Comparison between algorithms for MPP search in photovoltaic systems in different irradiance and temperature conditions [*]

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Abstract: The generation of electric energy is an essential factor for society, both for economic and social development. Within this context, renewable sources have been gaining ground, such as photovoltaic systems. However, its efficiency presents non-linear characteristics due to thresholds in temperature and irradiance, mainly caused by climatic factors. This problem affects the load power supply, thus loosing effectiveness. To minimize this problem, it is necessary the operation at the maximum power point (MPP), made by means of some systems, called Maximum Power Point Trackers (MPPT). This paper discusses the implementation of two intelligent MPPT algorithms: the fisrt one using a metaheuristic called Radial Movement Optimization (RMO), and the second one based on the cooperation of RMO, and a traditional MPPT, called Perturb and Observe (P&O).The results show that although providing stable outputs after finding the MPP, the metaheuristic presents a larger oscillation during the search procedure in comparison with P&O.

Keywords: Energy, Photovoltaic, MPPT, Dynamic conditions, Intelligent Algorithms

1. INTRODUCTION

The operation of photovoltaic systems is naturally sensitive to climate changes and full or partial shading. Partial shading is a phenomenon that affects photovoltaic modules in such a way that may cause the emergence of hot spots, which consist of cell overheating due to accumulated current dissipation. The main consequence caused by these problems is related to the reduction of power delivered to the load. So, in order to obtain maximum momentary output - taking into account operating thresholds, it is essential to operate at the maximum power point (MPP). The procedure used for this purpose is called Maximum Power Point tracking Lefevre et al. (2018), which is performed by the so-called Maximum Power Point Trackers, MPPT's.

MPPT's usually operates by using control or logic circuits to detect the MPP. This allows the power inverter to pull out the maximum available power from the module. Briefly, the optimization of the operating voltage of the modules occurs, so the current provided to the load is maximized Kalogirou (2016).

There are several traditional MPP tracking techniques in the techinical literature, for example: Short-circuit current Noguchi et al. (2002), Control ripple correlation Casadei et al. (2006) and Perturb and Observe (P&O) Lin et al. (2011). However, these techniques present efficiency losses in a couple of situations, especially when there are sudden climatic thresholds or overheating caused by other factors. The trend in these cases is to find global maxima in the power curve. Nevertheless, when dealing with these difficulties, the traditional techniques begin to lose their efficiency. One possible solution to these challenges is the study of the so-called intelligent algorithms, mostly because of their advantages its advantages in working with non-linear problems.

Methods based on computational intelligence include optimization (evolutionary, probabilistic or deterministic methods), hybrid approaches (neural networks, *fuzzy*, among others). Bio-inspired algorithms (inspired by the behavior of living beings) are well present in the literature. Some can be cited, such as research by Cuckoo (Ahmed and Salam, 2013), bats (Seyedmahmoudian et al., 2018), ant colony (Priyadarshi et al., 2019) and differential evolution (Tajuddin et al., 2013).

Exploring these issues, the present work seeks to compare the use of two intelligent MPPT algorithms with the performance of the traditional P&O. The first one is called Radial Movement Optimization (RMO) and is based on swarm intelligence. The second one is a cooperation between RMO and P&O, where a decision criterion is made in order to achieve better performance in the power generation. Cases with real data are simulated, where changes in temperature and irradiance are observed on the panels, and all the results are analysed over optimal criterion. The data obtained and the panel models used were taken from the Laboratory of Alternative Energies (from the acronym *LEA* in Portuguese) in the Federal University of Ceará.

The paper is organized as follows: in section 2 some particularities of the problem are discussed. On Section 3 the simulated system is shown and all the algorithms are described. Finally the results are presented on Section 4, followed by conclusions.

