Probabilistic Global Maximum Power Point Tracking Algorithm for Continuously Varying Partial Shading Conditions on Autonomous PV Systems

Kha Bao Khanh Cao, Vincent Boitier

Energy and Power Engineering, 2023, 16, 21-42
https://www.scirp.org/journal/epe
ISSN Online: 1947-3818
ISSN Print: 1949-243X

Probabilistic Global Maximum Power Point Tracking algorithm for continuously varying partial shading conditions on autonomous PV systems

Kha Bao Khanh CAO, Vincent BOITIER

LAAS-CNRS, University of Toulouse, Toulouse, FRANCE
Email: kha-bao-khan.cao@laas.fr, vboitier@laas.fr

How to cite this paper: K.B.K Cao, V. Boitier (2023) Probabilistic Global Maximum Power Point Tracking algorithm for continuously varying partial shading conditions on autonomous PV systems. *Energy and Power Engineering*, 16, 21-42.
https://dx.doi.org/10.4236/epe.2024.161002

Received: November 25, 2023
Accepted: January 28, 2024
Published: January 31, 2024

Abstract

A photovoltaic (PV) string with multiple modules with bypass diodes frequently deployed on a variety of autonomous PV systems may present multiple power peaks under uneven shading. For optimal solar harvesting, there is a need for a control schema to force the PV string to operate at global maximum power point (GMPP). While a lot of tracking methods have been proposed in the literature, they are usually complex and do not fully take advantage of the available characteristics of the PV array. This work highlights how the voltage at operating point and the forward voltage of the bypass diode are considered to design a global maximum power point tracking (GMPPT) algorithm with a very limited global search phase called Fast GMPPT. This algorithm successfully tracks GMPP between 94% and 98% of the time under a theoretical evaluation. It is then compared against Perturb and Observe, Deterministic Particle Swarm Optimization, and Grey Wolf Optimization under a sequence of irradiance steps as well as a power-over-voltage characteristics profile that mimics the electrical characteristics of a PV string under varying partial shading conditions. Overall, the simulation with the sequence of irradiance steps shows that while Fast GMPPT does not have the best convergence time, it has excellent convergence rate as well as causes the least amount of power loss during the global search phase. Experimental test under varying partial shading conditions shows that while the GMPPT proposal is simple and lightweight, it is very performant under a wide range of dynamically varying partial shading conditions and boasts the best energy efficiency (94.74%) out of the 4 tested algorithms.

Keywords

Photovoltaic, PV, Global Maximum Power Point Tracking, GMPPT, fast varying partial shading conditions, autonomous PV systems, GMPPT review

1. Introduction

The photovoltaic (PV) market is primarily dominated by large scale installations such as industrial-size PV plants or residential PV installations [1], but these are not the only applications where solar panels excel at. In autonomous power supplies for embedded systems not connected to the grid, solar is usually the only viable source of ambient energy to ensure the system's continuous operation. Here are provided the examples of two categories of such applications: Figure 1A of a stationary off-grid PV measurement system to monitor the health of a pond in the context of project ECONECT [2], and Figure 1B of a mobile PV system which is a bicycle electrically assisted by solar panels [3].

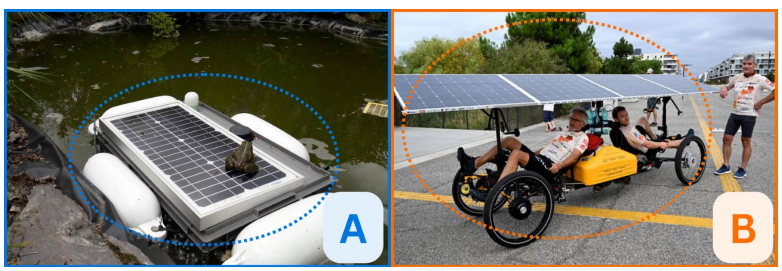

Figure 1. Examples of autonomous PV systems. Section A depicts an autonomous PV system to power ecological sentinels, section B depicts a solar assisted bicycle.

In the context of autonomous solar harvesting, the deployed systems usually suffer from continuously varying partial shading conditions (CVPSC). Looking back at the examples shown in Figure 1, this could either happen as tree branches oscillate above a stationary solar panel powering ecological sentinels or as the solar bicycle passes under trees. While large scale PV systems such as PV power plants and residential PV systems also face some CVPSC, the occurrence is lower because most shadows would be stationary or vary very slowly throughout the day.

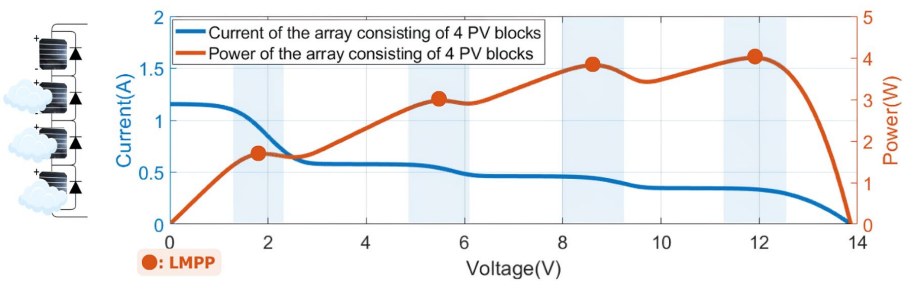

Figure 2. Power-over-voltage characteristics of a partial shading PV string consisting of 4 PV modules with 4 bypass diodes. Highlighted in blue are the regions where the potential LMPPs could be found as well as the GMPP of the PV string.

The impact of partial shading must be evaluated to understand why VPSC negatively impacts solar harvesting. Without bypass diodes, when one module of the string is shaded, there is a substantial power loss and hot spots could occur which accelerate aging of the shaded module [4]. Therefore, most deployed PV strings will have bypass diodes installed. However, while the power-over-voltage (P-V) characteristics of an evenly irradiated PV string exhibit only a single power peak, the P-V characteristics of a partially shaded PV string with bypass diodes may have multiple local maximum power peaks (LMPP) (example shown in Figure 2) among which the Global Maximum Power Point (GMPP) could be identified. The presence of LMPP complicates the optimization of solar energy harvested and therefore, the Global Maximum Power Point Tracking (GMPPT) problem received widespread attention in the literature because all PV systems, from low to high power, will suffer from partial shading throughout its lifetime.

This paper focuses on solving the problem of solar harvesting under fast and constantly varying partial shading conditions on autonomous PV systems by proposing a novel Fast GMPPT method that is performant under a wide range of VPSCs (slow varying, fast varying, light PSC, heavy PSC, etc.) An initial review of existing GMPPT methods discusses what has been achieved in GMPPT research and evaluates their advantages and drawbacks. Then, an overview of how PV strings with bypass diodes under PSC are modelled in the literature is discussed to help recreate the P-V characteristics of the PV string in the laboratory. From there, a fast and lightweight probabilistic GMPPT algorithm based on the GMPP distribution that could be easily implemented on a low power microcontroller is proposed. To evaluate the strength of this algorithm, a theoretical evaluation of its tracking capabilities using some simplified hypothesis is first discussed, then some simulations to observe its tracking behavior, and finally experimental results under VPSC to convincingly prove that it could maximize energy generation for a wide range of PV applications.

2. Review of existing GMPPT methods

2.1. MPPT algorithms

Before discussing GMPPT algorithms, it is important to discuss conventional MPPT methods because they will serve as a basis for the following discussion on GMPPT algorithms. The most widely used algorithm is Perturb and Observe (P&O) which is very simple to implement and is independent from the parameters of the PV string. Its operating principle is to perturb the voltage of the array in a certain direction to try to increase the power generation. However, it suffers from several drawbacks such as oscillation around the MPP (improvements proposed by Ahmed and Salam [5], Killi and Samanta [6]), slow convergence time (improvements proposed by Ahmed and Salam [5], Scarpa et al. [7]), and loss of tracking in rapidly increasing irradiance (improvement proposed by

Killi and Samanta [6], Sera et al. [8]). Another commonly discussed MPPT schema is Incremental Conductance which relies on the fact that the derivative of power over voltage at MPP is zero (Hussein et al. [9]). Overall, it slightly better than P&O but also suffers from several same setbacks such as slow convergence time (solution proposed by Liu et al. [10]) and loss of tracking under rapidly varying irradiance (solution proposed by Hsieh et al. [11]).

