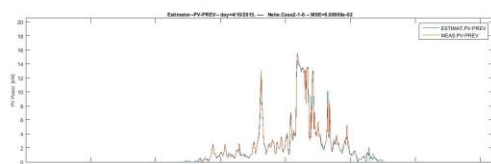
Figure 3 – PV power estimation

The result obtained shows a great accordance between the

two values, as evidenced by the very low value of MSE.

The behavior of the PV power production in a medium period is documented in the next figure where the trend of MSE of the estimator during a period of about 40 days is reported. The period refers to September/October 2015 (it includes the test day). As it is evident the behavior is fairly uniform and reliable.
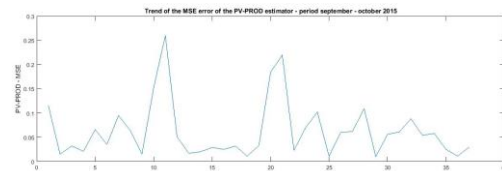
Figure 4 – MSE of PV power estimation in 40 days

CONCLUSIONS

In this paper we proposed an estimator of the PV power production for a field of PV panels installed in the RSE microgrid. This is an application tailored for the renewable production forecast, as part of the microgrid control system. It is based on the Artificial Neural Network technology. This estimator is easily configurable, requires a light set of data, five days at most for training and test, is daily redefined and ensures a high reliability as witnesses the experimental results reported.

In the next future we are going to improve the model defined including a preliminary component analysis to evaluate and weight the contribution of each variable identified in the current model.

ACKNOWLEDGMENTS

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