Adaptive voltage control for MPPT-firefly algorithm output in PV system

L N Palupi\textsuperscript{1,*}, T Winarno\textsuperscript{1}, A Pracoyo\textsuperscript{1} and L Ardhenta\textsuperscript{2}

\textsuperscript{1} Department of Electrical Engineering, State Polytechnic of Malang Soekarno Hatta St. 9 Malang, Indonesia
\textsuperscript{2} Department of Electrical Engineering, Brawijaya University, MT Haryono St. 167 Malang, Indonesia

*lucky.nindya.palupi@gmail.com

Abstract. In general, Photovoltaic (PV) array is not able to generate maximum power automatically, because some partial shading caused by trees, clouds, or buildings. Irradiation imperfections received by the PV array are overcome by applying Maximum Power Point Tracking (MPPT) to the output of the PV array. In order to overcome these partial shading problems, this system is employing Firefly Algorithm (FA) as MPPT method. It optimizes the output power of the solar PV array by Zeta Converter. Output voltage of MPPT has high rate such that it needs stepdown device to regulate certain voltage. Constant voltage will be the input voltage of Buck Converter and controlled using Adaptive PID. Adaptive control based on MRAC has design that almost same as the conventional PID structure and it has better performance in several conditions. The proposed system is expected to have stable output and able to perfectly emulate the response of the reference model. From the simulation results, it appears that FA have high tracking accuracy and high tracking speed to reach maximum power of PV array. In the output voltage regulation, adaptive control does not have a stable error status and consistently follows the set point value.

1. Introduction

Energy is very necessary in human life, this utilization represents economic and social development. Many countries try to find ways to solve energy problems that include energy resources, environmental pollution, global warming, and energy inefficiency. This is why researchers around the world are interested in studying renewable energy sources, such as Photovoltaic (PV) [1]. PV generally cannot work directly at its maximum power, because the PV operating voltage mostly follow the battery voltage connected to the PV. Therefore, the application of Maximum Power Point Tracking (MPPT) must be used to regulate PV module in order to achieve Maximum Power Point (MPP) [2-4]. Commonly problems in PV that are connected in an array certainly not all receive the same level of irradiation and maybe even some of them are covered in shadows caused by trees, clouds, or other objects. In this condition, the power generated from each PV module becomes unbalanced, such that the total output power will decrease and also cause multi-peak on the PV characteristic curve [5-8].

Many researchers have developed various MPPT methods to track PV's maximum power points and overcome problems caused by partial shadows, and several methods have reached an optimal solution [8-11]. For this reason, a metaheuristic algorithm with an examination concept is used as an optimization
problem without defining a definite objective function. Firefly Algorithm (FA) can obtain global peaks by utilizing randomization to avoid trapping algorithms at local peak [12,13]. To keep the voltage value maintained in accordance with the reference value of the maximum power value obtained by MPPT, the right controller is needed. DC-DC converters are a real form of DC voltage regulators both up, down, or both. System dynamics are needed to design controllers that are able to achieve the desired value. PID control is widely applied in the industrial world with a variety of adjustment techniques [14]. One of the adaptive techniques is that MRAC has succeeded in increasing the system response rather than the fixed parameter PID controller [15-18] by providing a reference model followed by the system response. MIT rules are used in this study to determine adaptive PID parameters [19]. Therefore, the main objective of this research is to emphasize how to design an MPPT system that has a constant output voltage.

2. System description
In this system uses two DC-DC converters, a zeta converter and a buck converter that connects the PV array to generate power in load demand. In order to obtain the maximum power of the PV array, this research is using zeta converter. The second DC-DC converter or buck converter is used to control the output voltage at 12V. The system will be simulated according to the original conditions, starting from the PV array, zeta converter, buck converter and load as a given disturbance. The block diagram of the proposed system is illustrated in Figure 1.

