Abstract — This paper presents particle swarm optimization based perturb and observe (PSO-P&O) algorithm for maximizing output power of photovoltaic (PV) array under partially shaded conditions (PSC). During PSC, the P-V characteristic of PV will become more complex with multiple maximum power points (MPP). Most of the conventional maximum power point tracking (MPPT) algorithms, such as P&O, will be trapped at the local MPP and hence limiting the maximum power generation. As such, investigation on PSO-P&O algorithm is carried out to maximize the PV generated power principally under PSC operation. The performances of conventional P&O and the proposed PSO-P&O algorithms are investigated particularly on the transient and steady state responses under various shaded conditions. The simulation results show the developed PSO-P&O algorithm is able to facilitate the PV array to reach the global MPP and assist the PV array to produce more stable output power compared to the conventional P&O algorithm.

Keywords - photovoltaic array; partially shaded conditions; particle swarm optimization; perturb and observe; MPPT

I. INTRODUCTION

The photovoltaic (PV) power generation has shown a significant potential in supplying renewable and environmental friendly energy. The recent report of REN21 showed the global operation of solar power generation had increased from 139 GW in year 2013 to 177 GW in year 2014 or equivalent to 27.3 % increment [1]. Although research and development on solar cell design and fabrication are carried out continuously to improve the efficiency of energy conversion, the improvement on the operating condition of PV system using maximum power point tracking (MPPT) approach is important to empower the solar energy generation [2, 3].

The MPPT approach is implemented to track the maximum available output power of the PV system, or known as maximum power point (MPP), hence it ensures the maximum power can be extracted regardless of the dynamic environmental changes, such as irradiance and temperature. Various studies have been carried out on MPPT approaches. For instance, perturb and observe (P&O) algorithm and hill climbing (H&C) algorithm are widely used as MPPT due to their simplicity [4, 5]. Although these approaches perform well in high solar irradiance, the tracking efficiency will drop significantly when they are operated under low solar irradiance condition.

Recently, the MPPT research trend has been focusing on partially shaded condition (PSC) [6, 7]. In practice, multiple PV modules will be connected together to create a solar farm with desired voltage and capacity of loading current. The PSC is inevitable because each PV module in the array will receive different levels of sunlight intensity due to shadow effects from clouds, buildings, etc.

Under the non-uniform irradiance conditions, multiple peaks will appear in the P-V characteristic graph of the PV array. The complication of the characteristics is depending on the orientation of the PV array and the shading patterns. The occurrence of multiple MPPs will cause the conventional MPPT algorithms to trap at the local MPP. Therefore, several artificial intelligence (AI) techniques have been introduced for adapting conventional MPPT algorithms to allocate the global MPP (GMPP) and consequently optimizing the power generation of PV array [8, 9, 10].

Punitha et al. [11] proposed artificial neural network (ANN) based incremental conductance algorithm for GMPP tracking in PSC. Their simulation studies have shown a significant improvement in tracking via ANN compared to fuzzy based H&C and P&O algorithms. Genetic algorithm based MPPT algorithm has been proposed by Ramaprabha and Mathur [12]. The results show that the proposed GA is able to track the GMPP for various shading patterns. Chir et al. [13] proposed fuzzy logic controller (FLC) to adapt P&O algorithm for manipulating the step size of the perturbed voltage, \( \Delta V \), so that the GMPP can be tracked and reached faster. They also tested their algorithm under variable changes of solar irradiance and cell temperature. The results showed the fuzzy based MPPT is able to optimize the PV power with less oscillation in the output power compared to P&O algorithm [14].

Although the AI techniques are able to track the GMPP faster with less oscillation in the steady state, investigations on the various MPPT algorithms are still ongoing with the...
 ultimate goal to find a simple, low cost and highly efficient algorithm. Kamarzaman and Tan [15] have compared the characteristics and performances of AI based MPPT. They summarized that the algorithm structures of FLC and ANN are complex, whereas the sensitivity of GA to the environmental changes is moderate.

Therefore, this paper aims to formulate PSO based P&O algorithm to acquire the optimum operating point for the PV system in order to extract maximum power from the PV array. In this study, the PV array is formed by four PV panels connected in series. The P&O algorithm is developed to track the GMPP while the PSO algorithm will tune the perturbation size of P&O algorithm for having faster tracking speed (transient response) and more stable output power (steady state response).

