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

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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 an 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. 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].

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.

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.

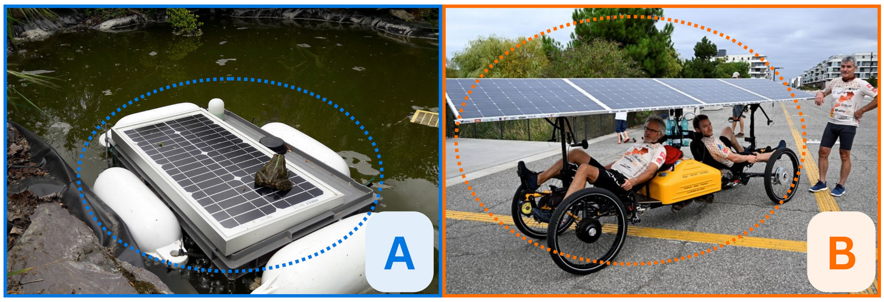

Figure 1. Examples of autonomous PV systems. Section A depicts an autonomous PV system to power ecological sentinels, section B depicts a solar assisted bicycle.

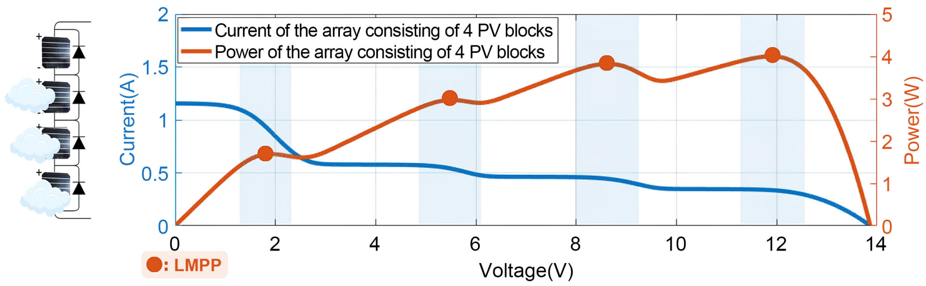

Figure 2. Power-over-voltage characteristics of a partial shading PV string consisting of 4 PV modules with 4 bypass diodes. Highlighted in blue are the regions where the potential LMPPs could be found as well as the GMPP of the PV string.

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 implement, 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**.

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.

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 W·m^{-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 298.15 K, I_0 the reverse saturation current of the diode in the PV module, q the electron

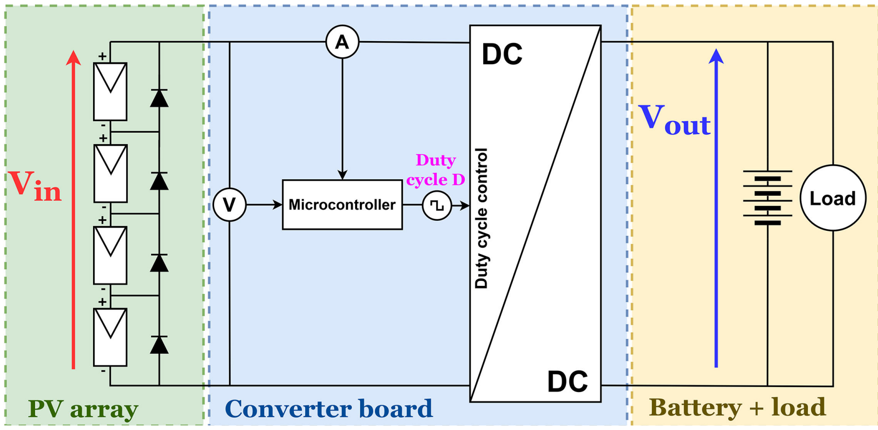

Figure 3. Generalized architecture of the autonomous PV system we used in this research.