**Figure 1.** Block diagram of proposed system.

2.1. *MPPT-firefly algorithm in PV array*
PV array is a combination of several PV modules that are expected to produce high voltage or current or even power than a PV module. The power generated has a higher voltage value so that it can be used for more loads. In this research using a PV array with 3 PV modules that are connected in series and have a partial shadow issues or failure of the PV module. The voltage at MPP, current at MPP, and MPP from PV module are successively represented by $V_{mp}$, $I_{mp}$, and $P_{mp}$ as shown in Figure 2. Thus, the voltage on the MPP of the PV array connected in series is $3 \times V_{mp}$, the current at MPP is $I_{mp}$, and the maximum power is $3 \times P_{mp}$.
PV arrays using the FA algorithm applied to MPPT are expected to be able to achieve global MPP values with non-uniform irradiation conditions. This algorithm is applied to DC converters namely Zeta Converter as shown in Figure 3. This converter has buck capability and boost capability but has non-inverting output voltage values. The FA algorithm has two basic functions of flickering, namely for communication between fireflies (aim to attract other fireflies) and to attract their prey. The attractiveness of fireflies is determined by the brightness of the fireflies associated with the value of the objective function. The inputs of FA are the output voltage and current of PV array.

The relative attraction value $\beta$ depends on the evaluation of other fireflies. Thus, the attraction will vary according to the distance $r_{ij}$ between fireflies $i$ and fireflies $j$. The attraction of $\beta$ can be determined by

$$\beta = \beta_0 e^{-\gamma r^2}$$

where $\beta_0$ is the attraction at $r = 0$ or the initial attraction. $\gamma$ usually varies between 0.1 to 10 [4].
The distance between the two fireflies $i$ and $j$ at the positions $x_i$ and $x_j$ can be defined as Cartesian distance

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2}$$ (2)

where $x_{i,k}$ and $x_{j,k}$ are the $k$-component in the spatial coordinates of the firefly $i$ and firefly $j$, and $d$ is the dimension number. For the MPPT case, which is a 1-dimensional case, the value $d = 1$ is used.

Movement of fireflies that are attracted to fireflies that are brighter is determined by

$$x_i = x_i + \beta \cdot (x_j - x_i) + \alpha \cdot (\text{rand} - \frac{1}{2})$$ (3)

The second part of equation (2-9) shows the movement of fireflies based on their appeal to lighter fireflies. The third part of equation (2-9) shows the movement based on random values where $\alpha$ is a random parameter with $\alpha \in [0,1]$ and rand is a random perturbation value between 0 to 1 [4]. Randomization provides a good way to avoid local search and to move to search on a global MPP. In general, small $\alpha$ values tend to lead to local search, while large $\alpha$ leads to global search [8].

On the MPPT system, $x_i$ or the position of the fireflies is $V_{ref}$ and it is compared the brightness of the fireflies or the output power of PV ($P$) in that position. Other variables of FA that are converted to PV systems can be seen in Table 1.

**Table 1. Conversion of PV systems to FA variables.**

| FA               | PV System                  |
|------------------|----------------------------|
| Position of fireflies ($x_i$) | Input voltage ($V_{ref}$)  |
| Distance between fireflies ($r_{ij}$) | Voltage Deviation ($\Delta V_{ref}$) |
| Attraction ($\beta$) | Exponential function of $\Delta V_{ref}$ |
| Brightness       | MPP ($P$)                  |
| Brightness of the brightest fireflies | Global MPP ($P_{greatest}$) |

Because the converter can only respond to one command at a time, the fireflies are initialized and then treated in the same manner in succession. The flow diagram of the FA control behavior for MPPT is shown in Figure 4.

