Performance of Artificial Neural Network and Particle Swarm Optimization Technique based Maximum Power Point Tracking for Photovoltaic System Under Different Environmental Conditions

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Abstract. Photovoltaic (PV) array may receive different levels of solar irradiance and temperature under different environmental conditions, such as partially shaded by clouds or nearby building. However, all PV systems have two major drawbacks: the efficiency of PV power generation is very low and the output power of a PV system is nonlinear, which depends closely on weather conditions, such as ambient temperature and the solar irradiance. Hence, tracking the maximum power of the PV arrays at real time is very important to increase the whole system performance. Multiple peak power points occur when PV module is under partially shaded conditions, which would significantly reduce the energy produced by PV without proper control. Therefore, a Maximum Power Point Tracking (MPPT) algorithm is used to extract maximum available PV power from the PV array. However, most of the conventional MPPT algorithms are incapable to detect global peak (GP) power point with the presence of several local peaks (LP). A hybrid Artificial Neural Network and Particle Swarm Optimization (ANN-PSO) algorithm is proposed in this report to detect the global peak power. A PV system which consists of PV array, DC–DC boost converter, a hybrid ANN-PSO Algorithm, and a resistive load, is simulated using MATLAB/Simulink. The simulation results are carried out, compared and discussed. The proposed algorithm should perform well to detect the Global Peak of the PV array under different environmental conditions.

1. Introduction
Photovoltaic (PV) is one of the most promising renewable sources due to its environmental friendliness and low maintenance cost [1,2]. However, there are two major challenges that need to be tackled for small-scale PV systems to be implemented: (1) high installation cost, and (2) low efficiency in PV conversion [3,4]. Moreover, the PV output characteristics are nonlinear as it always varies with solar irradiance and module temperature. Due to these characteristics, a maximum power point tracking (MPPT) controller is utilized to extract the maximum available power from PV array. The MPPT algorithm is used to control the duty cycle of the DC–DC or DC–AC converter which is inserted in between the PV modules and the load [2, 4].
Over the years, numerous MPPT algorithms for PV array under uniform irradiance have been proposed [5]. They widely used techniques including Perturb and Observe (P&O) [5, 6], Incremental Conductance (IC) [6], Hill Climbing (HC) [7, 8], open-circuit voltage [8], and short-circuit current algorithm [8, 11]. Recently, several artificial intelligent methods, i.e., Fuzzy Logic Controller (FLC) [9, 10], Artificial Neural Network (ANN) [7, 9, 10] are explored. The above-mentioned conventional MPPT algorithms are not capable of tracking the true Maximum Power Point (MPP) if the PV array is partially shaded, such as covered by heavy clouds, falling tree leaves, birds’ litters on the array or shaded by buildings [10] and so on. PV cells under low illumination (shaded condition) could be damaged by overheating problem (known as “hot-spot heating”) attributed to a larger current that flows from other fully illuminated PV cells. This problem can be overcome by inserting bypass diode across the PV cells [11]. However, the insertion of bypass diodes creates multiple peaks, namely global peak (GP) and local peaks (LP), in which only the GP is the true MPP on P–V characteristic curve. The conventional algorithms are not intelligent enough to differentiate among the Global Peak and the Local Peak, where the control of operating point tends to linger around the LP [12].

Particle Swarm Optimization (PSO) is a global gradient less stochastic search method. It is used to search for continuous variable for optimization problems [11, 12]. Artificial Neural Network (ANN) is an information processing paradigm, which is based on the functional concepts of biological nervous systems. In this work, a performance of PSO and ANN technique is proposed to extract the GP under different environmental conditions. The ANN algorithm initializes the optimal voltage, initial value at the prevailing solar irradiance and temperature levels and aids the PSO algorithm to locate GP. This initial voltage is then fed into the PSO to reach the GP location. Therefore, PSO can reach the true GP in a shortest computational time. This avoids the operating point from lingering at LP and guarantees the reach of GP.

2. Particle Swarm Optimization and Artificial Neural Network technique based Maximum Power Point Tracking

2.1. Description of the ANN algorithm

The inputs of the ANN algorithm are the solar radiation \( G \), the temperature \( T \) and the PV short-circuit current \( I_{pv} \) and the output of the algorithm is the voltage \( V_{pv} \) with thirty hidden neurons (layers) as shown in Figure 1.