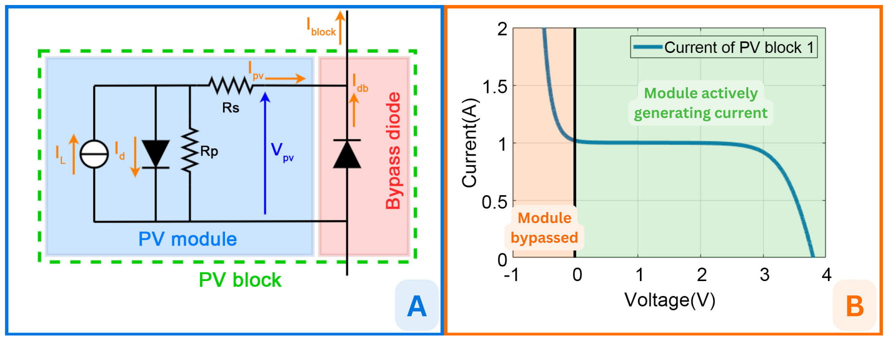

Figure 4. Electrical model of a PV block (A) and current-over-voltage characteristics of a PV block (B).

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 coefficient 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.

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

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

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

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

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}	$V \cdot K^{-1}$
K_i	3×10^{-3}	$A \cdot K^{-1}$
R_p	1200	Ω
R_s	0.2	Ω
q	1.6×10^{-19}	As
K	1.38×10^{-23}	$m^2\ kg \cdot s^{-2} \cdot K^{-1}$
A	9.5	Unitless
V_f	0.26	V
R_{don}	0.18	Ω

$$I_{db} = \begin{cases} 0 & \text{if } -V_{pv} < V_f \\ \dfrac{-V_{pv} - V_f}{R_{don}} & \text{if } -V_{pv} \geq V_f \end{cases} \tag{5}$$

$$I_{block} = I_{pv} + I_{db} \tag{6}$$

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.

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

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

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

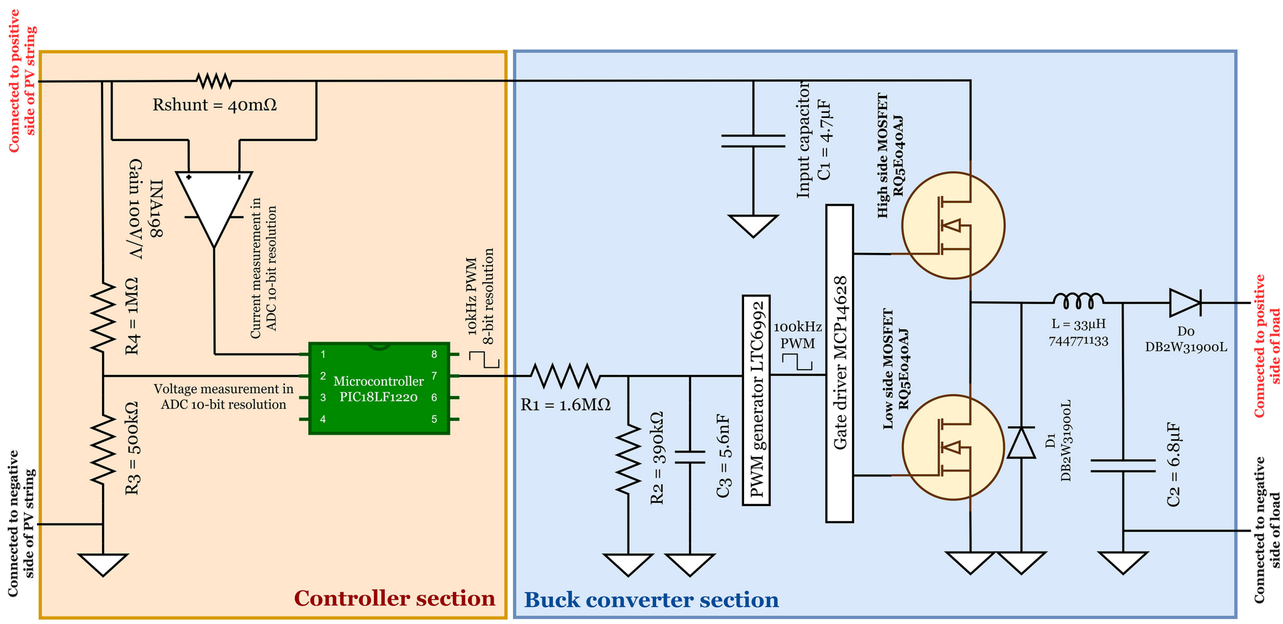

Figure 5. Simplified schema of the converter board used in this research consisting of a controller section and a buck converter section.

