Grey wolf optimization for track maximum power of photovoltaic system In multiple peak power characteristics

I D Sara¹*, R Faulianur¹
1 Department of Electrical Engineering & Computer, Engineering Faculty of Syiah Kuala University, Jl. Tgk. Syech Abdulrauf No.7, Darussalam Banda Aceh 23111 Indonesia
E-mail: ira.sara@unsyiah.ac.id

Abstract. A Photovoltaic (PV) module has a nonlinear current and voltage characteristic. The maximum power is obtained when the current and the voltage reach its maximum point. This maximum power fluctuates with the changes in irradiance and temperature conditions. To track the maximum power produced by a PV device under a shading condition, a maximum power point tracking (MPPT) method is required. The grey wolf optimisation (GWO) algorithm has been used to obtain the maximum power point of a PV array. However, how it performs to track the maximum power point of a shaded PV module is still not understood. Therefore this study focuses on the investigation of the GWO algorithm to track the maximum power of a PV module under a partial shading condition. The shaded PV module is simulated based on a one-diode model using the Matlab/Simulink. Different shading conditions are generated to test the performance of the GWO algorithm in tracking the maximum power of a tested PV module. Its performance is also compared to that of the perturb and observe (PNO) algorithm. The findings show that the accuracy of the GWO algorithm is higher than the PNO algorithm. In average, the GWO algorithm is able to track the maximum power point of a shaded PV module with an accuracy of 97%. Comparing to the GWO method, the PNO method is not preferable to track the maximum power point of a shaded PV module.

1. Introduction
A photovoltaic (PV) module is a device used to convert sunlight into electrical energy. There are some advantages of using PV modules as electricity generation i.e.: environmentally friendly, easy to maintain and to install and silence. A part from its advantages, it also has a disadvantage, i.e.: its output power fluctuates with changes in the irradiance and temperature conditions. Another condition such as partial shading also contributes to the fluctuation in the power output of a PV module. The relationship between the current and voltage (I-V) characteristic of a solar module is nonlinear. The maximum power is obtained when the current and the voltage output of the PV module reach its maximum point. A maximum power point tracking (MPPT) method is required in order to operate the PV module at its maximum power point.
There have been several methods developed to track the maximum power of a PV module such as a Perturb and Observe (PNO) method, an Incremental Conductance (IC) method and a Hill Climbing

* Corresponding author: ira.sara@unsyiah.ac.id
(HC) method. All of these methods only work very well to track the maximum power point of a PV device under normal environmental conditions. However, when a PV device produces a multiplempeak power at one irradiance condition, the optimisation methods fail to find the highest peak of the output power. The output power with multiple peaks occurs when the PV module equipped with bypass diodes experiences a partial shading condition [1, 2, and]. Other optimisation method such as a Grey Wolf Optimisation (GWO) [5] and an improved Particle Swarm Optimisation (IPSO) have been studied in [4,6] to exploit their capability in finding the maximum power of a PV device. The capability of this method to find the maximum power point of a PV array under a partial shading condition has been investigated by [6]. The study found that the GWO method performs much better than the PNO and the IPSO methods in obtaining the maximum power point of a PV array under a partial shading condition. However, how the ability of the GWO algorithm to track the maximum power point of a shaded PV module is still not understood. Therefore, this study aims to investigate the ability of the GWO algorithm to track the maximum power point of a PV module with multiple peaks under a partial shading condition. The GWO method will be tested and analysed to obtain the global maximum power point of a PV module under the partial shading condition.

2. Modelling of a Photovoltaic module

A PV module consists of solar cells connected in a series and parallel configuration. The configured cells form a module and then the several modules are connected in series-parallel to form an array. The connection of the PV modules in an array is suited to the requirement of the load condition. A solar cell is generally modelled using a one-diode model as shown in figure 1.

As shown in the figure 1, there are several parameters used to represent a solar cell such as a photon current $I_{ph}$, a diode current $I_d$, a shunt current $I_s$ which flows through a parallel resistance $R_p$, and a series resistance $R_s$. The relationship between the current and the voltage of the solar cell based on these parameters is expressed as follows:

$$I = I_{ph} - I_d - \frac{V + R_s I}{R_p}$$  \hspace{1cm} (1)

$$I = I_{ph} - I_o \left[ \exp \left( \frac{V + R_s I}{n k T} \right) - 1 \right] - \frac{V + R_s I}{R_p}$$  \hspace{1cm} (2)

Where $I_{ph}$ is the photocurrent; $I_o$ is the reverse saturation current of diode; $q$ is the electron charge ($1.6 \times 10^{-19}$ Coulomb); $k$ is the Boltzmann’s constant ($1.38 \times 10^{-23}$ J/K); $T$ is the module temperature (°K); $n$ is the diode ideality factor.
A PV module can be modelled based on the series and parallel configuration of its cells. The equivalent circuit of a PV module is illustrated in figure 2.

