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Hybrid photovoltaic maximum power point tracking of Seagull optimizer and modified perturb and observe for complex partial shading

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ABSTRACT

Due to natural randomness, partial shading conditions (PSCs) to photovoltaic (PV) power generation significantly drop the power generation. Metaheuristic based maximum power point tracking (MPPT) can handle PSCs by searching PV panels' global maximum power point (GMPP). However, trapped at local maxima, sluggishness, continuous power oscillations around GMPP and inaccuracy are the main disadvantages of metaheuristic algorithm. Therefore, the development of algorithm under complex PSCs has been continuously attracting many researchers to yield more satisfying results. In this paper, several algorithms including conventional and metaheuristic are selected for candidate, such as perturb and observe (P&O), firefly (FF), differential evolution (DE), grey wolf optimizer (GWO) and Seagull optimizer (SO). From the preliminary study, SO has shown best performance among other candidates. Then, SO is improved for rapid global optimizer. Modified variable step sizes perturb and observe (MVSPO) is applied to enhance the accuracy tracking of SO. To evaluate the performances, high complexity multipeak partial shading is used to test the algorithms. Statistical results are also provided to analyze the trend of performances. The proposed method performances are shown better fast-tracking time and settling time, high accuracy, higher energy harvesting and low steady-state oscillations than other candidates.

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1. INTRODUCTION

Among the renewable sources, solar power is the most attractive one since solar energy is available anywhere in the world and it is pollution-free. Furthermore, the fast technology development on solar panel also reduced the prices of photovoltaic (PV) panel and made it accepted world-wide. The solar PV energy output is dependent much on the amount of solar irradiance. Since solar irradiance is fluctuating, it is important to operate PV array at maximum power point (MPP) to maximize energy harvesting. Maximum power point tracker is a system designed to operate PV at MPP. Maximum power point tracking (MPPT) consists of power electronics converter and optimizer algorithm controller. To increase energy harvesting, MPPT should reach MPP as fast as possible. Uniform irradiance generates PV characteristics of single MPP. Contrarily under partial shading conditions (PSCs) generate multipeak of local maximum power point

(LMPP) and GMPP [1]. Furthermore, under complex PSCs, mostly of MPPT techniques failed to work effectively.

MPPT techniques can be classified into [2] conventional, intelligent, and swarm-based optimizer. Conventional techniques include perturb and observe (P&O), incremental resistance/conductance, and parasitic capacitance. P&O MPPT have the main advantage of their simplicity. According to its name, P&O technique works based on perturbation. The perturbation direction is correct if higher power is generated, vice versa. This technique works well to overcome irradiance change. However, the main disadvantage of this technique is producing power oscillations around MPP. Variable step size can be used to avoid the oscillations but tracking time will increase. Some researchers have proposed locking mechanism to eliminate the oscillations [3]. However, considering that locking mechanism will stop the tracking at designated condition, it may reduce accuracy of targeted global maximum power point (GMPP). Other researchers have proposed variable step sizes algorithms, which called as variable step sizes P&O (VSPO) [4]. This technique works in high-speed tracking and accurately reaches maximum point for uniform irradiance. Unfortunately, these techniques cannot handle tracking to find GMPP under PSCs. An adaptive P&O MPPT has been proposed to detect rapidly the GMPP under PSCs. The main idea is to select the search area by developing clusters of potential GMPP locations. The magnitudes of each cluster are calculated to estimate the highest peak. Finally, P&O will start works from the chosen area to reach GMPP [5]. The tracking speed can be improved effectively by this technique, but it can be trapped by LMPP under complex PSCs [6].

Some researchers have proposed intelligence based MPPT techniques to handle the drawbacks of conventional method. The techniques used are artificial intelligence (AI) [7], fuzzy logic control (FLC) [8], [9], machine learning (ML) [10], and deep learning [11]. Artificial neural network (ANN) works based on its ability to learn from data set input. Therefore, to perform at its best, massive dataset is required. Fuzzy logic control performs fast tracking and low fluctuations. But fuzzy logic has disadvantages of uncertain rule to determine fuzzy membership and time consuming. Machine and deep learning can provide optimal step size considering irradiance level. However, they need large data and excessive training. Although this group of techniques can avoid LMPP and finding GMPP, they generally required complex process and time-consuming due to massive dataset to be used in the training.

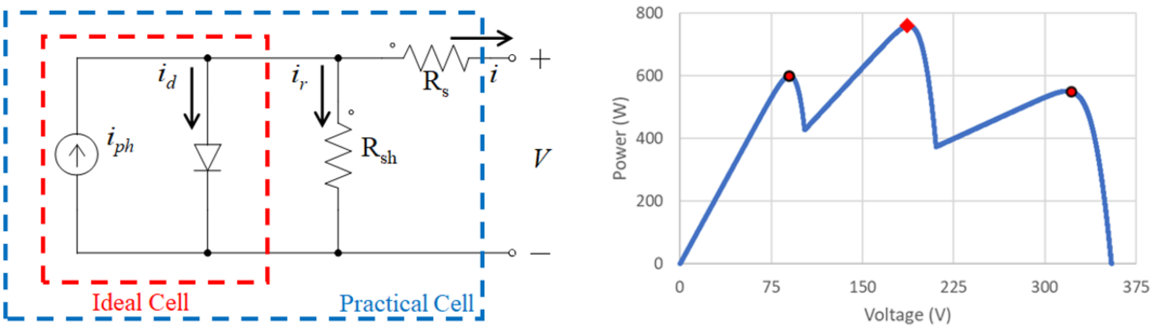
Meta-heuristic techniques have been also explored in MPPT applications. Its ability to handle complex multi-objective problem of MPPT has attracted many researchers to apply in MPPT application. Meta-heuristic techniques can be further divided into swarm intelligence (SI) [12]–[14], evolutionary algorithms [15]–[17], bio-inspired [18]–[21], physical/chemistry phenomena based [22]–[24], social human behavior [25]–[27] and game-based algorithm [28], [29]. The algorithms can work well to find GMPP which very useful under PSCs. Despite their advantages, particularly in handling PSCs, all meta-heuristic algorithms exhibit one common drawback: sluggishness [30]. Moreover, they may search continuously around GMPP, wherein a situation, one or more particles reach GMPP, but other particles still cannot reach GMPP. Although particles may have very close value, but they produce several power levels. These conditions can lead to produce power oscillations and low energy harvesting. Furthermore, power oscillations can generate frequency oscillations in electrical power system [31]. Some researchers have applied termination mechanism for optimizer searching, such as maximum iteration [32], temperature stopping criteria [33], maximum searching time [34], and minimum voltage difference [35]. While other researchers have implemented hybrid approach to achieve a rapid convergence to a GMPP. Ant-colony optimization (ACO) and P&O method are hybridized to improve tracking speed and more efficient convergence [36]. The global search ability of ACO and local search capability of P&O is combined. A hybrid between the adaptive perturb and observe and particle swarm optimization (PSO) is proposed [37]. The search-skip-judge (SSJ) mechanism to minimize the search area is adopted by the PSO. Artificial bee colony (ABC) algorithm is integrated with the conventional P&O algorithm to track the GMPP efficiently under PSC [38]. However, P&O has drawbacks as mentioned above, oscillating around GMPP. Therefore, it faces a dilemma, if the iteration is terminated, it will lead to inaccuracy. Oppositely, if it is not terminated, it will generate power oscillations. Additionally, speed of tracking becomes an important aspect for increasing energy harvesting. Nevertheless, the development of algorithm under complex partial shading has been continuously attracting many researchers to yield more satisfying results. According to previous explanations, the challenges of designing MPPT algorithm under complex partial shadings can be summarized: i) increasing success rate of finding GMPP and avoiding LMPP under PSCs; ii) increasing speed of GMPP tracking, although working under complex PSCs; and iii) increasing accuracy by reaching exact point of GMPP to increase energy harvesting and avoiding power oscillations. To countermeasure those issues, the MPPT is proposed based on improved Seagull optimizer and modified variable step size perturb and observe (ISOP). The key contributions of proposed MPPT are highlighted: i) ISOP can avoid LMPP and reach the GMPP, ii) ISOP has short settling time and fast tracking which increases energy harvesting under complex PSCs, and iii) modified variable step sizes perturb and observe (MVSPO) is adopted to work accompany metaheuristic algorithm to reach GMPP accurately which increases energy harvesting and produces zero steady-state oscillations.

