Short-term irradiance forecasting on the basis of spatially distributed measurements

Antonino Laudani, Gabriele Maria Lozito, Valentina Lucaferri and Martina Radicioni

Roma Tre University, Rome, Italy
martina.radicioni@uniroma3.it

Abstract. The output power of photovoltaic (PV) systems is heavily influenced by mismatching conditions that can drastically reduce the power produced by PV arrays. The mismatching power losses in PV systems are mainly related to partial or full shading conditions, i.e. non-uniform irradiation of the array. An essential point is the detection of the irradiance level in the whole PV plant. The use of irradiance sensors is generally avoided because of their cost and necessity for periodic calibration. In this work, an Artificial Neural Network (ANN) based method is proposed to forecast the irradiance value of each panel constituting the PV module, starting from a number of spatially distributed analytical irradiance computations on the array. A 2D random and cloudy 12 hours irradiance profile is generated considering wind action; the results show that the implemented system is able to provide an accurate temporal prevision of the PV plant irradiance distribution during the day.

Keywords: photovoltaic · mismatch · irradiance · neural networks.

1 Introduction

The technological progress of the last decades together with the demographic increase have shown the need of finding renewable energy sources able to stem global warming and pollution produced by fossil fuels and to meet the global energy demand [6]. These features have led to a rapid expansion of PV technologies in the world market. However, although several advances have been made in PV technology, some factors still persist that severely lower the efficiency of PV devices. Differences in the principal parameters of the modules of a PV system may produce discrepancies in the modules behavior; this problem is addressed as mismatching [17]. Among mismatch effects, shading is the principal concern as it is the main aspect that decreases the output power [5, 1]. Shading is also responsible for overheating and aging of the cells or modules [15]: the reduction in current production affecting a shaded PV cell influences the whole PV device behavior since hot spots may appear causing irreversible damages. A common practice aimed at limiting the effects coming from these power losses is the use of bypass diodes that are generally connected in parallel to each cell or group of cells [18, 2]; however, this strategy makes multiple peaks arise in the P-V characteristic of the device and this heavily affects the efficiency of the system showing

ICCS Camera Ready Version 2019
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-22750-0_57

the need of Maximum Power Point Tracking (MPPT) methods [9, 7]. As a matter of facts, the presence of multiple peaks makes the detection of the Global MPP (GMPP) hard since, despite the accuracy of traditional MPPT methods, they may remain trapped in Local MPP (LMPP). Hence, in this situation, more sophisticated MPP tracking strategies are needed. It is evident the impact that the identification of a shading scenario has on the choice and use of the afore mentioned strategies. The particular shading pattern on a device affects the nature of the procedure to be applied. As a result, a tool able to provide a time prediction of the shadow distribution is an essential requirement. In this paper a method is proposed to forecast the trend of the shadows on a PV array in order to obtain a satisfying shading prevision in a 12 hours period. The approach makes use of an ANN based method and does not need any irradiance sensors since the measurement of such a quantity is performed by an analytical strategy based on the well-known five-parameters model for PV systems. As a matter of facts, it is better to avoid the use of pyranometers because of their cost and tricky setup; to face this problem several alternative strategies have been developed to assess the value of irradiance without making use of sensors [3, 14, 4]. The cost reduction and the simplicity of using this analytical method make devices based on it integrable in large-scale PV systems. Moreover, the ANN choosen ensures accuracy and speed, despite of its simple architecture [12]. The paper is organized as follows: in Section 2 the five-parameters model, also known as one-diode model, is explained and in the second the closed-form formulation the analytical extraction of irradiance is shown; the ANN based method developed is presented in Section 3; in Section 4 the conclusions will follow.

2 Analytical irradiance sensor

2.1 Circuital model for PV devices

Several mathematical models for PV cells and modules are available in literature; among them the most used is the one-diode model also known as five-parameters model. The model, shown in Figure 1 allows to express the current I of the device as a function of the five parameters and of the number of cells connected in series, N_s:

$$I = I_{irr} - I_D - \left(\frac{V + IR_S N_s}{R_P N_s}\right) \tag{1}$$

with the diode current, I_D, equivalent to:

$$I_D = I_0 exp(\frac{V + IR_S N_s}{(\frac{nKT}{q})N_s}) \tag{2}$$

The parameters appearing in the afore mentioned formulas are here explained: I_{irr} is the photo-current, $q = 1.602 \times 10^{-9} C$ is the electron charge, $k = 1.38 \times 10^{-23} \frac{J}{K}$ the Boltzmann constant, n the diode ideality factor, R_s and R_p the series and shunt resistances and I_0 the diode reverse saturation current.