![Figure 1. The block diagram of the specification of ANN algorithm in the simulation.](image-url)
The performance of ANN algorithm is defined by the graphs of the mean squared error (MSE) against number of epochs (Figure 3). It can be noticed that train set error, and validation set error have same characteristics as the blue line converges to the best for the 2655 epochs graph. Its best validation performance is 0.0073. Therefore, 2655 epochs are chosen for the ANN algorithm.

2.2. Particle Swarm Optimization Algorithm: Codes in MATLAB environment

2.2.1. Problem formulation of MPPT

The objective function (OF) required here must be a maximization problem. The maximum power point tracking of photovoltaic generators can be formulated as an optimization problem where the objective is to maximize the power by summing the operating voltages of all the photovoltaic generators. Therefore, the objective function (OF) is expressed as:

\[
P(OF) = \text{fitness}(I_{pv}, G_1, T_1, G_2, T_2, G_3, T_3, G_4, T_4)
\]

\[
V_1 = NN_{PV}(I_{pv}; G_1; T_1)
\]

\[
V_2 = NN_{PV}(I_{pv}; G_2; T_2)
\]

\[
V_3 = NN_{PV}(I_{pv}; G_3; T_3)
\]

\[
V_4 = NN_{PV}(I_{pv}; G_4; T_4)
\]

In the fitness function, for each PV module, the voltage \( I_{pv} \) is determined using the current value (the Position x) defined in the PSO Algorithm, Solar Radiation \( G \) and Temperature \( T \) of the PV Generators obtained from the model ANN of the latter. The objective function defined above is subjected to:
\[ P_{ANN,PSO} = \text{max} \sum_i^n V_{\text{pv,n}} \times I_{\text{best}} \]  

\[ V_{\text{opt}} = V_1 + V_2 + V_3 + V_4 \]  

\[ P_{ANN,PSO} = V_{\text{opt}} \times I_{\text{best}} = I_{\text{best}} \times (V_1 + V_2 + V_3 + V_4) \]

Where \( P_{ANN,PSO} \) is the power at the MPP given by the hybrid algorithm, \( V_{\text{opt}} \) the output voltage of the PV array Generators as the sum of the voltages across all Generators in series and \( NN_{PV} \) is the neural network of the PV generators, \( V \) is the voltage of the module, \( I \) is the current of the PV array, \( G \) is the solar radiation and \( T \) is the temperature.

2.2.2. PSO Algorithm: Main program

The initial population (swarm) of size \( N \) and dimension \( D \) is denoted as \( X = \left\{ X_i, X_2, ..., X_N \right\}^T \), where \( ^T \) denotes the transpose operator. Each individual (particle) \( X_i (i = 1, 2, ..., N) \) is given as \( X_i = \left\{ X_{i,1}, X_{i,2}, ..., X_{i,D} \right\} \). Also, the initial velocity of the population is denoted as \( V = \left\{ V_1, V_2, ..., V_N \right\}^T \). Thus, the velocity of each particle \( X_i (i = 1, 2, ..., N) \) is given as \( V_i = \left\{ V_{i,1}, V_{i,2}, ..., V_{i,D} \right\} \). The index \( i \) varies from 1 to \( N \) whereas the index \( j \) varies from 1 to \( D \). The detailed algorithms of various methods are described below for completeness [11].

\[ V_{i,k+1}^+ = \omega V_{i,k}^+ + c_1 r_1 (P_{\text{best}}^k - X_{i,k}^k) + c_2 r_2 (G_{\text{best}}^k - X_{i,k}^k) \]  

\[ X_{i,k+1} = X_{i,k} + V_{i,k+1}^+ \]

In equation (9), \( P_{\text{best}}^k \) represents personal best \( j^k \) component of \( i^k \) individual, whereas \( G_{\text{best}}^k \) represents \( j^k \) component of the best individual of population up to iteration \( k \). Figure 2 shows the search mechanism of PSO in multidimensional search space [12,14].

