Real Time Techniques and Architectures for Maximizing the Power Produced by a Photovoltaic Array

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Abstract. The inherent low conversion efficiency, from solar to electrical energy, of the photovoltaic cells makes the use of techniques and architectures aimed at maximizing the electrical power a photovoltaic array is able to produce at any weather condition mandatory. In order to understand what are the challenging problems cropping up in some modern applications, an overview of the main techniques for photovoltaic arrays modeling is given first. Afterwards, the control strategies for the maximum power point tracking used in commercial products dedicated to photovoltaic strings and modules are compared and their advantages and drawbacks are put into evidence, with a special emphasis on their efficiency. Some methods presented in literature and based on the use of artificial neural networks are compared with more classical ones. Finally, a brief overview of other applications of artificial neural networks to photovoltaic-related problems is also given.

1 Introduction

Photovoltaic (PV) technology in its modern era is referred to be dated by 1954 [1]. It was described that a p-n semiconductor junction under the effect of sun light could generate electricity. A cheap widespread source of energy is since then used to increasingly satisfy human needs of electric power [2]. Furthermore, this technology is a key issue to satisfy nowadays requirements to reduce CO_2 emission rates due to the use of fossil fuels in electricity production. PV devices can be tailored to supply power electricity in different scale ranges, from single cells for energy harvesting purposes aimed at supplying remote sensors, to small module applications involving a few number of cells, up to the huge scale of grid connected high power plants requiring a large number of parallel connected strings made of series connected panels. Up to now, the largest part of the research efforts and of the commercial products have been devoting to large power applications involving grid connected power plants. In such cases, all the PV panels are of the same type/model and they have the same orientation towards the sun. The plant

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is installed in a flat site without any obstacle in the neighborhood, so that the maximum possible electrical power production is ensured from sunrise to sunset.

More recently, the scientific community as well as many companies operating in the field of PV systems have shown a large interest in applications dedicated to small power loads. These range from harvesting systems dedicated to remote sensors and communication systems up to battery chargers for sustainable mobility applications. In such cases, the number of PV cells electrically connected in series is quite low, so that the main issue is to raise up the voltage level up to that one required by the load. Nonetheless, very often in these applications the cells do not have the same orientation towards the sun, also changing dynamically as in applications to mobility, and some of them can be subjected to a time varying shadowing effect. The latter also occurs in Building Integrated PV (BIPV) applications, which are of interest to the aim of making buildings as much autonomous as possible from the point of view of the energy production.

In order to describe the behavior of a PV generator, regardless of its size, thus a cell, a module, a panel, a string or a large field, working in such a non conventional conditions some dedicated models and numerical methods are needed. This task is of fundamental importance in order to understand the mechanisms that affect the power production of a so-called *mismatched* PV generator and for preventing those operating conditions that might lead to a permanent damage of some cells. Furthermore, comprehensive models are the basis for developing strategies that allow a proper control of the PV generator also in presence of mismatched conditions, especially ensuring that the maximum available power is harvested at any time. The latter is not a trivial task: as demonstrated by the huge amount of papers that can be found in literature, Maximum Power Point Tracking (MPPT) is a challenging problem in any PV system, because of the need of extracting the maximum electrical power from the PV generator without having any knowledge about the type/model of cells and without measuring neither the irradiation level nor the temperature at which the cells work. The MPPT operation becomes much more involved if the PV generator works in mismatched conditions, because the MPPT algorithm must be able to distinguish the absolute maximum power point from the relative ones in a multi-modal characteristic.

In this paper an overview of the methods presented in literature and used in commercial products for affording the problems mentioned above is given. First of all, some of the main techniques used for modeling and simulating PV generators working both in uniform and in mismatched conditions are compared. Such approaches are usually based on a proper description of the PV non linearities and on an effective solution of the non linear system of equations that follows. A special attention is devoted to the PV modeling methods that are based on Artificial Neural Networks (ANNs). In fact, ANNs seem to be an effective tool for describing a complex system, which is strongly non linear and depending on a large number of time varying parameters, as in the case of PV generators is. In fact, some parameters like the irradiation level and the operating temperature, but also some others related to the semiconducting material the cells are made of, may assume unpredictable values which are also subjected to some drifts. The ANNs profit from their ability of learning from a training set, which might be made of some experimental data taken from the real PV generator working in different conditions. The second part of this paper is dedicated to the the real time techniques and to the architectures that are commonly used for maximizing the power produced by a PV array. Advantages and drawbacks are put into evidence, especially by referring to the solutions that are used in the largest part of products available on the market and dedicated to large scale systems as well as to single PV modules. The power electronics solutions and system architectures used for grid connected as well as stand alone systems are overviewed. The role of the MPPT efficiency in the design of a PV power processing system will be emphasized and the factors, especially the effect of noises, affecting it are discussed. Some solutions for achieving a high MPPT efficiency in noisy conditions are mentioned and compared. The role of ANNs in this field is analyzed by referring to some techniques introduced by recent papers appeared in literature.

In a final section, some applications of ANNs to PV-related problems are overviewed and the most recent literature on these topics is referenced. In fact, ANNs can be beneficial in the weather forecast, thus in the prediction of the irradiation level and temperature at which the PV generator will work, in the estimation of the power production and efficiency of PV plants as well as in their sizing, both in stand-alone and in grid-connected applications. Conclusions end the paper.