2. RESEARCH METHOD
2.1. Modeling of the PV system
Solar cell can be modeled as ideal cell and practical cell as shown in Figure 1. The ideal cell consists of current source and diode, while the practical cell has resistance. Solar cell equivalent circuit can be classified as single diode and double diode. The single diode is popular model due its simplicity. In this paper, solar cell equivalent circuit of single diode is used as shown in Figure 1(a). The circuit consists of dependent current source, diode, and series and shunt resistor. The circuit can be formulated as (1):

$$i = i_{ph} - i_d - i_r \tag{1}$$

which i is the current flowing out of the positive terminal of the solar panel. i_{ph}, i_d and i_r are current represents light energy converted by solar cells to electrical energy, diode current and shunt resistor current, respectively.

PSC is occurred when PV arrays receive inequal irradiance. Under PSC, PV arrays generate much lower power. Moreover, PSCs generates unequal current in series connection which producing hot-spot and mismatching effects. Bypass diode helps to avoid hotspot and produces multiple peaks in P-V curves as shown by Figure 1(b). The maximum number of peaks on the P-V curve is equal to the number of modules in series. The peaks can be categorized into LMPPs and is only one GMPP. GMPP and LMPP is indicated by red diamonds and red-black dots, respectively.



(a) (b)

Figure 1. Solar cell characteristics (a) cell equivalent circuit and (b) pattern of P-V curve under PSC

2.2. Proposed MPPT technique
The proposed technique is based on Seagull optimizer (SO) [39] and MVSPO. SO is a metaheuristic algorithm under swarm intelligence group. It is well known that metaheuristic algorithms can find GMPP in multi peaks of complex fitness function. Mostly, the fitness function is only mathematical formula which has no impact to any system during its optimizing process. But the optimizing process in PV electrical power system has direct effect to the system. Therefore, the adoption of algorithm to MPPT technique should consider to electrical aspects for performance such as accuracy, tracking time, settling time, power oscillations, and energy harvesting.

Figure 2 shows principal operation of the proposed techniques. Figure 2(a) shows the general curve of PSC. GMPP is located at duty cycle of D_{GMPP} and has power of P_{GMPP}. An LMPP can be very close to GMPP, so a MPPT technique can misidentify LMPP as GMPP. Then optimizer will be trapped in LMPP and instead of reach GMPP. Moreover, optimizer can be confused by LMPP and will be slowly convergence. Figure 2(b) shows zoomed rectangle in Figure 2(a). Figure 2(b) shows particles position around GMPP. The best particle is located at D_{gbest} and has power of P_{gbest}. D_H and D_L are maximum and minimum duty cycle of particles, respectively. D_H and D_L will be used to calculate perturb step. Theoretically, all particles will approach and finally reach GMPP positions. But practically, particles may move continuously around GMPP. The movement of particles around GMPP will produce power oscillations ΔP as shown on Figure 2(c). To avoid this situation, MVSPO will take the task to find exact position of GMPP. Note that, MVSPO works using particles from SO iteration results. When GMPP reached by MVSPO, power oscillations will disappear, accurately reach GMPP and increase energy harvesting. Moreover, there is no need to use iteration termination mechanism. The proposed MPPT flowchart consists of improved Seagull optimizer (ISO) and MVSPO is shown in Figure 3.

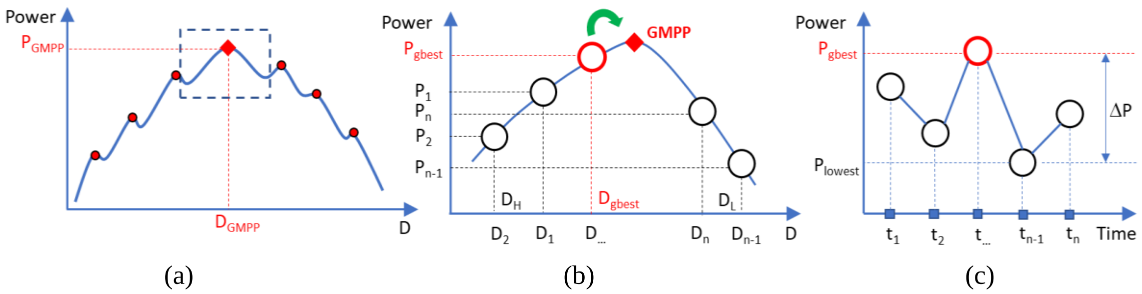


Figure 2. The proposed techniques (a) GMPP and LMPPs, (b) typical particles position around GMPP, and (c) power oscillations by particles