The drawbacks of the conventional MPPT techniques have inspired wave of research on more advanced techniques based on artificial neural networks (ANN) [12–18] and fuzzy logic controller (FLC) [19–24] for better MPPT algorithms. These methods generally allow for very fast convergence time when compared to conventional techniques (e.g. ANN results from Jyothy and Sindhu [14] and FLC results from El Khateb et al. [23]). However, their common setbacks are the heavy dependance of the controller on the parameters of the PV string and their complexity [19]. Furthermore, if instant convergence is desired, there are other simpler methods with similar tracking performance such as the proposals to estimate the P-V curve using the Lambert by Farivar et al. [25] or using the Thevenin equivalent model by Moradi et al. [26].

2.2. GMPPT algorithms

The above methods are, by themselves, unable to correctly track GMPP, which is why dedicated GMPPT techniques received significant attention from the solar community. The first set techniques could be grouped up as voltage scanning with the basic idea being to perform a sweep of operating points between zero and open circuit voltage of the PV string. This technique is rarely used alone but rather as a hybrid tracking technique with other MPPT schema such as with P&O (Deboucha et al. [27]) or FLC (Shah and Rajagopalan [28]). While they are good at tracking GMPP, they suffer from slow convergence time. A second set of techniques is an extension of voltage scanning where the controller only performs strategic searches where LMPPs could occur which is called nV_{oc} method. This is implemented by calling an MPPT subroutine with a starting operating point in the regions where LMPP could be found and letting the controller track toward LMPP. After having found all LMPPs, the controller could pick out the GMPP. It was studied to complement the P&O technique by Zhou et al [29], to complement the INC technique by Tey and Mekhilef [30], and to complement the fractional open circuit voltage technique by Barbosa et al. [31]. With a more limited search, nV_{oc} is generally more efficient than voltage scanning but requires knowledge of the parameters of the PV string.

Fuzzy logic and artificial intelligence-based techniques have also been explored to tackle the problem of GMPPT. The majority of works found could only be classified as classical

ANN-based MPPT coupled with metaheuristic algorithms such as the proposal to use PSO for the global search phase and ANN controller for the local search phase by Rahman and Islam [32]. However, recent studies have also explore the possibility of directly using ANN controller for GMPPT purpose such as the work by Ahmad et al. [33] and Ye et al. [34].

Finally, GMPPT researchers have also explored the application metaheuristics algorithms inspired by the mathematical field of optimization. The first paper that set the trend was a proposal to use Particle Swarm Optimization (PSO) by Miyatake et al. [35] where the authors showcased the advantages of using metaheuristic optimization algorithms: they allow for a limited global search which improves convergence time yet do not require knowledge of the parameters of the PV string. From there, many other optimization algorithms have been studied for GMPPT: Deterministic Particle Swarm Optimization (DPSO) by Ishaque and Salam [36], Gravitational PSO by Leong et al. [37], Grey Wolf Optimization (GWO) by Motamarri et al. [38], Fireflies Optimization by Farayola et al. [39], Artificial Bee Colony Optimization by Motahhir et al. [40], Dragonfly Optimization by Lodhi et al. [41], Grasshopper Optimization by Sridhar et al. [42], Flower Pollination Optimization by Prasanth Ram and Rajasekar [43], Ant Colony Optimization by Titri et al. [44], Population Based Optimization by Pal and Mukherjee [45], Most Valuable Player Optimization by Pervez et al. [46], Teaching-Learning Optimization by Rezk and Fathy [47], Simulated Annealing Optimization by Lyden and Haque [48], Henry Gas Optimization by Mirza et al. [49], Quantum Annealing by Liu et al. [50], Lévy flight PSO by Motamarri and Nagu [51], Buttyfly Optimization by Mathi and Chinthamalla [52]. These algorithms could also be coupled with conventional MPPT techniques for better tracking performance under lightly varying irradiance situations such as Gravitational Particle Swarm Optimization with P&O (Leong et al. [37]) or using Artificial Bee Colony with P&O (Pilakkat and Kanthalakshmi [53]). While most authors successfully showed the advantages of these metaheuristic algorithms over conventional MPPT techniques, their advantages over one another are debatable, and the results are sometimes inconsistent because of setup differences. This complicates the task of accurately ascertain the true capabilities of each proposal (e.g., inconsistent PSO efficiency results between Miyatake et al. [35] and Liu et al. [54]). So far, without normalizing the experimental setup, the only discernable difference would be their implementation complexity.

Based on the existing literature, this work proposes a lightweight and Fast GMPPT algorithm based that could be considered an extension of voltage scanning and nV_{oc}. Metaheuristics methods were not chosen because they suffer from significant power jittering during the global search phase (Rahman and Islam [32]). Furthermore, while the capabilities of intelligence-based techniques are promising, they are far from simple to imple-

ment, requiring an extensive tuning step for a specific PV system. The proposed algorithm consists of a limited global search phase with only a few candidate solutions checked at specific voltage targets which could be deduced using easily accessible specifications of the PV system. Then, the operating point with the highest power observed will be chosen as a seed to initiate P&O. Given that the limited search range may not guarantee convergence, a preliminary theoretical evaluation inspired by the statistical analysis done by Lyden and Haque [48] is first performed. The proposed GMPPT is then tested in both simulation and experimental setup as with most of the existing literature. Furthermore, besides the frequently used irradiance steps, varying irradiance conditions are also included for a better real-world representation. This is inspired by the EN50530 standard frequently employed by MPPT researchers to study the performance of MPPT on single power peak PV systems under varying irradiance conditions (e.g., Ahmed and Salam [5], Lian et al. [55]). However, a mathematical model to simulate the evolution of the P-V characteristics of a PV string under VPSC has to be developed because an equivalent standard for partial shading does not exist yet, which will be presented along side with the experimental results.

3. Autonomous PV system for performance evaluation

To evaluate the performance of the proposed algorithm compared to existing methods, the tests are performed on an autonomous PV system comprising of 4 PV modules with 4 bypass diodes in series, a buck converter driven by a microcontroller that surveys the current and voltage of the PV string, a battery, and a load. Its generalized architecture can be found in Figure 3.

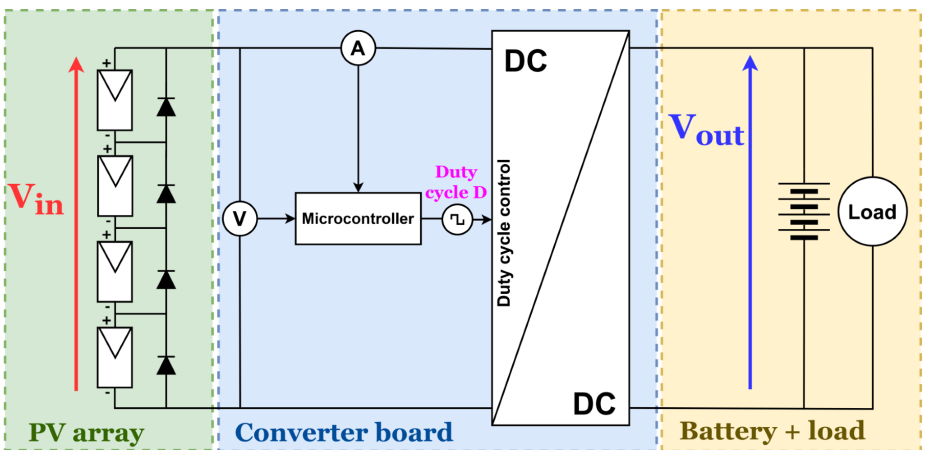

Figure 3. Generalized architecture of the autonomous PV system we used in this research.

3.1. Characteristics of the PV string with bypass diodes

First, let us discuss the electrical model of a PV module. A single PV cell could be modelled at different levels of accuracy, from the ideal single diode model, to a practical single diode model where Joule losses are considered, and up to a highly accurate two diode model (Villalva et al. [56]). Villalva et al. consider the practical single diode model to be a good compromise between accuracy and computational complexity. Scaling up to PV module modelling, Nguyen Ngoc Ban [57] provided a mathematical proof that the practical single diode model of a PV cell could be applied to a full PV module consisting of multiple PV cells. This is called the equivalent single diode model, and it would be used to model the PV modules in this work. Next, each PV module in the string has an associated bypass diode which could be modelled using the linear piecewise equation. Looking at the PV string, it is possible to group each module and its associated bypass diode into a PV block. The electrical model and electrical characteristics (current-over-voltage or I-V) of a PV block can be found in Figure 4A. Finally, adding the voltages of the multiple PV blocks given the same current gives the I-V and eventually P-V of a PV string.