![Figure 2. The equivalent circuit of a photovoltaic module][1]

Where $N_s$ is the number of cells in series; $N_p$ is the number of cells in parallel in a module.

The relationship of the current and the voltage of a PV module is given in (3):

$$I = N_p * I_{ph} - N_p * I_o * \left[ \exp \left( \frac{V/N_s + I * R_s/N_p}{n * k * T/q} \right) - 1 \right] - \frac{V * N_p/N_s + I * R_s}{R_p}$$

where,

$$I_{ph} = [I_{sc} + K_v(T - 298)] * \frac{G}{1000}$$

$$I_o = I_{rs} \left[ \frac{T}{T_r} \right]^3 \exp \left[ q * E_{g0} \left( \frac{1}{T} - \frac{1}{T_r} \right) \right]$$

$$I_{rs} = I_{sc} / \left[ \exp(q * V_{oc}/N_s k T) - 1 \right]$$

Where $E_{g0}$ is the bandgap energy of a semiconductor material for Si at 300K is 1.12 eV; $I_{sc}$ is the short-circuit current (A); $I_{rs}$ is the reverse saturation current of diode (A); $G$ is the solar irradiance (W/m²), $K_v$ is the temperature coefficient for the short-circuit current (0.0013 A/°C); $T$ is the module’s temperature (°K); $T_r$ is the reference temperature (°K), $k$ is the Boltzmann’s constant (1.38x10⁻²³ J/K); $q$ is the electron charge (1.6x10⁻¹⁹ Coulomb); $n$ is the diode quality constant (from 1 to 2); $R_s$ is the series resistance (Ohm); $R_p$ is the parallel resistance (Ohm), $V$ is the output voltage (V), $V_{oc}$ is the open circuit voltage (V) and $I$ is the output current (A).

3. The Grey Wolf Optimization for The Maximum Power Point Tracking (MPPT)

A Grey Wolf Optimization (GWO) algorithm works based on the hunting behaviour of wolves in nature. The hunting process consists of several steps, i.e.: tracking, chasing and approaching the prey, pursuing, encircling and harassing the prey until it stops moving and finally attacking the prey. Different wolves lead this process. There is a leadership hierarchy of the grey wolves in hunting the prey as illustrated in figure 3 [5]. The first level of the hierarchy is the leader of the wolves and named [5].
as the alpha wolf ($\alpha$). It is considered as the dominant wolf in the group. It has responsibility for hunting and attacking the preys. All of the wolves in the group have to follow his order. The second level is the subordinate wolf or the helper of the alpha wolf. It is called as the beta wolves ($\beta$). The responsibility of this helper wolf is to supports the alpha wolf in hunting and making decisions. The beta wolf can replace the alpha’s position if the alpha passes away. The third level is the Delta wolves ($\delta$). They are the worker wolves. Their role in the group is to warn other wolf members in case of any dangers, to watch the boundaries of their territory, to support the alpha and the beta in hunting and to safeguard the wounded wolves. The lowest level is the omega wolves ($\omega$). They are considered as the followers and have to follow the orders of all the dominant wolves.

In the grey wolf optimizer, the alpha wolf leads the hunting of the prey. The beta and the delta might involve in the hunting operation occasionally. If a prey is found during the hunting, the three levels of wolves i.e.: $\alpha$, $\beta$, and $\delta$ surround the prey. This hunting operation is mathematically modelled as shown in (7) and (8).

\[
D = \left| C \cdot X_p(t) - A \cdot X(t) \right| \tag{7}
\]
\[
X(t + 1) = X_p(t) - A \cdot D \tag{8}
\]
\[
A = 2a \cdot r_1 \cdot a \tag{9}
\]
\[
C = 2 \cdot r_2 \tag{10}
\]

Where $t$ is the current iteration, $A$ and $C$ are the coefficient vectors, $X_p$ is the position vector of the prey, $X$ is the position vector of a grey wolf, $r_1$ and $r_2$ are random vectors $\in [0,1]$, $a$ is a component which linearly varies from 2 to 0 over the course of iteration. The vector $A$ is a random value in interval $[-2a, 2a]$.