II. MODELLING OF PHOTOVOLTAIC SYSTEM

This section describes the mathematical model of a solar cell, which can be further implemented for PV array modeling. A PV system basically consists of a PV array, a controller unit, and load, as illustrated in Fig. 1.

The PV array presented in this paper consists of four PV modules connected in series, as shown in Fig. 2. A buck-boost converter can be used to interface the voltage from the PV array to the load. While the PV array generates power for the load, the output voltage and current of PV are fed to the digital controller to perform iterative tracking for the MPP. The controller will determine the new operating voltage for the PV array by adjusting the duty cycle of the buck-boost converter.

A PV module or PV panel is formed by m connected PV cells in series or parallel. The equivalent circuit of PV cell is demonstrated in Fig. 3. A PV cell consists of a photo current source, $I_{pv}$, a diode, $D_m$, the equivalent parallel resistor, $R_p$, and the equivalent series resistor, $R_s$. $R_p$ in the solar cell is caused by the usual p-n junction leakage current in the cell whereas $R_s$ is due to the contact resistance of the metal base within the semiconductor layer.

The $I-V$ characteristic of a solar cell comprised of $D_m$ is described by the Schockley equation, as derived in (1):

$$I = I_{pv} - I_o \left[ \exp \left( \frac{V + IR_s}{nV_T} \right) - 1 \right] - \frac{V + IR_s}{R_p}$$

(1)

where $I$ is the solar cell terminal current, $I_{pv}$ is the solar cell light-generated current, $I_o$ is the reverse biased saturation current of $D_m$, $V$ is the solar cell terminal voltage, $n$ is the ideality factor of the diode, and $V_T$ is the thermal voltage. The function of thermal voltage is described as (2):

$$V_T = \frac{kTN_s}{q}$$

(2)

where $N_s$ is the numbers of solar cells connected in series, $k$ is the Boltzmann constant ($1.381 \times 10^{-23}$ J K$^{-1}$), $T$ is the operating temperature of the solar cell in unit Kelvin, $q$ is the electron charge ($1.602 \times 10^{-19}$ C).

The external influences, such as solar irradiance and cell temperature will affect the generation of charge carrier in PV module and eventually affect the $I_{pv}$, as described in (3):

$$I_{pv} = I_{pv0} + K_I \Delta T$$

(3)

where $I_{pv0}$ is the PV module light-generated current in the nominal condition, $K_I$ is the ratio of short-circuit current to temperature coefficient, $\Delta T$ is the difference of actual temperature to the nominal temperature.

III. PARTICLE SWARM OPTIMIZATION BASED MPPT

Inspired by the behaviors of nature bird flocking under environment with little knowledge to search for food, PSO is a computational intelligence method that optimizes a problem by emulating a flock searching over candidate solutions (information carried by the particles) through search space [16, 17]. Fig. 4 illustrates the flowchart of PSO.

In this paper, the particles of PSO are referred to the potential perturbation sizes of P&O. This algorithm allows all the random particles to search for the optimum solution in the search space through iterative process. Each particle will learn their best experience while interacting with each other to share their knowledge.
The learning process of particles is based on two rules: attracted towards the global best position discovered by others (social influence) and drawn towards its local best promising position (cognition influence). The position of each particle will be evaluated by a fitness function. In this work, the fitness function utilizes the output voltage, \( V \) and output current, \( I \) to calculate the fitness value (output power) of each particle. The global and local best positions are defined by how much power generated by a specific operating voltage. The highest power generated is the best.

During the searching process (iterative process), the velocity and position of each particle is updated based on the inertia, social component and cognitive component, as shown in (4) and (5):

\[
v_{i+1} = v_i + c_1 r_1 (LB_i - x_i) + c_2 r_2 (GB - x_i) \quad (4)
\]

\[
x_{i+1} = x_i + v_{i+1} \quad (5)
\]

where \( v_i \) is velocity of particle \( i \), \( GB \) is the global best position, \( x_i \) is the current position of particle \( i \) respectively.

The PSO searching process will be terminated when the maximum number of iteration is fulfilled. Parameters of the PSO algorithm are shown in Table I.