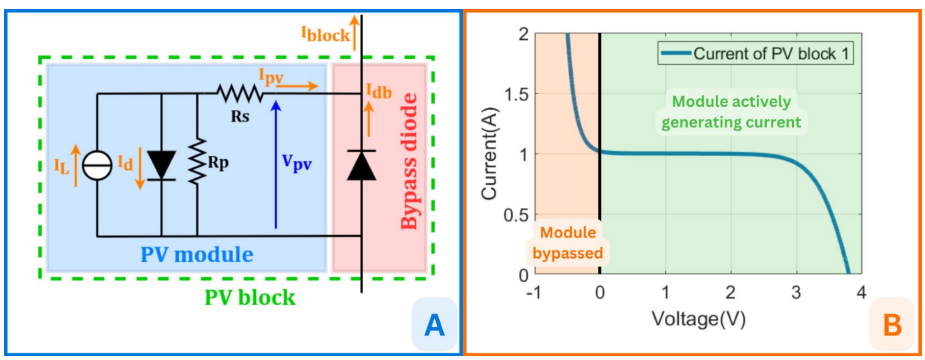

Figure 4. Electrical model of a PV block (A) and current-over-voltage characteristics of a PV block (B).

The mathematical equations necessary to arrive at the current-over-voltage characteristics of the PV block shown in Figure 4B are given in equations (1) to (6). The description of the parameters are as follows: I_L the equivalent photocurrent of the PV module, G the irradiance received by the PV module, G_{ref} the reference irradiance at Standard Test Condition (STC) of 1000 Wm^{-2}, I_{scn} the nominal short circuit current of the PV module, R_s the equivalent series resistance of the PV module, R_p the equivalent parallel resistance of the PV module, k_i the current temperature coefficient of the PV module, T the temperature of the PV module, T_{ref} the reference temperature at STC of 298.15K, I_0 the reverse saturation current of the diode in the PV module, q the electron charge, A the diode ideality factor of the diode in the PV module, k the Boltzmann constant, V_{ocn} the nominal open circuit current of the PV module, k_v the voltage temperature coeffi-

cient of the PV module, V_{pv} is the nominal open circuit voltage of the PV module and also of the PV block, I_d the current traversing the diode in the PV module, I_{pv} the current generated by the PV module, I_{db} the current traversing the bypass diode, V_f the forward voltage of the bypass diode, R_{don} the on resistance of the bypass diode, and I_{block} the current traversing the PV block. A summary of all parameters and their values can be found in Table 1.

$$I_L = \frac{G}{G_{ref}}\left(I_{scn}\left(1+\frac{R_s}{R_p}\right)+k_i(T-T_{ref})\right) \quad (1)$$

$$I_0 = \frac{I_{scn}+k_i(T-T_{ref})}{e^{\left(\frac{q}{AkT}(V_{ocn}+k_v(T-T_{ref}))\right)}-1} \quad (2)$$

$$I_d = I_0\left(e^{\left(\frac{q}{AkT}(V_{pv}+I_{pv}R_s)\right)}-1\right) \quad (3)$$

$$I_{pv} = I_L - I_d - \frac{V_{pv}+I_{pv}R_s}{R_p} \quad (4)$$

$$I_{db} = \begin{cases} 0 & if\ -V_{pv} < V_f \\ \frac{(-V_{pv}-V_f)}{R_{don}} & if\ -V_{pv} \geq V_f \end{cases} \quad (5)$$

$$I_{block} = I_{pv} + I_{db} \quad (6)$$

Table 1. Summary of modelling parameters for the PV modules and bypass diodes

Parameter	Value	Unit
V_{ocn}	3.725	V
I_{scn}	1.05	A
V_{mpp}	3	V
I_{mpp}	0.98	A
K_v	-11× 10^{-3}	VK^{-1}
K_i	3× 10^{-3}	AK^{-1}
R_p	1200	Ω
R_s	0.2	Ω
q	1.6×10^{-19}	As
K	1.38×10^{-23}	$m^2kgs^{-2}K^{-1}$
A	9.5	Unitless
V_f	0.26	V
R_{don}	0.18	Ω

3.2. Characteristics of the buck converter

The converter board used has a synchronous buck converter driver by a PWM signal generated by the PIC18LF1220 microcontroller as shown in Figure 5. It surveys the voltage and current of the PV string to periodically update the duty cycle driving the converter. The sampling time is 8ms, a good compromise between the response time of the test platform and the computational capability of the microcontroller. The specific parameters of the board can also all be found in Figure 5.

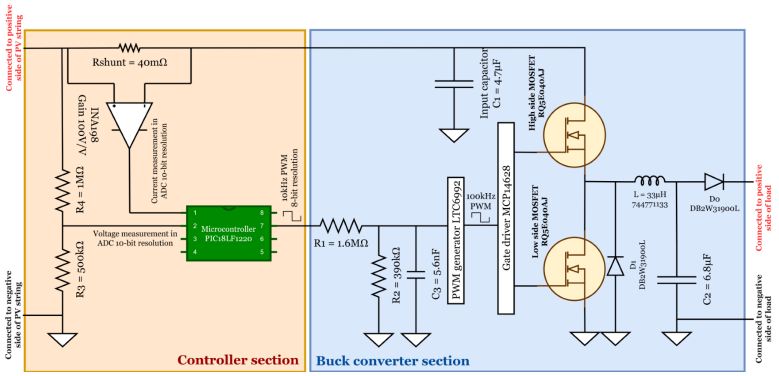

Figure 5. Simplified schema of the converter board used in this research consisting of a controller section and a buck converter section.

4. Proposal of a probabilistic GMPPT algorithm

Seeing that a wide global search is detrimental to the overall performance of the algorithm, a very limited search of a single voltage point is proposed where GMPP could potentially occur, which is equivalent to all the regions where LMPP could occur. Generally, a string of n PV modules with n bypass diodes could have up to n LMPPs occurring close to

$$iV_{mpp} - (n-i)V_f \ (i \in \{1..n\}), \tag{7}$$

where V_{mpp} is the nominal voltage at MPP of a single PV module, and V_f the forward voltage of the bypass diode. Therefore, the algorithm starts with a voltage search phase where it evaluates the power harvested at n voltage targets of value

$$v_{target}^{i} = iV_{mpp} - (n-i)V_f \ (i \in \{1..n\}). \tag{8}$$

For example, if implemented on the PV string with 4 PV modules and 4 bypass diodes, these voltage targets would be $\{v_{target}^{1} = 2.2V; v_{target}^{2} = 5.5V; v_{target}^{3} = 8.7V; v_{target}^{4} = 12V\}$. The microcontroller can then take voltage target having maximum power as a starting point to initiate a P&O to reach GMPP. This GMPPT schema is called "Fast GMPPT" because the core idea is trading efficiency and convergence rate for a shorter global search.

The concrete implementation of Fast GMPPT consists of 4 main phases as shown in the flowchart in Figure 6: initialization of variables, voltage search to find the initial seed for P&O, improved P&O, and steady state. The initialization phase is where all the parameters are loaded into the program memory, and the steady state phase is implemented similarly to DPSO and GWO. Therefore, there are two important phases to discuss, the voltage search phase and the improved P&O phase.

In the voltage search phase, n voltage targets are evaluated, and the maximum is chosen as a seed for the subsequent improved P&O phase. Due to measurement noise, the "point" requirement of each voltage target i is relaxed to a "narrow voltage window" represented by the optimal point v_{target}^{i}, the upper limit v_{up}^{i}, and the lower limit v_{low}^{i}. If the voltage of the PV string is in this window, the voltage target is considered reached. However, since the duty cycle is the direct control variable, a simple proportional controller is added in the form of

$$D^{k} = D^{k-1} + p(V_{pv}^{k} - v_{target}^{i}) \tag{9}$$

where D^{k} is the duty cycle to be sent at iteration k, V_{pv}^{k} is the measurement from the current iteration, and p is the proportional coefficient. An array of initial guessed duty cycles was given as d_{est}^{i} and it is constantly updated at every voltage search phase with the duty cycle that gets to the voltage target to accelerate subsequent searches.

Next, the improved HC phase is implemented to address two main drawbacks of the basic HC algorithm: the oscillation around the peak and the potential loss of tracking. To remove the oscillation, it is possible to detect when it happens and force the system to a steady state at GMPP (Ahmed and Salam [5]). The controller examines how many times the duty cycle variation is inverted inv as well as the streak of samples without inversion $ninv$. When $ninv$ exceeds a limit of $ninv_{limit}$, the algorithm is in the search phase or that the irradiance is varying, so inv is reset to 0. When an inversion occurs, inv is incremented and $ninv$ is reset to 0 only if $ninv$ is non-zero, otherwise the system is probably in continuous inversion indicating varying irradiance and inv is reset. Finally, the oscillation is confirmed when inv exceeds a certain limit inv_{limit}. Regarding tracking loss, a simple iteration counter $cter$ is added in the HC phase, and the algorithm reverts to the sweep phase when it exceeds $cter_{limit}$.

