Day-ahead PV Power Forecast by Hybrid ANN Compared to the Five Parameters Model Estimated by Particle Filter Algorithm

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Abstract. A comparison between the hybrid method (PHANN – Physical Hybrid Artificial Neural Network) and the 5 parameter Physical model, which have been determined by the particle filter algorithm, is presented here. These methods have been employed to perform the day-ahead forecast of the output power of a photovoltaic plant. The aim of this work is to assess the forecast accuracy of the two methods.

Keywords: Day-ahead energy forecast · Artificial neural networks · Particle filter algorithm

1 Introduction

Photovoltaic (PV) systems and, more in general, Renewable Energy Sources (RES) are highly unpredictable due to the uncertainty of the weather forecast. The energy prediction has been often applied to the electric loads and is a typical application of time series analysis methods. In recent years several power forecasting models related to PV plants have been developed. Many methods have been employed to perform the day-ahead forecast of the hourly output power curve (given from 24 up to 48 h in advance) as reported in [1]. The existing methods can be mainly classified into three categories: physical, statistical and hybrid. A physical algorithm can be defined as a deterministic model which mathematically identifies the relationship between the input and the output of the system. An Artificial Neural Network, instead, stochastically describes the relationships between the input parameters and the output of the system with a weighted average sum of the input. A hybrid method is considered as any combination of the previous groups of forecasting models. Some of these models have been employed to forecast solar radiation [2,3], while other works present models specifically dedicated to the forecasting of the hourly power output from PV plants [4,5]. Nowadays the most applied techniques to model the stochastic nature of solar irradiance at the ground level, and thus the power output of

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PV installations, are the statistical methods. In particular, regression methods are often employed to describe complex non-linear atmospheric phenomena for few-hours ahead forecast and specific soft-computing techniques based on artificial neural network (ANN) are used for few-hours power output forecast [6]. Some other authors using physical methods report the comparison of the results obtained with different models based on two or more forecasting techniques [7]. Only a few papers describe the forecasting models used to predict the daily irradiance or directly the energy production of the PV plant for all the daylight hours of the following day [7–9].

ANN needs to be trained with historical data, and sometimes these data are not available. Therefore, it is necessary to adopt a different forecasting algorithm combining weather forecast with the PV plant physical parameters [10] estimated by knowing the specific model of the PV system.

In this paper a comparison between two forecasting models, namely a physical and a hybrid one is provided. The first is the well known five parameters model of the PV module, which are estimated with the particle filter algorithm, and the second is the recently developed PHANN (Physic Hybrid Artificial Neural Network), presented in [11].

2 Physical Model of the PV Cell

One of the most complete physical model to describe the PV module power is based on five parameters. The equivalent circuit in Fig. 1 includes $R_{SH,c}$ called "cell shunt resistance", which is connected in parallel to the photo-current generator I_{PV} and second resistance ($R_{S,c}$), called "cell series resistance", which is connected in series to the cell terminals. Therefore the five-parameter model, can be defined by:

- I_{PV}, the light-generated current,
- I_D, the reverse saturation current of the PN junction,
- n, the diode ideality factor.

$$I = I_{PV} - I_0 \cdot \left(e^{\dfrac{V + R_{s,c} \cdot I}{n \cdot V_t}} - 1 \right) - \frac{V + Rs,c \cdot I}{R_{SH,c}} \tag{1}$$

The IV characteristic curve of the PV cell mainly depends on solar irradiance and PN junction temperature. The latter depends on several parameters such as: the actual irradiance G_{TOT} on the cell, the ambient temperature T_{amb}, the wind speed and the wind direction. The cell temperature can also be evaluated starting from the measurement of the ambient parameters by means of two different models: the nominal operating cell temperature (NOCT) [12], which is the cell operating temperature under certain conditions (T_{amb} = 20°C, G_{NOCT} = 800 W/m^2, wind speed = 1 m/s without thermal convection on the back of the PV module), and the SANDIA model [13].