![Figure 4. PSO search mechanism in multidimensional search space.](image)

The different steps of PSO are as follows [11]:

**Step 1:** Set parameters \( W_{\text{min}} \) and \( W_{\text{max}} \), \( c1 \) and \( c2 \) of PSO

**Step 2:** Initialize population of particles having positions \( X \) and velocities \( V \)

**Step 3:** Set iteration \( k = 1 \)

**Step 4:** Calculate fitness of particles \( F_i^k = f(X_i^k), \forall i \) and find the index of the best particle \( b \)

**Step 5:** Select \( P_{\text{best}}^k = X_i^k \) \( \forall i \) and \( G_{\text{best}}^k = X_b^k \)

**Step 6:** \( \omega = \omega_{\text{max}} - \frac{\omega_{\text{max}} - \omega_{\text{min}}}{\text{Iter}_{\text{max}}} \times \text{Iter} \)

**Step 7:** Update velocity and position of particles

\[ V_{i,k+1}^+ = \omega \times V_{i,k}^+ + c_1 r_1 (P_{\text{best}}^k - X_{i,k}^k) + c_2 r_2 (G_{\text{best}}^k - X_{i,k}^k) \]

\[ X_{i,k+1} = X_{i,k}^k + V_{i,k+1}^+ \]

**Step 8:** Evaluate fitness \( F_i^{k+1} = f(X_{i,k+1}^+), \forall i \) and find the index of the best particle \( b' \).
Step 9: Update $P_{best}$ of population $\forall i$,
If $F_{b1}^{k+1} > F_{b}^{k}$ then $P_{best_i}^{k+1} = X_i^{k+1}$, else $P_{best_i}^{k+1} = P_{best_i}^{k}$,
Step 10: Update $G_{best}$ of population,
If $F_{b1}^{k+1} > F_{b}^{k}$ then $G_{best}^{k+1} = P_{best_{bi}}^{k+1}$, else $G_{best}^{k+1} = G_{best}^{k}$,
Step 11: Print optimum solution as $G_{best}^{k}$.

The parameters used in the PSO algorithm are considered as follows:
- Inertial weight: $\omega_{max} = 0.9$ to $\omega_{min} = 0.4$
- Acceleration factors ($c1$ and $c2$): $c1=1.2$ to $c2=1.6$
- Population size: 10 to 100
- Maximum iteration ($MaxIt$): 50 to 1000
- Initial velocity: 10% of position

The block diagram which show the combination of the hybrid ANN and PSO Algorithm is illustrated in Figure 5.

Figure 5. Flowchart of the proposed ANN-PSO Algorithm.
3. Modelling and simulation setup

3.1. Design and implementation process of scale solar photovoltaic

The simulation setup consists of four PV modules connected in series to form the PV array as shown in Figure 6. Each PV module is modelled using the single diode equations with bypass diodes connected across a group of PV cells based on the specifications of 1Soltech 1STH-215-Polycrystalline solar panel [11]. The specifications of the described PV module are tabulated in Table 1. The inputs of the PV array are the values of solar irradiance and temperature. Therefore, the inputs of the PV modules were varied for different environmental weather conditions.

### Table 1: The specifications of 1Soltech 1STH-215-Polycrystalline PV module

| Module data & Parameters                  | Symbol | Typical value |
|-------------------------------------------|--------|---------------|
| Open circuit voltage                      | Voc    | 36.9 V        |
| Short circuit current                     | Isc    | 8.09 A        |
| Maximum power voltage                     | Vmp    | 29.6 V        |
| Maximum power current                     | Imp    | 7.58 A        |
| Maximum Power                             | Pmax   | 224.368 W     |
| Temp. coefficient of current              | Ki     | 0.12 %/°C     |
| Temp. coefficient of voltage              | Kv     | -0.36 %/°C    |
| Number of solar cell                      | Ncell  | 60            |
| Light generated current                   | IL     | 8.1056 A      |
| Series resistance                         | Rs     | 0.37039 ohms  |
| Shunt resistance                          | Rsh    | 333.95 ohms   |
| Irradiance at STC                         | G      | 1000 W/m²     |
| Temperature at STC                        | T      | 25°C          |

As in Figure 6 shows the final model of PV array developed using Simulink includes irradiation and temperature as the inputs parameter and in voltage output \( V_{pv} \) and current output \( I_{pv} \) as the results. This model simulates a photovoltaic string for different environmental conditions and plot its I-V and P-V curves by changing the values of radiation and temperature. Here are the steps to follow to draw the I-V and P-V characteristic curves by setting the irradiance and temperature profile in the Solar Radiation Block and run Simulink.