The GWO algorithm starts by initializing the number of grey wolf population ($\alpha, \beta, \delta$ and $\omega$), the component of $a$, the coefficient vectors of $A$ and $C$. Firstly, it is assumed that the alpha, beta and delta wolves know the potential location of the prey ($X_p$) very well. The search for the prey is applied according to the position of the wolves ($X$). The wolves diverge each other to search for the prey and converge to attack the prey based on the value of the coefficient vector $A$. The hunting process depends on the value of the coefficient vector $A$. If the value of $|A|<1$, the wolves converge to attack the prey and finish the hunt. When $|A|>1$, the wolves diverge from the prey and find the fitter prey. The GWO optimises the value of the alpha, the beta and the delta. The fittest solution is considered as

\[\text{Figure 3. The social hierarchy of grey wolves in hunting their preys [5].}\]
the alpha, then the second fittest solution is the beta and the third fittest solution is the delta. These three best solutions are saved, and their positions are updated according to the position of the best search agents as follows:

\[
D_\alpha = |C_1 \cdot X_\alpha - X| \\
D_\beta = |C_2 \cdot X_\beta - X| \\
D_\delta = |C_3 \cdot X_\delta - X| \\
X_1 = X_\alpha - A_1 \cdot (D_\alpha) \\
X_2 = X_\beta - A_2 \cdot (D_\beta) \\
X_3 = X_\delta - A_3 \cdot (D_\delta) \\
X(t + 1) = \frac{X_1 + X_2 + X_3}{3}
\]

Applying the GWO algorithm for searching the maximum power point of a PV module under one irradiance and temperature condition requires a DC-DC converter. The type of the DC-DC converter used is the Boost converter. The electrical circuit of the combination of the GWO algorithm and the Boost converter in searching for the maximum power point of a PV module is shown in figure 4. The Boost converter is used to increase the magnitude of the input voltage to a certain level. It consists of an inductor, a capacitor, a diode and a Mosfet as a switch. The output voltage of the Boost converter is greater than its input voltage and it is very sensitive to the changes in duty cycle \((k)\) of the Mosfet. The relationship between the duty cycle of the Mosfet and the output voltage is given in (18).

\[
V_{\text{out}} = \frac{V_{\text{in}}}{1 - k}
\]

Where \(V_{\text{out}}\) is the output voltage, \(V_{\text{in}}\) is the input voltage and \(k\) is the duty cycle.

**Figure 4.** The electrical circuit of a Boost converter combined with a PV module and the GWO algorithm.
The Mosfet used in this study has a switching frequency of 20 kHz, the input capacitor $C_i$ has a magnitude of 100µF, and both the inductor $L$ and the output capacitor $C$ have a value of 3.3 mH and 1651µF respectively. The load $R$ connected at the output of the Boost converter has a value of 7 Ω. The GWO algorithm functions as a controller in the circuit. It is used to find the best duty cycle for the Mosfet. The controller requires two input parameters for searching the best duty cycle of the Mosfet, i.e.: the current and voltage of a tested PV module. These two parameters are used to produce the output power of the tested PV module by multiplying them together. The output power is written as a function of duty cycle of the Mosfet as shown in (19).

$$Power = f(duty \ cycle)$$

(19)

The prey of the GWO in this MPPT method is the output power of the PV module. The position of the grey wolves is represented by the duty cycle. The fittest solution of the GWO is the duty cycle of the Mosfet for reaching the maximum voltage. The initial value of the parameter $a$ is set at 2 and its value decreases linearly to 0 during the iteration process. The total number of iterations used is 50.

4. Methods

In this study, a 100 Wp photovoltaic module is selected for the test. The electrical parameters of the tested PV module under standard test condition (STC) are shown in table 1.

| Table 1. The Electrical Parameters of a 100 Wp Photovoltaic Module [8] | Parameter                  | Value       |
|------------------------------------------------------------------------|---------------------------|
| Number of series cell ($N_s$)                                          | 36                        |
| Maximum Power ($P_{max}$)                                              | 100 Wp                    |
| Voltage at maximum power ($V_{mp}$)                                    | 18 Volt                   |
| Current at maximum power ($I_{mp}$)                                    | 5,55 Ampere               |
| Open circuit voltage ($V_{oc}$)                                        | 21,6 Volt                 |
| Short circuit current ($I_{sc}$)                                       | 6,11 Ampere               |