ICCS Camera Ready Version 2019
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-22750-0_57

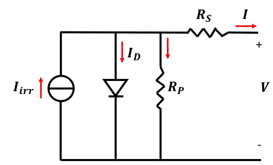

Fig. 1. One-diode model for a PV device.

The parameters appearing in (1) are, in turn, dependent on the values of irradiance and temperature. Such dependancies are shown in the following part. It has to be mentioned that SRC, i.e. *Standard Reference Condition*, is used to refer to parameters measured in the condition of $T = 25\ C^{\circ}$ and $G = 1000\ \frac{W}{m^2}$:

$$I_{irr} = I_{irr(SRC)} + K(T - T_{SRC}))\frac{G}{G_{SRC}} \tag{3}$$

$$I_0 = I_{0,SRC}\left(\frac{T}{T_{SRC}}\right)^3 e^{\left[\frac{E_{g,ref}}{kT_{SRC}} - \frac{E_g}{kT}\right]} \tag{4}$$

$$R_p = R_{p,SRC}\frac{G_{SRC}}{G} \tag{5}$$

$$R_s = R_{s,SRC} \tag{6}$$

$$n = n_{SRC} \tag{7}$$

$$E_g = E_{g,SRC}(1 - 0.0002677(T - T_{SRC})) \tag{8}$$

The extraction of the five parameters $[11, 10, 13]$is a key point since allows the application of the analytical formula for the calculation of irradiance through the PV plant. This paper makes use of the procedure proposed in [11] where an efficient algorithm ensuring global convergence; this strategy allows to provide feasible solution to the system of non- linear equations.

2.2 Closed-form formulation for irradiance

The topic of irradiance sensing is of central importance for PV applications since needs to be measured on the surface of the device under exam. As a matter of fact, while measuring temperature is trivial, knowing the value of irradiance is quite hard. Such a quantity is highly dependent on the inclination of the panel with respect to sunrays, therefore, to exactly estimate the value of irradiance shades have to be carefully taken into account. As a result of this, a standard practice consists in placing sensors close to the device. This leads to some relevant issues: firstly, measurements based on the use of pyranometers are generally expensive because of the cost of the device itself and the need of periodic calibrations, then, the measurement system is quite difficult to be set up since the pyranometer should be hold perfectly parallel to the PV plant and, lastly, the PV device may have a different spectral response from that of the sensor. Hence, the

ICCS Camera Ready Version 2019
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-22750-0_57

analytical calculation of irradiance on the PV array is a suitable option allowing to avoid the mentioned drawbacks. In [3] the authors propose a closed-form expression for solar irradiance based on the knowledge of the five parameter of the circuital model of the PV cell:

$$\begin{aligned}\frac{G}{G_{STC}}\left(N_p I_{irr,STC} + N_p \alpha_T \left(T - T_{STC}\right) - \frac{V + I N_s R_{s,STC}/N_p}{N_p N_s R_{p,STC}/N_p}\right) = \\ I + N_p I_0 \left[e^{\left(\frac{V + I N_s R_{s,STC}/N_p}{N_S n k T}\right)} - 1\right]\end{aligned} \tag{9}$$

Given these information togheter with the value of temperature and the measurement of operating voltage and current, the formula of equation (9) is able to accurately estimate irradiance in any point of the PV array.

3 Irradiance prediction system

3.1 Irradiance calculation based on spatial distributed measurements

The proposed approach is based on a set of distributed measurements of solar irradiance on a number of modules of the array, that are collected at a certain timestep t. Let us focalize on a set of such modules, for example 5 elements arranged to form a cross shape; at each timestep, t, the triplet $V(k,t), I(k,t)$ and $T(k,t)$ of each k^{th} device is measured. In order to use expression (9), the five parameter of the model have to be extracted. Following the method shown in [11], a unique and reasonable solution for the five parameters identifying the one-diode model is found. Such a procedure is based on some algebraic manipulations of (1), allowing to estabilish that, among the five parameters, R_s and n are the only independent variables of the problem: thus the search space is a two-dimensional one and it is possible to use very fast and accurate algorithms for searching the solution. Then, the operating point of each module and its temperature are collected through measurements on the device; these information, togheter with the values of the five parameters are injected into (9) to obtain the values of irradiance on the five cross-shape arranged modules.

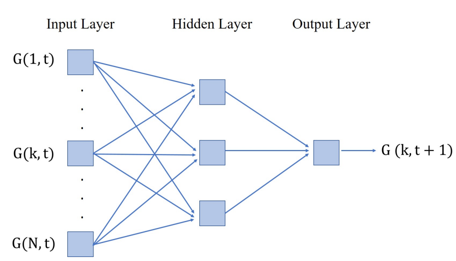

Fig. 2. Architecture of the proposed FFNN.