### Table I. Parameters of PSO Algorithm

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Symbol</th>
<th>Typical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of particles in a swarm</td>
<td>-</td>
<td>20</td>
</tr>
<tr>
<td>Stopping criteria</td>
<td>-</td>
<td>100 iterations</td>
</tr>
<tr>
<td>Cognition learning factor</td>
<td>( c_1 )</td>
<td>0.7</td>
</tr>
<tr>
<td>Social learning factor</td>
<td>( c_2 )</td>
<td>0.3</td>
</tr>
<tr>
<td>Random search probability</td>
<td>-</td>
<td>0.01</td>
</tr>
<tr>
<td>Range of perturbance voltage</td>
<td>( \Delta V )</td>
<td>( 0 \leq \Delta V \leq 2 )</td>
</tr>
</tbody>
</table>

IV. PERTURB AND OBSERVE

The P&O algorithm has been selected to track MPP of the PV array due to its simplicity and ease of implementation. P&O is initiated by applying a perturbed voltage, \( \Delta V \) to alter the operating voltage of the PV array. The change of output power at the present and the previous sampling interval are subsequently compared. Based on the instantaneous output power of the two sampling intervals, the algorithm will decide to regulate the PV array to be operated either at larger or lower operating voltage. The PV array will pursue numerous iteration processes but eventually the PV system will operate at a particular optimum power point. At this stage, PV array will be generating maximum output power. The tracking principal of P&O algorithm is illustrated in Fig. 5.

![Flowchart of PSO algorithm](image-url)
Even though the optimal operating voltage is successfully identified, P&O algorithm will continuously iterate the operating voltage with the aim to track the next MPP. As a result, the perturbation process will lead to the voltage and power fluctuation issues. The fluctuation is obvious when a large perturbation size is applied. By optimizing the perturbation size of $\Delta V$, the oscillation of the PV operating voltage is anticipated to be minimum hence reducing power loss in the PV system.

V. MODELLING AND SIMULATION

In this paper, the simulation study is carried out with Matlab m-file. The Sharp NE-80E2EA multi-crystalline silicon PV module with 80 W maximum power is selected as the reference model for this work. Parameters of the selected PV module are tabulated in Table II.

The partially shaded effect of PV array is simulated by arbitrarily setting the insolation on the series-connected PV modules. The unshaded PV module is considered to be fully illuminated at 1,000 W m$^{-2}$, whereas the insolation on the shaded PV module is varied from 0 to 1,000 W m$^{-2}$. The proposed PSO based P&O algorithm and the conventional P&O algorithm are tested for three different shading patterns, as described in Table III.

The $I$-$V$ and $P$-$V$ characteristics for the three Cases are shown in Fig. 6 and Fig. 7 respectively. Fig. 7 shows the GMPP occurs at the first peak (most left side) in Case I; in Case II, the GMPP occurs at the third peak (middle); whereas the GMPP occurs at the last peak (most right side) in the Case III. The current generated by PV array under PSC is different from the current generated under standard test condition (STC). At STC, constant current of approximate 5.2 A is produced along the functional operating voltage from 0 V to 60 V. However, when the PV array is under PSC, the generating current is unable to maintain at a constant value (dropping like a staircase).

Fig. 7 shows that the $P$-$V$ characteristic of PV array exhibits multiple peaks under PSC. The Case I exhibits two peaks because it receives only two different levels of irradiance, whereas the Case II and III exhibit four peaks as both cases receive four different levels of irradiance. The Case III has the highest GMPP because it receives more average insolation on its PV panels.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Symbol</th>
<th>Typical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open circuit voltage</td>
<td>$V_{oc}$</td>
<td>21.3 V</td>
</tr>
<tr>
<td>Short circuit current</td>
<td>$I_{sc}$</td>
<td>5.16 A</td>
</tr>
<tr>
<td>Maximum power voltage</td>
<td>$V_{mp}$</td>
<td>17.1 V</td>
</tr>
<tr>
<td>Maximum power current</td>
<td>$I_{mp}$</td>
<td>4.68 A</td>
</tr>
<tr>
<td>Maximum power</td>
<td>$P_{mp}$</td>
<td>80.0 W</td>
</tr>
<tr>
<td>Temperature coefficient for current</td>
<td>$K_{I}$</td>
<td>0.053 % °C$^{-1}$</td>
</tr>
<tr>
<td>Temperature coefficient for voltage</td>
<td>$K_{V}$</td>
<td>- 0.360 % °C$^{-1}$</td>
</tr>
<tr>
<td>Numbers of solar cell</td>
<td></td>
<td>36 (in series)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE III. SHADING PATTERNS</th>
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<tbody>
<tr>
<td><strong>Ambient Conditions</strong></td>
</tr>
<tr>
<td>Case I</td>
</tr>
<tr>
<td>Case II</td>
</tr>
<tr>
<td>Case III</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Case</th>
<th>PV Panel 1</th>
<th>PV Panel 2</th>
<th>PV Panel 3</th>
<th>PV Panel 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>II</td>
<td>27 °C</td>
<td>30 °C</td>
<td>700 W m$^{-2}$</td>
<td>400 W m$^{-2}$</td>
</tr>
<tr>
<td>III</td>
<td>27 °C</td>
<td>30 °C</td>
<td>700 W m$^{-2}$</td>
<td>400 W m$^{-2}$</td>
</tr>
</tbody>
</table>