2 Photovoltaic Source Modeling

A PV generator is made of a parallel connection of strings obtained by connecting in series a number of panels. The number of panels in a string is dictated by the input voltage requirements of the power processing systems, while the number of strings to put in parallel depends on the required power level. Each PV panel is made of a few number of PV modules electrically connected in series and assembled in the same frame. Commercially available PV panels consist in usually two or three modules, each one of them formed by about twenty cells equipped with an anti-parallel diode, as shown in Fig.1.

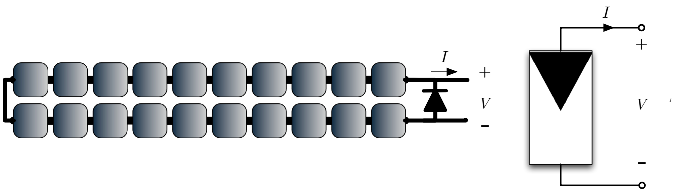

Fig. 1. PV module made of a number of series-connected cells and the anti-parallel bypass diode

If the PV generator is made of cells that are exactly equal, in terms of characteristics of the semiconductor material they are made of, and working in exactly the same conditions, especially temperature and irradiation level, its current vs. voltage (I-V) curve is merely a scaled up version of the same curve referred to a single PV cell. The voltage value is scaled up by the number of cells connected in series and the current value is multiplied by the number of strings electrically connected in parallel. This leads to the curves shown in Figg. 2 and 3. The curves are in normalized units and clearly put into evidence the non linear and time dependent nature of the PV generator. The peak in the power vs. voltage (P-V) curve must be tracked in order to ensure that the PV field delivers the maximum power to the load. The peak position changes due to the irradiance level G the field is subjected to, but it is also affected by the ambient temperature T_a. The former mainly affects the current level, but it is related to the voltage by a logarithmic law. On the contrary, the voltage values are mainly influenced by the working temperature of the cells, because at a higher temperature the open circuit voltage decreases.

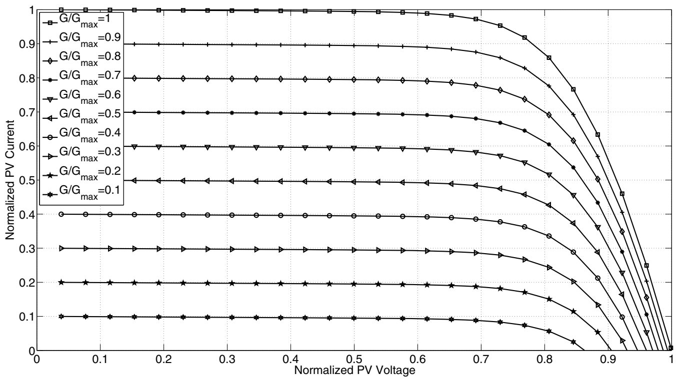

Fig. 2. Current vs. voltage characteristic of a PV panel: effect of irradiation G

The behavior of the PV generator, at whichever granularity level (cell, module, panel, string and field), is described by the equivalent circuit shown in Fig. 4 and by the corresponding equation (1).

$$I = I_{ph} - I_{sat} \cdot \left(e^{\frac{V+I\cdot R_s}{\eta V_t}} - 1 \right) - \frac{V + I \cdot R_s}{R_p} \tag{1}$$

In (1) V_t is the thermal voltage, I_{sat} is the saturation current and I_{ph} is the photoinduced current, depending on the type of cell used and on the irradiation level and on the temperature [3]. The resistances R_s and R_p represent the various loss mechanism taking place in the cell and in the whole PV array. As stated above, equation (1) allows to model any type of PV generator working in uniform conditions, provided that the values assumed by the parameters and the variables appearing in it, that are supposed to be known for a single cell composing the generator, are scaled up properly.

Unfortunately, such a simple, although non linear, model is too rough to be used for describing the mismatched operation of a PV array, so that much more sophisticated tools have been presented in literature.

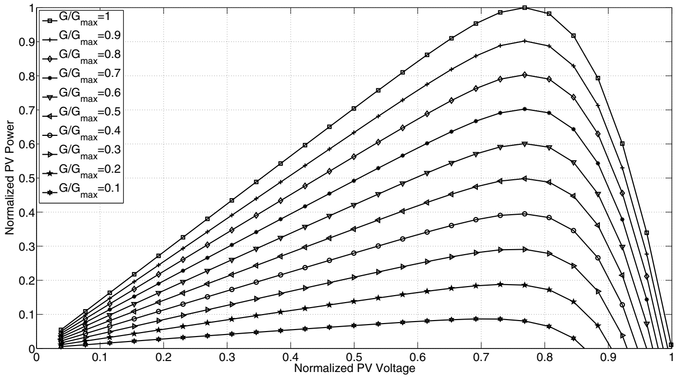

Fig. 3. Power vs. voltage characteristic of a PV panel: effect of irradiation G

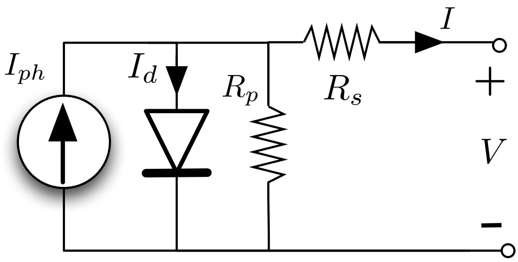

Fig. 4. Single diode model accounting for ohmic losses

2.1 Classical Modeling Approaches

A first step in obtaining a compact model of a mismatched PV array, which also have the advantage of ensuring a fast numerical simulation, is the manipulation of the equation (1) that is not able to give explicitly neither the voltage nor the current values as a function of the other electrical variable. In literature, the Lambert W function has been used fruitfully in order to achieve this result. In [4] many details and useful references about the Lambert W function can be found, but the main thing to know is that it is the solution of the equation:

$$f(x) = x \cdot e^x \tag{2}$$

which evidently occurs in (1), and that can be calculated by means of a suitable series expansion [4]. The LambertW function allows to obtain a compact expression giving the value of the current at whatever voltage value, with a clear dependence on all the parameters depending on the semiconductor material used to realize the cells, as well as on irradiance and temperature:

$$I = \frac{R_p \cdot \left(I_{ph} + I_{sat}\right) - V}{R_s + R_p} - \frac{\eta \cdot V_t}{R_s} \cdot LambertW\left(\theta\right) \tag{3}$$

where:

$$\theta = \frac{(R_p//R_s) \cdot I_{sat} \cdot e^{\frac{R_p \cdot R_s \cdot \left(I_{ph}+I_{sat}\right)+R_p \cdot V}{\eta \cdot V_t \cdot (R_p+R_s)}}}{\eta \cdot V_t} \tag{4}$$

As shown in [5], in the same way the explicit expression of the current flowing into a PV module, including a string of cells equipped with the anti-parallel bypass diode, takes the following expression, wherein θ assumes the form already given in (4):

$$I = I_{ph} - I_{sat} \cdot \left(e^{\frac{V+I \cdot R_s}{\eta V_t}} - 1\right) - \frac{V + I \cdot R_s}{R_p} + I_{sat,dby} \cdot \left(e^{-\frac{V}{\eta_{dby} V_{t,dby}}} - 1\right) \tag{5}$$

In this expression, the part with the subscript *dby* refers to the bypass diode. This formula allows an effective simulation of one PV panel, consisting of a two or three modules in series, operating with different irradiation, temperature or exhibiting different values of the material parameters for each module. In this way, the level at which a PV can be simulated is reduced at the module, not panel, level, thus is reduced at one half or one third of a panel. Such scaling factors, the half or one third, are cited as examples because of the real numbers used in commercially available panels. For instance, the Suntech STP280 polycrystalline panel has 72 cells, organized into six rows of twelve cells, with three bypass diodes, each one connected in anti-parallel to twenty four cells. The approach proposed in [5] profits from (5) and from the properties of the Lambert W function. In fact, it allows to achieve an explicit expression also for the differential conductance, that is the derivative of the PV module current with respect to its voltage. In this way, the non linear system of equations, that allows to calculate the operating points of all the PV modules in a string at whatever value of the string voltage, can be solved effectively by means of any classical algorithm, e.g. the Newton-Raphson method. The method allows to reconstruct the mismatched I-V curve at the desired level of accuracy, but it can be also useful for the real time simulation of the string in environments like PSIM or PSPICE.

An approach that concentrates the calculation effort across the so-called *inflection points* is introduced in [6]. It allows to calculate in an effective way the voltage values where, starting from the low voltages at which only the module receiving the highest irradiation produces power, the bypass diodes end their conduction and the modules with a lower short circuit current start giving their contribution. According to the authors of [6], the method is able to give an approximate version of the mismatched curve quite quickly, but may lack in the accurate reconstruction of the whole curve.

In mismatched conditions, the PV curve of the array is multimodal, namely it does not look like those ones shown in Fig.3, characterized by a single maximum power point, but it shows multiple peaks. This is due to the bypass diode operation, so that some modules are bypassed and absorb some electrical power. This determines a power loss, which is fortunately low thanks to the low activation voltage of the anti-parallel bypass diode. Such a small power loss is the price to pay in order to avoid that the modules that receive a higher irradiation are penalized because of the draft series connection with those ones producing less power. Fig.5 shows an example of PV curves in uniform

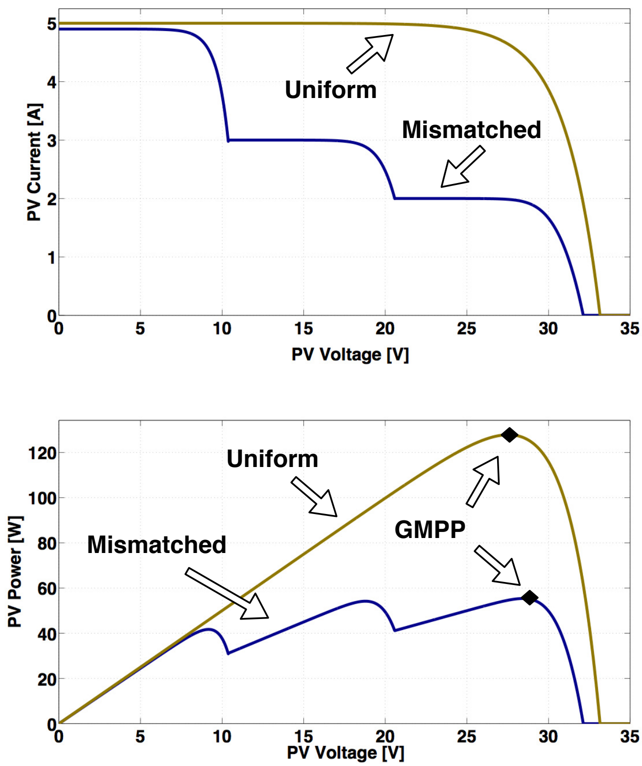

Fig. 5. Photovoltaic characteristics in homogeneous and partial shading conditions. a) Current vs. Voltage curve, b) Power vs. Voltage curve.