![Figure 6. PV String Simulink Model.](image-url)
3.2. Boost converter design and components parameters
The boost power stage is utilized in power supply because the required output voltage is always higher than the input voltage. The input current for a boost power stage is continuous and is the same as the inductor current. The output capacitor supplies the entire load current for the switching cycle.

Selection of component parameters [12]:

**Table 2:** Boost power converter initial components parameters

| Components parameters                | Symbol | Typical value |
|--------------------------------------|--------|---------------|
| Minimum input voltage                | Vin    | 128 V         |
| Switching frequency                  | fs     | 25 kHz        |
| Initial output voltage               | Vout   | 300 V         |
| Power converter                       | Pc     | 897.313 W     |
| Conversion efficiency of the boost   | n      | 0.9           |
| percent of the output voltage        | Dv_percent | 1            |

The boost converter parameter calculation and its design in Matlab Simulink.

1. D: Duty cycle

\[
D = 1 - \frac{V_{\text{in}} \times D}{V_{\text{out}}} \quad \%D = 1 - \frac{128 \times 0.9}{300} = \%61.60
\] (11)

2. di: input current

\[
di = I_{\text{ripple}} \times I_{\text{out}} \times \frac{V_{\text{out}}}{V_{\text{int}}} = 0.4 \times 3.33 \times \frac{300}{128} = 3.122 \text{ A}
\] (12)

I_{\text{out}} = 3.33 \text{ A}

3. L: inductance(Henry)

\[
L = \frac{V_{\text{in}} \times (V_{\text{out}} - V_{\text{in}})}{(di \times fs \times V_{\text{out}})} = \frac{128 \times (300 - 128)}{0.9375 \times 25,000 \times 300} = 0.00313 \text{ H}
\] (13)

4. dv: Output voltage ripple

\[
dv = V_{\text{out}} \times \frac{dv \_\text{percent}}{100} = 300 \times 1/100 = 3 \text{ V}
\] (14)

5. C: Capacitor (Farad)

\[
C = \frac{I_{\text{out}} \times D}{fs \times dv} = \frac{I_{\text{out}} \times 0.616}{25,000 \times 3} = 0.000273 \text{ F}
\] (15)

6. R: Resistive load

\[
R = \frac{V_{\text{out}}}{I_{\text{out}}} = \frac{300}{3.33} = 90.10 \Omega
\] (16)

7. The above equation is usually expressed as a ratio of the output voltage, \(V_{\text{out}}\), to the input voltage, \(V_{\text{int}}\), and is usually called \(M\) as shown:

\[
M = \frac{V_{\text{out}}}{V_{\text{int}}} = \frac{1}{1 - D} \times \frac{1}{\frac{R}{1 - D^2}} = \frac{300}{128} = 2.344
\] (17)

\(D = 0.616; \ V_{\text{in}} \_\text{min} = 128; \ fs = 25,000; \ L = 87.04 \times 10^4; \ C = 1.11606 \times 10^4; \ R = 90.10; \ M = 2.344.\)
To reach the desired maximal voltage level, a DC–DC boost converter is used as the power stage interface between the PV system and the resistive load. The pulse width modulation (PWM) technique achieved by the MPPT duty cycle is applied to electronic switch of converter which is MOSFET(Q). The duty cycle is expressed by the following parameters.

![Figure 7. DC-DC boost converter Simulink model.](image)

3.3. Modelling of the MPPT PV system

The simulation setup consists of four PV modules connected in series to form the PV array as shown in Figure 9. The module data and model parameters of the described PV module 1Soltech 1STH-215-Polycrystalline solar panel are tabulated in Table 1. The inputs of the PV array are the values of solar irradiance and temperature.

The input of the DC-DC boost converter is the PV voltage which is generated by the PV array. The proposed hybrid PSO-ANN algorithm worked with PID controller to control the PWM block. The feedforward neural network algorithm consists of three inputs (solar irradiance \( G \), Temperature \( T \) and the PV current \( I_{pv} \) for the four PV modules) and one output (PV voltage \( V_{pv} \)).