ICCS Camera Ready Version 2019
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-22750-0_57

3.2 Forecasting an irradiance profile by using Artificial Neural Networks

The mapping capabilities of an ANN depend on its non-linear nature that can be attributed to the non-linear activation function. In absence of this latest element the ANN would be equivalent to a linear interpolator. The implemented ANN is able to forecast the future irradiance on any module of the cross at time $(t+1)$ by knowing the past values at instant t on the whole cross, that we suppose constituted by N modules. Firstly, a random 12 hours (from 6 a.m. to 6 p.m.) 2D cloudy irradiance profile is generated. In particular, each PV module of the array is supposed to be irradiated by a waveform coming from the overlapping of a set of randomly generated spikes to a Gaussian waveform with a peak value of 1000 W/m^2. The array is a square matrix with 100 points per side: each couple of coordinates identifies a single PV module of the array.The implemented ANN is a multi-input and single-output feed-forward neural network (FFNN) with a hidden layer constituted by 3 neurons, Figure 2. 10000 timesteps have been considered: 1000 have been used for the training set and the other 9000 constitute the validation one; the training samples are choosen randomly on the whole set in order not to have them accumulated in a specific area. Each of the inputs of the ANN is a row with the values of irradiance of one of the N modules of the array calculated for each timestep, while the target is a row containing the values of irradiance on the k^{th} module, with k to be choosen from the N panels set, with an assigned time shift. The greater the time shift, the greater the forecast time gap. The prevision is efficient even when increasing the elements of the cross. The presented ANN achieves satisfactory performances, with a Mean Squared Error below 10 % on the whole dataset, even if it does not involve a recurrent architecture (RNN). As a matter of facts, the choice of an FFNN allows to avoid problems that generally affect RNNs, i.e. the issue of vanishing or exploding gradients [16, 8], that make the training of the neural network hard, especially when dealing with large datasets. Moreover, the use of RNNs requires a very careful initialization of the neural network parameters. In addition, the training of an RNN is performed through complex and computationally demanding algorithms, unlike an FFNN that can be effciently trained by using simply implementable on-line algorithms; this aspect is relevant since makes the neural network suitable for embedded solutions, able to provide a real-time training of the FFNN. The proposed method is described in the flowchart of Figure 3. The results of the presented solution are shown in Figure 4 for a PV cross of 5 modules. It can be seen that the FFNN is able to correctly fit the irradiance trend on the whole time frame.

4 Conclusions

This work has presented an ANN based procedure able to predict the time trend of solar irradiance on a PV array. A 12 hours random cloudy profile has been generated and its development over time has been simulated by using a shift function. A preliminary part has seen the extraction of irradiance values over

ICCS Camera Ready Version 2019
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-22750-0_57

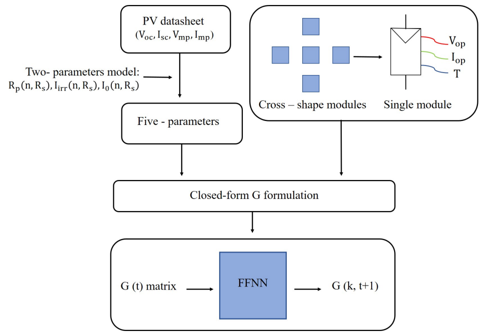

Fig. 3. Flowchart of the implemented algorithm.

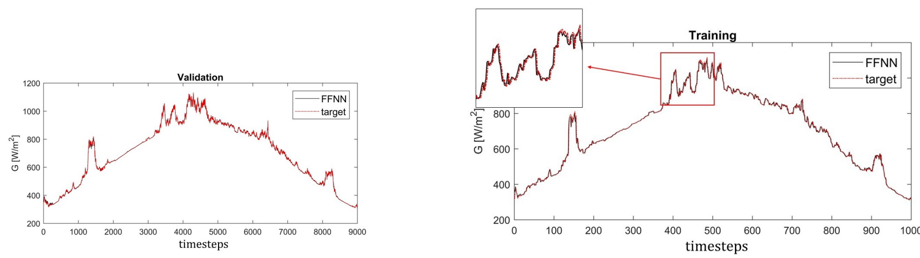

Fig. 4. Training and validation results of the FFNN-based solution.