**Figure 4. Flowchart of MPPT-firefly algorithm.**
2.2. Adaptive control in buck converter

Adaptive controller is applied to second DC converters namely buck converter. The configuration of buck converter is shown in Figure 5. The desired output voltage is a step down voltage which is generated by the Pulse Width Modulation (PWM). PWM sets the ignition on the buck converter switch based on the duty cycle value. In this study, buck converter operates in CCM (Continuous Conduction Mode) so that the inductor current is always greater than zero. The advantages of buck configuration are high efficiency, simple circuit, no need for transformers, low stress level on switch components, and small ripple at the output voltage, furthermore, the filter needed is relatively small. The buck converter circuit does not have an isolation component to maintain the system between input and output.

![Buck Converter Block Diagram](image)

**Figure 5.** Block diagram of adaptive control using Buck converter

The state space averaged model is obtained by combining the ON and OFF condition, the mathematical expression for buck converter is shown in (4).

\[
\begin{bmatrix}
\dot{x}_1 \\
\dot{x}_2
\end{bmatrix} =
\begin{bmatrix}
0 & -\frac{1}{L} \\
\frac{1}{C} & -\frac{1}{RC}
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2
\end{bmatrix} + \frac{d}{L} V_i
\]

Designing an adaptive control according to reference model (MRAC) is one type of adaptive control structure by developing adaptation parameters for PID control using certain rules.

The Buck converter uses one inductor and one capacitor, which means this system is a 2\(^{nd}\) order system. The system model is described as:

\[
\frac{Y(s)}{U(s)} = \frac{b}{s^2 + a_1s + a_2}
\]

The second-order reference model given by:

\[
\frac{Y_m(s)}{U(s)} = \frac{bm_1s^2 + bm_2s + bm_3}{s^2 + am_1s + am_2 + am_3}
\]

The adaptation error:

\[
\varepsilon = Y_r - Y_m
\]
The cost function is denoted as:

\[ J(\theta) = \frac{1}{2}(\varepsilon^2(\theta)) \]  

(8)

Where \( \varepsilon \) is the difference between the output system and the output model reference or error. MIT rule is employed in this adaptive control design, the change in error respects to the parameter \( \theta \) and the change in parameter \( \theta \) respects to time can determine the value of the cost function to be close to zero so that it obtains the same value as the reference value. \( \gamma \) is a definite positive value that indicates the adaptability of the controller.

\[
\frac{d\theta}{dt} = -\gamma \frac{\partial J}{\partial \theta} = -\gamma \varepsilon \frac{\partial \varepsilon}{\partial \theta} \\
\frac{dK_p}{dt} = -\gamma_p \frac{\partial J}{\partial K_p} = -\gamma_p \varepsilon \frac{\partial \varepsilon}{\partial Y_p} \\
\frac{dK_i}{dt} = -\gamma_i \frac{\partial J}{\partial K_i} = -\gamma_i \varepsilon \frac{\partial \varepsilon}{\partial Y_i} \\
\frac{dK_d}{dt} = -\gamma_d \frac{\partial J}{\partial K_d} = -\gamma_d \varepsilon \frac{\partial \varepsilon}{\partial Y_d}
\]  

(9)

Where, \( \frac{\partial J}{\partial \varepsilon} = \varepsilon \cdot \frac{\partial \varepsilon}{\partial Y_p} = 1 \)

The adaptive PID controller parameters \( K_p, K_i, \) and \( K_d \) are shown in (10).

\[
\frac{dK_p}{dt} = -\gamma_p \frac{\partial J}{\partial K_p} = -\gamma_p \varepsilon \frac{b s}{s^2 + (a_1 + b K_p) s^2 + (a_2 + b K_p) s + b K_p} \left[ R(s) - Y_p(s) \right] \\
\frac{dK_i}{dt} = -\gamma_i \frac{\partial J}{\partial K_i} = -\gamma_i \varepsilon \frac{b s^2}{s^2 + (a_1 + b K_i) s^2 + (a_2 + b K_i) s + b K_i} \left[ R(s) - Y_i(s) \right] \\
\frac{dK_d}{dt} = -\gamma_d \frac{\partial J}{\partial K_d} = -\gamma_d \varepsilon \frac{b s^2}{s^2 + (a_1 + b K_d) s^2 + (a_2 + b K_d) s + b K_d} \left[ R(s) - Y_d(s) \right]
\]  

