A Novel Photovoltaic Maximum Power Point Tracking Method Using Feedback Conductance Integral Compensation

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Abstract. Environmental concerns are driving significant research in energy-efficient devices, namely in the photovoltaic (PV) area. Recent scientific papers focus in photovoltaic cells modeling, converter topologies to directly interconnect low voltage solar modules to high voltage inverters, and maximum power point tracking (MPPT) methods able to extract the maximum energy from PV assemblies.

Several research works are aimed at increasing the amount of energy extracted from PV panels, by introducing novel MPPT strategies. Some works propose promising MPPT methods and improved results. However, they often lack comparisons with already existing MPPT techniques. This paper proposes a novel MPPT technique based on the integral feedback of the conductance. Additionally, a comparison with some of the most well-known MPPT algorithms is presented, such as the classic perturb and observe, incremental conductance and the most recent techniques based on fuzzy logic and neural networks. The comparative analysis of the MPPT algorithms is made based on parameters as complexity and performance, under different test conditions.

Keywords: Maximum Power Point Tracking (MPPT) · Photovoltaic · Solar energy · Linear integrator

1 Introduction

With the increase of the environmental metrics and the growing necessity to reduce pollution from fossil fuels, adoption of renewable energy production technologies has been growing over the last decades [1]. This has driven researcher interests to the search of new methods of maximizing the power production of PV installations [2].

Published by Springer Nature Switzerland AG 2022
L. M. Camarinha-Matos (Ed.): DoCEIS 2022, IFIP AICT 649, pp. 158–166, 2022.
https://doi.org/10.1007/978-3-031-07520-9_15

The tracking of the Maximum Power Point (MPP) of a photovoltaic (PV) panel is a difficult task due to the non-linearity of P-V Curves and the varying response in produced power in respect to the irradiance, temperature, solar incidence angle and output load [3].

MPP can be calculated based on several existing methods; mostly presented in [4]. The Maximum Power Point Tracking (MPPT) algorithms are generally divided into offline and online tracking [5]. The offline methods are generally simpler methods such as the fractional Open Circuit Voltage (OCV) or fractional Short Circuit Current (SCC) [5]. These strategies are classified as offline due to its necessity to disconnect the load during some time to measure the OCV or SCC to compute the present MPPT. Furthermore, the offline methods are not truly MPPT methods because of their inability to continuously track the most efficient operating point of a given PV cell.

The online MPPT methods allow continuous tracking of the MPP considering different conditions such as the temperature or irradiance, not requiring the disconnection of the PV panels. One of the best-known methods in industry and academia is Perturb and Observe (P&O) [6–7], immensely used in commercial products due to its simplicity and low computational requirements [7]. Another well-known MPPT method is the Incremental Conductance (INC) [8], that appears in literature with a lot of modifications in its search algorithm, some of them with adaptive step size [8].

During the decades of 90s and 00s, with the increase of computing power, more complex controllers like Fuzzy Logic (FL) [3], neuro-fuzzy controllers [9], Artificial Neural Networks (ANN) [1], and more recently reinforcement learning [10] have been proposed in the literature to track the MPP.

This paper proposes a new method which combines the incremental conductance concept with a classic linear integral compensator. The main advantage is the possibility of using linear control theory to estimate the integral compensator gain. The proposed MPPT controller is compared with four of the most popular MPPT algorithms in terms of power extracted from the PV panel, response time, and oscillations around the MPP. These analyzed MPPT strategies are: P&O, INC, FL, and ANN. All these methods are tested using time varying irradiance conditions.

The paper is organized as follow: Sect. 2 presents the relationship with the conference theme. Section 3 presents the topology presented for the evaluation of the MPPT methods under study that are described in Sect. 4. Then, simulation results are presented in Sect. 5. Finally, Sect. 6 presents conclusions and future work.

2 Relationship to Technological Innovation for Digitalization and Virtualization

Nowadays, the society we live in is increasingly competitive and focused on optimizing systems and energy efficiency [1], with microgrids having a highly important role in this development. These microgrids are closely associated with the optimization of renewable energy sources such as wind turbines and PV due to their intermittent nature.

MPPT controllers are commonly used in the production of electricity from renewable energy sources [10], which are mandatory to provide clean power to systems running digital twin models of technological processes. Digital twins and virtualization replace the authentic physical experience or assets with digital models, while needing and contributing to renewable energy extraction efficiency. With the technological advances of the last two decades, it is increasingly evident that the implementation of digital twins and virtualization in embedded systems is often associated with concepts such as Internet of Things (IoT) and smart grids, being connected to central servers that control the microgrid power flow sending setpoints for the converters to optimize and adjust their operation.

