A meta-heuristics search algorithm as a solution for energy transfer maximization in stand-alone photovoltaic systems

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ABSTRACT

This paper studies the problem of MPPT (maximum power point tracking) for photovoltaic systems. The paper offers new solution framework for the above mentioned popular problem in two senses. Firstly a novel MPPT technique is presented. The main idea behind it is to improve the computational efficiency of the traditional incremental conductance tracking algorithm. This is achieved by integration with the fractional open circuit voltage method leading to fast and accurate convergence to the MPP. Secondly, with the aid of certain class of meta-heuristics search algorithms – inspired from the real ant behavior – the MPPT problem is amenable to solution for two different and well known control schemes namely incremental conductance plus proportional integral controller and fuzzy control. A comparison with conventional approach reflects the superiority of the new framework even under fast changing climatic conditions.

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1. Introduction

In the world of today there is a need for alternatives to the large coal and oil fired power plants. Renewable energy is one way to go, and in particular solar photovoltaic and wind turbines have proven to be a solution [1]. The arrival of the new power devices technologies, new circuit topologies and novel control strategies are contributing to the success of the renewable energy generation technologies.

Due to low energy conversion efficiency and high initial cost of the photovoltaic (PV) systems, it is desirable to work with the maximum possible efficiency and to optimize the design of all elements for such systems. In this environment, maximum power point tracking (MPPT) controllers are becoming an essential element in PV systems. The main aim of such tracker is to vary the module operating current and voltage such that the maximum output power is achieved in a fast and accurate manner under variable atmospheric conditions. The task of this controller can be realized through a DC–DC converter with variable duty cycle (D) [2].

To extract the maximum power from PV generators, many approaches have been proposed such as perturb-and-observe [3], incremental conductance (IncCond) [4], curve fitting [5], fractional open circuit voltage (F.O.C.V) and short circuit current techniques [6–7]. Recently maximum power point (MPP) tracking techniques can be implemented using fuzzy logic methods [8], and neural networks [9].

Simple feedback control that depends on linear control theory such as the proportional Plus Integral (PI) controller has also been used because of its simple structure, better robustness and high reliability; see for instance [10–12]. In [10], based on the fact that a linear relationship exists between Impp and the level of irradiance, the current Impp is thus found by sensing the irradiance level and a PI controller is used such that the PV array current follows Impp. While, in [11], Impp and Vmpp are computed from equations involving temperature and irradiance levels, which are not usually easy to measure. Once Impp and Vmpp is obtained, feedback control is used to force the PV array to operate at the MPP. In [12], the IncCond technique was presented by adding the instantaneous and the incremental conductance to generate an error signal. This error signal goes to zero at MPP, so a simple PI control was used to drive e to zero. This conventional approach of such an application demands the implementation of a PI controller characterized by two main drawbacks, the slow transient response and the possible
undesirable oscillations around the MPP. Specifically, PI controller requires sufficient time for the system to reach steady state operation increasing the time interval between two successive reference outputs from MPPT controller and hence deteriorating dynamic performance [13]. Moreover, the inherent nonlinearities in the PV power source may cause the performance of the PI controller to severely degrade due to improper tuning for its gain parameters that even lead to instability and loosing energy from PV panels. Various solutions for these problems are offered in the literature [14, 15]. In [14] a robust control using a PI regulator is used to track this MPP. The synthesis of this regulator (Kp and KI) has been achieved by using Bode method. The authors in [15] ensured energy utilization efficiency for a photovoltaic-powered permanent magnet DC motor drive system by using a dynamic error loop supported PID controller that operates as an adaptive type multipurpose controller capable of handling parameter changes, load, and/or source excursions. The dynamic PID controller's performance is enhanced using tri loop activation to improve PV array-load bus maximum power matching condition. In [13], a Fixed Step-Model Predictive Controller based on the modified incremental conductance algorithm is implemented. Although, these different techniques offer a solution for the above mentioned problems associated with conventional approaches, the most obvious limitations in these applications are the required computational effort and the quality of the microprocessor used in implementation of efficient control techniques.

The area of auto-tuning of PID controller using artificial intelligence such as fuzzy systems has attracted many authors [15–17]. However, a common bottleneck encountered in fuzzy controller design is that derivation of fuzzy rules is often difficult and time-consuming, and relies on expert knowledge.