The complete dissertation of this model, linking solar radiation, ambient temperature and PV power output of the module is described in [10,14].

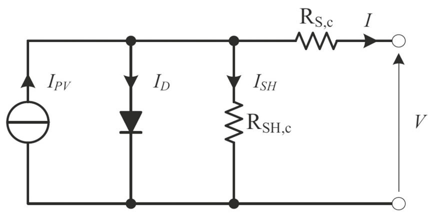

Fig. 1. Circuit of the five-parameter equivalent model.

3 Physical Hybrid Artificial Neural Network

In this work the recently developed [11] Physic Hybrid Artificial Neural Network (PHANN) is adopted to enhance the forecast by combining both the physical Clear Sky Solar Radiation Algorithm (CSRM) by Hottel [15] and the stochastic ANN method. The physical algorithm has been used to identify the maximum solar radiation exploitable in a given PV plant, the sunrise and the sunset hours, in order to exclude all the night time steps with null PV power output.

4 Particle Filter

In this section, an innovative algorithm for state and parameter estimation will be applied for the evaluation of characteristic quantities associated to a PV module. Then the results obtained with the following technique will be compared to those derived from the PHANN method reported in this paper.

Particle filters are a set of algorithms based on Monte Carlo technique for the estimation of the dynamic evolution of a system [16]. Let's consider a dynamical system in the continuous time, described by:

$$\dot{x} = f_1(x, u, \theta, w) \tag{2}$$

$$y = g_1(x, u, \theta, v) \tag{3}$$

where $x \in \mathbb{R}^n$ is the vector of state variables, $u \in \mathbb{R}^q$ is the vector of control quantities, $y \in \mathbb{R}^m$ is the set of output measured variables and $\theta \in \mathbb{R}^p$ is the space of unknown parameters; w and v represent the random variables used to express the uncertainty associated to the model and to the measurement procedure.

In order to implement the technique, it is necessary to first discretize the model of both the system evolution and of the measurement procedure.

$$x_k = f_2(x_{k-1}, u_{k-1}, \theta_{k-1}, w_{k-1}) \tag{4}$$

$$y_k = g_2(x_k, u_k, \theta_k, v_k) \tag{5}$$

In this context, the model has been applied mainly for parameter estimation; thus it is convenient to add a fictitious dynamic of the unknown parameters in order to take into account the incremental estimation process:

$$\theta_k = \mathbb{H}(\theta_{k-1}, \epsilon_{k-1}) \tag{6}$$
$$y_k = \mathbb{G}(\theta_k, \eta_k) \tag{7}$$

In (6) and (7) the fictitious model associated to the parameter evolution and the actual measurement process description are shown, respectively. In general, both $\mathbb{H}$ and $\mathbb{G}$ are non-linear functions subjected to white noise.

4.1 Particle Filter Implementation

The particle filter algorithm based on Sequential Monte Carlo simulation [16] has been implemented for the parameter estimation. This technique is based on the Bayesian approach and it aims at identifying, among a group of N independently simulated dynamical evolutions of the system called *particles*, the ones that are most likely to match the actual condition of the equipment, according to the comparison with measured data. At each time step, the filter evaluates the probability distribution a posteriori of each unknown state or parameter, starting from a given state supposed a prior. Each particle is then weighted according to its likelihood function.

One of the problems associated with the Bayesian approach is that it needs to deal with probabilistic functional analysis, as all the terms involved are probability distribution functions. In general it is not so easy to analytically derive the product of these functions, especially in non-linear systems having non-Gaussian distributions. Therefore a Monte Carlo scheme may be adopted to numerically retrieve the result. A certain number N of independent dynamics of the systems (*particles*) are simulated and each of them is weighted by the likelihood function, in order to assess its coherence with the measurements performed on the system.