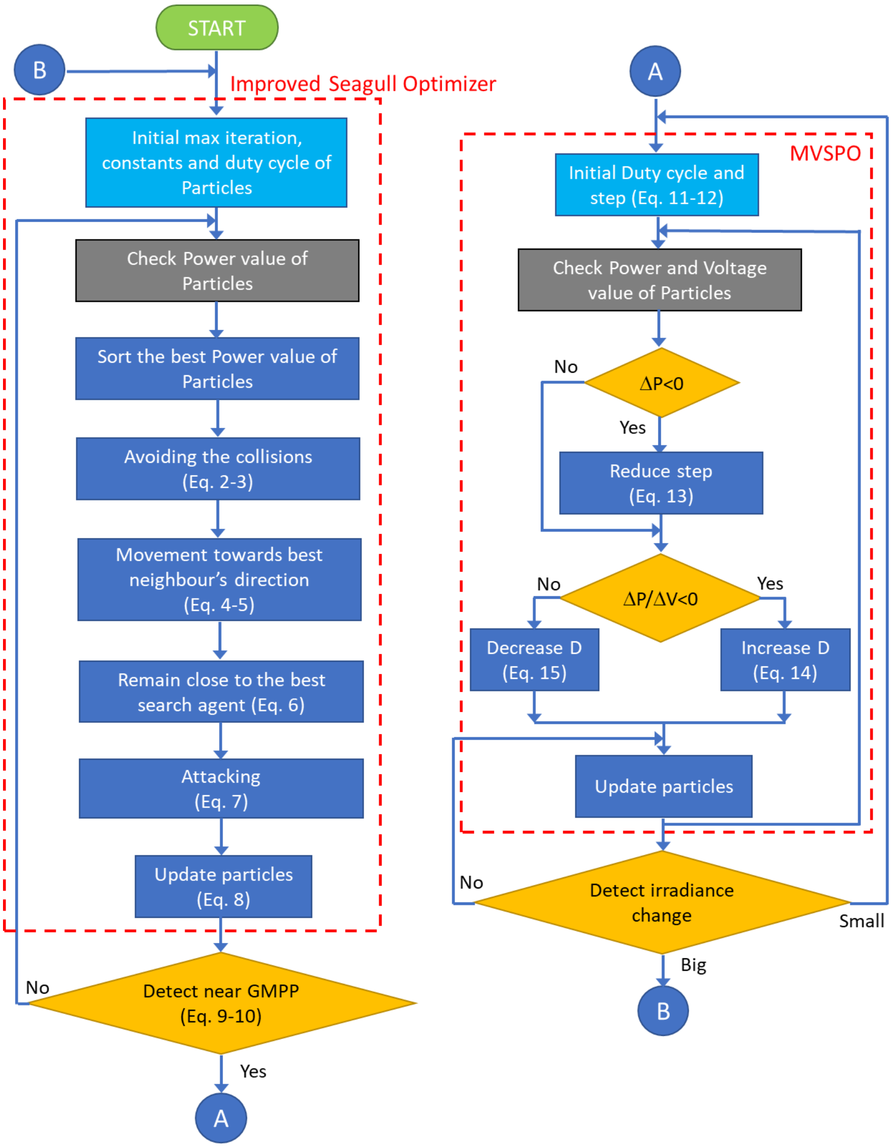


Figure 3. Proposed MPPT flow chart

The formulations of SO algorithm are expressed as (2):

– Avoiding equal duty cycle:

$$\overrightarrow{C_s} = A \times D_n^x \tag{2}$$

where $\overrightarrow{C_s}$ calculates the value of duty cycle which does not equal with other duty cycles, D_n^x represents the current value of duty cycle, x indicates the current iteration, n indicates index number of particles and A represents the movement behavior of duty cycle in a given search space:

$$A = f_c - \left(x \times \left(\frac{f_c}{Max\_iter}\right)\right) \tag{3}$$

where x=0, 1, 2, . . ., max iteration, where f_c is introduced to control the frequency of employing variable A which is linearly decreased from f_c to 0.

– Movement of duty cycle towards best duty cycle's direction:

$$\overrightarrow{M_s} = B \times (Dbest - D_n^x) \tag{4}$$

where $\overrightarrow{M_s}$ calculates the values of duty cycle D_n^x towards the best fit duty cycle $Dbest$ (i.e., best particle). The value of B is randomized which is responsible for proper balancing between exploration and exploitation mode. B is calculated as:

$$B = 2 \times A^2 \times r_d \tag{5}$$

where r_d is a random number lies in the range of [0, 1].

– Remain close to the best duty cycle:

$$\overrightarrow{D_s} = \left|\overrightarrow{C_s} + \overrightarrow{M_s}\right| \tag{6}$$

where $\overrightarrow{D_s}$ calculates the distance between the duty cycle and best duty cycle (i.e., best particle which power value is best).

During attacking phase, particles can change the duty cycles value by mimicking the spiral movement behavior of Seagulls in the air of x', y', and z'planes. According to pre-work for understanding the algorithm behavior, x', y', and z' planes are shown affects dominantly to updated value of duty cycle. Therefore, improvement for SO is focused on this formula. Then, x', y', and z' is improved which expressed as (7):

$$(x' \times y' \times z') = r^3 \times \cos(k) \times \sin(k) \times k \times \frac{1}{2\pi}\left[1 - \left(x \times \left(\frac{1}{Max\_iter}\right)\right)\right] \tag{7}$$

The updated value of duty cycle is calculated using (8):

$$D_n^{x+1} = \begin{cases} \left(\overrightarrow{D_s} \times x' \times y' \times z'\right) + D_n^x, if\ R \geq 0.3 \\ \overrightarrow{C_s} + D_n^x, if\ R < 0.3 \end{cases} \tag{8}$$

which R is random value between [0, 1]. Where D_n^{x+1} saves the best solution and updates the value of other duty cycles.