and mismatched conditions, by putting into evidence the existence of a Global Maximum Power Point (GMPP). The detrimental effect of the local maxima has been well illustrated in [7] where some experimental studies have been carried out on different commercial products.

The methods mentioned above assume that the smaller entity to be modeled in the PV array is the module, thus considering that all the cells belonging to the module work in the same conditions or, otherwise, that an average behavior of the module can be determined if some mismatching event occurs at a sub-module level. Unfortunately, this granularity level is not satisfying if *hot spot* phenomena must be modeled and if the real behavior of a PV array in which a few number of cells is subject to shadowing must be reproduced. In fact, if a single cell in a module receives an irradiation that is significantly lower than the one at which the others work, its operating voltage can be placed at its own breakdown value, which is deeply negative, with a positive value of the current. Thus, the module works at a low voltage, with the positive one of the fully irradiated cells that is compensated by the negative one of the shadowed cell. In such conditions, the bypass diode does not enter into conduction and the shadowed cell dissipates a significant power that can damage it irreversibly. Such a mechanism, that is explained in [3], is analyzed in some papers (e.g. [8]) and requires a heavy simulation model, which takes into account thermal effects and describes each cell, instead of each module. It is evident that such approach might be non adequate if it has to be used for processing a huge amount of data, i.e. for evaluating the annual PV energy yield. Moreover, by considering the strongly nonlinearity of PV systems, in some cases, it is very difficult or almost impossible to determine an analytical or numerical model for describing the whole PV generator, especially if the extreme variability of the climatic conditions has to be taken into account. In such a case, behavioral models are more suitable to characterize the whole system because they are not focused on the identification of the exact value of a specific variable but rather they have the objective to estimate a value with a given level of confidence.

2.2 Artificial Neural Network Based PV Modeling

In recent literature some applications of the ANNs to PV systems modeling have been presented. All of them put into evidence the advantage given by ANNs of being independent of the complexity of the relationship between the PV array current and its voltage as well as the involved and interleaved dependency on the physical and weather parameters. ANNs process the information in parallel through many simple elements: the neurons. All these neurons are interconnected and every connection has a given weight. Finally, each neuron supplies an output through an activation function. This structure fits with the need, in PV systems modeling, of describing the system on the basis of the relationship between the given inputs (e.g. irradiance, temperature, voltage) and desired outputs (e.g. current). If compared with the mathematical model described above, the ANN does not require the knowledge of internal system parameters, involves less computational effort and offers a compact solution for such a multiple-variable problem.

In [9], a neural network based PV panel model that uses (1) describing the equivalent circuit shown in Fig.4 is considered. The ANN training is done by taking five operating points per panel at some given couples of irradiance and temperature values. On this basis, the ANN is able to determine the values of the five parameters in (1), that are $\{I_{ph}, I_{sat}, \eta, R_s, R_p\}$, at whichever irradiance and temperature values, so that the whole curve is available in any condition. The authors show a very good accuracy of the curve reconstruction at a low irradiation, just where the classical approaches based on the parameters identification in Standard Test Conditions (STC) show the larger inaccuracy with respect to experiments. Unfortunately, such a method does not allow to keep into account mismatching conditions at a panel level.

In [10] a Multi Layer Perceptron (MLP) was trained by using experimental measurements and it shows good results, especially if the reconstruction of the I-V curve is required at low irradiation levels.

In [11], it was pointed out that the approach based on a MLP ANN may be characterized by a slow training process, which can also remain trapped into local minima. Such limitations are avoided by using a radial basis function network, which can be designed by affording a sort of curve fitting problem in a multi dimensional space. This training task is afforded by means of an orthogonal least squares method. In [12], the optimization of the hidden layers is performed by using a genetic algorithm. In this way, the number of the radial basis functions is not too low, with a poor function approximation performance, and not too high, with an over fitting of the input data taken from experiments on the PV array. In both [11] and [12] the ANN takes the radiation, the ambient temperature and the PV array voltage as inputs and calculates the array current as output. The procedures are good candidates for predicting the path described by the maximum power point along the day, according to the current weather conditions.

In a recent paper [13], the importance of taking into account the spectral distribution of the incident light, especially at a low irradiance level and for cell technologies having a spectral response narrower than mono crystalline silicon, has been put into evidence. In [13], the authors have included the information about the spectral distribution of the light as a further input of an ANN. They have also implemented a non-random selection of the data used as training set, with an improved performance of the network trained with the spectral information. The price to pay for this accurate modeling is in the amount of data representing the spectral information, which have to be given to the ANN as an input, and in the pre-processing of the training set, which is a time consuming procedure. In [13], the reader can also find an up-to-date glance at the most recent papers published in the field.

