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A novel simple GMPPT method based on probability distribution of global maximum power point under partial shading conditions

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Abstract— A photovoltaic (PV) array with multiple modules in series with bypass diodes may present multiple power peaks under uneven shading and requires a control schema to regulate the system to global maximum power point (GMPP). While a lot of methods have been proposed in the literature, they are usually quite complex and does not fully take advantage of available characteristics of the PV array. This work will highlight a method to plot the probability distribution of MPP voltage under various shading conditions and temperatures for an array of 4 custom made PV modules using MATLAB. From this distribution, we propose a fast GMPPT algorithm that can reach true MPP more than 90% of the time for both an assumed equal probability distribution as well as for a real-world irradiation measurement. An experimental test to compare our method against several others like deterministic particle swarm optimization (DPSO), grey wolf optimization (GWO) and perturb and observe (P&O) is presented.

Keywords—Partial shading, Lambert W function, probability distribution, MATLAB/Simulink, experimental results, global maximum power point tracking (MPPT)

I. INTRODUCTION

Harvesting energy using photovoltaics is usually the simplest and sometimes only viable source of energy for systems away from the grid (i.e., bioresearch sensors in the wild, portable solar power banks). Unlike PV power plant, the harvestable PV area is low and irradiation levels may not be very stable. Therefore, the power conditioning algorithm must be resilient against varying irradiation and partial shading, yet simple enough to be put on low power microcontrollers (μC) like PIC18 8-bit μC family from Microchip.

To increase the power output per converter, PV modules are usually connected in series which has a slight advantage over parallel installation which requires an anti-reverse diode which may incur extra power loss. But, when one module is shaded in the series, the entire array's current output is limited by the shaded module which incur severe power loss [1]. Bypass diodes are therefore installed in parallel with PV modules to provide a path for current to flow around them in case of shading and alleviate the hotspot problems due to mismatched irradiation, but this leads to multiple power peaks which complicates the control scheme [2] (Fig. 1).

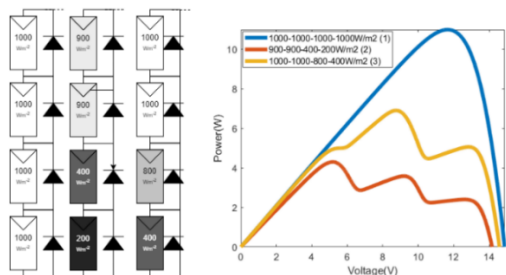


Fig. 1. Power output of 4 PV modules in series with bypass diodes under different irradiation conditions

Seeing that under even irradiation the PV array still exhibit a maximum power point, there are great interest on optimizing PV systems in the literature which can be classified into 2 categories: single peak capable and multiple peaks capable. For the former category, the most notable is Perturb and Observer (P&O) which is the simplest schema out there that basically involves slightly disturbing the operating point, measure the power obtained and move toward one that yield better power [3]. Due to its proven efficacy, it received a lot of optimization over the years like reduced convergence time [4], reduced oscillations around MPP [5] and reduced loss of tracking on fast varying irradiation [6]. Other methods in the single peak capable class are Incremental Conduction [7], β -parameter method [8], fractional open circuit voltage (Voc) [9], MPP locus characterization [10] and temperature based approximation of MPP [11]. In general, these algorithms are easy to implement, efficient under stable weather condition, but they may not give optimal power acquisition under bad weather conditions. That is why there exist the multiple peak capable methods designed to tackle the complex power-voltage profile caused by bypass diodes under uneven irradiation. The first type of algorithms is those based on optimization algorithms like genetic algorithm [12], differential evolution [13], particle swarm optimization (PSO) [14], deterministic PSO (DPSO) [15], artificial bee colony (ABC) [16], grasshopper optimization [17], grey-wolf optimization (GWO) [18], [19], flower pollination algorithm (FPA) [20], student psychology based optimization [21], dragonfly algorithm [22], ant colony optimization [23], Henry gas solubility optimization (HGO) [24] and cuckoo search algorithm [25]. These approaches can identify GMPP albeit not a sure guarantee due to their stochastic nature, and they also suffer from several drawbacks like implementation complexity (e.g., heavy floating points operations, exponentials, logarithms) and heavy power swings during the search phase. There are also several works that seek to mitigate P&O's inability to find true MPP in case of multiple peaks by extending the search zone [26] or by adding an optimization based algorithm phase before the P&O [16], [27], [28], which take well advantage of P&O's reliability but the optimization phase still has the same drawbacks. Another class of methods are fuzzy logic controllers like [29]–[31] which provide extra flexibility while being reasonably lightweight but requires a complex tuning phase. Finally, we have the powerful yet resource intensive neural network based controllers [32]–[36] that are regrettably only tested for single MPP cases and not for complex partial shading conditions.