In order to improve on the tracking efficiency, artificial intelligent approaches such as fuzzy logic methods [8], and neural networks [9] have been proposed to adjust the duty cycle of the converter for MPP tracking. Although neural network control methods can provide better MPPT performance than traditional and fuzzy logic control (FLC) methods, neural network control methods require the measurements of solar radiation and cell temperature.

Fuzzy logic controllers have been introduced in the tracking of the MPP in PV systems [2, 18]. They have the advantage to be robust and relatively simple to design as they do not require the knowledge of the exact model. They do require on the other hand the complete knowledge of the operation of the PV system by the designer [18]. A FLC can easily incorporate all the qualitative knowledge about the behavior of the system required to perform the MPPT.

A Mamdani FLC has been proposed to perform the MPPT, these kinds of controllers are usually used in feedback control mode, because they are computationally simple, present low sensibility to noise in the input (which is important in power system), and can easily represent the knowledge about the control action [19].

The fuzzy controller introduced in [20] uses dP/dI and its variations ∆dP/dI dl as the inputs and computes MPPT converter duty cycle. The shortcoming of this approach is the ignorance of duty cycle variations, which results in an acceptable accuracy level with poor dynamic characteristics (Fig. 11 of [20]). The fuzzy tracker of [21] considers variation of duty cycle, but replaces dP/dI by the variation of panel power. This tracker has fine dynamic behavior with limited accuracy (Fig. 21 of [15]). The authors in [22] used a combination of fuzzy logic presented in [20, 21] as a solution for the trade off problem between the dynamic behavior and the accuracy level. However, despite of the good results provided by all the aforementioned works, all have some common drawbacks that can be summarized in the following points:

(a) The behavior of a FLC depends on shape of membership functions and the rule base.
(b) The design of the FLC was done according to the trial-and-error method rather than a guided approach.
(c) The presence of an expert knowledge is compulsory; conversely, in the absence of such knowledge, their design is usually slow and not optimized [23].

To provide a way of surmounting this shortcoming, the authors in [24–25] choose the Genetic Algorithms (GAs) tool to optimize the FLC of their MPPT tracker. In [26], swarm optimized T-S fuzzy logic controller for MPPT is suggested. These proposed solutions lead to a good performance improvement of the MPPT tracker addressed. Nevertheless, a literature review in the area of FLC’s design [27] reveals that in such a situation, the designed FLC is not yet optimal and still requires the use of an expert’s experience to design the control rules.

Meta-heuristics find many applications in a variety of practical and difficult combinatorial optimization problems in wide fields ranging from management science to computer science. Under the umbrella of meta-heuristics there are varieties of heuristics procedures such as genetic algorithms, greedy random adaptive search procedures, simulated annealing, tabu search, and ant algorithms.

Recently, the social inspired optimization algorithms become a successful alternative for the conventional tuning method to adapt the PID controllers. Using these new methods, the global optimal or suboptimal solutions of the optimized control scheme are found. These algorithms are adopted by many researchers for tuning PID controller in its classical and intelligent forms. One such approach is Ant System Optimization (ASO) which was founded on the foraging behavior of ants and their indirect communication based on pheromones, see for instance [28]. ASO has been applied to several combinatorial problems such as job scheduling, routing optimization in data communication networks and telephone networks [29].

This paper is considered as an attempt to incur the limitations associated with conventional PID and traditional FLC design via proposing an automated method for adapting the FLC parameters and the PID gains using ant colony optimization approach. Hence, an easy to implement MPPT technique without any additional cost is offered. ASO is employed and tailored to design the PI-MPPT and Fuzzy-MPPT controller gains or weights. The objective of ant system optimization in this paper is to improve both the design efficiency of PI and fuzzy control systems and its performance to get optimal PI gains and fuzzy agent parameters. The paper presents design procedures for a model free ant based PI and adaptive fuzzy controllers. The optimal gains of the both controllers are obtained using settling time and steady state error of unit step response of the PV closed loop system as the performance indexes.

This paper has three main contributions. Firstly, a modified technique that incurs the limitations of the traditional MPPT techniques is presented. Secondly, an optimized PI and adaptive fuzzy controllers based MPPT have been designed for standalone PV system using certain class of meta-heuristics search algorithms. Thirdly, depending on these two improvements a satisfactory dynamic closed loop PV system performance is achieved with respect to the conventional control method and traditional fuzzy system approach.