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

For example, if implemented on the PV string with 4 PV modules and 4 bypass diodes, these voltage targets would be { $v_{target}^{1} = 2.2\text{ V}$; $v_{target}^{2} = 5.5\text{ V}$; $v_{target}^{3} = 8.7\text{ V}$; $v_{target}^{4} = 12\text{ V}$ }. 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

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

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 $cter_{limit}$.

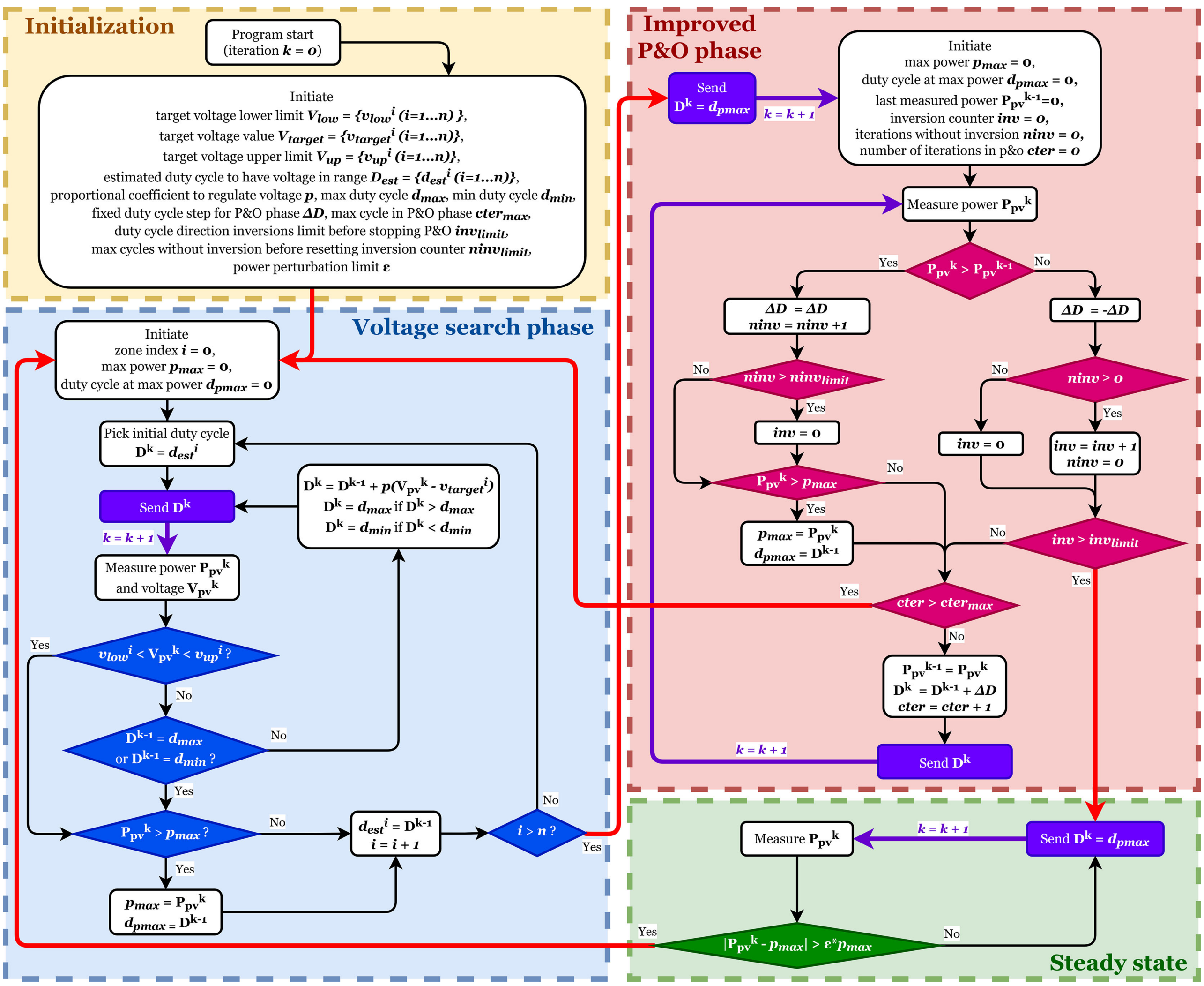

Figure 6. Flowchart of the proposed Fast GMPPT method.