Considering the status of the literature and the use case, we would like to propose a novel simple and lightweight method based on P&O that can quickly identify the GMPP. For this, we have developed an efficient method to visualize the distribution of GMPP on the voltage range using MATLAB.

Even though our work was based on a system of 4 PV modules in series with 4 bypass diodes, it is extendable in a reasonable degree to a higher number of modules with more bypass diodes. Using the distribution information, we will be proposing a fast sweep that coupled with a P&O phase can most of the time identify the GMPP, as well as proposing a way to evaluate this probability. A comparison with several algorithms will also be proposed in this paper, notably conventional P&O, DPSO and GWO, both via a Simulink simulation and an experimental setup using the solar simulator Keysight E4360 and a buck converter.

II. MODELING THE PV MODULE

Our PV modules are based on a single SunPower C60 cell cut into 6 parts and then connected in series without any bypass (Fig. 2). To model our module, we used a variation of the PV cell model as shown in Fig. 3 and from the work of [37], we arrive at the mathematical equations describing system (1).

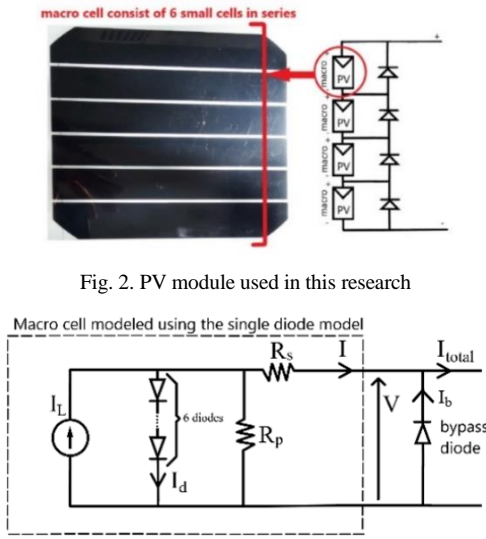


Fig. 2. PV module used in this research

Fig. 3. PV module with its bypass diode model

$$I = I_L - I_d - \frac{V + IR_s}{R_p} \quad (1)$$

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

$$I_d = I_0 (e^{\frac{q}{AKT}(V + IR_s)} - 1)$$

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

Since we need to quickly simulate a multitude of weather conditions of our system, it is necessary to solve (1) to have an acceptable simulation time using MATLAB. Having an exponential and polynomial term, Lambert function is the go-to option and allows us to solve current for a given voltage (V), temperature (T) and irradiation (G) [38]. The final expression describing the current output of the PV module and its bypass diode can be found in (2). We used the simplified Shockley diode equation in this model.

$$I_{total} = X - \frac{\text{Lambert}(KYR_s e^{KXR_s})}{KR_s} + I_r e^{\frac{-qV}{NkT}} = f(V, G, T) \quad (2)$$

$$\text{with } X = \frac{I_L + I_0 - \frac{V}{R_p}}{(1 + \frac{R_s}{R_p})}, Y = \frac{I_0 e^{KV}}{(1 + \frac{R_s}{R_p})} \text{ and } K = \frac{q}{AKT}$$

Since each of these PV module + bypass diode blocks are connected in series, their combined output voltage corresponds to each module's voltage operating under a given current. However, (2) only gives us $I_{total} = f(V, G, T)$ and we need $V = g(I_{total}, G, T)$ (3) to deduce the array's voltage output. The reason we could not work directly with the latter expression is due to double precision numerical limit being exceeded during intermediary calculations. Therefore, we chose to first use (2) and then perform an interpolation using MATLAB's built-in `interp1()` to find relationship (3). By storing the pre-calculated table of V-I pairs for all G and T, quick additions can be made to generate the voltage output profile of the array under any conditions imaginable (Fig. 4). Since our PV modules were not standard made, we had to extract their parameters from characterization and SunPower C60 datasheet. Bypass diodes parameters are also extracted from characterization in the lab. All necessary parameters for this research can be found in TABLE I.