The paper is organized as follows: Section 2 presents the idea of the two MPPT techniques that will be combined together to obtain the proposed technique. The proposed MPPT technique is applied to PV system in Section 3. Section 4 addresses new solution frameworks using ant system algorithm. Section 5 shows the simulation results of PV system using the proposed technique. Finally, a conclusion is set in Section 6.
2. MPPT techniques

The $I-V$ and $P-V$ characteristics of the photovoltaic module under study are shown in Fig. 1. These characteristics are for the studied module BP7185S-Saturn 7 series. The maximum power occurs at the knee of the $I-V$ curve as shown in the same figure. Many MPPT techniques were developed in the literature aiming at fast and accurate tracking. The following MPPT techniques are adopted and combined together in order to enhance the output power response of the proposed standalone PV system as will be shown in the following sections. In the literature there are many other MPP tracking techniques but would not be discussed in this paper.

2.1. Fractional open-circuit voltage

This method uses the approximate ratio of the PV module MPP voltage $V_{\text{MPP}}$ to its open circuit voltage $V_{\text{OC}}$ which is nearly constant as a simple feed forward technique for tracking the maximum output power, as can be seen:

$$V_{\text{MPP}} \approx K_1 \times V_{\text{OC}}$$  \hspace{1cm} (1)

The factor $K_1$ has been reported to be between 0.71 and 0.78. Once the constant $K_1$ is calculated, VMPP is computed by measuring $V_{\text{OC}}$ periodically using pilot PV cells. The problem is that the factor $K_1$ is temperature and irradiance dependent as was stated in [2] and hence the obtained results of such a technique are not accurate. Although the implementation of this method is simple and cheap, its tracking efficiency is relatively low due to the utilization of inaccurate values of the constant $K_1$ in the computation of $V_{\text{MPP}}$.

2.2. Incremental conductance

This method is based on the principle that the slope of the PV module power–voltage curve is zero at the MPP. The operating voltage is changed until $dP/dV$ equals zero which occurs at the MPP as stated in [4]. Using Fig. 1, the ratio $\Delta P/\Delta V$ follows one of the cases described in (2). The incremental conductance method requires both voltage and current sensors in addition to a DSP or microcontroller. The accuracy of this technique is good but it is usually better when combined with the P&O MPPT technique.

$$\frac{\Delta P}{\Delta V} = \begin{cases} 
0 & \text{at MPP} \\
> 0 & \text{left of MPP} \\
< 0 & \text{right of MPP}
\end{cases}$$  \hspace{1cm} (2)

The IncCond MPPT algorithm usually uses a fixed iteration step size, which is determined by the accuracy and tracking speed requirements. Thus, the corresponding design should satisfactorily address the trade-off between the dynamics and steady state oscillation. To solve these problems, a modified IncCond MPPT with variable step size and constant voltage tracking (CVT) at the start process [30] has been proposed to tune the step size automatically according to the inherent PV array characteristics. However, the high complexity of the method requires high sampling accuracy and fast control speed, which might result in a high cost system.

3. Proposed MPPT technique

The first proposed MPPT technique blends the incremental conductance method with the fractional open circuit voltage technique to drive an optimized PI regulator that depend on social inspired optimization algorithm known as ant colony system. This MPPT tracker changes the duty cycle of the DC–DC converter till the peak power point is obtained.

The second proposed MPPT technique has the same structure but with the aid of optimized adaptive fuzzy logic controller. In [2], the traditional fuzzy agent is adapted by adding different weights for the two inputs of the fuzzy agent. The authors suggested that the error signal should have the full weight while the fine tuned signal which is the change in the error signal may have a smaller weight compared to the error signal. This idea results in a good response even under variable atmospheric conditions (Fig. 12 of [2]). In this paper, the input gains for the traditional Mamdani fuzzy agent suggested in [2] are optimized using ant colony system.