Variable step size P&O has been proven effectively and exactly find maximum power point. This technique is adopted to improve SO performances. MVSPO will be activated if particles are located around GMPP. Particles position around GMPP can be detected by the difference between power values of particles. The (9) and (10) are used to detect position of particles around GMPP.

$$P_{ave} = \frac{\sum_{p=1}^{n} P_p}{n} \tag{9}$$

$$\frac{P_{ave}}{P_{best}} < \alpha \tag{10}$$

Where P_{ave} and P_{best} are average power and highest power from all particles. n is number of particle population. α is used to measure gap of power between particles. If α is equal to 1, it means all of particles equal to P_{best}.

Initial condition is determined by utilizing particles' duty cycle and power from the last SO iteration, which expressed by (11) and (12):

$$D = Dbest \tag{11}$$

$$\Delta D_{HL} = \frac{D_H - D_L}{n} \tag{12}$$

where D and ΔD_{HL} are duty cycle and average distance between duty cycle of particles, respectively. MVSPO has ability to reduce step size to approach closer to GMPP and to avoid over jump continuously. Step size will be reduced if power is lower than previous iteration. The equation (13) shows the formula to reduce step size, where k is value between 0 and 1.

$$if\,(dP < 0)\ then\ \{\Delta D_{HL} = \Delta D_{HL} * k\} \tag{13}$$

Duty cycle is reduced or increased by considering position of particle at left or right side from GMPP, as expressed by (33) and (34).

$$if\left(\frac{dP}{dV} < 0\right)\ then\ \{D = D + \Delta D_{HL}\} \tag{14}$$

$$if\left(\frac{dP}{dV} > 0\right)\ then\ \{D = D - \Delta D_{HL}\} \tag{15}$$

Finally, GMPP will be reached accurately by all particles, so then power oscillations will disappear. Furthermore, by keeping power electronics converter operates at GMPP, it will increase energy harvesting. Note that, the MVSPO no needs to utilize termination mechanism. Furthermore, MVSPO will help to reach the highest power point although trapped in LMPP.

3. RESULTS AND DISCUSSION

The proposed MPPT is implemented using power simulations (PSIM). Figure 4 presents the PSIM simulator circuit for the overall system. Algorithm is coded in C++. An overall system specification is shown in Table 1. PV panel used in this simulation is Kyocera solar KD250GX-LFB. PV arrays consist of 10 series connection are used. PV panel inputs are the irradiance and temperature. Bypass diode is installed in PV panel to enable multi peaks power. The outputs are the PV voltage (Vpv) and current (Ipv). They are measured by using voltage and current sensor. Voltage and current values are fed to the MPPT block which finally calculates the value of duty cycle D. Tests are done ten times for every technique. To keep fairness of tests, initial duty cycle of particles all algorithms are set at same value for each test. Number of particles are 5 particles and maximum iteration 50 or equal to 0.5 s. Note that, initial duty cycle of P&O only needs a single value. Optimizers are tested under high complexity of P-V curve consists of five peaks and ten peaks in Figure 5 from Figures 5(a) and 5(b) respectively. Parameters of MPPT techniques are shown in Table 2. Parameter f_c is a hyperparameter which the major challenge to determine. Improper values of hyperparameter might yield unwanted results. Through trial and error, the value of f_c is obtained 0.03 for best results.

Performance of optimizers are evaluated by their tracking time T_t, settling time T_s, power oscillations ΔP, success to reach GMPP S, energy harvesting effectivity E_h and accuracy A. The tracking time is the time taken by a technique to track the GMPP for the first time. The settling time is the time taken by all the particles to settle at GMPP without further oscillation or fluctuation. The power oscillations ΔP is determined by maximum and minimum power occurred at last 20% of maximum iteration. S is success level of optimizer to reach global maximum. S can be classified as G and L, which means convergence in GMPP area and in LMPP area at the end of maximum iteration, respectively. Energy harvesting effectivity E_h can be expressed as (16):

$$E_h = \frac{\int_{t=0}^{t=tmax} P_{pv}dt}{\int_{t=0}^{t=tmax} P_{GMPP}dt} \times 100\% \tag{16}$$

and accuracy A can be expressed as (17):

$$A = \frac{P_{ave}}{P_{GMPP}} \times 100\% \tag{17}$$

which P_{ave} is average power value of n particles at the last iteration.

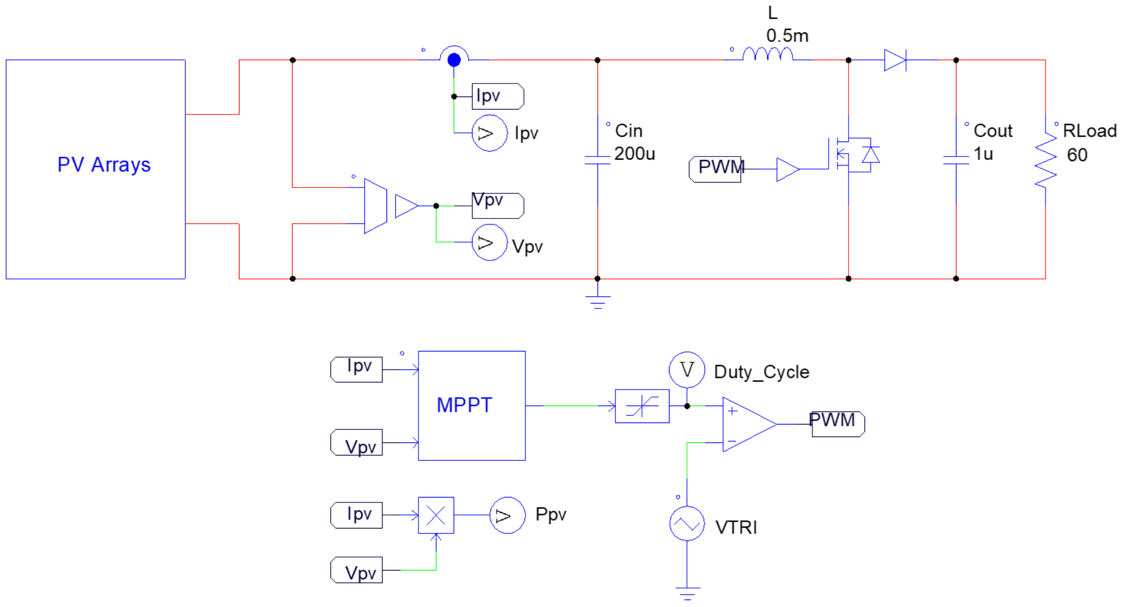
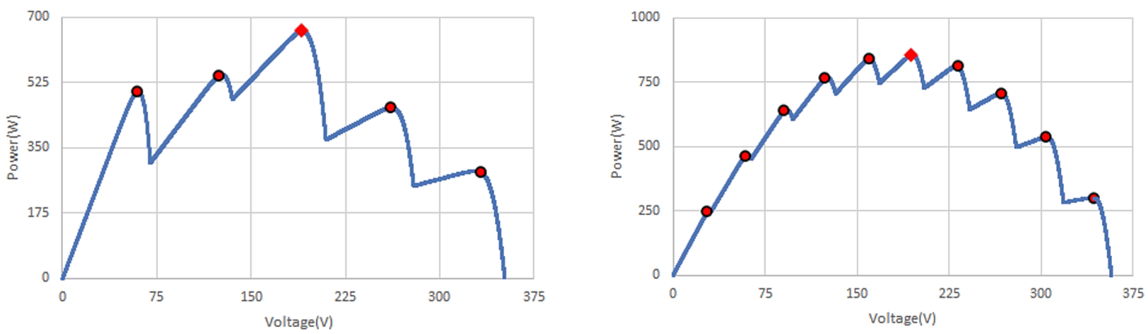