![Figure 8. Output voltage signal of the boost converter.](image)
4. Results and discussion

4.1. Varying irradiation, fixed temperature

As the results based per pattern in the Table 2 are proven, the I-V and P-V characteristics with varying irradiation and temperatures are obtained.

\[
E = \frac{P_{PSO,ANN}}{P_{max}} \times 100
\]  

(18)
Table 3: Varying irradiation G, fixed temperature Tr patterns for PV generators

| Case    | Irradiance   | Vmpp(V)   | Imp(R)    | Pmpp(W)   |
|---------|--------------|-----------|-----------|-----------|
| Pattern1| 200W.m\(^{-2}\) | 117.0750  | 1.5227    | 178.2681  |
| Pattern2| 400W.m\(^{-2}\) | 119.1015  | 3.0436    | 362.5009  |
| Pattern3| 600W.m\(^{-2}\) | 119.4375  | 4.5607    | 544.7186  |
| **Pattern4** | **800W.m\(^{-2}\)** | **119.1015** | **6.0725** | **723.2465** |
| Pattern5| 1000W.m\(^{-2}\) | 118.0485  | 7.5781    | 897.3083  |

Figure 12. Performance of ANN-PSO output power at varying irradiation-fixed temperature.

\[ E_1 = \frac{P_{PSO\_ANN}}{P_{max}} \times 100 = \frac{665.7782}{723.2465} = 92.05\% \]  \hspace{1cm} (19)

4.2. Fixed irradiation, varying temperature

The irradiation input is set to 1000 W/m\(^2\) and the temperatures are set as 15°C, 25°C, 35°C, 45°C and 55°C. This is to observe the PV characteristics output of the PV module when varying the irradiation shown in Figures 13 and 14. As for the increases in operating temperature, the output current increases while the voltage drops accordingly. This leads to decreasing value in PV power output.

Figure 13. P-V characteristics fixed irradiation, varying temperature.  
Figure 14. I-V characteristics fixed irradiation, varying temperature.
Table 4: Fixed irradiation $G$, varying temperature $T_r$ patterns for PV generators

| Case   | Temperature | $V_{mpp}$(V) | $I_{mpp}$(A) | $P_{mpp}$(W) |
|--------|-------------|--------------|--------------|--------------|
| Pattern1 | 55°C        | 102.0705     | 7.6984       | 785.7795     |
| Pattern2 | 45°C        | 107.4780     | 7.6636       | 823.6726     |
| **Pattern3** | **35°C**    | **112.9275** | **7.6231**   | **860.8619** |
| Pattern4 | 25°C        | 118.4085     | 7.5781       | 897.3083     |
| Pattern5 | 15°C        | 123.9105     | 7.5294       | 932.9775     |

Figure 15. Performance of ANN-PSO output power at fixed irradiation-varying temperature.

$$E_2 = \frac{P_{PSO\_ANN}}{P_{max}} \times 100 = \frac{834.6977}{860.8619} = 96.96\%$$ (20)

4.3. Constant weather conditions

The output characteristic curves of the photovoltaic generators on the constant weather conditions test which means the temperature and the solar radiation are uniform in all the PV modules in series.

Figure 16. P-V characteristics curves of PVG at constant condition.

Figure 17. I-V characteristics curves of PVG at constant condition.
Table 5: Constant weather conditions patterns for series-connected PV generators

| Case   | Irradiance (W/m²) | Temp. (°C) | Voltage (V)  | Current (A) | Power (W)  |
|--------|-------------------|------------|--------------|-------------|------------|
| Pattern 1 | 200               | 20         | 120.5624     | 1.5164      | 182.8222   |
| Pattern 2 | 900               | 35         | 113.3008     | 6.8666      | 777.9857   |
| Pattern 3 | 700               | 29         | 117.1067     | 5.3308      | 624.2679   |
| Pattern 4 | 500               | 27         | 118.2562     | 3.8079      | 450.3117   |
| Pattern 5 | 300               | 25         | 118.4302     | 2.2837      | 270.4569   |

Figure 18. Performance of ANN-PSO output power of PVG at PSC.

$$E_3 = \frac{P_{PSO,ANN}}{P_{max}} \times 100 = \frac{247.7043 \times 100}{270.4569} = 91.59\%$$

4.4. Effect Partial Shading Condition
Under a Standard Test Condition (STC), when the entire strings PV or the PV array receive a uniform irradiance and temperature, the typical P-V curve shows a single MPP, as illustrated in the curves of Figures 11 and 13 with different radiations and temperatures in each case.

Figure 19. The P-V characteristics curves of PV generators at PSC.