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

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

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.

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 ±0.3 V (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: $v_{target}^2 = 5.5\text{ V}$; $v_{target}^3 = 8.7\text{ V}$; $v_{target}^3 = 8.7\text{ V}$ } are accessible. Therefore, each voltage target could be 7 different values between $v_{target}^i - 0.3\text{ V}$ to $v_{target}^i + 0.3\text{ V}$ at a step of 0.1 V. Given that there are 3 points targets total, there 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 boxplot 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.

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 3.7 V to simulate the relatively stable voltage of a Li-ion battery.

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.

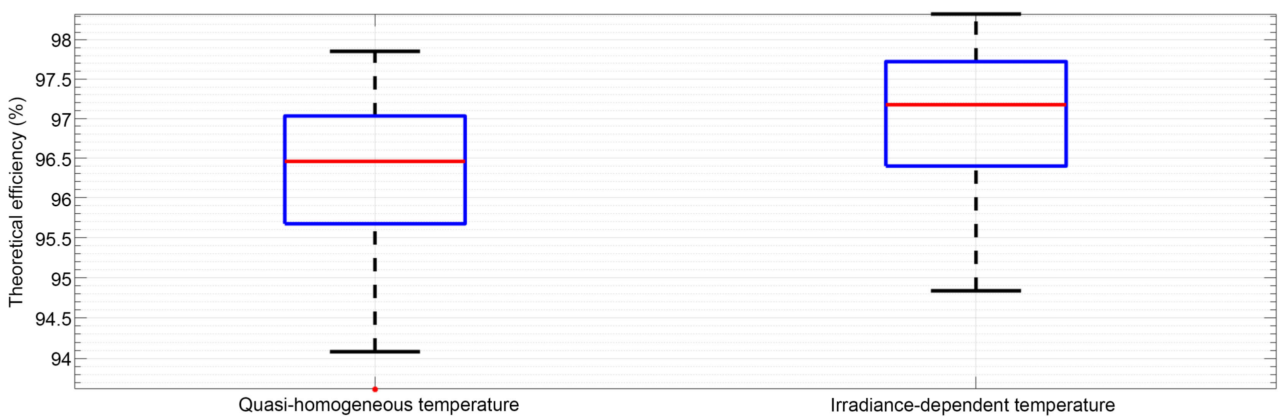

Figure 7. Theoretical convergence rate of the proposed fast GMPPT method when we assume that all irradiance conditions are equally probable and assume that the temperatures of the module are either quasi-homogeneous or irradiance-dependent.