TABLE I. PARAMETER DESCRIPTION AND NUMERICAL VALUES OF THE PV MODULE AND BYPASS DIODES USED

Name	Description	Value	Unit
G	PV module irradiation	Variable	Wm ⁻²
G _{ref}	Standard irradiation	1000	Wm ⁻²
T	PV module temperature	Variable	K
T _{ref}	Reference temperature	298.15	K
V _{ocn}	Open circuit voltage	3.8	V
I _{scn}	Short circuit current	1	A
R _s	Equivalent serial resistance of PV module	0.2	Ω
R _p	Equivalent parallel resistance of PV module	1200	Ω
k _v	Voltage temperature coefficient	-0.0026	VK ⁻¹
k _i	Current temperature coefficient	0.0023	AK ⁻¹
A	PV module equivalent diode ideality factor	9.5	
q	Electron charge	1.6x10 ⁻¹⁹	C
k	Boltzmann constant	1.38x10 ⁻²³	JK ⁻¹
I _r	Bypass diode reverse saturation current	0.017	A
N	Bypass diode ideality factor	4.23	

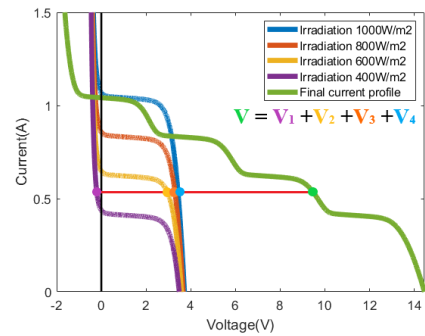


Fig. 4. Illustration of the method to construct voltage output of the array under any condition

III. GMPP DISTRIBUTION OF THE PV ARRAY

Using the previously described method, we vary the irradiation of each module from 0 to 1000Wm⁻² in steps of 10Wm⁻². For the array's temperature, we assume that they are homogenous, or each module's temperature is at least close enough to one another to be considered homogenous. We plot the distribution of voltage at GMPP for 5 different temperatures and obtain the following result as observed

in Fig. 5. A total of around 22 million operating conditions were simulated in this result. We also assumed that each irradiation and temperature condition are equally probable, which does not perfectly reflect reality. However, it still confirms that GMPP can be found in clear clusters on the voltage range and therefore a limited search space could guarantee a high probability of finding true MPP. While this is not the first work to consider the probability aspect of GMPP position [39], this is the first time such a wide range of conditions were checked to visualize the GMPP zones with such clear delineation. Furthermore, this also confirmed the zoning theories that were used in works like [6], [26] and may also be used in tandem with them to improve implementation.

To increase the predicting capabilities of our program, we also performed a bicycle test ride to estimate the irradiation that each PV module should receive during operation. The bicycle test ride is great for this purpose because of the randomness nature of shading patterns. Measurements were made using 4 SP Lite2 pyranometers strapped on a wooden board on the back of our bicycle, spaced out properly to represent where the 4 PV modules should be. The test ride was made on 21/06/2021 in Toulouse, France and lasted around 1h. The sampling frequency used was 5kHz per pyranometer and later filtering made the effective sampling frequency 100Hz. We had to filtered out power peaks below 1W because realistically, our converter and its on-board measurement will have difficulty regulating such a small amount of power. The resulting distribution graph can be found in Fig. 6.