3 Maximum Power Point Tracking (MPPT)

Due to the time varying environmental condition such as temperature and solar irradiation, the P-V characteristic exhibits a maximum power point (MPP) which is strongly variable in P-V plane. This fact is quite evident by looking at Fig.3 where the variation of the MPP due to the irradiance excursion is documented. Unfortunately, the joined effect of the irradiance and temperature variations leads to a change of the voltage at which the MPP occurs along the day in a wide region, so that the locus of the MPP's is not a line or a curve, but an area. This large variation makes the straightforward connection of the PV array to a constant voltage port wrong. In fact, the PV generator can be used for recharging a battery or can be plugged at a DC bus that is the input port of a DC/AC converter, the latter feeding the grid or an AC load. At a constant voltage value, the PV field does not deliver the maximum power, unless the DC voltage at which it is forced to work is exactly the MPP voltage. A coarse matching between the DC voltage and the PV array might force the latter, at some values of the irradiance and of the ambient temperature, to work at a voltage level that is higher than the open circuit voltage, with a zero power produced.

In order to ensure the optimal utilization of PV arrays, a MPP Tracking (MPPT) is realized by means of a suitably controlled power converter, which can be a DC/DC converter or an inverter. This is helpful for adapting the PV optimal operating point to the load or grid requirements [14].

The MPPT operation must be able to ensure that the PV operating point is as much close as possible to the MPP, both in steady state weather conditions and when irradiance transients, which are faster than temperature ones, occur. As a consequence, a MPPT efficiency can be defined as the ratio between the energy extracted from the PV array and the energy that the same array would have been able to produce by always working at its MPP. In practice, this efficiency is less than one because the MPPT algorithm is not able to stay in the MPP in steady state conditions and it is not prompt enough for tracking the MPP when the irradiation level changes suddenly (e.g. in presence of clouds moving at high speed due to the wind or in PV applications to sustainable mobility) [15]. Furthermore, noise affecting PV current and voltage worsen the tracking performances of the MPPT algorithm [16]. Example of noise are the switching ripple introduced by the converter that operates the MPPT and the quantization effect introduced by the use of A/D converters and digital controllers implementing the MPPT algorithm. A further noise source is the DC/AC stage in single phase applications: the low frequency voltage oscillation at the DC bus, at a frequency that is the double of the AC voltage one, back propagates up to the PV sources, thus degrading the MPPT performances.

A classical double stage architecture for AC PV applications is shown in Fig.6: the bulk capacitance, placed between the two conversion stages, is used to manage the fluctuating AC power and consequently a voltage ripple with a frequency that is the double of the grid frequency appears at its terminals.

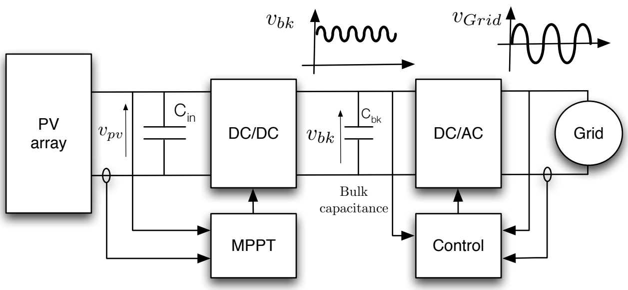

Fig. 6. Double stage grid-connected inverter

The amplitude of the voltage ripple is given by:

$$\Delta V_b = \frac{P_{PV}}{2 \cdot \omega_{grid} \cdot C_{bk} \cdot V_{bk}} \tag{6}$$

where P_{PV} is the DC power extracted by the PV field.

The oscillation affecting the voltage of the bulk capacitor has detrimental effects on both the DC and the AC part of the power processing system, so that a large electrolytic capacitor is almost always used at the DC link. In fact, as (6) reveals, the larger the bulk capacitance the smaller the voltage oscillation. Unfortunately, this component is a weak point of the conversion chain, because of the effects that the operation temperature has on the electrolytic capacitors lifetime. A significant effort is done by PV inverters manufacturers in order to keep the working temperature of the bulk capacitor as close as possible to that one at which the capacitor manufacturer has tested the component for some thousands of hours, so that the Mean Time Between Failures (MTBF) is increased. A reduced value of the bulk capacitance might allow to use film capacitors instead of electrolytic ones, if suitable control techniques or different topologies must be adopted in order to reduce such an effect. In [16], the way in which the control network of the DC/DC stage can be designed for achieving such objective has been explained.

In the next subsection the main MPPT techniques are overviewed and some control methods aimed at reducing the low frequency disturbances in AC applications are compared.

3.1 Classical MPPT Approaches

The switching converter would be able to ensure the maximization of the power produced by the PV generator provided that the parameter, or the parameters, which allow to change its input voltage/current levels are suitably controlled. In the largest part of PV power processing systems, e.g. that one shown in Fig.6, the circuit that performs the MPPT operation is a DC/DC converter and the control parameter is the duty cycle, as shown in Fig.7.