Figure 6. $I$-$V$ characteristics of PV array at PSC.
VI. RESULTS AND DISCUSSION

The performances of the proposed PSO-P&O algorithm in all cases are compared to the conventional P&O algorithm. The perturbation size for P&O algorithm is preset as 2.0 V during the transient state and 0.4 V during the steady state based on STC for reducing oscillation in output power. The simulation results of proposed PSO-P&O and P&O algorithms in Case I, II and III are shown in Fig. 8, Fig. 9 and Fig. 10 respectively.

In Case I, the GMPP occurs at the first peak. Hence both P&O and PSO-P&O algorithms are able to track the GMPP without trapped at local MPP, as shown in Fig. 8. Although both algorithms have obtain same output power, PSO-P&O algorithm has shown a better steady-state response compared to P&O algorithm. In 260th iteration, PSO-P&O algorithm showed an outlier point. This is due to the inherent learning ability (social influence) of PSO that try to search for other global best solution.

The results in Fig. 9 indicate the PSO-P&O algorithm has better performance than P&O algorithm in Case II (non-uniform irradiance and operating at various temperatures). The conventional P&O algorithm is trapped at the local MPP and the output power is fluctuated during the steady state. The PSO-P&O algorithm is able to decide various size of $\Delta V$ according to the instantaneous environmental circumstances. Large perturbation size is chosen to reduce the iteration process and improve the transient response at the beginning stage. When the output power is reaching GMPP, the proposed algorithm will determine the suitable $\Delta V$ for MPPT so that the output power consist less fluctuation, or better steady state response.

Figure 7. P-V characteristics of PV array at PSC.

Figure 8. Performances of PSO-P&O and P&O in Case I.

(a) Output power of PV array

(b) Operating voltage of PV array
In Case III, the PV array receives non-uniform irradiance from the sunlight but operates at constant temperature. The conventional P&O algorithm slowly increases the operating point at the beginning of the process. When it reaches the first peak (around 60 W), the algorithm is trapped at the local MPP, as shown in Fig. 10. During 90th to 100th iteration, the output power of P&O has bigger fluctuation compared to the output power after 100th iteration due to the perturbation size of P&O algorithm at that respective period (2.0 V) is higher.

On the other hand, the proposed PSO-P&O algorithm is able to tack the GMPP (around 210 W) in Case III. The results in Fig. 10 also shows the fluctuation of operating voltage for PSO-P&O algorithm is smaller and hence its output power is very stable compared to P&O algorithm. This is because the PSO-P&O algorithm will adapt its control actions in changing the operating voltage based on the situation. During the transient response, the PSO will boost to the maximum perturbation size for the PV system. Once the GMPP is tracked, the PSO will stop to manipulate the perturbation size. The performances of P&O and PSO-P&O algorithms in the three cases are tabulated in Table IV.

### VII. CONCLUSION

The performances of the proposed particle swarm optimization based perturb and observe (PSO-P&O) are investigated when PV array performs under partially shaded conditions. In this work, PV array is modeled based on four series connected PV modules. The developed PSO-P&O algorithm is tested under three different cases and its performances in optimizing the output power are compared...
to the conventional P&O algorithm. From the simulation results, PSO-P&O algorithm is able to optimize the generation of PV system by tracking the GMPP faster when the ambient conditions (solar irradiance and temperature) are changed. When the output power is approaching GMPP, PSO-P&O algorithm will select smaller voltage perturbation size to minimize the fluctuation of the output power in the steady state. In addition, the proposed algorithm can control the PV system to perform at a more precise operating steady state. In addition, the proposed algorithm can control the PV system to perform at a more precise operating steady state. In addition, the proposed algorithm can control the PV system to perform at a more precise operating steady state. In addition, the proposed algorithm can control the PV system to perform at a more precise operating steady state. In addition, the proposed algorithm can control

ACKNOWLEDGMENT

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REFERENCES