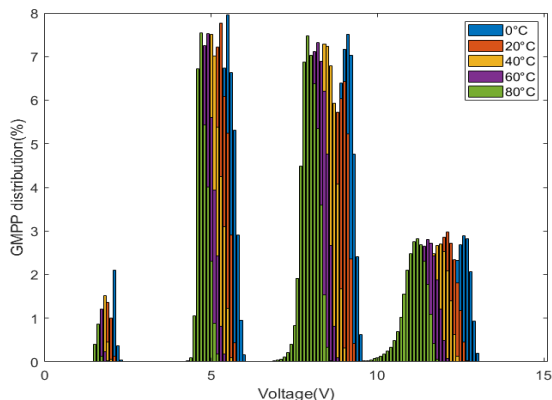


Fig. 5. GMPP probability distribution of 4 PV modules in series with 4 bypass diodes (equal probability)

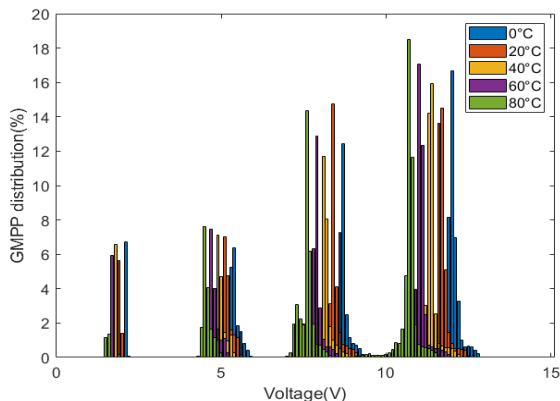


Fig. 6. GMPP probability distribution of 4 PV modules in series with 4 bypass diodes (real test ride)

IV. PROPOSED IMPROVED P&O FAST GMPPT METHOD

From the distribution in Fig. 5, randomly searching the voltage range is clearly inefficient and we should be limiting

our search space to only a few points. Therefore, we propose a fast heuristic where we only measure the power obtained in 3 specific voltage values and just choose the operating point yielding highest power. Since only have direct control over the duty cycle and not input voltage, an extra regulation phase to find the 3 voltage levels is needed. By saving the duty cycles that allowed us to reach the 3 correct voltage values, we can reuse them for a later search phase which should drastically reduce the time necessary to find them again. After having measured the power at these 3 voltage values and chosen the operating point yielding max power, we then apply P&O to help converter reach the GMPP given that it has no problem handling local peaks with zoning [4]. For the algorithm to properly start a search phase, it is necessary to have a steady state phase which can be implemented via an oscillation detection mechanism like what was proposed in [5]. After oscillation is detected, we can safely assume that P&O has found the GMPP, and the converter can enter steady state. Another known problem of P&O is the tracking loss [6] which is handled via a time limit for the P&O to converge. Exceeding this limit, the converter will revert to the sweep phase to try and find a new starting point for P&O.

To evaluate the success rate of this method, we added a section checking whether our proposed algorithm can theoretically reach GMPP under each condition during distribution sweep. The criteria for success will be whether the power gradient between the chosen point and true MPP is constantly increasing or decreasing, as illustrated in Fig. 7. Next, we need to remove conditions where our buck converter cannot properly harvest, notably where power at GMPP is below 1W and where voltage at GMPP is below the battery voltage (around 4V). From this result, supposing equal probability and excluding invalid conditions, we achieved a 96.43% success rate. As for the theoretical capability of our algorithm on the experimental test ride, it manages 99.4% success rate. However, these numbers still assumes that the algorithm has the necessary time to converge, meaning that after the search phase is launched, the power output condition is stable so that the algorithm can enter steady state.

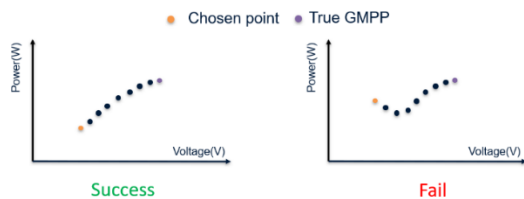


Fig. 7. Illustration of success criteria to evaluate the proposed algorithm

V. TEST RESULTS

To verify the algorithms capabilities, we performed an experimental test using a buck converter controlled by a PIC18LF1320 and compare our GMPPT (called Fast GMPPT in later sections) with regular P&O, DPSO and GWO. The latter two were chosen for their relatively simple implementation suitable for the PIC18. The most complex operation would be the intensive array manipulation in DPSO [15] and random number generation as required by GWO [19], which is already significantly less complex than other algorithms requirements like floating point divisions in ABC [16], trigonometric functions in FPA [20] or logarithms/exponentials in HGO [24]. Furthermore, the respective papers for DPSO and GWO have demonstrated experimental potentials, albeit on different hardware setup, which is not the case with a lot of literatures referenced in this