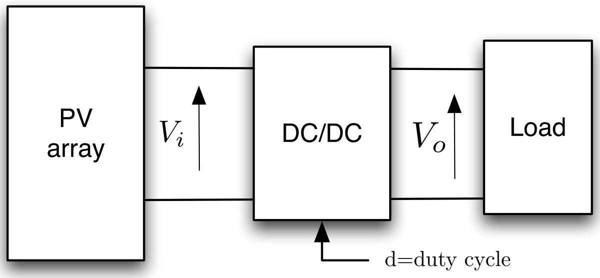

Fig. 7. Connection scheme of a dc/dc converter dedicated to the dynamical optimization of a PV generator

The two main techniques that are used in commercial systems for performing the MPPT function are the Perturb and Observe (P&O) and the Incremental Conductance (IC) methods. They are perturbative approaches that change the PV array voltage repeatedly until the PV power is maximized. PV current and voltage measurements are needed in order to determine the PV power produced by the array at each value of the PV voltage settled by the MPPT algorithm through the switching converter. The perturbed variable is usually the converter duty cycle, but in literature there are evidences of the fact that the reference signal in a closed loop switching converter is the best variable to control for achieving the MPPT [16]. This choice allows to improve the steady state and the transient performances of the MPPT algorithm. In fact the converter's dynamics can be improved by a proper design of the feedback compensator, so that the time between two consecutive perturbations can be shortened. Additionally, the perturbation amplitude can be reduced as well, because the closed loop transfer function of the converter can be designed in order to have a very low gain of the output-to-input closed loop transfer function in the noise bandwidth.

The superiority, claimed in some papers, of the IC method with respect to the P&O one in terms of MPPT efficiency [17] does not have a practical confirmation, essentially because of the noise that in practice affects both the PV array voltage and current. The perturbed variable is in any case the PV voltage because of a logarithmic dependence from the irradiation level.

As discussed in the recent literature, the proportionality between the irradiation and the PV current worsens the tracking capability of any current-based MPPT technique, in particular when a significant irradiation drop occurs. This problem has been addressed by using an innovative control technique that matches the sliding mode control with the P&O MPPT technique [18]. The approach guarantees a high tracking promptness, an intrinsic independence of the MPPT technique from the PV array parameters and a inherent rejection of the noises propagating from the output towards the input of the switching converter.

As for the observed variable, whose value has to be maximized by the MPPT algorithm, in the basic systems, that are the majority, it is the PV power, obtained as the product of the digitalized values of the PV current and voltage. Nevertheless, the non linear relation between the PV voltage and the efficiency of the converter can lead to the paradox of having the maximum power produced by the PV array that is processed by a switching converter that does not work at its highest efficiency. The best tradeoff is achieved by tracking the maximum of the power at the converter output. This solution may allow to save the voltage sensing and may require a current sensor only [19] [20].

Many variants of IC and P&O algorithms have been proposed in literature. Some of them adopt a variable perturbation amplitude in order to achieve a high MPPT performance in steady state conditions and a good promptness in presence of a varying irradiance [21]. The algorithms are almost always implemented in a digital way, in order to profit from both the flexibility and the IP protection ensured by modern digital devices at a reasonable cost. Nevertheless, some approaches that can be implemented by means of analog circuitry only are also presented in literature [22] [23] [24]. They are based on the evaluation of the effect that a small PV voltage oscillation has on the PV power: if the operating point is on the left side of the MPP, the forced PV voltage oscillation and the consequent PV power oscillation are in phase. On the contrary, if the operating point is on the right side of the MPP, the two oscillations are in phase opposition. At the MPP, the PV power oscillation falls below a given threshold and the objective is achieved. This method, often referred to as *ripple correlation control* or *extremum seeking control*, improves the steady state MPPT efficiency because the repeated climbing across the MPP required by P&O and IC is avoided. An excellent promptness during irradiance transient is also obtained, but the price to pay is the reduced flexibility if an analog implementation of such methods is adopted.

The MPPT operation becomes more complicated when the PV array works in mismatching conditions, because the whole PV curve is multimodal, namely characterized by multiple peaks, thus the maximum global peak or Global Maximum Power Point (GMPP) is not tracked easily. Conventional MPPT algorithms, which are based on an hill climbing approach, are not able to distinguish the GMPP from the local peaks, so that they are trapped into a voltage range across a power maximum, without knowing if it is the GMPP. In some cases, e.g. depending on the shading pattern, the GMPP can occur at a voltage that is out of the working range of the inverter, so that the best peak falling in that range must be tracked. In literature some approaches to the tracking of the GMPP are proposed, but they need quite complicated algorithms and require some preliminary assumptions. As a consequence, in practice, the GMPP is detected by means of a periodical, and energy costly, sweep of the P-V curve performed by the MPPT algorithm.

Such a puzzling problem can be avoided by using Distributed MPPT (DMPPT) architectures [25], which employ a small power switching converter dedicated to each PV panel. In this case, each panel is controlled independently from the other ones and a multiple peak P-V curve can appear at a panel level only. Should the panel level MPPT not be able to track the GMPP, but it remains trapped in one of the other few MPP's, the power loss remains limited to the mismatched panel. Two solutions have been proposed in literature and have been becoming products available on the market [26]. The first one uses a DC/DC converter for each panel, the output terminals of the converters being connected in series and plugged to the inverter's input port. This architecture does not require unusual values of the voltage conversion ratio, but it gives rise to significant control problems in presence of a large different in the operating conditions of panels in the same string. The other possible solution employs DC/AC converters that inject the PV power produced by each panel straightforwardly into the grid. The maximum modularity of this architecture is counterbalanced by the need of having a large voltage conversion ratio, with a conversion efficiency that is lower than 95%.