Using (2) and Fig. 1, the parameter $\Delta P/\Delta V$ will be defined as the error signal $E$ which should be equal to zero for best performance and it will be fed to either PI regulator or adaptive fuzzy agent for the purpose of MPP tracking. At the MPP, the error signal equals zero and hence it is desired to keep the error signal at zero value in order to track the MPP. For the fine tuning purpose of adaptive fuzzy agent, the variation of the error signal $\Delta E$ is furthermore defined as a second input for the fuzzy agent. For simulation purposes, the PV model driven in [2] will be adapted to the available

Fig. 1. $I-V$ and $P-V$ characteristics of the studied PV module.
practical module and will be used. The error $E$ and its change $\Delta E$ can be defined by (3) and (4) respectively.

$$E(k) = \frac{P(k) - P(k - 1)}{V(k) - V(k - 1)}$$  \hspace{1cm} (3)$$

$$\Delta E(k) = E(k) - E(k - 1)$$  \hspace{1cm} (4)$$

4. New solution frameworks using ant system algorithm

In this section, the ant system algorithm is tailored to address MPPT problem for simulated stand-alone PV module with battery load. Two different control schemes are used successfully in the new proposed framework.

4.1. Heuristic based ant search algorithm

Meta-heuristics can be classified based on the design methods into one that uses adaptive memory, and another that uses the neighborhood solution space exploration and another as the one that takes into account the number of solutions that is passed along successive iterations. According to Digalakis and Margaritis [31], ”Meta-heuristics for optimization problem may be described summarily as a walk through neighborhoods search trajectory through the solution domain of the problem”. Meta-heuristics incorporate various strategies inspired from natural behaviors of species, mathematical reasoning, physical science, nervous systems, and statistical mechanics. Studies indicate that the meta-heuristic based search procedures help to arrive at solutions of higher quality to practically hard problems in business and industry.

The ant system is the first member of a class of algorithms called Ant Colony Optimization (ACO) that was initially proposed by Colomi et al. [32]. This technique is adopted in this paper due to its simplicity. The main underlying idea, loosely inspired by the behavior of real ants, is that of a parallel search over several constructive computational threads based on local problem data and on a dynamic memory structure containing information on the quality of previously obtained result. In this algorithm, computational resources are allocated to a set of artificial ants that exploit a form of indirect communication mediated by the environment to find the shortest path from the ant nest to a set target. Ant algorithms have been proved to be a quick global optimal solution finder when compared to other heuristics methods such as simulated annealing and genetic algorithms. It also states that the ant algorithms have the quality to find new optimal solution without reinitializing the computations from scratch. Fig. 2 represents a generalized flow chart of the ant algorithms.

4.2. PI controller

Many PI controllers were presented in literature, the expression of PI control law for a continuous time system is given as follows:

$$u(t) = K_P e(t) + K_I \int_0^t e(t) \, dt$$  \hspace{1cm} (5)$$

where $e(t)$ is the error between the input and the output of the system; $u(t)$ is the control action generated by the PI controller; $K_P$ is the proportional gain and $K_I$ is the integral gain.

4.3. Fuzzy agent controller

4.3.1. Fuzzification

Membership function values are assigned to the linguistic variables, using five fuzzy subsets: NB (negative big), NS (negative small), ZE (zero), PS (positive small), and PB (positive big). The partition of fuzzy subsets and the shape of membership functions, which can adapt shape up to appropriate system, are shown in Fig. 3. The choice of the membership functions is based on the error signal variations with voltage as can be seen from Fig. 4. The output (V) membership functions are shown in Fig. 5.

4.3.2. Inference method

The composition operation is the method by which a control output is generated. Several composition methods such as Max-Min and Max-Dot have been proposed in the literature. The commonly used method, Max-Min, is used in this paper. The output membership function of each rule is given by the Min (minimum) operator and Max (maximum) operator. Table 1 shows the rule base of the FLC. The fuzzy rule base table depends basically on the error $E$ variations with voltage change shown in Fig. 3. From Fig. 3, it is clear that the error is positive constant till $V = 25$ V and then it will be positive decaying till $V = 36$ V (at MPP). After the MPP, the error is negative decaying. As long as the error is positive, the voltage should be increased and the rate of increase depends on the rate of change of the error signal $E$ which is used for fine tuning. When the error is negative, the voltage should be decreased and the rate of decrease depends on the fine tuning factor ($\Delta E$).

4.3.3. Defuzzification

The output of this fuzzy controller is a fuzzy subset of control. To get a non-fuzzy value of control, a defuzzification stage is necessary. Defuzzification for this system can be performed by height method. The non-fuzzy value of control output can be gained using a discrete time integrator simply and quickly because the output is the voltage change $\Delta V$.