Figure 4. PSIM simulator circuit for the overall system

Table 1. Boost converter specifications

No	Component/parameter	Label	Value
1	Switching frequency	f_s	10 kHz
2	Inductor	L	0.5 mH
3	Capacitor output	C_{out}	1 uF
4	Capacitor input	C_{in}	200 uF
5	Load resistor	R_{load}	60 Ω



(a) (b)

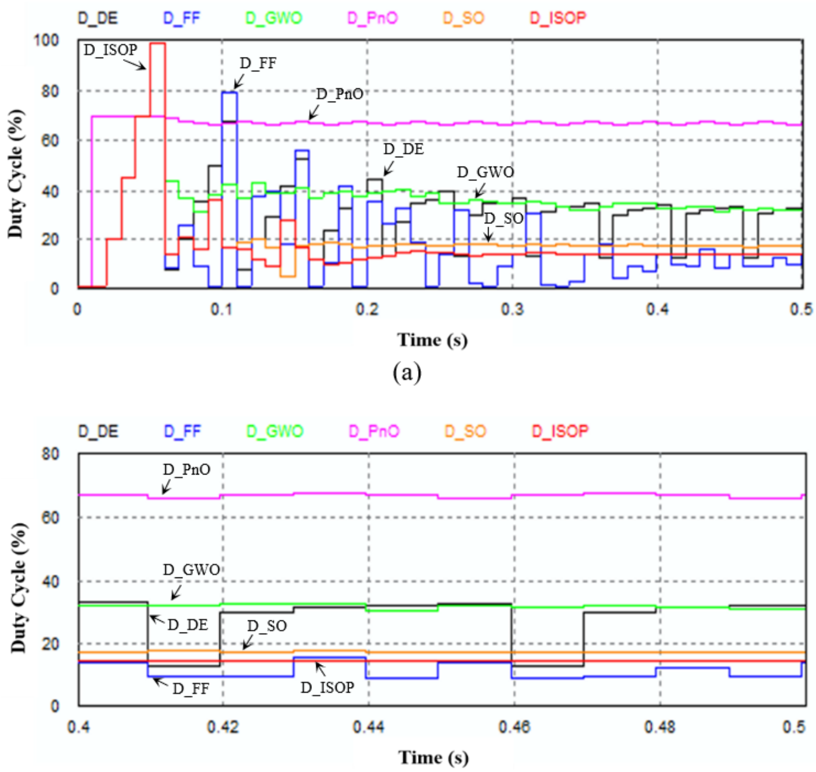
Figure 5. P-V curve for partial shading test (a) five peaks and (b) ten peaks

Table 2. Parameters of MPPT techniques

DE	FF	GWO	P&O	SO	ISOP
C_r=0.5	α=1	a=2	ΔD=1%	f_c=0.03	f_c=0.03
	β_0=0.9			u=1	u=1
	γ=0.5			v=1	v=1
					α=0.96

3.1. Simulation results

Figures 6 to 9 show the example results from ten peaks tests. Figure 6 shows duty cycle plot of all optimizers. Figure 6(a) shows that at initial time, all optimizers are set to apply same duty cycle. SO and ISOP rapidly turn to GMPP duty cycle. FF and DE duty cycle oscillate highly up to 70% of. FF and DE achieve GMPP, but they need longer iteration. GWO shows sluggishly approaching GMPP. P&O is trapped in LMPP area since the beginning of iteration. As shown in Figure 6(b), near end of iteration SO and ISOP almost reach GMPP. SO produces small duty cycle oscillation, while ISOP produces no oscillation. GWO approaches GMPP at duty cycle of 15% and produces small oscillation. FF and DE continuously produce oscillation up to 15% until the end of iteration. P&O continuously produces oscillation caused by fixed steps.



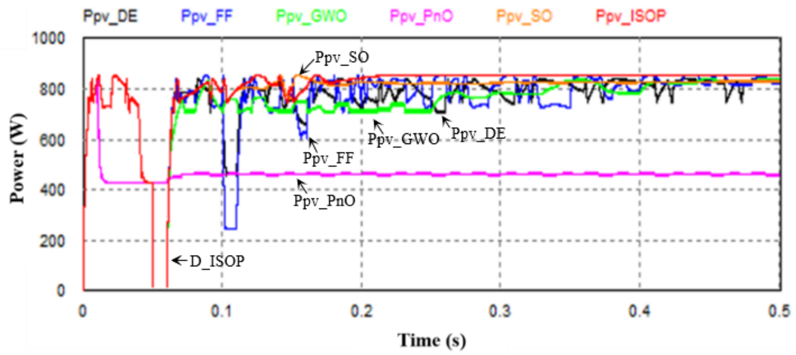
(a)

(b)

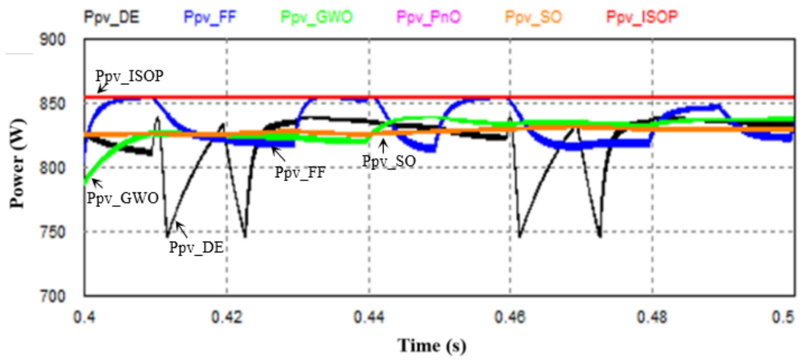
Figure 6. Duty cycle plot (a) duty cycle comparison between techniques, in percent, and (b) zoomed duty cycle in 0.4-0.5 s, in percent