In literature, some hybrid DMPPT solutions, with a distributed power processing and a centralized MPPT algorithm have been presented [20]. They maximize the total output power, thus accounting for the non constant conversion efficiency of the DC/DC converters, and save a number of current sensors with respect to the basic solution.

4 ANN Based MPPT Approaches

Although conventional MPPT algorithms operate very well under uniform irradiation conditions, and in fact they are widely used in commercial products, several works recently appeared in literature have been focused on the use of artificial intelligence techniques for tracking the maximum power point. Truly speaking, many of them, also appeared recently, are focused on the MPPT in wind energy systems [27], instead than on PV ones. To this aim, ANNs are also combined with other soft computing methods: for instance, Evolutionary Algorithms (EA) or the Particle Swarm Optimization (PSO) have been fruitfully applied in [28,43] in conjunction with ANNs.

In [29] a comparison between a Fuzzy Logic Control (FLC) algorithm and an ANN-based approach has been presented. By assuming that the PV field works in uniform conditions, it has been demonstrated that the FLC controller is able to generate up to 99% of the actual maximum power while the ANN controller can reach the 92% value only. However, although the FLC-MPPT tracking is more effective than the ANN method, the former requires extensive processes which include fuzzification, rule base storage, inference mechanism and de-fuzzification operations. Consequently, a compromise has to be made between the tracking speed and the computational cost.

The joined use of ANNs and and fuzzy logic is also effective in the MPPT under mismatched operating conditions, where the GMPP position depends on shading patterns (see fig.5) and the voltage at which it occurs may change within a large voltage range. In [30] a ANN is trained by using many different partially shaded conditions to determine the corresponding GMPP voltage of the whole array. The ANN output is the voltage reference for the FLC used to generate the required control signal for the power converter; the proposed configuration is shown in fig.8.

The input signals for the ANN are the irradiance level (G) and the cell temperature (T_c). The neural network predicts the global MPP voltage (V^*_{dc}) and power (P^*_{dc}) and those values are compared with the actual voltage and power expressed in V_{dc} and P_{dc}. The predicted output voltage (V^*_{dc}) is used as a reference signal for the FLC voltage based MPPT controller. The proposed method has been experimentally validated, so that the reliability and the performances of such an MPPT algorithm have been demonstrated to be superior to the conventional P&O method in mismatched conditions.

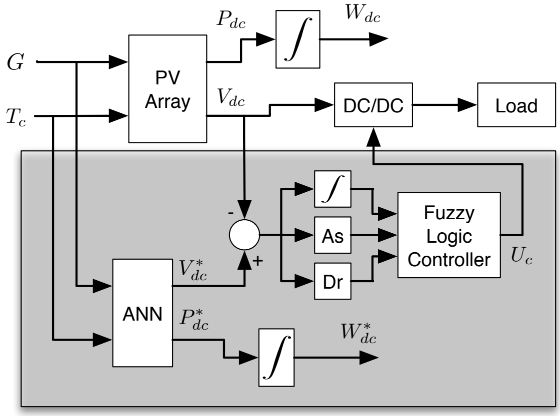

Fig. 8. ANN-FLC mppt architecture

In [31] an approach that uses a ANN and a FLC is also introduced. In this case, the neural network is used for tuning automatically the membership functions of a FLC that is employed to track the MPP. The method has been compared in simulation with the standard P&O technique and with a manually tuned FLC. Results presented in the paper show that the proposed optimized FLC provides a fast and accurate tracking of the PV maximum power point under various operating conditions, including mismatched ones. Fig.9 shows how in presence of a mismatched condition the operating point moves towards the MPP's. The proposed approach is the only one that is able to drive the operating point towards the GMPP.

In [32] a full-bridge inverter is chosen as an active low-frequency ripple-control circuit (ALFRCC). Fig.10 shows the scheme of the proposed architecture: the additional stage is used to remove the DC-bulk capacitor and operates with an AC-bulk capacitor (C_{bo}). In this configuration the full-bridge inverter works for injecting a suitable

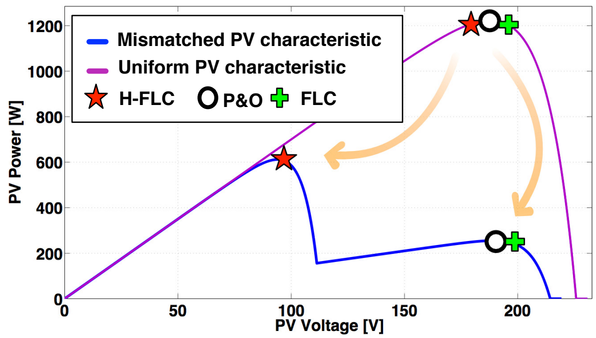

Fig. 9. MPP under partial shading $G_1 = 200W/m^2$ and $G_2 = 1000W/m^2$

compensation current into the high-voltage bus. Although such approach is not new, its novelty is in the adoption of a combination of an adaptive linear network and a sliding mode control for generating the driving command for the ALFRCC that is able to mitigate the low frequency ripple at the PV terminals. The ALFRCC effectiveness has been verified by numerical simulations and experimental results. Its superiority is indicated in comparison with a conventional high-pass filter and a proportionalintegral controller.