Finally in steady state phase, the microcontroller stops updating the duty cycle and continues to monitor the power output of the PV string. If it detects a power variation exceeding a certain threshold, it will initiate a new voltage search phase. Mathematically, this could be represented as

$$\left|P_{pv}^{k} - p_{max}\right| > \varepsilon p_{max}, \tag{10}$$

where P_{pv}^{k} is the power generated by the PV string measured at iteration k, p_{max} is the maximum power point found in the improved P&O phase, and $\mathcal{E}$ is the threshold. This steady state phase is inspired by the works of Miyatake et al. [58] and is also widely among existing GMPPT proposals.

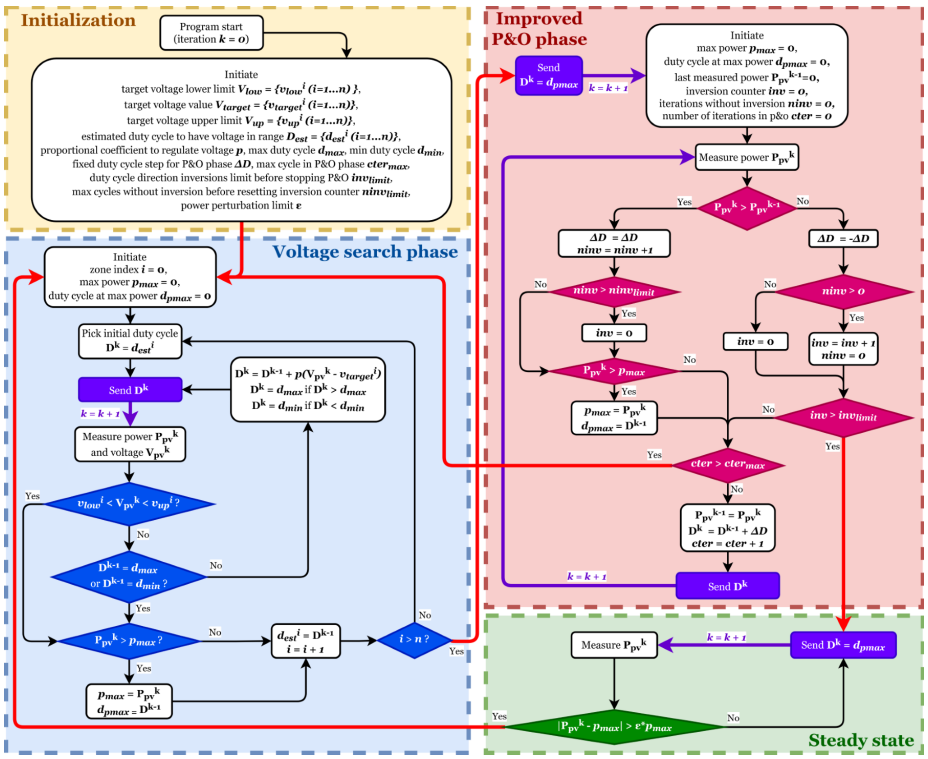

Figure 6. Flowchart of the proposed Fast GMPPT method.

5. Evaluate the performance of the proposed algorithm

In this section, the performance of Fast GMPPT against 3 other existing algorithms is evaluated: P&O, DPSO, and GWO. P&O is the most widely used tracking schema that has been criticized for its inability to track GMPP, so it was included to set a baseline. As for DPSO and GWO, they are 2 performant GMPPT algorithms (as demonstrated by Ishaque and Salam [36] and Mohanty et al. [59] respectively) that are resource efficient enough to be implemented on the PIC18 low-power microcontroller.

Before moving forward with testing the algorithm tracking itself, a theoretical probabilistic estimation of its capabilities must be verified. Then, the algorithms are evaluated under 2 different test scenarios: a sequence of irradiance steps where the tracking behavior of each algorithm could be carefully examined, and a set of different VPSC where their

energy efficiency could be evaluated. The sequence of irradiance steps was tested using simulation, while testing under VPSC was done experimentally.

5.1. Theoretical evaluation

P&O is very reliable when the power gradient between its initial starting point and the GMPP is strictly increasing. Assuming this, it is possible to simulate a multitude of P-V characteristics of the PV string under different irradiance and temperature conditions and evaluate the power gradient between the point chosen by the voltage search phase and GMPP. If it is indeed strictly increasing, it is possible to conclude that P&O will converge correctly and vice versa.

A total of 13,263,825 P-V characteristics of the PV string of 4 PV modules and 4 bypass diodes are simulated. Specifically, there are 4,421,275 different partial shading conditions under 3 different temperature assumptions. The first set of temperature conditions called quasi-homogeneous temperatures assumes that the temperature of all PV modules is relatively close to one another. The second set of temperature conditions called irradiance-dependent temperatures assumes that the irradiance received by each PV module heats them up a certain amount over ambient temperature.

The theoretical evaluation is done in the context of the test hardware described in the previous section. Due to the usage of a digital proportional controller to reach the voltage targets, the power measurements may not be taken precisely at the voltage targets, but they could deviate up to $\pm 0.3V$ (this value arises from the implementation Fast GMPPT). Furthermore, given that the output of the buck converter is limited by the voltage of the Li-ion battery, only 3 voltage targets $\{v_{target}^2 = 5.5V; v_{target}^3 = 8.7V; v_{target}^4 = 12V\}$ are accessible. Therefore, each voltage target could be 7 different values between $v_{target}^i - 0.3V$ to $v_{target}^i + 0.3V$ at a step of 0.1V. Given that there are 3 points targets total, there are are total of 7^3=343 different possible combinations of voltage targets.

The success rate of these 343 different combinations of voltage targets on the set of 13,263,825 P-V characteristics are evaluated under two different temperature assumptions, quasi-homogeneous and irradiance-dependent, and compiled the results in a box-plot graph shown in Figure 7. Overall, Fast GMPPT should track correctly toward GMPP between 94% and 98%, which is remarkable given the limited global search.

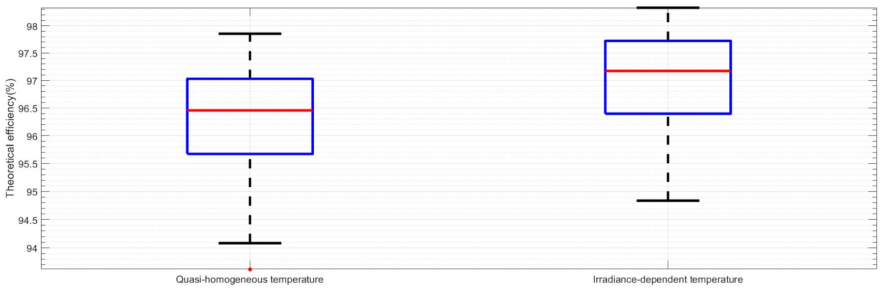

Figure 7. Theoretical convergence rate of the proposed fast GMPPT method when we assume that all irradiance conditions are equally probable and assume that the temperatures of the module are either quasi-homogeneous or irradiance-dependent.

5.2. Simulation results

Simulink was the platform of choice to simulate the autonomous PV system and the algorithm for convenience. While Simulink did provide built-in PV module model, a customed model based on the works of Nguyen and Nguyen [60] as shown in Figure 8 is developed to avoid solver issues. The synchronous buck converter was modelled using an average model to avoid solver issues. The synchronous buck converter was modelled using an average model [61] as shown in Figure 9 which bypasses the need to simulate switching events resulting in fast simulation time (Gragger et al.). As for the battery and load, they are modelled using a simple resistance in parallel with a voltage source of 3.7V to simulate the relatively stable voltage of a Li-ion battery.