work that only provided limited testing with simulations (e.g. [16], [21], [22], [24], [25], etc.). All algorithms will be tested at the same sampling time of 8ms to make sure that the results represent a fair comparison. The solar input is generated by the Agilent E4360A Solar Simulator and the output is a battery simulated using a pair of Keithley 2440 Source Meter, one sinking current and one forcing a battery voltage of 4V. Measurements were done using Keysight DSOX3014T oscilloscope with one channel measuring the input voltage and another channel measuring the input current with a Hall effect sensor. All instruments were synchronized and piloted using a MATLAB interface.

The first test result is done using the 3 power profiles shown in Fig. 1, with each one being sent during 1s in order from (1) to (3). The results for this test can be found in Fig. 9 and a result summary can be found in

TABLE II. The orange signal is the experimental measurements, and the blue signal is the theoretical voltage max or power max that the algorithm should find. We conclude that our method slightly trails behind DPSO in convergence time for all 3 conditions, but with much less power variations during the search phase, beats out P&O in condition (1) and (2) on convergence time and power output respectively and consistently performed better than GWO in convergence time in all 3 test conditions. As for power output at steady state, only P&O has a GMPP tracking failure at condition (2), which can be easily explained when we look at that condition's power output.

Even though the above tests are sometimes presented as the only setups to showcase an algorithm's performance (e.g. [13], [17]–[22], [24], [25], etc.), it is usually insufficient because it does not represent a realistic condition that the converter may have to handle. Therefore, we propose a test condition as shown in Fig. 8 where a shading blob such as a small branch passes by and covers 2 out of the 4 PV modules. By using the Agilent E4360A Solar Simulator to ensure that the shading pattern over time is consistent, we managed to produce the results as shown in Fig. 10. Again, the orange signal is the experimental measurements, and the blue signal being the theoretical estimations for MPP voltage and power. For this test, DPSO managed to stick very close to the theoretical MPP, but it also generates a lot of power disturbances during the search phase. The result for P&O showcases its ineffectiveness against partial shading conditions, particularly ones that change over time. Even though this is already discussed consistently in the literature (e.g.), For GWO, its stochastic nature shows some weakness in these slower varying situations where it presents quite an inconsistent response where it sometimes can hit the GMPP and others it cannot. Our algorithm performs well under this situation, sticking to the MPP most of the time. However, a common weakness of Fast GMPPT, DPSO and GWO can be found at around 3s and 4s where we can see that the max power is increasing and the voltage at MPP has changed but none of the three manages to respond in time. This is

explained by the nature of the shading situation: when both G3 and G4 are shaded, we are effectively harvesting the MPP of G1 and G2 under stable irradiation (Fig. 8). Supposing that loss to bypass diode is negligible comparing to array's output, when the shading is gone on G3 and G4, the same operating point that the converter is operating at does not see any significant power variation. This problem was not discussed in the original papers of DPSO [15] nor GWO [18], as well as many others because most proposed the observation of the power variation during steady state and starting GMPPT only when this variation exceeds a certain limit (e.g. [12], [13], [20]–[22], [24], etc.). However, this only works consistently when we started from an evenly irradiated array. So far, we have not yet arrived at an elegant solution to this problem, and it will be the subject of on-going research.