4.4. Ant based controller optimization problem

Usually, the optimization process consists of finding the controller (here PI and/or adaptive fuzzy (AF) scheme is used) parameters such that to minimize or maximize a given cost function of the closed loop system consisting of an ant based controller and an unknown plant. The optimization of step response of the system under control by minimizing a suitable performance criterion is the aim of this work. The effectiveness of the proposed ant based PI and AF MPPT are quantified by the following performance criteria that are evaluated at the end of a step response experiment. It includes the settling time $t_s$ and steady state error $e_{ss}$ of the system unit step response. The performance criterion of the system $F$ in either case is designed as follows:

$$F = \lambda_1 f_1 + \lambda_2 f_2$$  \hspace{1cm} (6)$$

where $\lambda_1$ and $\lambda_2$ are two weighting coefficients for $f_1$ and $f_2$ which are defined as follows:

$$f_1 = \frac{t_s}{t_s} \text{ and } f_2 = \begin{cases} \frac{e_{ss}}{e_{ss}}, & \text{if } e_{ss} \neq 0 \\ 0, & \text{if } e_{ss} = 0 \end{cases}$$  \hspace{1cm} (7)$$

where $t_s$ and $e_{ss}$ are the reference performance values obtained from trial and error tuning formula. The values of $t_s$ and $e_{ss}$ can also be obtained from a predefined approach like that in [34] as a good initial starting value for better optimization.

Now, the control problem in this paper can be formulated as follows:

*Given* a plant $G(s)$ to be controlled either in Fig. 6 or Fig. 7, *determine* either the optimal PI parameters $K_P$ and $T_I$ or the optimal input adaptive fuzzy agent weighting parameters using ant system algorithm, *so that* the control system has the minimum value of given performance criterion “$F$” (6).
Fig. 6 or Fig. 7 depicts the closed loop control system used in this paper. Using the same technique presented in [33], we can assume that the value of PI gain parameters or fuzzy agent parameters has three digits; one digit before decimal point and the other two digits after the decimal point. Using ant system optimization framework a planar structure of 10 rows and six lines in Fig. 8 are adopted. 10 rows mean numbers from 0:9; six lines mean six bits of two gain parameters $K_p$ and $T_i$ for the PI scheme or two input gain parameters $a_1$ and $a_2$ for the fuzzy agent input weights. The nodes of lines 1, 2 and 3 are the 1st, 2nd and 3rd bits of $K_p$ or $a_1$; lines 4, 5 and 6 are the 1st, 2nd and 3rd bits of $T_i$ or $a_2$. So there are totally 60 nodes. $n_j$ is used to denote the node $j$ on line $L_i$. The coordinate of the node $n_j$ is denoted by $j$. Let an ant depart from the origin $O$. In its each step forward, it chooses a node from the next line $L_i (i = 1, 2, \ldots, 6)$ and then moves to this node along the straight line. When it moves to a node on line $L_6$, it completes one tour. Its moving path can be expressed as $\text{Path} = \{O, n_{11}, n_{22}, \ldots, n_{60}\}$. The following formula's gives the values of $K_p$, $T_i$ (or $K_I$) and $a_1$, $a_2$ represented by the path.

$$K_p = y_{1j} + 0.1y_{2j} + 0.01y_{3j}$$

$$T_i = y_{4j} + 0.1y_{5j} + 0.01y_{6j}$$

$$a_1 = y_{1j} + 0.1y_{2j} + 0.01y_{3j}$$

$$a_2 = y_{4j} + 0.1y_{5j} + 0.01y_{6j}$$

**Fig. 2.** Generalized flow chart for ant algorithms as in [32].
where $y_{ij}$ can be easily defined from Fig. 8. From the moving path in Fig. 8, the values of $K_p$ and $T_i$ represented by the path are easily obtained.

Based on the generalized flow chart in Fig. 2, the design procedures for a model free ant based PI and adaptive fuzzy controllers can be summarized as follows:

1. Start the ant colony algorithm with the aid of predefined controller (PID and adaptive fuzzy) gains.
2. Get $K_p$, $T_i$, $a_1$ and $a_2$ according to Eqs. (8) and (9) by running the ant colony algorithm.
3. Get different unknown parameters in (7) by running Matlab/Simulink simulation for the closed loop system in Figs. 6 and 7.
4. Find the values of “$F$” using (6) for each ant.
5. Repeat (2) and (3) until the max number of iteration reached or the whole ants have the same path (Fig. 8).

Substitute the final obtained gains values again in the closed loop system to find the optimal system dynamic performance.