**Standard Test Conditions (STC):**

- Solar irradiance: 1000 W/m²
- Temperature: 25°C

The tested PV module consists of 36 cells connected in series. The number of peak powers produced by a shaded PV module is varied according to the number of bypass diodes connecting the cells in the PV module. A two-peak power of a shaded PV module can be produced by dividing the cells into two groups using two bypass diodes. In total, there are 6 bypass diodes used to obtain different peak power conditions. Different combinations of bypass-diodes connecting the number of cells in a string will form different peak power characteristics of a shaded PV module. The global peak is considered as the highest power gained under a partial shading condition. The tested PV module is modelled using a one-diode model as shown in (3) and simulated using the Newton-Raphson algorithm. The simulation is done using Matlab/simulink software as shown in figures 5 and 6. The connection of the tested PV module to the circuit, which consists of the combination of the GWO algorithm and the Boost converter, is also simulated using Matlab/simulink software.
5. Result of the simulation

This simulation was performed with several scenarios to investigate the ability of the GWO method to obtain the maximum power with multiple-peak power characteristics. Based on reference [7] the multiple peak power is developed in two circumstances:

- Multiple peaks due to the effect of the location and the number of cells undergoing shading.
- Multiple peaks due to the effect of partial shading and temperature.

5.1. Simulation result

The simulation result of how the GWO algorithm obtains the maximum power point of a tested PV module under a partial shading condition is shown in figure 7.
The performance of the GWO algorithm in tracking the maximum power point of a shaded PV module with a two-peak power output at irradiance level of 300 W/m².

As shown in figure 7a, the PV module under test produces a two-peak power output under a partial shading condition. The highest peak power is reached at 30 Watts. The GWO is able to reach the same maximum power of a shaded PV module within 0.15 seconds at 30 Watts.

The performance of the GWO method in finding the maximum power point of a PV module at different shading conditions is shown in table 2. Its performance is also compared to the PNO algorithm. In any shading conditions, the GWO outperforms the PNO algorithm in reaching the global peak of the shaded PV module. In average, its accuracy is more than 97% for any shaded condition. The PNO algorithm is not reliable in finding the maximum power of a shaded PV module at any shading conditions with an accuracy of 59% in average. Therefore, it is not preferable for tracking the maximum power point of a shaded PV module.
Table 2. The comparison of GWO and PNO algorithms in obtaining the maximum power point of a shaded PV module.

| Number of peaks | P-V curve | Maximum Power (Watts) | Accuracy (%) |
|-----------------|-----------|------------------------|--------------|
|                 | Local peak | Global peak (Maximum Power) | GWO | PNO | GWO | PNO |
| 2               | 56.25      | 58.22                  | 56.24        | 38.50 | 96.59 | 66.12 |
| 2               | 56.25      | 58.22                  | 56.25        | 38.50 | 96.59 | 66.12 |
| 2               | 36.92      | 54.09                  | 53.45        | 24.40 | 98.81 | 45.11 |
| 2               | 36.92      | 54.09                  | 53.24        | 24.40 | 98.42 | 45.11 |
| 2               | 36.92      | 54.09                  | 53.71        | 24.40 | 99.38 | 45.11 |
| 4               | 11.52      | 36.90                  | 35.93        | 24.40 | 97.37 | 66.12 |
| 4               | 11.52      | 36.90                  | 35.93        | 24.40 | 97.37 | 66.12 |

6. Conclusion
In conclusion, the GWO algorithm outperforms the PNO algorithm in tracking the maximum power point of a PV module under any partial shading conditions. It is also faster in reaching the maximum point power of a shaded PV module within 0.15 seconds. In average, the GWO algorithm is able to track the maximum power point of a shaded PV module with an accuracy of 97%. Comparing to the GWO method, the PNO method is not preferable to track the maximum power point of a shaded PV module.

7. References
[1] Patel H and Agarwal V 2008 IEEE Trans Energy Convers 23 pp 302–310
[2] Sera D, Mathe L, Kerekes T, Spataru SV and Teodorescu R 2013 IEEE J Photovoltaics 3 pp 1070-1078
[3] Tiong Meng Chung TMC, Daniyal H, Sulaiman MH, Bakar MS 2016 Comparative study of P&O and modified incremental conductance algorithm in solar maximum power point tracking Institution of Engineering and Technology In 4th IET Clean Energy and Technology Conference (CEAT 2016) pp 43 (6 .)-43 (6 .)
[4] Ishaque K, Salam Z, Shamsudin A, Amjad M 2012 Appl Energy 99 pp. 414–422
[5] Mirjalili S, Mirjalili SM, and Lewis A 2014 Adv Eng Softw 69 pp 46–61
[6] Mohanty S, Subudhi B, and Ray PK 2016 IEEE Trans Sustain Energy 7 pp 181-188
[7] Nguyen XH 2015 Environ Syst Res 7 pp 1-10.