2. CHARACTERIZATION OF THE PROBLEM

The photovoltaic system studied consists of a single chain of six modules with a total capacity of 1.5 kWp. Each module is composed of 60 multicrystalline silicon cells, ensuring a conversion efficiency close to 15.3%. Since the array is made up of 6 modules in series, the open circuit voltage of the matrix becomes 6×38.4 V = 230.4 V, while the short-circuit current remains the same. The irradiance (W/m^2) and temperature (^{o}C) data were taken from LEA on March 12, 2018, over 24 hours. Figure 1 respectively presents a slice of 140 minutes of the irradiance and temperature used for the simulations.
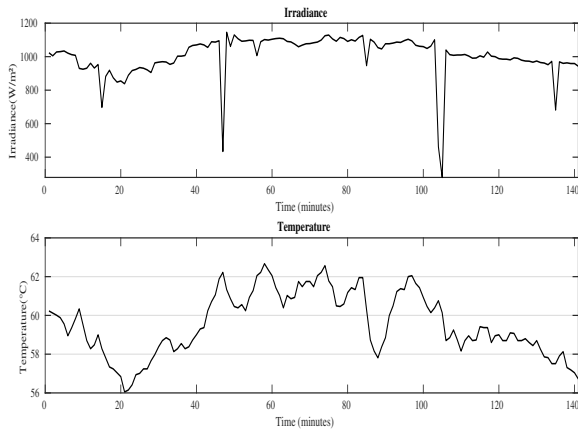

Figure 1. Irradiance and temperature curves at the array's input

The test procedure is performed online, including the DC-DC converter, photovoltaic arrangements and loads. Figure 2 briefly describes the components.

3. METHODOLOGY

3.1 DC-DC Converters

DC-DC converters are understood to be systems consisting of symmetrical devices operating in an interrupted manner and by passive elements that aim to control the input power flow in relation to an output Petry (2001).

There are numerous types of converters, with several functions. For this work, the simulations are performed with the buck-boost converter. Its choice is given by its properties, having characteristics of both buck converters (the output voltage will be lower than the input voltage) and the boost ones (the output voltage will be greater than the input voltage) Barbi (2006).

Another reason to choose this converter is due to the need need for controlling the energy flow without without concerning saturation areas, which would be harmful to the fed loads. To this end, Barbi (2001) indicates the use of this type of converter, since it has inductive accumulation. In Figure 3, there is a representation of the buck-boost converter.
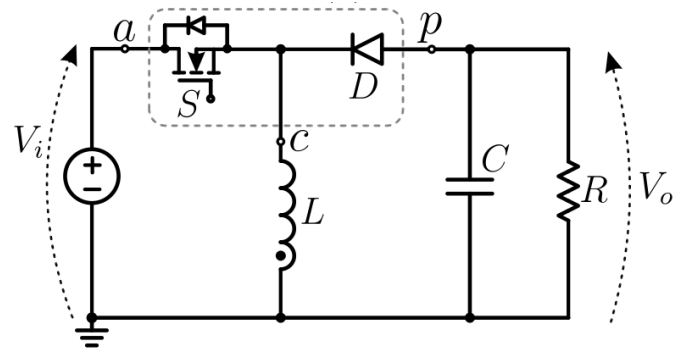

Figure 3. Buck-Boost converter circuit representation

3.2 Perturb and Observe

One of the most widespread algorithms for MPP search is P&O. This is mostly due to the fact that its execution is relatively simple and consists of the use of small stimuli provided to the photovoltaic system. Its operation consists of a periodic voltage disturbance and the observation of the corresponding output power.

A small disturbance is imposed to the system, forcing the output power to be different. If the power increased, the algorithm understands that it must maintain the voltage disturbance in the same direction, otherwise, the disturbance is reversed. When the power reaches the maximum point, the voltage thresholds on the system are minimal Atallah et al. (2014). The process of P&O operation is described by the Algorithm 1.

Remembering that:

- P_i : current power;
- P_{i-1} : previous power;
- V : voltage;
- V_{i-1}: previous voltage;
- V_{ref} : reference voltage.