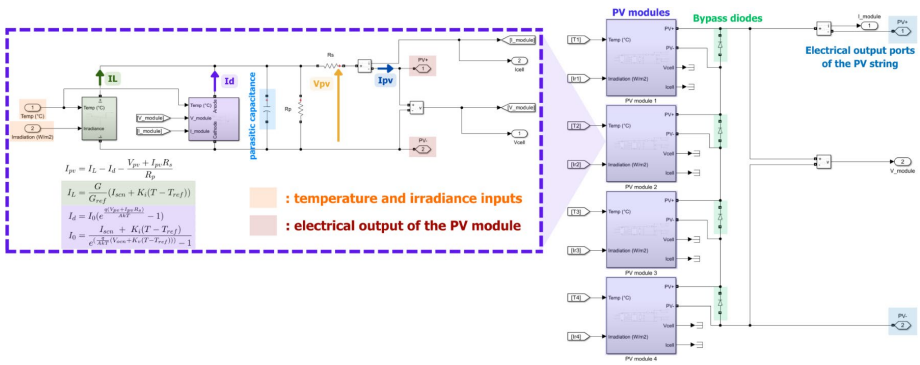

Figure 8. Simulink model of the PV string of 4 PV modules and 4 bypass diodes.

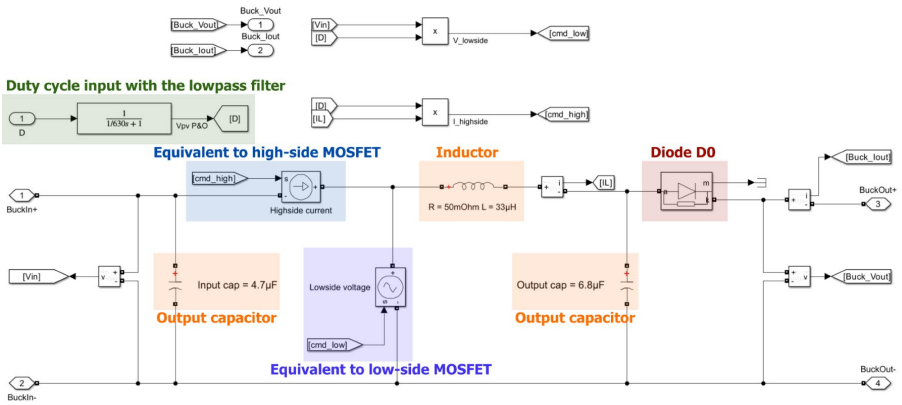

Figure 9. Averaged model of the synchronous buck converter in Simulink.

We selected 5 PSC conditions enumerated from 1 to 5 where their respective P-V profiles can be found in Figure 10. They are simulated in that order where each condition lasts 1s and the simulation result is presented in Figure 11. where the orange data are the measured power and voltage of the PV string while the blue data are the estimated voltage and power at GMPP. The sampling time of the algorithms are all set to 8ms for a fair comparison.

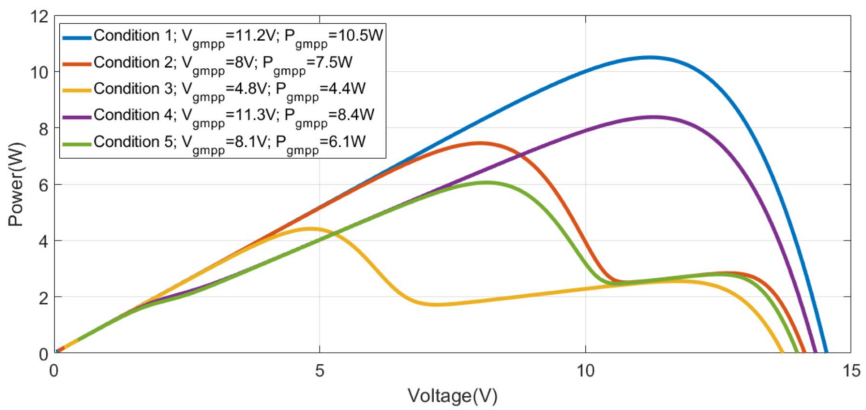

Figure 10. P-V characteristics of the PV string under 5 different PSC conditions.

First, the response of P&O showcases its inconsistency under PSC where it failed to correctly track toward GMPP at condition 3. Its convergence time varies widely from a very low 8 iterations up to 34 iterations (64ms to 272ms) which confirms its dependence on the initial starting point. Next are the tracking response by DPSO that progressively converges toward the GMPP between 12 to 18 iterations (96ms to 144ms), and it manages to converge accurately under all 5 PSC. This is overall the best convergence time at a relatively good consistency. However, significant perturbations during the search were ob-

served which could be detrimental when it eventually faces VPSC. The result for GWO shows that it converges correctly under all 5 PSC and has a very consistent convergence time of 24 iterations (192ms). As is the case with DPSO, significant power jittering is observed during its search phase which is not ideal if it is deployed to handle VPSC. Finally, Fast GMPPT converges after around 20 to 32 iterations (160ms to 256ms). While the tracking time is not the best among the algorithms tested, it did track toward GMPP successfully under all 5 shading conditions while causing little power perturbations.

However, these irradiance steps could be easily cherry-picked to highlight performance numbers. For example, a more challenging situation to force P&O to fail to converge every time could be arbitrarily created, or cherry-picking the outlier results where the metaheuristics algorithms fail. This is the reason why the emphasis is put into the commentaries on the tracking mechanisms of the algorithms under these irradiance steps rather than their actual efficiency. To truly evaluate the latter aspect, their performance under varying partial shading conditions must be carefully examined.

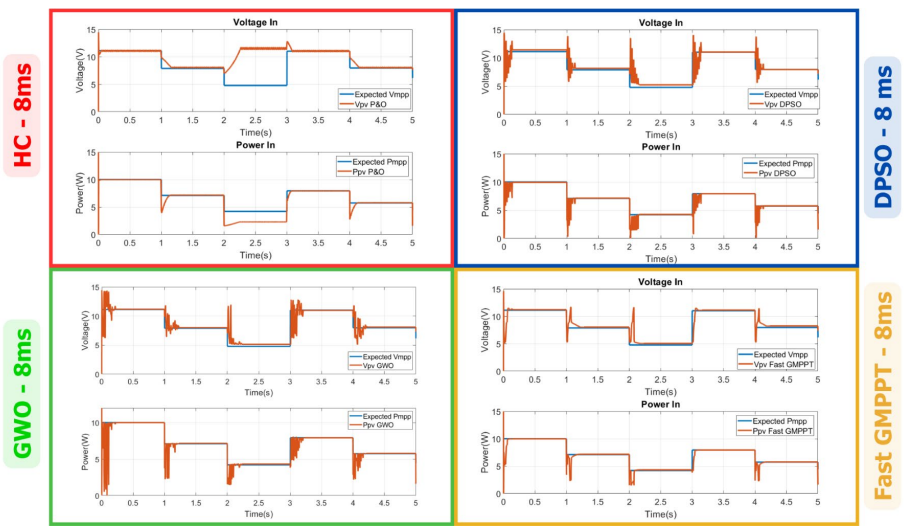

Figure 11. Step irradiance results of the 4 tested algorithms. Orange is the measured voltage and power, while blue is the estimated voltage and power at GMPP.

5.2. Experimental result

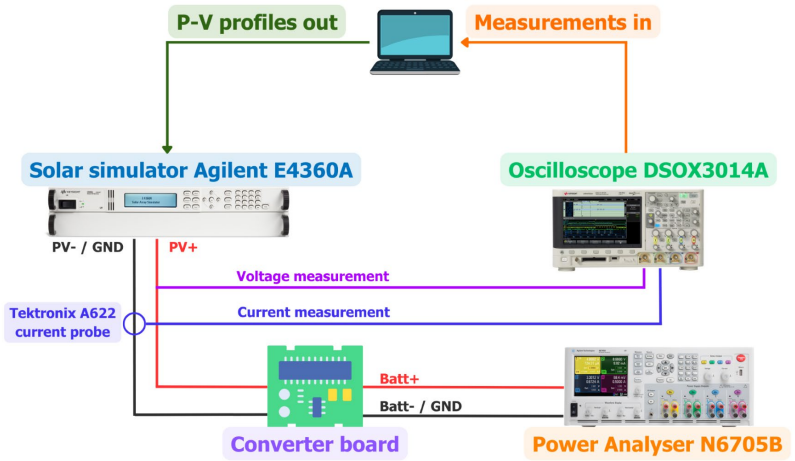

Figure 12. Detailed description of the experimental setup to consistently recreate VPSCs.

The experimental test setup is summarized in Figure 12. The different VPSC are simulated by the Agilent E4360A solar simulator to ensure consistency and to allow for a fair comparison between the algorithms. The battery and load are simulated by the Keysight N6705B power analyzer. The measurements were taken by the Keysight DSOX3014A oscilloscope, and the current specifically was taken by a Tektronix A622 current probe with a 10V/A gain. A MATLAB interface pilots the solar simulator to create the VPSC and recuperate the measurements from the oscilloscope for processing.