Figure 7 show the power tracking to P_{GMPP}. In the beginning of iteration as shown in Figure 7(a), FF and DE show high power oscillations related to their duty cycle oscillations. At 0.1s, FF and DE produce high power oscillations of 582 W and 231 W, respectively. GWO produces lower power oscillation and slowly approach P_{GMPP}. P&O produces power oscillations caused by approaching PLMPP with fixed step duty cycle. SO and ISOP produce very low power oscillations. Near maximum iteration as shown in Figure 7(b), DE produces power oscillation which the largest power oscillations of 89 W. FF, P&O, GWO and SO produce less power oscillation at around 38, 9, 2 and 2 W, respectively. ISOP produces no power oscillations. The highest accuracy is reached by ISOP 99.87% followed by GWO 97.73%, FF 97.46%, SO 97.06%, DE 96.09%, and P&O 54.18%.

Figure 8 shows the operating point of PV array voltage. GMPP is located between 168 to 204 V which indicated by grey line. Figure 8(a) shows all MPPTs starts in GMPP area, excepts GWO. GWO slowly approaches GMPP. DE and FF produce high oscillations continuously. DE and FF leave GMPP area several times and then return. DE slowly approaches GMPP. Additionally, P&O loses the GMPP area since the start of iteration. SO and ISOP rapidly enter GMPP area since at the beginning. Figure 8(b) shows at the final iteration time FF, SO and ISOP keep in GMPP area. Energy harvesting effectivity by optimizers is shown in Figure 9. The highest energy harvesting effectivity reached by ISOP 93.48% followed by SO 92.25%, DE 89.01%, FF 88.85%, GWO 87.42%, and P&O 54.18%.

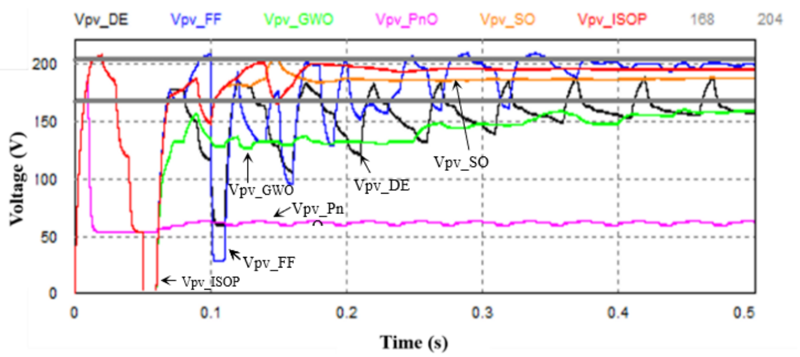


(a)

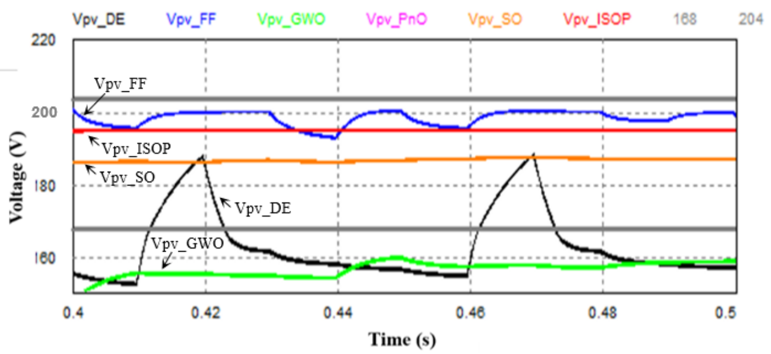


(b)

Figure 7. Power plot (a) power comparison between techniques, in watt and (b) zoomed power in 0.4-0.5s, in watt



(a)



(b)

Figure 8. PV array voltage (a) voltage comparison between techniques, in volt and (b) zoomed voltage in 0.4-0.5 s, in volt

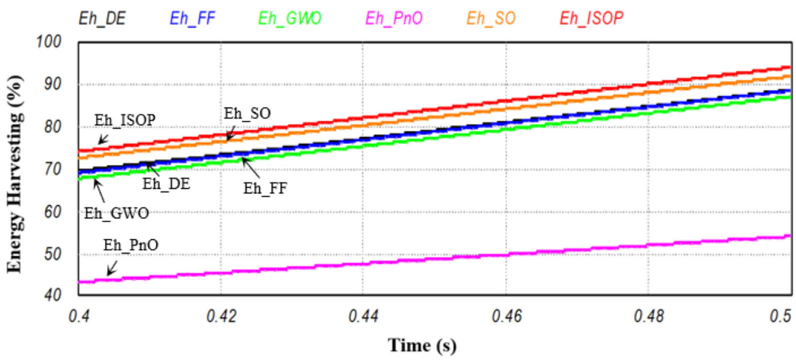


Figure 9. Energy harvesting effectivity comparison, in percent

Table 3 summarizes the tests that have been conducted for complex PSC. Bold texts show the best results. FF successfully approaches GMPP for all tests but continuously produces high power oscillations. ISOP, SO, DE, GWO and P&O have succeeded eight times, seven times, six times, four tests, and three times respectively. The lowest power oscillations are produced by ISOP which has no power oscillations, followed by P&O 8 W, SO 9 W, GWO 11 W, DE 48 W, and FF 85 W. Note that power oscillations shown in the Table are measured at near maximum iteration or time of 0.4-0.5 s. The fastest tracking time is reached by P&O. DE and FF have not succeeded to reach settling time several times. The highest energy harvesting is reached by ISOP, then followed by SO, GWO, FF, P&O and DE. The highest accuracy is reached by ISOP, then followed by SO, GWO, DE, FF, and P&O. Moreover, ISOP has the best performance as shown in average value.