The P&O can work with the duty cycle as the output from the algorithm instead of V_{ref}. The procedure is the same as presented.
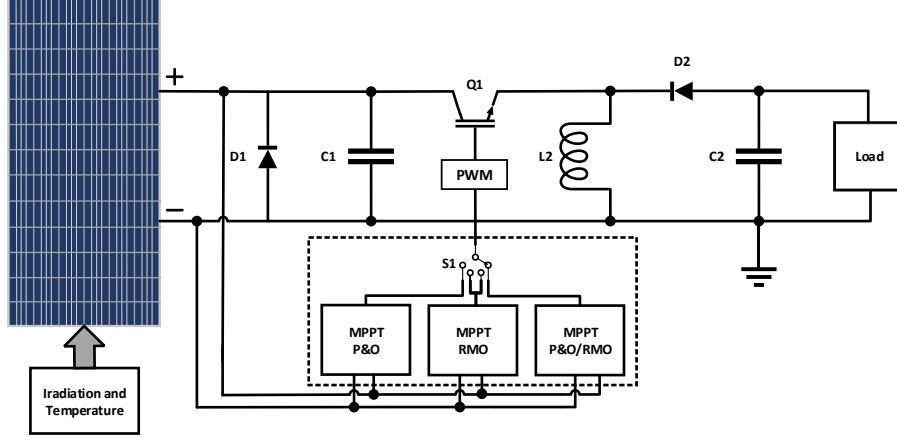
Figure 2. Representation of components used for simulation

Algorithm 1 Pseudocode for P&O

Measurement of V_{panel}, I_{panel};
Calculation of P_i, P_{i-1};
if $P_i - P_{i-1} = 0$ **then**
    return
else if $P_i - P_{i-1} > 0$ **then**
    if $V_i - V_{i-1} > 0$ **then**
        Increase V_{ref}
    else
        Decrease V_{ref}
    end if
    return
else if $V_i - V_{i-1} > 0$ **then**
    Decreases V_{ref}
else
    Increase V_{ref}
end if

3.3 Radial Movement Optimization

Radial Movement Optimization (RMO) is a stochastic optimization technique based on population, similar to Particle Swarm Optimization (PSO) and Differencial Evolution (DE). RMO search field is a vector space, where each particle present in the space has a location vector that represents a solution to the problem under investigation Rahmani and Yusof (2014).

Compared to other metaheuristic techniques, RMO has a different way of moving the particles. They are dispersed from one center and are constantly updated at each stage of the algorithm. Considering a three dimensional space, the idea is to distribute the particles along the radius of a sphere with varying speeds. An objective function evaluates the location of each particle in order to return the objective value and consequently the position of the best particle. This form of particle movement and constant updating improves exploitability, considerably increasing the search field Vanithasri et al. (2018). The operations to reproduce RMO are described in the Algorithm 2.

In addition to a better solution search, the RMO requires less memory allocation in its execution. Unlike other techniques that computational cost grows with the size of the problem, RMO uses particle updating at each iteration without the need for location and speed transfering between iterations. The particles move from the point updated at each iteration. To prevent the algorithm from getting stuck in sub-optimal locations, there is a vector of best global solutions Rahmani and Yusof (2014).

Algorithm 2 Pseudocode for RMO

Stochastic initial particle and velocity generation
Locate the center point
while Does not meet the stopping criterion **do**
    for $g = 1 \to n$ **do**
        count = 0
        Evaluate the fitness of each particle based on objective function $f(\overrightarrow{X}_i)$
        Search for the best center
        Sprinkle the particles from a radially shaped center
        Evaluate each particle against function $f(\overrightarrow{X}_i)$
        Get R_{best} $\overrightarrow{R}_p$;
        if countrer =1 **then**
            Update center with
            $centre_{new} = centre_{old} + C_1 \cdot R_{best}$
        else
            Update center with
            $centre_{new} = centre_{old} + C_1 \cdot R_{best} + C_2 \cdot G_{best}$
        end if
        Get G_{best} $\overrightarrow{G}_p$
        if $R_p < G_p$ **then**
            $R_p = G_p$
        else
            count = count + 1
        end if
    end for
end while

Remembering that:

- C1 and C2 : the social and congnitive learning rates, defined within]0,1];
- *Rbest* : particle with the best evaluation in the current iteration;
- *Gbest*: best of all *Rbest*.

4. RESULTS AND DISCUSSION

The findings of this work are presented in this section. All simulations are made with real data for a time of 280 seconds, time step of 3×10^{-7} seconds and analyzed in terms of power generated. For all curves, envelopes are applied in order to expose the noise of the array's output power apllied and to measure the noise of the panel power.