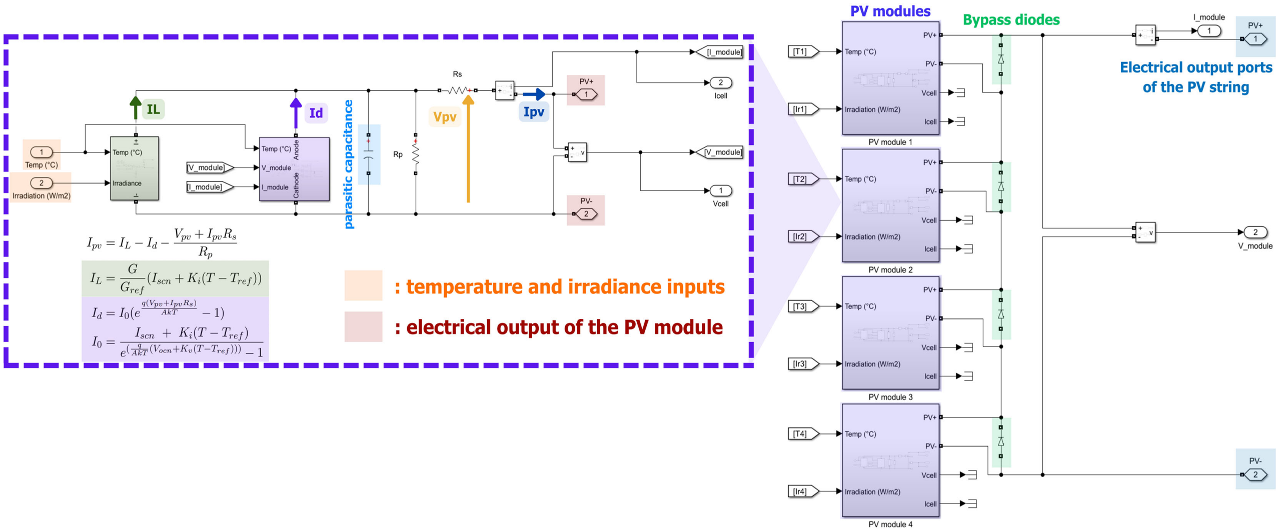

Figure 8. Simulink model of the PV string of 4 PV modules and 4 bypass diodes.

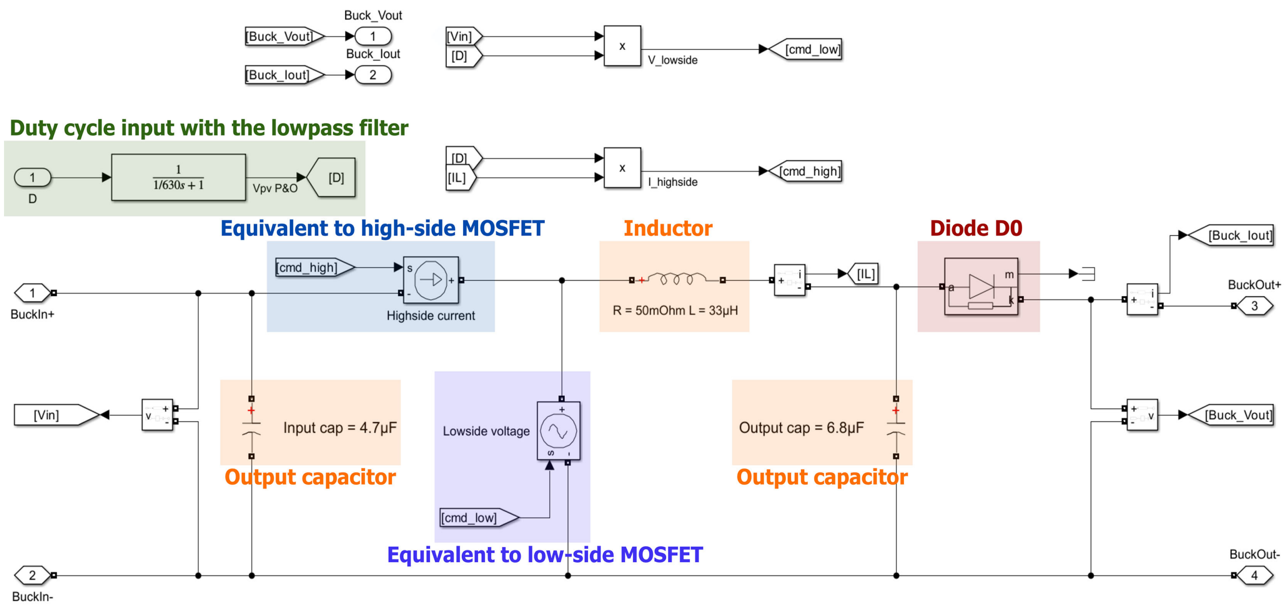

Figure 9. Averaged model of the synchronous buck converter in Simulink.

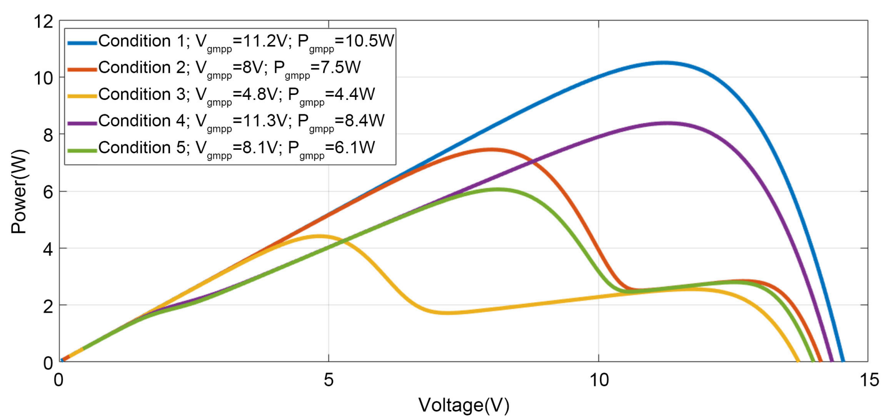

Figure 10. P-V characteristics of the PV string under 5 different PSC conditions.