Furthermore, the algorithms and methods presented in this paper are part of the digitalization and virtualization paradigm. The proposed new method aims to be implementable in inexpensive digital embedded systems with low computational power and low energy consumption, based on increasing the overall efficiency of the digital control and power systems. The experimental part is not yet included in this work, and this implementation is one of the points of future study.

3 PV Panel and Power Converter

For the study of the MPPT methods, a topology with a PV connected to a Boost converter that powers a resistive load is used as shown in Fig. 1a. Herein, the inductor value L is 550 μH and capacitors value C_{in} and C_{out} values are 150 μF. The PV panel considered in the simulations is the A10J-M60-240 from A10 Green Technology, with a maximum power of 240.54 W, being the characteristic P-V curve in Fig. 1b. The converter step-up topology was implemented due to its simplicity and common use in PV applications [11].

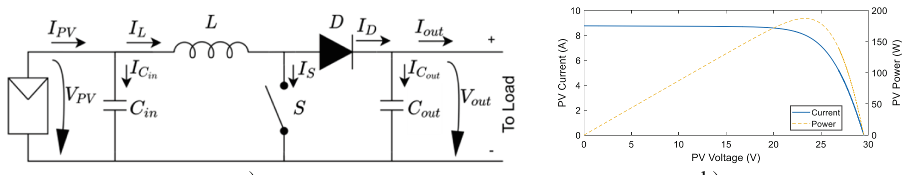

Fig. 1. a) Electric schematic of implementation, PV panel and boost converter; b) Typical Power-Voltage Characteristic of Photovoltaic Panels

The boost converter is used in this scenario to control the extracted current from the PV panel and at the same time increase the voltage. This is beneficial for future development when the boost will be connected to an inverter and inject power into a grid or a microgrid.

Voltage ripple in capacitor C_{in} at the PV terminals should be as small as possible since the MPP is dependent on voltage and current, and voltage as well as current ripples causes power losses. For this, the PV output capacitor should have enough capacitance to steady the PV output voltage and support the system during several switching periods.

4 Well-Known MPPT Control Methods

MPPT algorithms track the MPP in the power-voltage curves of PV panels. These curves are non-linear and strongly dependent on solar irradiance and temperature [2]. Consequently, MPPT algorithms should have a great elasticity to adjust and search for the MPP. Besides, the MPP in the characteristic power-voltage curve of a PV panel (Fig. 1b) is not a stable point.

One of the proposed algorithms is the P&O that affects the duty cycle (D) of the converter by a constant ΔD. To note that a bigger ΔD increment or decrement causes bigger limit cycles and consequently a bigger ripple in PV voltage and current, similarly a lower ΔD causes a lower ripple but slow convergence rate. Another disadvantage of this algorithm occurs in cases of a gradual increase in irradiance [7].

On this work, three different P&O algorithms are considered: the first one uses a fixed step (P&O) [6], while the others use two adaptive algorithms based on dP_{PV}/dV_{PV} (P&O Adapt) and $\log_{10}(dP_{PV}/dV_{PV})$ (P&O Adapt Log) [6].

INC is another very well know method in literature, and it is based on finding the V_{PV}, I_{PV} point where the power derivative relatively to the voltage is zero:

$$\frac{dP_{PV}}{dV_{PV}} = 0 \tag{1}$$

Considering the typical P-V curve, when the dP_{PV}/dV_{PV} is greater than zero the system is on the left side of MPP and the duty cycle should be decreased and when dP_{PV}/dV_{PV} is lower than zero, the system is working on the right side of MPP and duty cycle should be increased.

Considering the power given by $P_{PV} = V_{PV} I_{PV}$, from (1) the PV panel conductance (I_{PV}/V_{PV}) can be related to its incremental value (dI_{PV}/dV_{PV}). Sometimes, the INC approach also presents problems during variations of irradiance. When the irradiance changes the algorithm sometimes compute the dI_{PV}/dV_{PV} with the wrong values, which results in slower transient response and consequently in a momentaneous loss of power [12]. The INC algorithm herein implemented uses fixed and adaptive step based on dP_{PV}/dV_{PV} and $\log_{10}(dP_{PV}/dV_{PV})$ [8], namely INC, INC Adapt and INC Adapt Log, respectively.

Application of neural networks (NN) in MPPT is depicted in [8]. These networks are trained with irradiance and temperature as input data. Herein, a table with irradiance, temperature, and the corresponding outputs (V_{mpp}, I_{mpp}, and P_{mpp}) were used as data to train a NN with 10 neurons in a single hidden layer.

As the ANN used in this study is trained with irradiance and temperature to obtain a reference current and these parameters are different for each PV, for each it is necessary to create a different NN.

FL uses rules designed using linguistic variables to control complex systems [12]. This type of control typically doesn't need a mathematical model of the system under control. Instead, FL needs an expert on the system dynamics behavior to devise just a few membership functions and linguistic rules based on the knowledge of the system dynamics.