The use of the neural network for controlling the active filters is also proposed in [33] and [34] where it is employed to improve the power factor and to reduce the line current harmonics.

5 Further ANN-Based Techniques for PV Power Production Maximization

In [35] a wide overview of the possible contributions ANN methods and techniques can give in maximizing the power produced by a PV plant is given.

In the field of stand alone PV systems and of residential applications, ANNs are helpful because of their capability of foreseeing the PV energy production, which allows to manage the energy flows more effectively. The objective is not limited to the maximization of the PV energy production but extends to the matching with the local energy consumption in order to reduce the contribution coming from the AC grid. The encouragement, especially in residential applications, of the self-consumption is a key point of the future European Union strategies for a better use of the energy [36]. In [37] a control system based on an Active Demand-Side Management (ADSM) for PV residential application has been proposed. The ADSM is a distributed control system made of several ANNs dedicated to the different appliances in the house, so that appliances self-organize their activities and a coordinator corrects their actions in order to enhance self-consumption. The system acts in an almost transparent way to the user and it takes in charge the schedule of the household tasks for the next day on the basis of the foresee of the PV power production, thus leading to an increased energy efficiency.

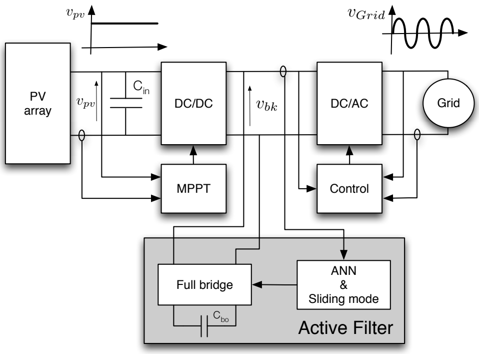

Fig. 10. Double stage grid-connected inverter with active filter at the bulk interface

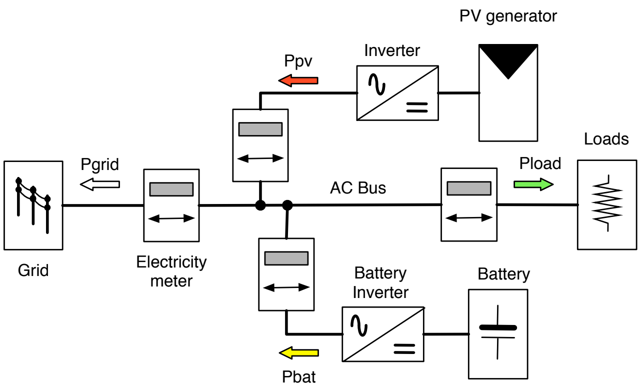

Fig. 11. Residential ADSM architecture

Fig.11 shows the proposed architecture, including the PV array, a storage element, a connection to the grid and a home automation system.

In [38], an ANN-based control of a stand alone system including a PV array, a diesel generator and a wind turbine has been proposed. The MPPT of the wind generator is performed by means of a ANN that regulates the blades pitch angle. A Radial Basis Function Network (RBFN) performs the PV MPPT function, Simulation results show that an efficient power sharing technique among energy sources is obtained and the voltages and power can be well controlled in presence of environmental variations.

In [39] the MPPT task employs a RBFN with a back-propagation network for predicting the effects of passing clouds on a stand alone PV system equipped with a storage unit. By using the irradiance as input signal, the network models the effects that the random cloud movement has on the electrical variables of the system, thus reducing the problems related to the overload/underload of the power lines due to the PV power variation in the short periods of time when the cloud movement affects the PV plant.

Both in large and in small PV plants, as well as in both grid connected and stand alone systems, a key factor in energy efficiency is the correct sizing of the generator.

In [35] a stand alone system operating under variable climatic conditions is modeled and simulated by means of a ANN. Electrical and weather parameters recorded during several years of operation of the plant have been used for the training and testing of the developed models. In [40], the concept of Loss of Load Probability (LOLP), related to the ability of the system to satisfy load requirements, is used in conjunction with a MLP neural network.

ANNs are also widely used in PV plant productivity estimation. In [41] the historical data concerning irradiance and temperature are used for a MLP ANN. In [42] an ANN trained by a Genetic Swarm Optimization (GSO) algorithm is used to foresee the production of a PV plant.

6 Conclusions

In this paper an overview of the techniques used for modeling, controlling and designing a photovoltaic system has been given. The non linearity of the model describing a photovoltaic generator, especially when it works in mismatched conditions, has been put into evidence. Some analytical models and a number of approaches based on the adoption of artificial neural networks have been mentioned and compared. The maximum power point tracking problem has been described and, also in this case, a glance to advantages and drawbacks of some techniques that are used in commercial systems and of novel ones based on artificial neural networks has been given. Finally, some attractive applications of the artificial neural networks, often used in conjunction with soft computing techniques, have been overviewed. The main ones are in the design of hybrid systems including generators employing renewable energies and backup devices.

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