5. Standalone PV simulation using the proposed technique

In this section, the proposed control techniques namely ant colony system based PI-MPPT (ASPI-MPPT) and ant adaptive fuzzy-MPPT (AAF-MPPT) are applied to the standalone PV system equipped with DC–DC converter and connected to a battery load as configured in Figs. 9 and 10 to achieve maximum power transfer to the load. The goal is to track the MPP on the PV power curve by forcing the PV panel to work at maximum power voltage on its I–V characteristics even under severe varying insulation levels.

5.1. Closed loop control system

At the point of maximum power on the PV power voltage curve, the change of power with respect to change of voltage is equal to zero ($dP/dV = 0$). In Figs. 10 and 11, the signal of $dP/dV$ is chosen as the feedback variable that is compared with zero reference signal and the resulting error signal and the change of this signal $\Delta E$ is

<table>
<thead>
<tr>
<th>Error $E$</th>
<th>Change of error $\Delta E$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$NB$</td>
<td>$NS$ $ZE$ $PB$ $PB$ $PB$</td>
</tr>
<tr>
<td>$NS$</td>
<td>$ZE$ $ZE$ $PS$ $PS$ $PS$</td>
</tr>
<tr>
<td>$ZE$</td>
<td>$PS$ $ZE$ $ZE$ $ZE$ $NS$</td>
</tr>
<tr>
<td>$PS$</td>
<td>$NS$ $NS$ $NS$ $ZE$ $ZE$</td>
</tr>
<tr>
<td>$PB$</td>
<td>$NB$ $NB$ $NB$ $ZE$ $PS$</td>
</tr>
</tbody>
</table>

Table 1
Fuzzy rule table.

Fig. 6. The proposed closed loop control.

Fig. 7. The proposed closed loop control (FLC).

Fig. 8. Ant system optimization planar structure.

Fig. 9. The proposed PV system configuration.

Fig. 10. PV API-MPPT system.
fed to an ant based PI controller and adaptive fuzzy controllers respectively that output a signal for the duty cycle control of the DC–DC converter. The output of the controller that depends on the incremental conductance method is enhanced by the fractional open circuit voltage technique to reduce the settling or tracking time by giving an initial estimation for the operating voltage. Same ant colony optimization algorithm in [35] is used. The idea is to start the proposed algorithm with already known controller (PI or fuzzy) gains then enhance the dynamic response of the closed loop system according to the performance index in (6) via the steps of the algorithm. Finally, the algorithm will reach the optimal parameters of either the PI-MPPT or AF-MPPT ensuring maximum power transfer from the standalone PV system. The proposed technique is applied to the BP7185S-Saturn 7 series module with the electrical characteristics shown in Table 2.

### Table 2
Electrical characteristics of BP7185S AT STC.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Warranted minimum power</td>
<td>185 W</td>
</tr>
<tr>
<td>Voltage at MPP (V&lt;sub&gt;MPP&lt;/sub&gt;)</td>
<td>36.5 V</td>
</tr>
<tr>
<td>Current at MPP (I&lt;sub&gt;MPP&lt;/sub&gt;)</td>
<td>5.1 A</td>
</tr>
<tr>
<td>Open circuit voltage (V&lt;sub&gt;OC&lt;/sub&gt;)</td>
<td>44.8 V</td>
</tr>
<tr>
<td>Short circuit current (I&lt;sub&gt;SC&lt;/sub&gt;)</td>
<td>5.5 A</td>
</tr>
<tr>
<td>Temperature coefficient of V&lt;sub&gt;OC&lt;/sub&gt;</td>
<td>(−160 ± 20) mV/K</td>
</tr>
<tr>
<td>Temperature coefficient of I&lt;sub&gt;SC&lt;/sub&gt;</td>
<td>(0.005 ± 0.015)%/K</td>
</tr>
<tr>
<td>Temperature coefficient of P</td>
<td>(−0.5 ± 0.05)%/K</td>
</tr>
<tr>
<td>NOCT (Air 20°C; sun 800 W/m&lt;sup&gt;2&lt;/sup&gt;; wind 1 m/s)</td>
<td>47 ± 2°C</td>
</tr>
<tr>
<td>Maximum series fuse rating</td>
<td>15 A</td>
</tr>
<tr>
<td>Maximum system voltage</td>
<td>1000 V (IEC 61215 rating)</td>
</tr>
</tbody>
</table>