First of all it is necessary to guess a state a priori for the Bayesian scheme. In order to keep track of the previous values of the parameter and improve the convergence rate of the estimation process, this state is evaluated starting from the estimation at the previous step, according to the fictitious dynamical process introduced in (6). In the following, a linear model is adopted.

$$\tilde{\theta}_{k,i} = \theta_{k-1,i} + \epsilon_{k-1,i} \qquad i = 1..N \tag{8}$$

Once the prior state is determined, the weight of each particle is evaluated considering a Gaussian distribution for the likelihood as in (9) and the normalized weights are obtained (10).

$$\mathcal{L}_{k,i}(y_k|\theta_{k,i}) = \frac{1}{\sqrt{(2\pi)^m |R_k|}} e^{-0.5(y_k - \mathbb{G}(\tilde{\theta}_{k,i}))^T R_k^{-1}(y_k - \mathbb{G}(\tilde{\theta}_{k,i}))} \tag{9}$$
$$w_{k,i} = \frac{\mathcal{L}_{k,i}}{\sum_{i=1}^{N} \mathcal{L}_{k,i}} \tag{10}$$

Once the weights of all the particles in all the independent N cases are known, it is possible to calculate the mean and standard deviation as compact indexes of the discrete probability distribution function, according to (11) and (12):

$$\theta_k = \sum_{i=1}^{N} w_{k,i}\tilde{\theta}_{k,i} \tag{11}$$

$$\sigma^2_{\theta_k} = \sum_{i=1}^{N} w_{k,i}(\tilde{\theta}_{k,i} - \theta_k)^2 \tag{12}$$

The whole process is then carried out iteratively for all the time steps.

5 Case Study and Data Analysis

In the considered application, the particle filter has been implemented for estimation of characteristic input of the five parameter model, described in Sect. 2. Indeed these quantities are peculiar for each PV module, are time-varying and they strongly depend on the actual operating conditions of the system. Thus a model-based algorithm able to track them in real time starting from the model equations and the measurements during operation may allow an effective estimation of such parameters.

The particle filter has been used, in particular to track the values of the series resistance R_s and the photo-generated current I_{PV}. The diode ideality factor n and the reverse leakage current I_0 have been taken from literature. The fictitious dynamical model explained in (8) by considering the *ClearSky* algorithm [15] which has been calculated in two successive samples of time $k-1$ and k, has been implemented as follows:

$$I_{PV}(k) = I_{PV}(k-1) \cdot \frac{ClearSky(k)}{ClearSky(k-1)} \cdot \epsilon \tag{13}$$

$$R_s(k) = R_s(k-1) + K \cdot Rs(k-1) \cdot \epsilon \tag{14}$$

where ϵ is a number randomly drawn by a Gaussian distribution. The filter is disabled when the $ClearSky$ algorithm predicts a null power production and the current is randomly initialized after the filter is reactivated.

As regards the measurement, the following equations can be derived from the equivalent model of the photovoltaic cell.

$$I_{out} = (I_{PV}(k) - I_D) \cdot \frac{R_p(k)}{Rs(k,i) + Rp(k,i)} - \frac{V_{DC}}{Rs(k,i) + Rp(k,i)} \tag{15}$$

$$P_{out} = (I_{PV}(k) - I_D) \cdot (V_{DC} + R_s(k)) - R_s(k) \cdot I_{out}^2 - \frac{(V_{DC} + R_s(k) \cdot I_{out})}{R_p} \tag{16}$$

In Fig. 2(a) a comparison between the particle estimator and the analytic solution of the model has been carried out. The last values have been derived considering the exact solution of the model, obtained assuming the values of the equivalent circuit parameters measured on the plant. These data have been assumed as reference values and are used in order to test the algorithm effectiveness. The error associated to the estimation process is reported in Fig. 2(b) with respect to the photo-generated current; here it is possible to see that the maximum difference is located in the first and last hours of each day, where the approximation introduced by the filter is higher; however it is possible to see an asymptotic decrease of the error thanks to the filter convergence.