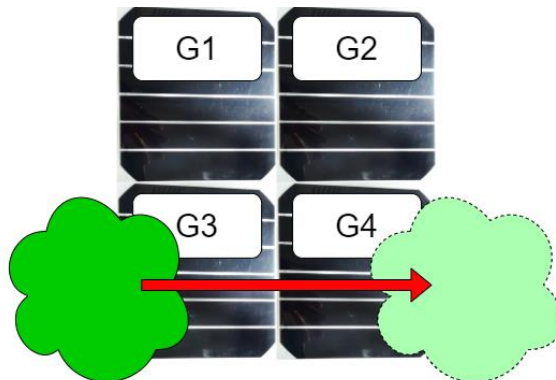


Fig. 8. A more realistic test case where 2 PV modules are covered by something like a branch over time

VI. CONCLUSION

This paper presents a novel MPPT based on the distribution of MPP voltage in wide array of temperature and irradiation patterns. Even though the result was done on an example of only 4 PV modules, the MATLAB program was optimized enough to ensure that the time needed to plot the distribution of up to 20 PV modules in series stay within a reasonable limit (around 24h). It also allows us to evaluate that the newly proposed method can reach the MPP more than 90% of the time, under both equal probability assumption as well as on a real-world distribution. Of course, more extensive real-world distribution measurements are needed because the test was done in a limited time window (around 1h) and using pyranometers is not the best way to estimate the output of the PV module. From Fig. 2, we see that a shadow of around 50% that covers evenly all 6 smaller cells should still means that the current output of the module is around 50%, but the output would be near zero if it covers 3 out of the 6 cells. Finally, an experimental test result for 2 test setup is presented and shows that our algorithm is competitive with other compared methods while being significantly less resource intensive. The problem of detecting changing shading patterns when operating under an already partially shaded array seen in Fig. 10 is still a subject of on-going investigation and refinements.

TABLE II. TEST RESULT RECAP OF 4 ALGORITHMS (DPSO, P&O, GWO, FAST GMPPT) UNDER 3 DIFFERENT POWER PROFILES

Algorithm name	Convergence time (ms) (1)	Power at steady state (W) (1)	Convergence time (ms) (2)	Power at steady state (W) (2)	Convergence time (ms) (3)	Power at steady state (W) (3)
DPSO	165	10.6	145	3.8	138	6.4
P&O	199	10.6	173	3.2	114	6.4
GWO	311	10.6	317	3.8	316	6.4
Fast GMPPT	167	10.6	178	3.8	153	6.4