#### 5.2. Closed loop control simulation results

Simulation experiments using MATLAB/SIMULINK environment are performed in this section to study the dynamic response of standalone PV system with ant colony system based PI and adaptive fuzzy closed loop control. At this point, it should be mentioned that for the simulation process a switched mode DC–DC boost converter was used based on the suggestions of the authors in [36]. The experiments can be categorized as follows:

- Case 1: PI and F-MPPT without F.O.C.V.
- Case 2: PI and F-MPPT with F.O.C.V.
5.3. Results of the ant system framework with PI Control scheme

Firstly the importance of the proposed MPPT technique that is dependent on blending fractional open circuit voltage method with incremental conductance method is reflected in Figs. 12–15. If no fractional open circuit voltage is used as the traditional techniques, the power response of the module will have a large settling time (35 ms) for the case of PI-MPPT and about 20 ms for the case of ASPI-MPPT as shown in Figs. 12 and 14 and hence the use of the fractional open circuit voltage leads to a faster power response as shown in Figs. 13 and 15. Secondly a comparison between PI-MPPT and ASPI-MPPT with and without the aid of fractional open circuit voltage is presented in Figs. 16 and 17. Thirdly, under changing the irradiance level as shown in Fig. 18, the power response of the PV system with ASPI-MPP is presented. Table 3 summarizes the results of each studied case. The proposed ASPI-MPPT method after a very short transient time transferred the maximum power with no overshoot and approximately zero steady state error even under irradiance changes. As it can be seen from the figures, the proposed control method outperforms the traditional control method.

<table>
<thead>
<tr>
<th>Case</th>
<th>$K_p$</th>
<th>$T_i$</th>
<th>$T_s$</th>
<th>$e_s$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.1</td>
<td>0.5</td>
<td>35</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>0.1</td>
<td>0.5</td>
<td>5</td>
<td>0.008</td>
</tr>
<tr>
<td>3</td>
<td>0.54</td>
<td>1.5</td>
<td>19</td>
<td>0.007</td>
</tr>
<tr>
<td>4</td>
<td>0.54</td>
<td>1.5</td>
<td>1</td>
<td>0.006</td>
</tr>
</tbody>
</table>

Fig. 16. PV output power for ASPI and PI-MPPT without F.O.C.V.

Fig. 17. PV output power for ASPI and PI-MPPT with F.O.C.V.

Fig. 18. PV output power for ASPI-MPPT with changing irradiance.

Fig. 19. PV output power for different MPPT with F.O.C.V.
Remark 1. Our approach is different from those of [13–15] in the following ways.

(a) Less computational effort than [13] is required.
(b) An easy to implement technique without any extra cost for the additional control loop [15] is achieved.
(c) A very fast transient response without oscillation around the MPP is performed.

Table 4
Summary of the fuzzy obtained results.

<table>
<thead>
<tr>
<th>Controller type</th>
<th>With F.O.C.V</th>
<th>Without F.O.C.V</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-MPPT</td>
<td>5</td>
<td>60</td>
</tr>
<tr>
<td>AF-MPPT</td>
<td>3</td>
<td>60</td>
</tr>
<tr>
<td>AAF-MPPT</td>
<td>1</td>
<td>73</td>
</tr>
</tbody>
</table>

Table 5
Comparison bet. The enhanced MPPT techniques.

<table>
<thead>
<tr>
<th>Evaluation criterion</th>
<th>Ant PI-MPPT</th>
<th>Ant AF-MPPT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Settling time</td>
<td>1 ms</td>
<td>3 ms</td>
</tr>
<tr>
<td>Steady state error</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dynamic response</td>
<td>Good</td>
<td>Very good</td>
</tr>
<tr>
<td>Analog/digital</td>
<td>Analog or digital</td>
<td>Digital</td>
</tr>
<tr>
<td>Hardware complexity</td>
<td>Simple</td>
<td>Complicated</td>
</tr>
</tbody>
</table>

Fig. 20. Duty cycle variation with F.O.C.V.

Fig. 21. PV output power for F-MPPT with and without F.O.C.V.

Fig. 22. PV output power for AF-MPPT with and without F.O.C.V.

Fig. 23. PV output power for AAF-MPPT with and without F.O.C.V.

Fig. 24. Input solar irradiance variation.