Table 3. Statistical results of algorithms

Test	P&O						DE					
Performance	Tt	Ts	ΔP	S	A	Eh	Tt	Ts	ΔP	S	A	Eh
5 peaks	**0.01**	**0.02**	184	40%	86.90%	82.65%	0.06	0.16	225	**100%**	99.56%	89.09%
10 peaks	**0.01**	**0.02**	297	30%	81.34%	78.48%	0.07	0.34	979	60%	97.65%	90.87%
Average	**0.01**	**0.02**	241	35%	84.12%	80.56%	0.07	0.25	602	80%	98.61%	89.98%
Test	FF						GWO					
Performance	Tt	Ts	ΔP	S	A	Eh	Tt	Ts	ΔP	S	A	Eh
5 peaks	0.06	0.21	1248	**100%**	96.79%	86.57%	0.08	0.09	58	**100%**	97.13%	90.45%
10 peaks	0.07	>0.5	1697	**100%**	94.48%	88.65%	0.08	0.13	227	40%	97.82%	91.89%
Average	0.07	0.5	1473	**100%**	95.64%	87.61%	0.08	0.11	142	70%	97.48%	91.17%
Test	SO						ISOP					
Performance	Tt	Ts	ΔP	S	A	Eh	Tt	Ts	ΔP	S	A	Eh
5 peaks	0.07	0.08	**0**	**100%**	99.53%	**93.75%**	0.07	0.08	**0**	**100%**	**99.84%**	93.71%
10 peaks	0.07	0.13	185	70%	98.23%	93.12%	0.07	0.13	**0**	**100%**	**98.75%**	**93.71%**
Average	0.07	0.11	92	85%	98.88%	93.44%	0.07	0.11	**0**	**100%**	**99.29%**	**93.71%**

Figure 10 shows the summary from test results of 5 peaks and 10 peaks. Figures 10(a) and 10(b) show P&O has the fastest tracking time and settling time. But P&O without exploration ability, mostly trapped to LMPP. Tracking time and settling time between ISOP, SO and GWO are almost similar. DE has longer settling time than GWO, SO and ISOP. FF has longest settling time which longer than simulation time. NA indicates that FF cannot reach settling time until the maximum simulation time. Figure 10(c) shows that ISOP has the lowest power oscillations followed by GWO, SO, P&O, DE, and FF. It is obvious that MVSPO helps ISOP to reduce power oscillations. Figure 10(d) shows that FF and ISOP have the highest success rate. Figures 10(e) and 10(f) show that ISOP has the highest A and E_h, followed by GWO, SO, DE, FF, and P&O. It can be concluded that combination of fast settling time, fast tracking time, reducing power oscillations and increasing accuracy will increase energy harvesting. The highest success rate S is FF and ISOP, followed by SO, DE, GWO and P&O. FF has high oscillations search mechanism which helps to reach GMPP certainly and avoids LMPP. But at the same time, FF produces high power oscillations, slow settling time and low accuracy which reduce energy harvesting. P&O performance is fully affected by step size and initial duty cycle. P&O reached GMPP or LMPP is fully determined by initial duty cycle. Additionally, power oscillations and energy harvesting are fully determined by step size. GWO competed SO, but its exploration mode is lower than SO which results trapped in LMPP several times. SO performed high success rate to reach GMPP and high energy harvesting. Furthermore, ISOP performs further exploitation mode by the help of MVSPO which reach exact point of GMPP and avoid power oscillations. ISOP shows better performances than SO's which confirmed that MVSPO improves ISOP performances. ISOP performs as rapid optimizer according to tracking time and settling time. Furthermore, ISOP has shown zero steady-state oscillations, high success rate to reach GMPP, high accuracy and high energy harvesting effectivity.

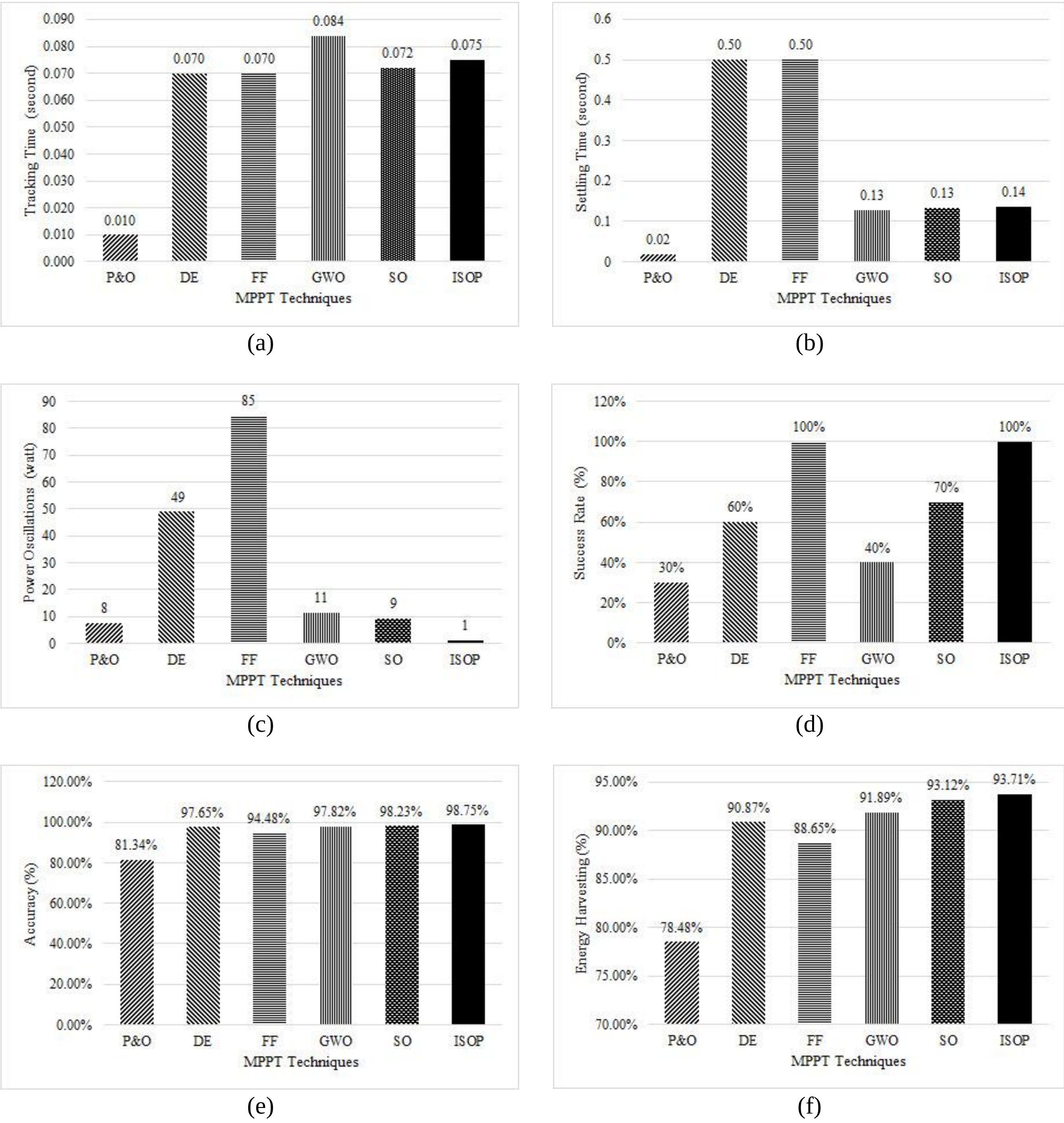
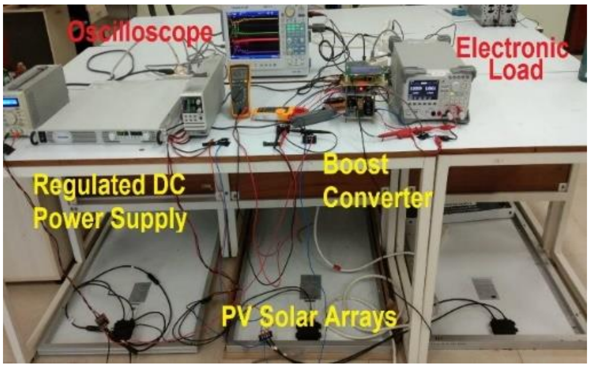