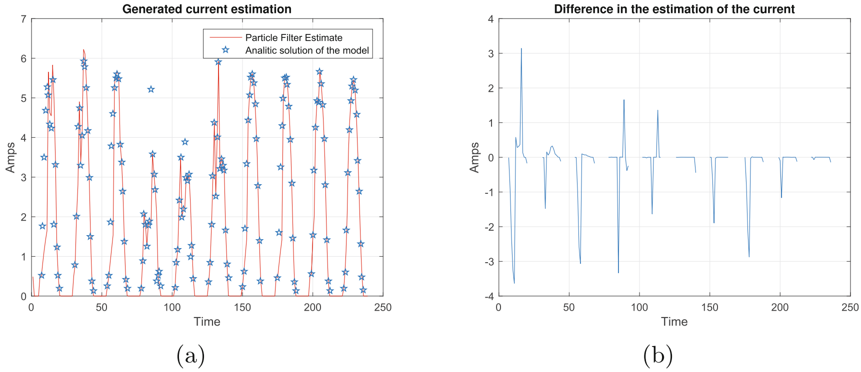

Fig. 2. Estimated photo-generated current and its error

5.1 Numerical Results and Discussion

The parameters of the physical model have been estimated by means of the particle filter, as already explained in the previous section. These parameters have been employed to forecast the PV power output and to make a comparison with the actual ones provided by a PV module. These experimental data are collected at the SolarTechLab, Politecnico di Milano (Italy), whose geographical coordinates are: latitude 45.502941N, longitude 9.156577E. One 245 Wp rated power crystalline silicon PV module facing South, 30 deg tilted is considered. The weather forecasts for this site are provided 24 h in advance by a meteorological service (at 11PM of the day before the forecast one). A full list of the parameters employed for the training of the PHANN is reporter here below:

- Day of the year and hour of the day
- Global Horizontal Clear Sky Solar Radiation
- Wind Direction and speed
- Pressure
- Humidity Relative
- Rain
- Ambient temperature
- Global Horizontal Solar Radiation
- PV module DC Power Output

According to preliminary setup, PHANN is composed by two layers with 100 neurons in the first hidden layer and 50 neurons in the second. The activation

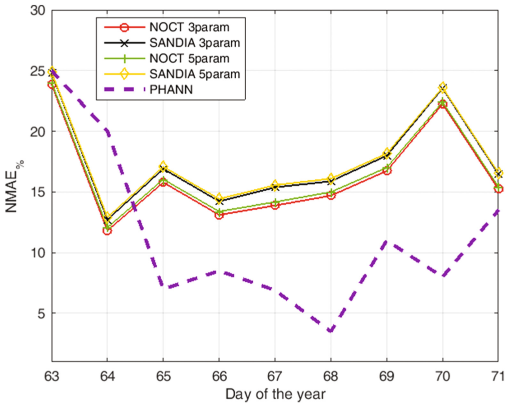

Fig. 3. Daily Normalised Mean Absolute Error calculated by different methods

function in the neurons is the sigmoidal function. These settings have been chosen after preliminary results which are exposed in a previous work [11]. PHANN is trained with the hourly parameters of the 11 days before of the forecast ones. The results shown in Fig. 3 are referred to 9 days between February and March 2014. This period is considered meaningful in terms of continuous succession of sunny and cloudy days and all the data are consistent without interruptions in the recordings. In this Figure these results are compared with those obtained considering different physical models, namely the combinations of thermal models (SANDIA and NOCT) of the considered PV cell power output with 3 and 5 parameter models described in Sect. 2.

Figure 3 shows the daily Normalised Mean Absolute Error NMAE. By observing this figure, the day-ahead forecast performed by the PHANN method is outperforming in several days the physical forecasting methods.

6 Conclusions

In this paper the comparison between the day-ahead forecast performed by the PHANN (Physical Hybrid Artificial Neural Network) and the 5 parameter Physical model (determined by the particle filter algorithm) has been assessed. The reported results show that the PHANN method generally provides better results and a more accurate forecast, with lower daily errors.

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