Fig. 25. PV output power for F&AAF-MPPT with changing irradiance.
5.4. Results of the ant system framework with fuzzy Control scheme

Figs. 19–23 depict the privileges of the proposed MPPT technique that enhances the traditional Fuzzy Logic tracking algorithm via integration with F.O.C.V method. If no fractional open circuit voltage is used as the traditional techniques, the power response of the module will have a large settling time compared with the case where the F.O.C.V is used. The following Table 4 represents the settling time for each controller. The use of the fractional open circuit voltage leads to a faster power response.

The MPP tracking dynamic performance in Fig. 19 for the PV system of the optimized adaptive fuzzy controller (AAF-MPPT) is obviously enhanced compared with the traditional trial & error adaptive fuzzy MPPT (AF-MPPT). The AAF-MPPT agent in turn controls the duty cycle of the DC–DC converter used for load matching in order to keep the operating point of the PV module at ($V_{MPP}$, $I_{MPP}$). For a load of 12 V DC as an example, the duty cycle of the buck converter will vary with time as shown in Fig. 20 through a fuzzy agent adapted by fractional open circuit voltage. As it can be depicted from Fig. 20, duty cycle variations is less for AAF-MPPT case which results in an acceptable accuracy level with good dynamic characteristics. Under changing the irradiance level as shown in Fig. 24, the power response of the PV system with AAF-MPPT in Fig. 25 can achieve accurate result compared with the traditional Fuzzy MPPT (F-MPPT) technique. The proposed AAF-MPPT method, after a very short transient time, transferred the maximum power with no overshoot and almost zero steady state error even under irradiance changes. As it can be seen from the figures, the proposed AAF-MPPT control method outperforms the traditional F-MPPT and AF-MPPT control methods.

Remark 2. Our approach is different from those of [2,20,21] in the following ways.

(a) Less duty cycle variations is obtained for AAF-MPPT case which results in an acceptable accuracy level with good dynamic characteristics.

(b) The AAF-MPPT used is enhanced using the ant colony optimization technique compared to that in [2].

(c) The ant algorithm succeeded in adapting the behavior of the fuzzy agent proposed in [2] by assigning a fine tuned weights for the fuzzy agent inputs.

(d) A very fast transient response without oscillation around the MPP is performed.

A general remark for the both cases can be stated as follows:

Remark 3.

- The Ant system algorithm – that belongs to meta-heuristics search algorithms – is tailored to address the problem of searching MPP for PV applications in two completely different control frameworks.
- The suitability of such robust optimization methodology is proven to a highly nonlinear application like the PV systems.
- The optimized ant PI and adaptive fuzzy logic namely ASPI-MPPT and AAF-MPPT can facilitate the tracking of maximum power faster and minimize the PV output power variation.

A comparison between both MPPT techniques is presented in Table 5. A tradeoff between system dynamic performance, real hardware design and cost of system components should be performed by PV system users.

Finally, Table 6 provides a brief comparison between the proposed technique in this paper and the genetic algorithm approach as a previously literature [37] to show the effectiveness of the designed technique.

In [38], from the simulation and experimental results, the fuzzy logic controller can deliver more power than the neural network controller and can give more power than other different methods in literature. Furthermore, in [9], the ANF Fuzzy logic based control low depends on Nonlinear Autoregressive Moving Average approach and a model of the plant needs to be identified on the basis of input–output data and then used in the model-based design of a neural network controller. So the suggested controller seems to be more complicated and may lead to increase in the computational burden if it is compared to our case.

6. Conclusion

A certain class of meta-heuristics search algorithms – inspired from the real ant behavior – is tailored to adapt the control law in two different and well known control schemes. In particular, PI controller and adaptive fuzzy agent are fine tuned using ant colony system algorithm and tested on a simulated stand alone photovoltaic array with battery load. The proposed MPPT tracking technique enhances the initial starting point of the traditional tracking algorithms. The optimization methodology depends on the ant colony algorithm and the fast maximum power transfer is achieved by the aid of the fractional open circuit voltage through an initial estimation of the MPP that lead to fast and accurate convergence to the MPP. The developed controllers not only ensure maximum power transfer but also outperform the conventional PI and fuzzy agent systems even under variable irradiance levels.

References


Letting Lawrence K, Munda Josiah L, Hamam Alex, Particle swarm optimized T-S fuzzy logic controller for maximum power point tracking in a photovoltaic system. IEEE- IPEC 2010.