The power signal for P&O is presented in Figure 4. This algorithm loses efficiency when shading occurs because it creates a local maxima in the optimization problem and often it ends up getting stuck in these regions. However, its curve has less noise.
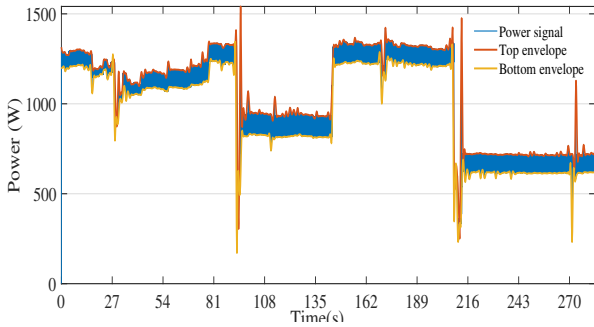

Figure 4. Power curve from P&O

Considering the RMO approach, on Figure 5 the power signal is represented. It is observed that the result is more oscillatory when compared to P&O. This setback happens because it is a population-based algorithm where each individual represents a different duty cycle (the objective function is power) which means that the output power will change randomly until the optimal one is found. However, it may be also seen that the power peaks are higher compared to P&O.
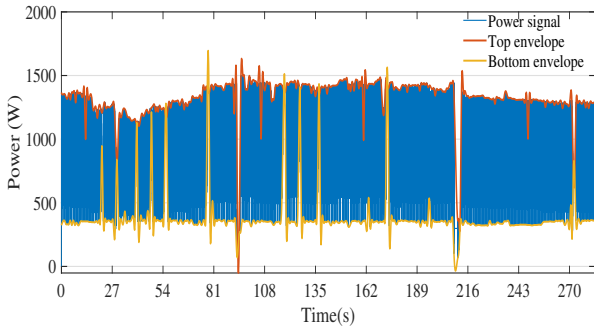

Figure 5. Power curve from RMO

The disadvantage of metaheuristics in relation to noise happens only in MPP search moments. This search may be triggered periodically, with some frequency depending on the required conditions. Metaheuristics work differently from P&O that incessantly pursues MPP, having an oscillatory nature during and after finding it. In metaheuristics, there is no such oscillation after finding MPP.

For the proposed MPPT algorithm, a cooperation between P&O and RMO is made by means of a decision system,

described in the Algorithm 3. This system consists of a switching scheme where a threshold is imposed according to the threshold of solar irradiance through (1).

$$\varepsilon = I_c - Ip \tag{1}$$

where:

- ε : irradiance threshold;
- I_p : previous irradiance;
- I_c : current irradiance;

Algorithm 3 Decision system based on a threshold

Acquisition of current irradiance;
Acquisition of previous irradiance
$\varepsilon = I_c - Ip$
Define threshold λ
if $\lambda \leq \varepsilon$ **then**
    Enable RMO
else
    Enable P&O
end if

The simulation is performed using three different thresholds (λ): 50, 100, and 200 W/m² which are chosen in order to observe the impact on power generation. The panel power curves generated are shown in Figures 6, 7 e 8.
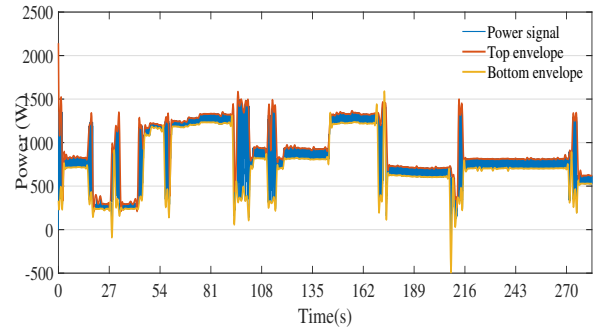

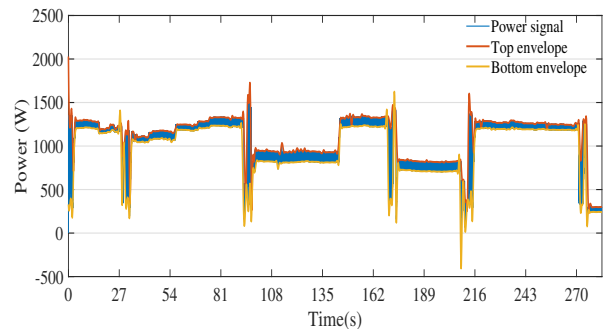Figure 6. Power curve from P&O/RMO with $\lambda = 50 \text{W/m}^2$