Regarding the MPPT based on FL, there are multiple implementations in the literature. Herein, it is considered [3], where six possible solutions for FL implementation in MPPT can be found.

To design a FL MPPT algorithm, the discrete form of dP_{PV}/dV_{PV}, represented as $S(k)$ and its discrete time derivative $\Delta S(k)$ are used [3].

For the implementation of FL, the Mamdani method was used as an inference engine and a center of gravity algorithm was used in the defuzzification process. The fuzzy rules are presented in [3] and the input and output membership functions can be found in Fig. 2. All the membership functions were adjusted from [3] and uniformized to generalize to different approaches or different topologies.

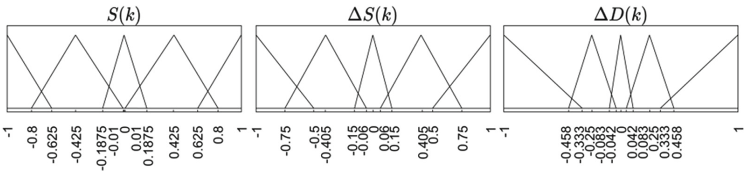

Fig. 2. Fuzzy logic membership functions.

5 Incremental Conductance with Linear Integral Compensator (LIC-INC)

The proposed approach is based on the INC algorithm, obtained from (1), written as $V_{PV}\frac{dI_{PV}}{dV_{PV}} + I_{PV} = 0$.

This form can be written as in a negative feedback system ($V_{PV}\frac{dI_{PV}}{dV_{PV}} - (-I_{PV}) = 0$). Moreover, during convergence, it can be admitted that the algebraic sum of the incremental conductance value dI_{PV}/dV_{PV} with the conductance I_{PV}/V_{PV} will not be zero, presenting some tracking error e_{MPPT}, or $V_{pv}\frac{dI_{pv}}{dV_{pv}} - \left(-I_{pv}\right) = e_{MPPT}$, re-written in (2). The tracking error value e_{MPPT} will be enforced to zero within a finite amount of time.

$$\frac{dI_{PV}}{dV_{PV}} - \left(-\frac{I_{PV}}{V_{PV}}\right) = \frac{e_{MPPT}}{V_{PV}} \tag{2}$$

Considering the Boost DC/DC converter, driven by a current controller to track the input current $i_{L_{ref}}$ at high frequency, it is possible to consider the boost inductor current $I_L \approx I_{L_{ref}}$. For simplicity, the panel current I_{PV} is here considered to follow the i_L current with a first order low pass filter dynamics with pole at $-1/(sTc)$. Then, $-I_{PV}/V_{PV}$ is (3):

$$-\frac{I_{PV}}{V_{PV}} \approx -\frac{I_{L_{ref}}}{V_{PV}}\frac{1}{1+sTc} \tag{3}$$

A linear integral controller K_i/s returning the set-point value $I_{L_{ref}}/V_{PV}$, can then be devised (Fig. 3) to ensure MPPT tracking (zero steady-state error).

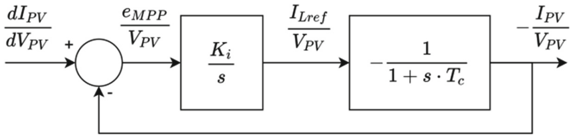

Fig. 3. Block Diagram of the novel linear integral compensator MPPT method.

To compute the integral gain K_i, the closed loop transfer function of the linear integral compensator MPPT represented in Fig. 3 is written in (4).

$$\frac{-\frac{I_{PV}}{V_{PV}}}{\frac{dI_{PV}}{dV_{PV}}} \approx \frac{-\frac{K_i}{T_c}}{s^2 + \frac{s}{T_c} - \frac{K_i}{T_c}} \tag{4}$$

Comparing the denominator of the closed loop transfer function to the canonical form denominator of a second order system $s^2 + 2\xi\omega_n + \omega_n^2$, it is obtained (5), where it is seen that for stability K_i should be negative definite, $K_i < 0$.

$$\omega_n^2 = -\frac{K_i}{T_c};\, K_i = -\frac{1}{2\xi^2 T_c} \tag{5}$$

The time constant T_c can be estimated considering the capacitor at the output of the PV panel. This capacitor in the diagram of Fig. 1 is the capacitor of input of boost converter represented by C_{in}. Considering an equivalent MPPT resistor given by $R_{PV} = V_{PV}/I_{PV}$, and determining the equivalent resistor value in the MPP, T_c can be written as (6).

$$T_c = C_{in}R_{pv} = C_{in}\frac{V_{MPP}}{I_{MPP}} \tag{6}$$

6 Simulation Results

The MPPT implementations were submitted into four test types, each one with different irradiance variations as: *i*) The step test was made with 3 values of irradiance: at the beginning the irradiance is 400 W/m^2, at 0.133 s this value is increased to 1000 W/m^2 and a second transition occurs at 0.266 s with a final value of 600 W/m^2; *ii*) The fast test has an initial irradiance value of 400 W/m^2, it is increased to 1000 W/m^2, stabilizes for 0.1 s and decreases from this value to 300 W/m^2; *iii*) The slow test irradiance values are 600 W/m^2, 700 W/m^2 and in final reaches 600 W/m^2, *iv*) steady state test was implemented under a irradiance value of 1000 //m^2.