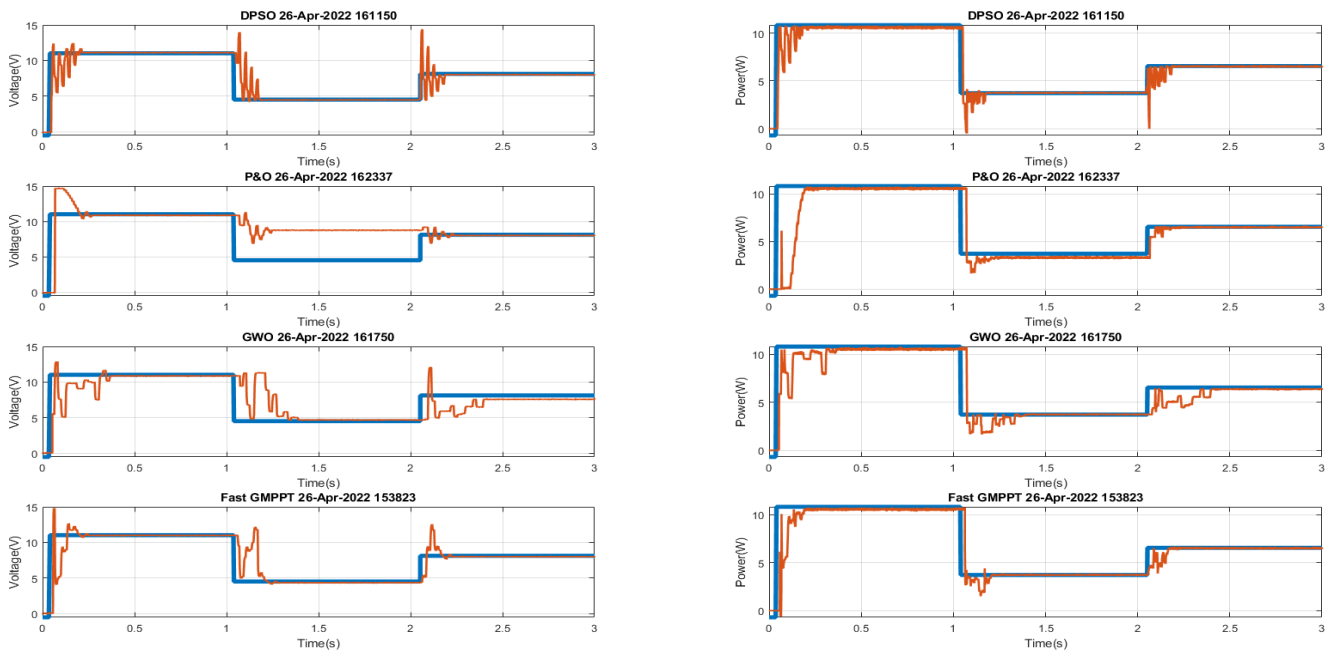


Fig. 9. Comparative test results of 4 algorithms (DPSO, P&O, GWO, Fast GMPPT) under 3 different power profiles

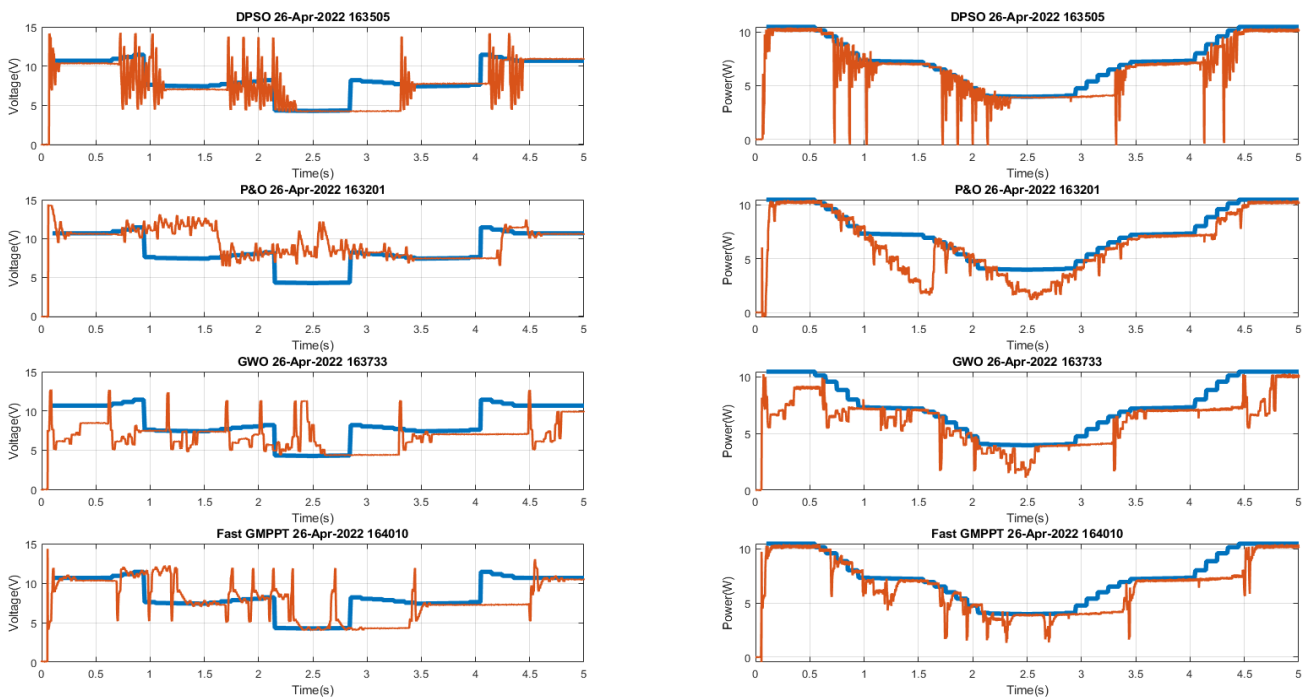


Fig. 10. Comparative test results of 4 algorithms (DPSO, P&O, GWO, Fast GMPPT) for the test condition shown in Fig. 8.

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