(10)

By stating that \( am_1 = a_1 + b K_p \); \( am_2 = a_2 + b K_p \); \( am_3 = b K_i \)

3. Results and analysis

In this study, using 3 PV modules installed in series as PV array. The use of PV array aims to get a graph that has a maximum of 3 peaks, two local peaks and one global peak. The SP-100-P36 is chosen for PV array modelling. The module has maximum power 60W and 36 series connected polycrystalline cells. The parameters of SP-100-P36 are provided in Table 2. In this research using the FA method to explore the maximum power value at the output of the PV array. Some parameter for FA are summarized in Table 3.

| Parameters                  | Value     |
|-----------------------------|-----------|
| Maximum Power \( P_{\text{max}} \) | 100 W     |
| Voltage at Maximum Power \( V_{\text{mp}} \) | 17.6 V    |
| Current at Maximum Power \( I_{\text{mp}} \) | 5.69 A    |
| Open Circuit Voltage \( V_{\text{oc}} \) | 22.6 V    |
| Short Circuit Current \( I_{\text{sc}} \) | 6.09 A    |

Table 2. SP-100-P36 solar module parameters.

| Parameter               | Value |
|-------------------------|-------|
| Number of Fireflies \( N \) | 5     |
| Firefly attractiveness \( \beta_0 \) | 1     |
| Light absorption coefficient \( \gamma \) | 1     |
| Random Parameter \( \alpha \) | 0.1   |
| Tolerance Value \( \epsilon_1 \) | 1     |

Table 3. FA parameters.
The output of the zeta converter is unstable at a certain value, so controller is required to make the output voltage stable. Constant voltage will be controlled using adaptive PID controller and the output voltage will be constant in set point. The second DC converter used in this research is buck converter. Buck converters have the following parameters, $L = 1mH$, $C = 470\mu F$, $R = 100\Omega$ and input voltage of $52V$.

In this system will have two scenarios, namely the first case is a situation where the PV array is affected by the shadow or not; and the second case is the input voltage of the buck converter changes. Table 4 shows MPP of each case.

| Case | Irradiation (W/m²) | MPP (W) |
|------|-------------------|---------|
|      | M1    | M2    | M3    |
| 1    | 1000  | 1000  | 1000  | 300.432 |
| 2    | 900   | 800   | 700   | 246.253 |

In Figure 6 and Figure 7 show the MPPT signal (proposed method and P&O) from the zeta converter to output voltage of buck converter at $1000W/m²$ irradiation uniformly and experiences different partial shadows on each module. Figure 6 shows the output power of MPPT accordance with the maximum power of PV is $300,238W$. There is a little error that occurs due to the determination of the parameters of the PSO that is not optimal yet. The voltage generated by the buck converter matches the desired voltage which is $12V$. The same results are shown in Figure 7, when the PV array gets unequal irradiation, the maximum power value obtained is $245,873$. Clearly, MMPT systems are able to achieve maximum power with tracking accuracy up to $98.76\%$ and tracking time is less than $0.3$ seconds. This shows that the designed MPPT and controller are work properly.

![Figure 6. (a) Output power of MPPT and (b) output voltage of buck converter in case 1.](image)
In order to find out the controller is working well, then in this study carried out changes in the input voltage of the buck converter as shown in Figure 8. The input voltage starts at 53V and then rises to 58 V at \( t = 0.2 \), the response of output voltage in accordance with the desired value of 12 V. The same thing happens when the input voltage drops to 45V at \( t = 0.3 \), the output voltage is fixed and does not change at set point value.

4. Conclusion
The FA method finds maximum power point accurately after that adaptive controller generate the stable output voltage. From the simulation results, it appears that FA have high tracking accuracy and high tracking speed to reach maximum power of PV array. Furthermore, the output voltage regulation, adaptive control does not have error steady state and consistently follows the set point value.