In Fig. 4 are presented the results of each algorithm for step variations. The figures of fast, slow and steady state tests are not depicted here due to lack of space, and its similarity. However, on Table 1 all the results are summarized.

Table 1 shows the effectiveness of the studied methods including the integral linear compensator. The effectiveness shown in table does not include the efficiency of the boost converter.

The results obtained from this study demonstrate that the methods presented have distinct responses when subjected to different variations of irradiance. It can also be verified that there is no perfect MPPT algorithm but all of them have effectiveness above 99% in steady state. In terms of analysis of response times and oscillation in the voltage and current of the PV, it is seen that the algorithm that faster reaches the MPPT value is the ANN. However, this algorithm needs training data from the PV panels to be trained beforehand, thus having high dependence on the panel characteristics. In addition this algorithm needs, as inputs, the irradiance and the temperature that are parameters whose measurement is more complex.

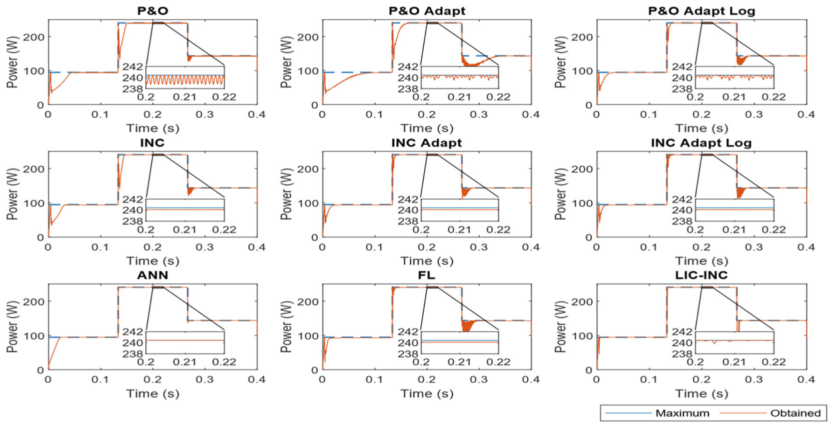

Fig. 4. Results of power produced from panel when step variations occur.

By analysis of Table 1, the algorithms with greater effectiveness are the ANN in steady state and the new proposed method in situations of irradiance variation.

Table 1. Results of MPPT efficiency for different algorithms and tests implemented.

Algorithm	*i*) Step variation	*ii*) Fast variation	*iii*) Slow variation	*iv*) Steady state
P&O	96.19%	97.61%	94.51%	99.67%
P&O adapt	93.36%	92.01%	94.97%	99.90%
P&O adapt log	98.36%	97.47%	98.42%	99.90%

(*continued*)

Table 1. (*continued*)

Algorithm	*i*) Step variation	*ii*) Fast variation	*iii*) Slow variation	*iv*) Steady state
INC	97.36%	98.36%	96.52%	99.98%
INC adapt	98.60%	98.02%	97.44%	99.86%
INC adapt log	98.81%	96.44%	98.65%	99.86%
FL	98.28%	98.20%	98.96%	99.88%
ANN	98.68%	98.79%	98.81%	**100.00%**
LIC-INC (proposed)	**99.24%**	**99.09%**	**99.62%**	99.98%

7 Conclusion

Observing the results, it is possible to conclude that the proposed algorithm has good tracking capabilities since the controller manages to maintain the search for the MPP even with different conditions.

This new method shows very good characteristics of speed in tracking the MPP and a very accurate detection of this point, however the controller generates some disturbances on voltage, current and consequently on power produced by the control objective dP_{PV}/dV_{PV}.

As future work is expected the test of this algorithm in partial shading to verify its ability to detect global MPP. Furthermore, this new method can also be combined with a NN or a deep learning algorithm to optimize the problems arising from dP_{PV}/dV_{PV} generated outliers.

The linear integral compensator method can use linear control theory to estimate the integral gain. This method can be used to improve the INC algorithms.

Acknowledgments. This work was supported in part by Portugal funds through Fundação para a Ciência e Tecnologia (FCT) with project reference UIDB/50021/2020 and by project PTDC/EEI-EE/32550/2017.

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