To create multiple VPSC, a simplified mathematical model to simulate the evolution of the P-V profile of the PV string when a shadow passes over it was devised as shown in Figure 13. This shading profile creator first has the string of 4 square solar panels of side length l placed in a square formation on the Oxy plane. They are receiving even G_{global} irradiance and all at the same temperature T_{global}. A shading object with arbitrary width w_{shade} and height h_{shade} starting from an arbitrary position (x_{shade}, y_{shade}) moves across the plane at a velocity described by vshade and its angle relative to Ox θ_{shade}. At each timestamp, the overlap between the shading object and the solar panels is calculated to obtain their instantaneous irradiance. Note that the shading factor of a photovoltaic module is assumed to be applied equally to all its individual cells. By changing the global irradiance, global temperature, and how the shading object moves, it is possible to conveniently created a set of 288 different VPSC profiles, each lasting an arbitrarily chosen 8s. This set contains examples of fast varying partial shading, slow varying partial shading, slight partial shading, and heavy partial shading.

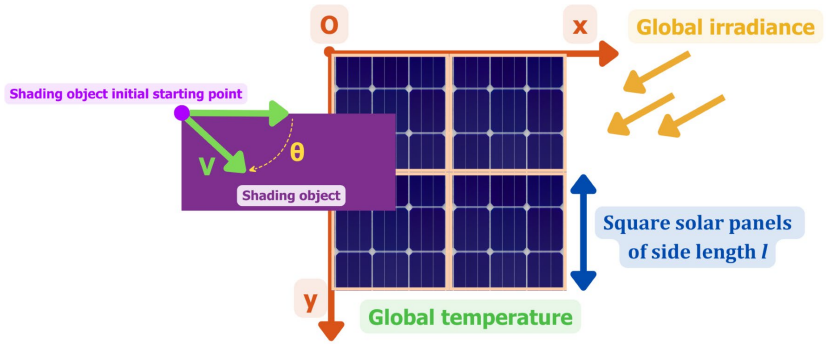

Figure 13. An illustration of the method to simulate the evolution of the P-V of the PV string under VPSC.

The energy efficiency of each algorithm under VPSC is individually recorded and compiled into the boxplots found in Figure 14, as well as into a summary of median, lowest, and highest efficiency figures found in Table 2. P&O having the worst lowest energy efficiency of 56.2% demonstrates that it lost track of GMPP under certain conditions, but its highest energy efficiency of 98.35% is also the best among the 4 tested methods. Fast GMPPT, DPSO, and GWO all have better lowest energy efficiencies, but slightly worse highest energy efficiency figures compared to P&O. This fact highlights the advantages and drawbacks of the global search phase. In challenging situations where P&O failed, the GMPPT algorithms managed to converge and extract power. However, in lighter PSC where the perturbation is relatively mild, P&O would have no difficulty following GMPP whereas the GMPPT algorithms initiated global searches causing power losses.

Fast GMPPT has the best overall median energy efficiency at 94.84%, followed by P&O at 93.64%, then DPSO at 90.68%, and finally GWO at 86%. Considering only the GMPPT algorithms, it seems that limiting the global search phase to only where GMPP could be found is indeed very advantageous. However, this is a compromise since it made Fast GMPPT dependent on the parameters of the PV string, while DPSO and GWO are still relatively independent from the parameters of the PV string.

Table 2. Summary of energy efficiency figures of 4 tested algorithms under the 288 VPSC.

Algorithm name	Summary of energy efficiency figures		
	Median	Lowest	Highest
P&O	93.64%	56.2%	98.35%
Fast GMPPT	94.74%	72.68%	97.74%
DPSO	90.68%	75.20%	97.42%
GWO	86%	71%	96.97%

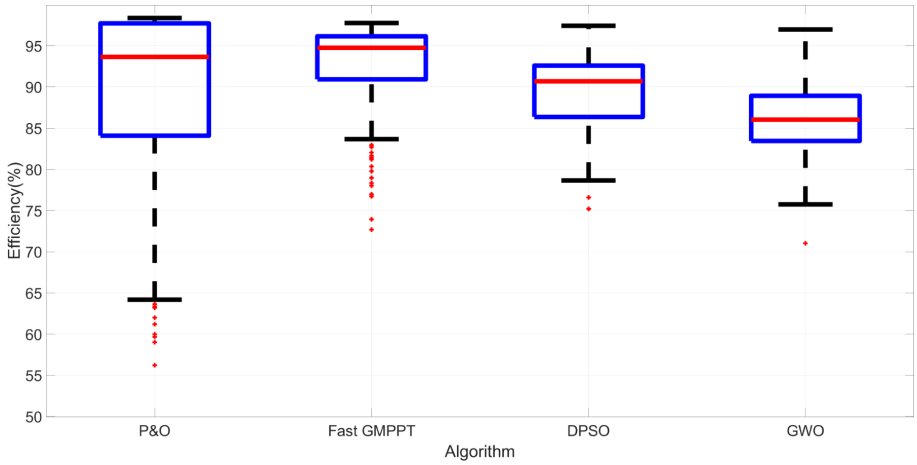

Figure 14. Boxplots showing the energy efficiencies of each algorithm when tested using the set of 288 VPSC.

6. Conclusion

In this work, the current literature of MPPT and GMPPT are discussed, and a lightweight and energy efficiency algorithm called Fast GMPPT is proposed. Statistically, the proposed method converges correctly around 94% to 98% of the time if the shading pattern is randomly distributed as shown by the theoretical evaluation. Its tracking phase causes significantly less perturbations which minimizes power loss during tracking as shown by the simulation results. Finally, Fast GMPPT has a median energy efficiency of 94.74%, the best out of the 4 tested algorithms, when tested under a wide range of VPSC. Coupled with the fact that the method is very simple to implement and is very lightweight, it is very competitive with other existing GMPPT algorithms in the literature. However, the work could benefit from a more accurate modelling of how the P-V characteristics of the PV string evolves under VPSC and some meta-analysis of potential VPSC that could occur in different types of autonomous PV applications. Future works that further develop these aspects could significantly improve the field of GMPPT research since accurately simulating varying partial shading conditions will help design ever more robust GMPPT schemas.

References

[1] Photovoltaics (PV) Market Size Share Trends & Growth Drivers Forecast, 2030. MarketsandMarkets. https://www.marketsandmarkets.com/Market-Reports/building-integrated-photovoltaic-market-428.html.

[2] CNRS. ECONECT – Ecosystèmes connectés Sentinelles de l'Environnement - https://econect.cnrs.fr/. https://econect.cnrs.fr/.