the PV plant. A performing analytical tool has been used able to accurately assess irradiance on each panel avoiding to embed costly pyranometers into the PV set-up. The strength of the closed-form irradiance computation consists in the requirement of simply obtainable information, i.e. operating voltage and current and cell or module temperature. Thus, the formulation allows an easy mapping of irradiance along the whole PV structure. The prediction part of the paper, has been based on the use of FFNNs that have been proved to be powerful tools with accurate forecasting capabilities, despite their static nature. The error, both on training and on test, is of about 10%, a satisfying precentage when dealing with time previsions. Moreover, the simplicity of the feed-forward architecture, consisting in a unique hidden layer, ensures fast training of the network: the time needed to train a single FFNN does not exceed half a second. Definitely, the developed method provides a fast and accurate way to forecats irradiance; as a matter of facts, the prediction of such a quantity is a central issue when addressing the problem of partial shading since irradiance knowledge is a critical factor for the adoption of strategies aimed at retrieving the power lost, thus allowing to increase the efficiency of any PV plant.

ICCS Camera Ready Version 2019
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-22750-0_57

References

1. Alonso-Garcia, M., Ruiz, J., Chenlo, F.: Experimental study of mismatch and shading effects in the i–v characteristic of a photovoltaic module. Solar Energy Materials and Solar Cells **90**(3), 329–340 (2006)
2. Bauwens, P., Doutreloigne, J.: Reducing partial shading power loss with an integrated smart bypass. Solar Energy **103**, 134–142 (2014)
3. Carrasco, M., Laudani, A., Lozito, G.M., Mancilla-David, F., Riganti Fulginei, F., Salvini, A.: Low-cost solar irradiance sensing for pv systems. Energies **10**(7), 998 (2017)
4. Cruz-Colon, J., Martinez-Mitjans, L., Ortiz-Rivera, E.I.: Design of a low cost irradiance meter using a photovoltaic panel. In: Photovoltaic Specialists Conference (PVSC), 2012 38th IEEE. pp. 002911–002912. IEEE (2012)
5. Dolara, A., Lazaroiu, G.C., Leva, S., Manzolini, G.: Experimental investigation of partial shading scenarios on pv (photovoltaic) modules. Energy **55**, 466–475 (2013)
6. Hepbasli, A.: A key review on exergetic analysis and assessment of renewable energy resources for a sustainable future. Renewable and sustainable energy reviews **12**(3), 593–661 (2008)
7. Ishaque, K., Salam, Z.: A review of maximum power point tracking techniques of pv system for uniform insolation and partial shading condition. Renewable and Sustainable Energy Reviews **19**, 475–488 (2013)
8. Jozefowicz, R., Zaremba, W., Sutskever, I.: An empirical exploration of recurrent network architectures. In: International Conference on Machine Learning. pp. 2342–2350 (2015)
9. Koutroulis, E., Blaabjerg, F.: A new technique for tracking the global maximum power point of pv arrays operating under partial-shading conditions. IEEE Journal of Photovoltaics **2**(2), 184–190 (2012)
10. Laudani, A., Fulginei, F.R., Salvini, A.: High performing extraction procedure for the one-diode model of a photovoltaic panel from experimental i–v curves by using reduced forms. Solar Energy **103**, 316–326 (2014)
11. Laudani, A., Fulginei, F.R., Salvini, A.: Identification of the one-diode model for photovoltaic modules from datasheet values. Solar Energy **108**, 432–446 (2014)
12. Laudani, A., Lozito, G.M., Fulginei, F.R., Salvini, A.: On training efficiency and computational costs of a feed forward neural network: a review. Computational intelligence and neuroscience **2015**, 83 (2015)
13. Laudani, A., Riganti Fulginei, F., Salvini, A., Lozito, G.M., Coco, S.: Very fast and accurate procedure for the characterization of photovoltaic panels from datasheet information. International Journal of Photoenergy **2014** (2014)
14. Mancilla-David, F., Fulginei, F.R., Laudani, A., Salvini, A.: A neural network-based low-cost solar irradiance sensor. IEEE Trans. Instrumentation and Measurement **63**(3), 583–591 (2014)
15. Manganiello, P., Balato, M., Vitelli, M.: A survey on mismatching and aging of pv modules: The closed loop. IEEE Transactions on Industrial Electronics **62**(11), 7276–7286 (2015)
16. Pascanu, R., Mikolov, T., Bengio, Y.: On the difficulty of training recurrent neural networks. In: International Conference on Machine Learning. pp. 1310–1318 (2013)
17. Petrone, G., Ramos-Paja, C.: Modeling of photovoltaic fields in mismatched conditions for energy yield evaluations. Electric power systems research **81**(4), 1003–1013 (2011)
18. Silvestre, S., Boronat, A., Chouder, A.: Study of bypass diodes configuration on pv modules. Applied Energy **86**(9), 1632–1640 (2009)

ICCS Camera Ready Version 2019
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-22750-0_57