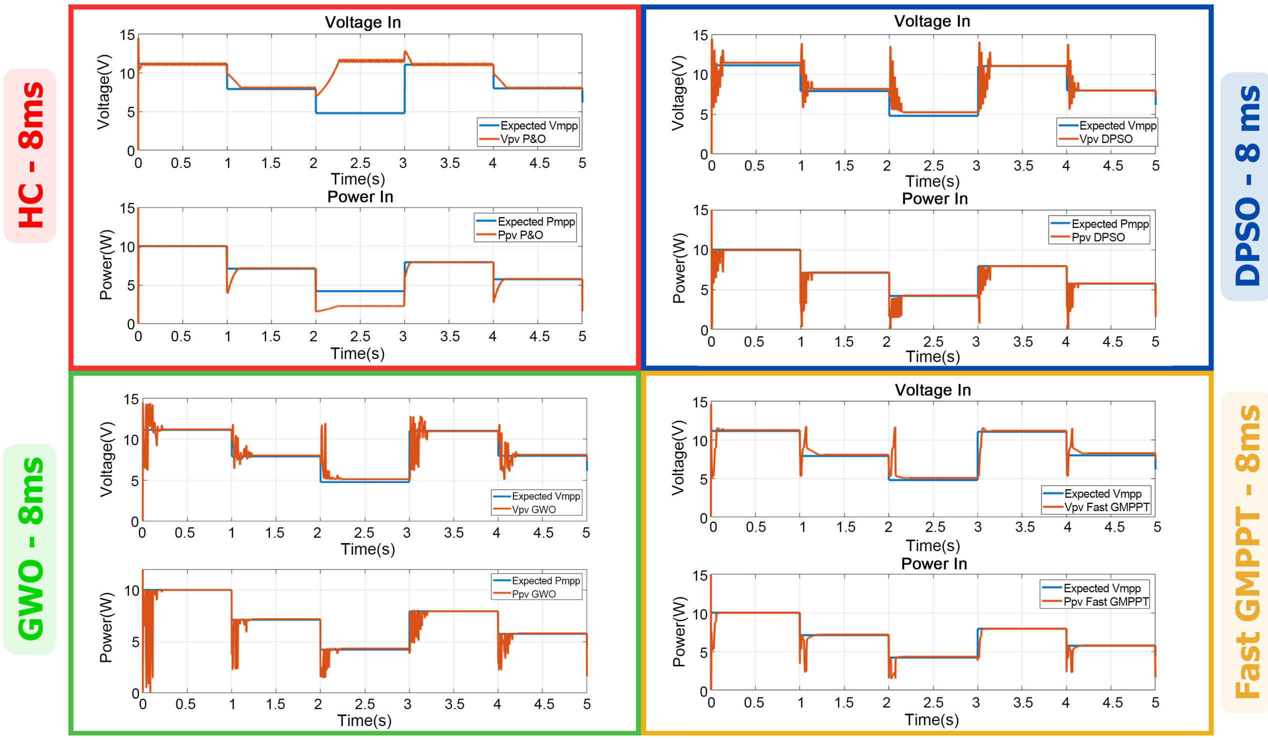

Figure 11. Step irradiance results of the 4 tested algorithms. Orange is the measured voltage and power, while blue is the estimated voltage and power at GMPP.

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.

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 (64 ms to 272 ms) 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 (96 ms to 144 ms), 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 observed 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 (192 ms). 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 (160 ms to 256 ms). 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.

5.3. Experimental Result

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 $\left(x_{shade}, y_{shade}\right)$ 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.

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.