Figure 20. The I-V characteristics curve of PV generators at PSC.
Table 6: Shading patterns for series-connected PV generators

| Case   | Ambient Conditions | PV module 1 | PV module 2 | PV module 3 | PV module 4 | Global Peak Pmax (W) |
|--------|--------------------|-------------|-------------|-------------|-------------|----------------------|
|        |                    | 1000 W/m²   | 1000 W/m²   | 900 W/m²   | 800 W/m²   | 784.9260             |
| Case I | 25°C               | 25°C        | 20°C        | 19°C        |             |                      |
| Case II| 800 W/m²           | 700 W/m²    | 400 W/m²    | 200 W/m²   |             | 313.5360             |
|        | 32°C               | 29°C        | 26°C        | 24°C        |             |                      |
| Case III| 600 W/m²         | 600 W/m²    | 250 W/m²    | 250 W/m²   |             | 261.7500             |
|        | 28°C               | 28°C        | 25°C        | 25°C        |             |                      |
| Case IV| 900 W/m²          | 500 W/m²    | 1000 W/m²   | 800 W/m²   |             | 551.5869             |
|        | 35°C               | 27°C        | 40°C        | 30°C        |             |                      |
| Case V | 300 W/m²          | 800 W/m²    | 900 W/m²    | 700 W/m²   |             | 490.3700             |
|        | 25°C               | 31°C        | 35°C        | 27°C        |             |                      |

Figure 21. Performance of ANN-PSO output power of PVG at PSC.

\[ E_4 = \frac{P_{PSO,ANN}}{P_{max}} \times 100 = \frac{783.4215 \times 100}{784.9260} = 99.81\% \] (22)

The PV system is simulated using Matlab/Simulink 2017 environment. The simulations are carried out and the proposed hybrid PSO-ANN algorithm is tested under different weather conditions: constant and uniform irradiation, rapidly varying irradiation and partially shading or non-uniform irradiation condition. Tracking the maximum power of the PV arrays at real time is very important to increase the whole system performance. The performances are evaluated in terms of the efficiency tracking and response time. The corresponding maximum power of PV generators for each conditions are recorded in tables.

4.5. Discuss on the limitation of the proposed system

To evaluate the performances of the proposed MPPT based on hybrid PSO and ANN algorithm controller during constant and non-uniform irradiance and temperature levels, four PV modules connected in series are partially shaded. Shading patterns for series-connected PV generators are simulated in five (05) cases with different ambient conditions (see Table 5). From the output P–V characteristic curves of the PV generator depicted, single and multiple power peaks are observed corresponding to the Local Maximum Power Point (LMPP) and the Global Maximum Power Point (GMPP). The proposed hybrid PSO and ANN algorithm controller based on MPPT has the ability to distinguish between the global peak (GMPP) and local peak (LMPP) through the scanning procedure.
Furthermore, it can be noticed that the method is able to track the GMPP on fully and partially illumination of PV generators as well as on partial shading conditions under non-uniform irradiance and temperature. The performances of the proposed hybrid ANN-PSO method maximum power point tracking of PV generators are computed and the proposed algorithm can always detect the maximum power even when the PV generators are partially shaded, partially of fully illuminated. So, the results show that the tracking efficiency of the PSO-ANN algorithm for each condition is in the range of 95.50%. Hence, the proposed algorithm can always reach to MPP if there is a change of solar irradiance and temperature.

5. Conclusion
The performance of the proposed particle swarm optimization with artificial neural network (ANN-PSO) is investigated when the PV generators perform under constant, standard test and partially shaded conditions. In this study, PV array is modeled based on four series connected PV modules. The developed hybrid ANN-PSO algorithm is tested under five different cases and its performances in optimizing the output power are given. The simulation results showed that the hybrid ANN-PSO algorithm is able to optimize the generation of PV system by tracking the Global Maximum Power Point (GMPP) when the ambient conditions (solar radiation and temperature) are changed. Furthermore, the proposed hybrid algorithm can control the PV system to perform at a more precise operating voltage. The hybrid ANN-PSO algorithm can always detect the Global Peak (GP), track the GMPP and provides better steady state during standard test and partial shading conditions. Power output of PV module is directly proportional to solar radiation. Hence, in order to select the best location to install PV module, the strength of solar radiation need to be considered. Besides that, environmental factors and local climate such as humidity, temperature and wind also need to be considered as it will affect the output power of PV module. These effects are shown clearly in this simulation result where the performances of PV module depend on the amount of solar radiation and also the temperature of surrounding.

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