[3] The Sun Trip. The Sun Trip - Solar Bike Adventures - Since 2013. The Sun Trip. https://www.thesuntrip.com/.
[4] Alonsogarcia, M., Ruiz, J. and Chenlo, F. (2006) Experimental Study of Mismatch and Shading Effects in the – Characteristic of a Photovoltaic Module. *Solar Energy Materials and Solar Cells*, **90**, 329–340. https://doi.org/10.1016/j.solmat.2005.04.022.
[5] Ahmed, J. and Salam, Z. (2016) A Modified P&O Maximum Power Point Tracking Method With Reduced Steady-State Oscillation and Improved Tracking Efficiency. *IEEE Transactions on Sustainable Energy*, **7**, 1506–1515. https://doi.org/10.1109/TSTE.2016.2568043.
[6] Killi, M. and Samanta, S. (2015) Modified Perturb and Observe MPPT Algorithm for Drift Avoidance in Photovoltaic Systems. *IEEE Transactions on Industrial Electronics*, **62**, 5549–5559. https://doi.org/10.1109/TIE.2015.2407854.
[7] Scarpa, V.V.R., Buso, S. and Spiazzi, G. (2009) Low-Complexity MPPT Technique Exploiting the PV Module MPP Locus Characterization. *IEEE Transactions on Industrial Electronics*, **56**, 1531–1538. https://doi.org/10.1109/TIE.2008.2009618.
[8] Sera, D., Teodorescu, R., Hantschel, J. and Knoll, M. (2008) Optimized Maximum Power Point Tracker for Fast-Changing Environmental Conditions. *IEEE Transactions on Industrial Electronics*, **55**, 2629–2637. https://doi.org/10.1109/TIE.2008.924036.
[9] Hussein, K., Muta, I., Hoshino, T. and Osakada, M. (1995) Maximum Photovoltaic Power Tracking: An Algorithm for Rapidly Changing Atmospheric Conditions. *IEEE Proceedings - Generation, Transmission and Distribution*, **142**, 59–64.
[10] Liu, F., Duan, S., Liu, F., Liu, B. and Kang, Y. (2008) A Variable Step Size INC MPPT Method for PV Systems. *IEEE Transactions on Industrial Electronics*, **55**, 2622–2628. https://doi.org/10.1109/TIE.2008.920550.
[11] Hsieh, G.-C., Hsieh, H.-I., Tsai, C.-Y. and Wang, C.-H. (2013) Photovoltaic Power-Increment-Aided Incremental-Conductance MPPT With Two-Phased Tracking. *IEEE Transactions on Power Electronics*, **28**, 2895–2911. https://doi.org/10.1109/TPEL.2012.2227279.
[12] Villegas-Mier, C.G., Rodriguez-Resendiz, J., Álvarez-Alvarado, J.M., Rodriguez-Resendiz, H., Herrera-Navarro, A.M. and Rodríguez-Abreo, O. (2021) Artificial Neural Networks in MPPT Algorithms for Optimization of Photovoltaic Power Systems: A Review. *Micromachines*, Multidisciplinary Digital Publishing Institute, **12**, 1260. https://doi.org/10.3390/mi12101260.
[13] Rahman, Md.M. and Islam, M.S. (2019) Artificial Neural Network Based Maximum Power Point Tracking of a Photovoltaic System. 2019 3rd International Conference on Electrical, Computer Telecommunication Engineering (ICECTE), 117–120. https://doi.org/10.1109/ICECTE48615.2019.9303531.
[14] Jyothy, L.P.N. and Sindhu, M.R. (2018) An Artificial Neural Network Based MPPT Algorithm For Solar PV System. 2018 4th International Conference on Electrical Energy Systems (ICEES), 375–380. https://doi.org/10.1109/ICEES.2018.8443277.
[15] Agha, H.S., Koreshi, Z. and Khan, M.B. (2017) Artificial Neural Network Based Maximum Power Point Tracking for Solar Photovoltaics. 2017 International Conference on Information and Communication Technologies (ICICT), 150–155. https://doi.org/10.1109/ICICT.2017.8320180.
[16] Rizzo, S.A. and Scelba, G. (2015) ANN Based MPPT Method for Rapidly Variable Shading Conditions. *Applied Energy*, **145**, 124–132. https://doi.org/10.1016/j.apenergy.2015.01.077.
[17] Elobaid, L.M., Abdelsalam, A.K. and Zakzouk, E.E. (2012) Artificial Neural Network Based Maximum Power Point Tracking Technique for PV Systems. IECON 2012 - 38th Annual Conference on IEEE Industrial Electronics Society, 937–942. https://doi.org/10.1109/IECON.2012.6389165.
[18] Dzung, P.Q., Khoa, L.D., Lee, H.H., Phuong, L.M. and Vu, N.T.D. (2010) The New MPPT Algorithm Using ANN-Based PV. International Forum on Strategic Technology 2010, 402–407. https://doi.org/10.1109/IFOST.2010.5668004.
[19] Ali, M.N., Mahmoud, K., Lehtonen, M. and Darwish, M.M.F. (2021) Promising MPPT Methods Combining Metaheuristic, Fuzzy-Logic and ANN Techniques for Grid-Connected Photovoltaic. *Sensors*, Multidisciplinary Digital Publishing Institute, **21**, 1244. https://doi.org/10.3390/s21041244.

[20] Li, X., Wen, H., Hu, Y. and Jiang, L. (2019) A Novel Beta Parameter Based Fuzzy-Logic Controller for Photovoltaic MPPT Application. *Renewable Energy*, **130**, 416–427. https://doi.org/10.1016/j.renene.2018.06.071.

[21] Yilmaz, U., Kircay, A. and Borekci, S. (2018) PV System Fuzzy Logic MPPT Method and PI Control as a Charge Controller. *Renewable and Sustainable Energy Reviews*, **81**, 994–1001. https://doi.org/10.1016/j.rser.2017.08.048.

[22] Kumar, R., Kumar, B. and D., S. (2018) Fuzzy Logic Based Improved P&O MPPT Technique for Partial Shading Conditions. 2018 International Conference on Computing, Power and Communication Technologies (GUCON), 775–779. https://doi.org/10.1109/GUCON.2018.8674917.

[23] El Khateb, A., Rahim, N.A., Selvaraj, J. and Uddin, M.N. (2014) Fuzzy-Logic-Controller-Based SEPIC Converter for Maximum Power Point Tracking. *IEEE Transactions on Industry Applications*, **50**, 2349–2358. https://doi.org/10.1109/TIA.2014.2298558.

[24] Alajmi, B.N., Ahmed, K.H., Finney, S.J. and Williams, B.W. (2011) Fuzzy-Logic-Control Approach of a Modified Hill-Climbing Method for Maximum Power Point in Microgrid Standalone Photovoltaic System. *IEEE Transactions on Power Electronics*, **26**, 1022–1030. https://doi.org/10.1109/TPEL.2010.2090903.

[25] Farivar, G., Asaei, B. and Mehrnami, S. (2013) An Analytical Solution for Tracking Photovoltaic Module MPP. *IEEE Journal of Photovoltaics*, **3**, 1053–1061. https://doi.org/10.1109/JPHOTOV.2013.2250332.

[26] Moradi, M.H., Reza Tousi, S.M., Nemati, M., Saadat Basir, N. and Shalavi, N. (2013) A Robust Hybrid Method for Maximum Power Point Tracking in Photovoltaic Systems. *Solar Energy*, **94**, 266–276. https://doi.org/10.1016/j.solener.2013.05.016.

[27] Deboucha, H., Kermadi, M., Mekhilef, S. and Belaid, S.L. (2023) Ultra-Fast and Accurate MPPT Control Structure for Mobile PV System Under Fast-Changing Atmospheric Conditions. *IEEE Transactions on Sustainable Energy*, **14**, 2168–2176. https://doi.org/10.1109/TSTE.2023.3260031.

[28] Shah, N. and Rajagopalan, C. (2016) Experimental Evaluation of a Partially Shaded Photovoltaic System with a Fuzzy Logic-Based Peak Power Tracking Control Strategy. *IET Renewable Power Generation*, **10**, 98–107. https://doi.org/10.1049/iet-rpg.2015.0098.

[29] Zhou, G., Bi, Q., Tian, Q., Leng, M. and Xu, G. (2022) Single Sensor Based Global Maximum Power Point Tracking Algorithm of PV System With Partial Shading Condition. *IEEE Transactions on Industrial Electronics*, **69**, 2669–2683. https://doi.org/10.1109/TIE.2021.3066920.

[30] Li, X., Zhu, Y., Wen, H., Du, Y. and Xiao, W. (2022) Reference-Voltage-Line-Aided Power Incremental Algorithm for Photovoltaic GMPPT and Partial Shading Detection. *IEEE Transactions on Sustainable Energy*, **13**, 1756–1770. https://doi.org/10.1109/TSTE.2022.3174614.

[31] Barbosa, E.J., Cavalcanti, M.C., Azevedo, G.M.S., Neto, R.C., Barbosa, E.A.O. and Bradaschia, F. (2023) Hybrid GMPPT Technique for Photovoltaic Series Based on Fractional Characteristic Curve. *IEEE Journal of Photovoltaics*, 1–8. https://doi.org/10.1109/JPHOTOV.2023.3323774.

[32] Rahman, M.M. and Islam, M. (2020) PSO and ANN Based Hybrid MPPT Algorithm for Photovoltaic Array under Partial Shading Condition. *Engineering International*, **8**, 9–24. https://doi.org/10.18034/ei.v8i1.481.

[33] Ahmad, W., Khan, Z.A., Khan, U.H., Alam, Z., Qasuria, H.T. and Mustafa, E. (2020) Neural Network Based Robust Nonlinear GMPPT Control Approach for Partially Shadow Conditions of Solar Energy System. 2020 International Conference on Emerging Trends in Smart Technologies (ICETST), IEEE, Karachi, Pakistan, 1–7. https://doi.org/10.1109/ICETST49965.2020.9080701.

[34] Ye, S.-P., Liu, Y.-H., Pai, H.-Y., Sangwongwanich, A. and Blaabjerg, F. (2024) A Novel ANN-Based GMPPT Method for PV Systems Under Complex Partial Shading Conditions. *IEEE Transactions on Sustainable Energy*, **15**, 328–338. https://doi.org/10.1109/TSTE.2023.3284866.