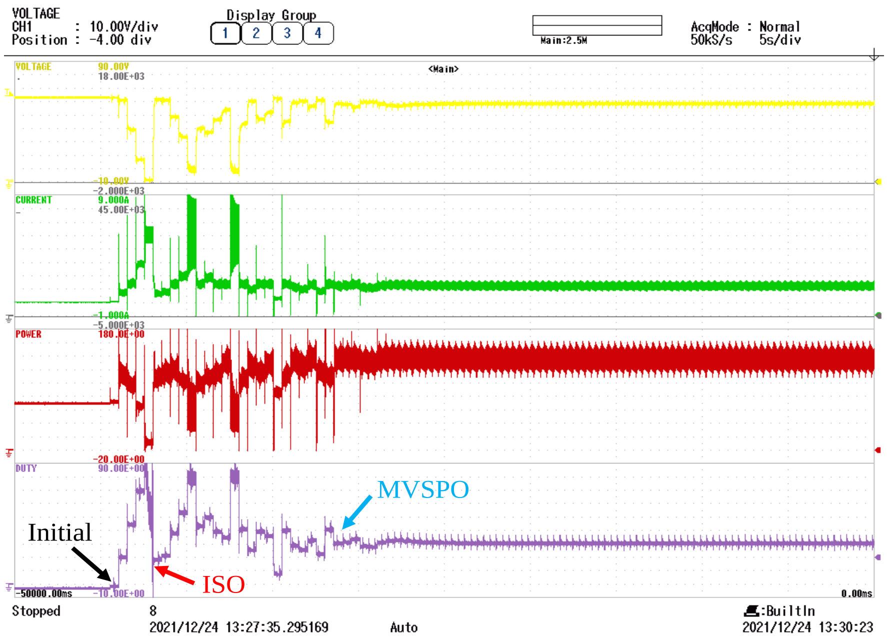
Figure 10. Average value of performances (a) tracking time, (b) settling time, (c) power oscillations, (d) success rate, (e) accuracy, and (f) energy harvesting

3.2. Experimental results

Figure 11 shows experimental works. As shown in Figure 11(a), electronic load is operated as constant resistor load. Oscilloscope is recorded the tracking process of MPPT. Boost converter specifications are L=0.5 mH, C=1500 uF, switching frequency 40 kHz, IGBT K40H1203, fast diode RURG8060 and microcontroller STM32F7 discovery. Test is emulated three peaks of partial shading condition using series of three PV panels 100 Wp and regulated direct current (DC) power supply. PV panels are emulated receiving irradiance of 1000 W/m^2, 500 W/m^2 and 400 W/m^2. For this condition, voltage, current and power at maximum power point are 59.17 V, 2.26 A and 133 W respectively. Figure 11(b) shows from top to bottom the voltage, current, power of PV arrays and duty cycle of boost converter, respectively. The working time of initial duty cycle, ISO and MVSPO are indicated by black arrow, red arrow, and blue arrow respectively. Initial duty cycles are 0%, 22%, 47%, 73%, and 100%. The initial duty cycles can be seen in early phase which forming like a ladder. The next phase, ISO has worked under exploration and exploitation mode to find GMPP area. During the exploration mode, duty cycle value can be seen very various to assure the GMPP area has been reach correctly. Oppositely, duty cycle can be seen less various in the exploitation mode. During exploitation mode, duty cycle has kept small changes to approach MPP in GMPP area. At the last phase, MVSPO has successfully led the best duty cycle to reach MPP exactly. Finally, the duty cycle has reach MPP at value of 32%. By applying this final duty cycle, PV arrays have generated power output of 131 W without power oscillation and accuracy has reach 99%.



(a)



(b)

Figure 11. Experimental works (a) experimental setup and (b) MPPT results

4. CONCLUSION

This paper introduces a novel MPPT technique by combining rapid optimizer and high accuracy finder. The proposed MPPT of ISOP is developed from ISO as rapid optimizer and MVSPO as high accuracy finder. ISO can rapidly handle complex problem PSCs. Then, MVSPO directed to reach GMPP exactly. ISOP has been compared with some popular MPPT techniques including FF, DE, GWO, P&O and SO. Moreover, ISOP is verified using simulation and experiment to work effectively under complex PSC. Overall, the results shown ISOP performed well. ISOP reduces tracking time and settling time, produces zero steady-state oscillations, increases success rate to reach GMPP, energy harvesting effectivity and accuracy. It can be concluded that ISOP is effective to enhance the output of the PV system under various PSCs. Due to the effectiveness of ISOP, the solar PV systems can be more efficiently utilized and increases renewable energy based electrical power generation.

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