Figure 7. Power curve from P&O/RMO with $\lambda = 100 \text{W/m}^2$

For the case of $\lambda = 50$, the total power produced is lower compared to the others. Raising the threshold to $\lambda = 100$. it is possible to see a significant improvement in both oscillations and the total power produced. For a $\lambda = 200$, there are also impovements noticeable in certain time slots.
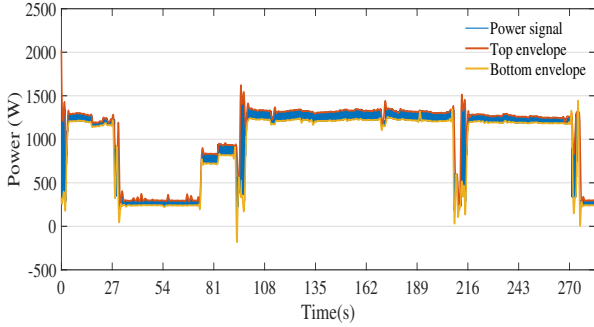
Figure 8. Power curve from P&O/RMO with $\lambda = 200$ W/m^2

It is noteworthy that for each λ, some regions of the curve are better when compared to the same region for other λ. This observation is more evident for the thresholds 100 and 200. Note that for $\lambda = 200$, especially around 50% of the simulation time, the produced power is greater than with $\lambda = 100$. However, around 25% of the simulation time, $\lambda = 100$ achieves better performance over the other threshold values.

In order to properly compare the results, the generated power and noise values are gathered in Table 1 for all algorithms. The values for power are obtained by summing all values on each curve and the noise values are calculated by subtracting the top envelopes from the bottom envelopes and summing the resulting vectors for each curve.

Table 1. Power and noise for P&O and RMO

Algorithm	Power (W)	Noise
P&O	2.1629e+08	2.1289e+07
RMO	1.8737e+08	1.9824e+08
P&O/RMO for λ=50	1.8249e+08	4.4778e+07
P&O/RMO for λ=100	2.2214e+08	3.1847e+07
P&O/RMO for λ=200	2.1469e+08	2.8214e+07

As noted, the results on the table only confirms what is observed on the power curvess. The noise is higher in the RMO approach, as evidenced by the envelope integral. This oscillation can be harmful to the load, sometimes causing problems on components and even deterioration. One possible solution to minimize these oscillations is to make modifications and optimizations to the RMO algorithm. In relation to P&O, the power curve is smoother during the search period, however with a tendency to fall into local maxima, hence delivering less power to the load.

Considering the power generated when $\lambda = 100$, it is possible to verify that it has the highest value, surpassing the P&O. Therefore, the combination of the two algorithms seems interesting, since it can extract more power from the system. However, caution is required, because depending on the value of λ, the operation will reveal a strong tendency to stick into one of the algorithms instead of alternating between them, supressing the benefit of extracting the best characteristics from their combination.

5. CONCLUSION

In this work, two types of MPPT's were explored: a classic one, P&O and a metaheuristic one, RMO. The simulations were performed with data collected experimentally from LEA. RMO presented some oscillations whenever a search procedure takes place. This instability corresponds to particles that are scattered randomly, as each represents a different duty cycle candidate. This causes large oscillations that are naturally transfered to the load. One solution to this is to adapt the algorithm in a way that minimizes the range of the oscillations. In regard to P&O, its thresholds are smaller than in RMO during the search procedures, but in several points of the simulation, the power delivered by RMO is higher.

Knowing the inherent difficulties of each algorithm, the the combination of both was performed in order to extract the best of each one and, thus, observe the power generated by the array. To do this, the irradiance threshold were used as input,and different threshold values (50, 100 and 200) were experienced. It was observed from the results that with a threshold of 50 W/m^2, lower power was generated by the array. However, regarding the thresholds of 100 and 200 W/m^2, greater performance was achieved. For future works, an intelligent algorithm that learns the right moment to alternate between P&O and RMO can be explored.

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