[35] Miyatake, M., Toriumi, F., Endo, T. and Fujii, N. (2007) A Novel Maximum Power Point Tracker Controlling Several Converters Connected to Photovoltaic Arrays with Particle Swarm Optimization Technique. 2007 European Conference on Power Electronics and Applications, 1–10. https://doi.org/10.1109/EPE.2007.4417640.

[36] Ishaque, K. and Salam, Z. (2013) A Deterministic Particle Swarm Optimization Maximum Power Point Tracker for Photovoltaic System Under Partial Shading Condition. *IEEE Transactions on Industrial Electronics*, **60**, 3195–3206. https://doi.org/10.1109/TIE.2012.2200223.
[37] Leong, J.Y., Gopal, L., Chiong, C.W.R., Juwono, F.H. and Basuki, T.A. (2023) Hybrid Gravitational Search Particle Swarm Optimization Algorithm for GMPPT under Partial Shading Conditions. *Green Technologies and Sustainability*, **1**, 100034. https://doi.org/10.1016/j.grets.2023.100034.
[38] Motamarri, R., Bhookya, N. and Chitti Babu, B. (2021) Modified Grey Wolf Optimization for Global Maximum Power Point Tracking under Partial Shading Conditions in Photovoltaic System. *International Journal of Circuit Theory and Applications*, **49**, 1884–1901. https://doi.org/10.1002/cta.3018.
[39] Farayola, A.M., Sun, Y. and Ali, A. (2022) Global Maximum Power Point Tracking and Cell Parameter Extraction in Photovoltaic Systems Using Improved Firefly Algorithm. *Energy Reports*, **8**, 162–186. https://doi.org/10.1016/j.egyr.2022.09.130.
[40] Motahhir, S., Chouder, A., Hammoumi, A.E., Benyoucef, A.S., Ghzizal, A.E., Kichou, S., Kara, K., Sanjeevikumar, P. and Silvestre, S. (2021) Optimal Energy Harvesting From a Multistrings PV Generator Based on Artificial Bee Colony Algorithm. *IEEE Systems Journal*, **15**, 4137–4144. https://doi.org/10.1109/JSYST.2020.2997744.
[41] Lodhi, E., Yang, P., Wang, L., Khan, M.A., Lodhi, Z., Javed, U. and Saleem, Q. (2021) Dragonfly Optimization-Based MPPT Algorithm for Standalone PV System under Partial Shading. 2021 IEEE International Conference on Emergency Science and Information Technology (ICESIT), 277–283. https://doi.org/10.1109/ICESIT53460.2021.9697000.
[42] Sridhar, R., Subramani, C. and Pathy, S. (2021) A Grasshopper Optimization Algorithm Aided Maximum Power Point Tracking for Partially Shaded Photovoltaic Systems. *Computers & Electrical Engineering*, **92**, 107124. https://doi.org/10.1016/j.compeleceng.2021.107124.
[43] Prasanth Ram, J. and Rajasekar, N. (2017) A Novel Flower Pollination Based Global Maximum Power Point Method for Solar Maximum Power Point Tracking. *IEEE Transactions on Power Electronics*, **32**, 8486–8499. https://doi.org/10.1109/TPEL.2016.2645449.
[44] Titri, S., Larbes, C., Toumi, K.Y. and Benatchba, K. (2017) A New MPPT Controller Based on the Ant Colony Optimization Algorithm for Photovoltaic Systems under Partial Shading Conditions. *Applied Soft Computing*, **58**, 465–479. https://doi.org/10.1016/j.asoc.2017.05.017.
[45] Pal, R.S. and Mukherjee, V. (2021) A Novel Population Based Maximum Point Tracking Algorithm to Overcome Partial Shading Issues in Solar Photovoltaic Technology. *Energy Conversion and Management*, **244**, 114470. https://doi.org/10.1016/j.enconman.2021.114470.
[46] Pervez, I., Shams, I., Mekhilef, S., Sarwar, A., Tariq, M. and Alamri, B. (2021) Most Valuable Player Algorithm Based Maximum Power Point Tracking for a Partially Shaded PV Generation System. *IEEE Transactions on Sustainable Energy*, **12**, 1876–1890. https://doi.org/10.1109/TSTE.2021.3069262.
[47] Rezk, H. and Fathy, A. (2017) Simulation of Global MPPT Based on Teaching–Learning-Based Optimization Technique for Partially Shaded PV System. *Electrical Engineering*, **99**, 847–859. https://doi.org/10.1007/s00202-016-0449-3.
[48] Lyden, S. and Haque, Md.E. (2016) A Simulated Annealing Global Maximum Power Point Tracking Approach for PV Modules Under Partial Shading Conditions. *IEEE Transactions on Power Electronics*, **31**, 4171–4181. https://doi.org/10.1109/TPEL.2015.2468592.
[49] Mirza, A.F., Mansoor, M. and Ling, Q. (2020) A Novel MPPT Technique Based on Henry Gas Solubility Optimization. *Energy Conversion and Management*, **225**, 113409. https://doi.org/10.1016/j.enconman.2020.113409.
[50] Liu, L., Zhang, R. and Chen, Q. (2022) High-Performance Global Peak Tracking Technique for PV Arrays Subject to Rapidly Changing PSC. *Chaos, Solitons & Fractals*, **160**, 112214. https://doi.org/10.1016/j.chaos.2022.112214.
[51] Motamarri, R. and Nagu, B. (2020) GMPPT by Using PSO Based on Lévy Flight for Photovoltaic System under Partial Shading Conditions. *IET Renewable Power Generation*, **14**, 1143–1155. https://doi.org/10.1049/iet-rpg.2019.0959.
[52] Mathi, D.K. and Chinthamalla, R. (2020) A Hybrid Global Maximum Power Point Tracking Method Based on Butterfly Particle Swarm Optimization and Perturb and Observe Algorithms for a Photovoltaic System under Partially Shaded Conditions. *International Transactions on Electrical Energy Systems*, **30**, e12543. https://doi.org/10.1002/2050-7038.12543.

[53] Pilakkat, D. and Kanthalakshmi, S. (2019) An Improved P&O Algorithm Integrated with Artificial Bee Colony for Photovoltaic Systems under Partial Shading Conditions. *Solar Energy*, **178**, 37–47. https://doi.org/10.1016/j.solener.2018.12.008.

[54] Liu, Y.-H., Huang, S.-C., Huang, J.-W. and Liang, W.-C. (2012) A Particle Swarm Optimization-Based Maximum Power Point Tracking Algorithm for PV Systems Operating Under Partially Shaded Conditions. *IEEE Transactions on Energy Conversion*, **27**, 1027–1035. https://doi.org/10.1109/TEC.2012.2219533.

[55] Lian, K.L., Jhang, J.H. and Tian, I.S. (2014) A Maximum Power Point Tracking Method Based on Perturb-and-Observe Combined With Particle Swarm Optimization. *IEEE Journal of Photovoltaics*, **4**, 626–633. https://doi.org/10.1109/JPHOTOV.2013.2297513.

[56] Villalva, M.G., Gazoli, J.R. and Filho, E.R. (2009) Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays. *IEEE Transactions on Power Electronics*, **24**, 1198–1208. https://doi.org/10.1109/TPEL.2009.2013862.

[57] Nguyen, N.B. (2014) Modeling and Simulation of Photovoltaic Generator. other, Laboratory on Plasma and Conversion of Energy (LAPLACE), UMR 5213, 2 rue Charles Camichel, BP 7122, 31071 Toulouse Cedex 7, 74. https://dumas.ccsd.cnrs.fr/dumas-01220257.

[58] Miyatake, M., Veerachary, M., Toriumi, F., Fujii, N. and Ko, H. (2011) Maximum Power Point Tracking of Multiple Photovoltaic Arrays: A PSO Approach. *IEEE Transactions on Aerospace and Electronic Systems*, **47**, 367–380. https://doi.org/10.1109/TAES.2011.5705681.

[59] Mohanty, S., Subudhi, B. and Ray, P.K. (2017) A Grey Wolf-Assisted Perturb & Observe MPPT Algorithm for a PV System. *IEEE Transactions on Energy Conversion*, **32**, 340–347. https://doi.org/10.1109/TEC.2016.2633722.

[60] Nguyen, X.H. and Nguyen, M.P. (2015) Mathematical Modeling of Photovoltaic Cell/Module/Arrays with Tags in Matlab/Simulink. *Environmental Systems Research*, **4**, 24. https://doi.org/10.1186/s40068-015-0047-9.

[61] Gragger, J.V., Haumer, A. and Einhorn, M. (2010) Averaged Model of a Buck Converter for Efficiency Analysis, **18**.