Acknowledgments
The authors would like to express the gratitude for research funding given by Penelitian dan Pengabdian Kepada Masyarakat Politeknik Negeri Malang (P2M – Polinema) through Penelitian Unggulan 2019.
References

[1] Chao K H, Chang L Y and Liu H C 2013 Maximum Power Point Tracking Method Based on Modified Particle Swarm Optimization for Photovoltaic Systems International Journal of Photoenergy 1-6

[2] Patel H and Agarwal V 2008 Maximum Power Point Tracking Scheme for PV Systems Operating Under Partially Shaded Conditions IEEE Transactions on Industrial Electronics 55 4 1689-1698

[3] Nema S, Nema R K and Agnihotri G 2010 Matlab / Simulink Based study of Photovoltaic Cells / Modules / Array and Their Experimental Verification International Journal of Energy and Environment 1 3 pp 487-500

[4] Yetayew T T, Jyothsna T R and Kusuma G 2016 Evaluation of Incremental Conductance and Firefly Algorithm for PV MPPT Application under Partial Shade Condition Proc. Int. Conf. Power Syst. pp 1-6

[5] Sundareswaran K, Peddapati S and Palani S 2014 Matlab / Simulink Based study of Photovoltaic Cells / Modules / Array and Their Experimental Verification International Journal of Energy and Environment 1 3 pp 487-500

[6] Yibin Z, Weiying W, Weirong C and Qi L 2016 Research on MPPT of Photovoltaic System Based on PSO under Partial Shading Condition Proceedings of the 35th Chinese Control Conference 8654-8659

[7] Syafaruddin S, Karatepe E and Hiyama T 2009 Artificial Neural Network-Polar Coordinated Fuzzy Controller Based Maximum Power Point Tracking Control Under Partially Shaded Conditions IET Renewable Power Generation 3 2 239-253

[8] Teshome D F, Lee C H, Lin Y W and Lian K L 2017 A Modified Firefly Algorithm for Photovoltaic Maximum Power Point Tracking Control Under Partial Shading IEEE Journal of Emerging and Selected Topics In Power Electronics 5 2 pp 661-671

[9] Yang X 2009 Firefly algorithms for multimodal optimization. Stochastic algorithms: foundations and applications (Springer Berlin Heidelberg) pp 169-178

[10] Yang X 2010 Nature-Inspired Metaheuristic Algorithms 2nd ed. (Frome: Luniver Press)

[11] Luque A and Hegedus S 2003 Handbook of Photovoltaic Science and Engineering (England: John Wiley & Sons Ltd)

[12] Zhang Q, Sun X, Zhong Y and Matsui M 2009 A Novel Topology for Solving the Partial Shading Problem in Photovoltaic Power Generation System (IEEE) pp 2130-2135

[13] Wang J, Yi Y, Yang Y, Zhang G and Huang S 2017 Research on Distributed Multi-peak Maximum Power Tracking Control (IEEE) pp 2337-2341

[14] Ang K H, Chong G and Li Y 2005 PID control system analysis, design, and technology IEEE Transactions on Control System Technology 13 4 pp 559-576

[15] Seborg D E, Edgar T F and Mellichamp D A 2004 Process Dynamic and Control 2nd edition (Wiley: New York)

[16] Bequett B W 2003 Process Control Modelling and Simulation (New Jerky: Prentice- Hall)

[17] Lavretsky E and Wise K A 2013 Robust and adaptive control: With aerospace applications, ser. Advanced textbooks in control and signal processing (London and New York: Springer)

[18] Krstic M, Kanellakopoulos I and Kokotovic P V 1995 Nonlinear and adaptive control design (New York: Wiley)

[19] Parks P C 1966 Liapunov Redesign of Model Reference Adaptive Control Systems IEEE Transaction on Automatic Control 11 6