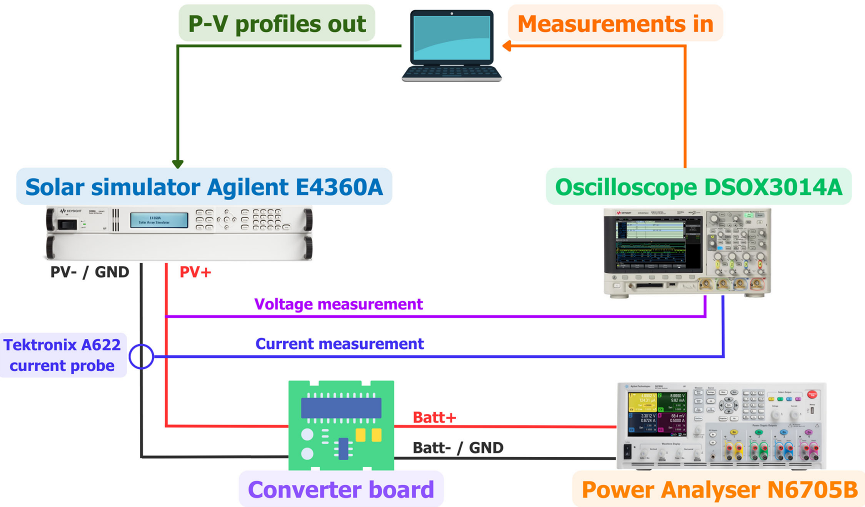

Figure 12. Detailed description of the experimental setup to consistently recreate VPSCs.

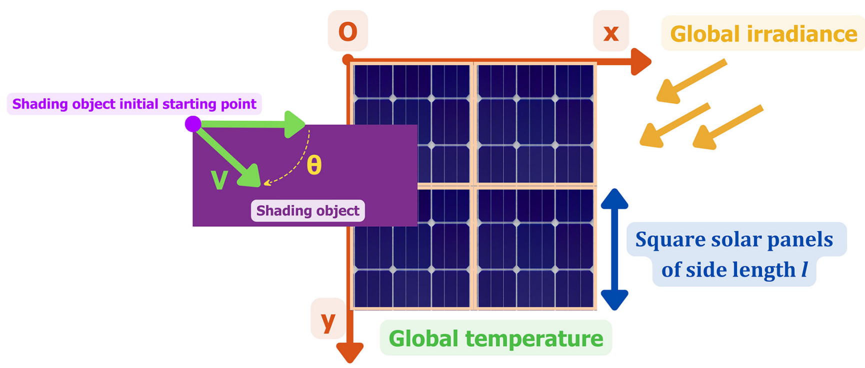

Figure 13. An illustration of the method to simulate the evolution of the P-V of the PV string under VPSC.

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%

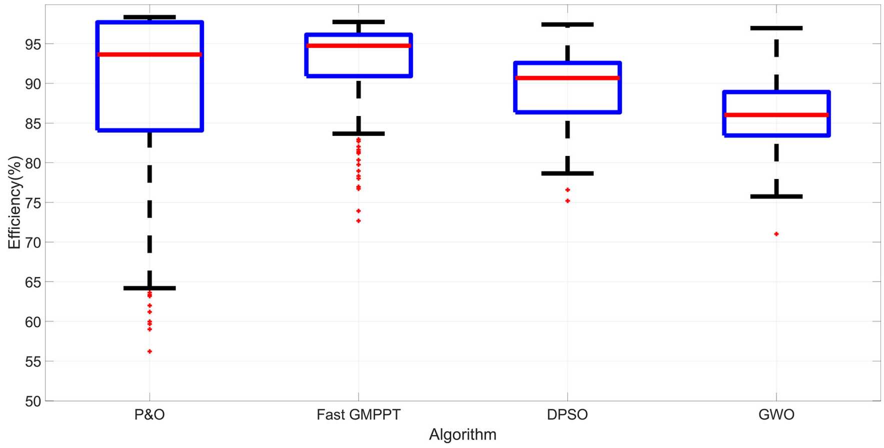

Figure 14. Boxplots showing the energy efficiencies of each algorithm when tested using the set of 288 VPSC.

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 fewer 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 evolve 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.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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