DSP Implementation of a novel artificial bee colony optimization-based MPPT for photovoltaic systems subject to in homogeneous insolation by using direct control

(to be changed)

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Abstract:

Optimal energy harvesting is a key point in any photovoltaic system where economic and efficiency aspects are strongly interrelated. In this paper a novel artificial bee colony optimization-based MPPT is proposed. The proposed Bee's algorithm allows the tracking of the maximal available power from a PV array under uniform and nonuniform illuminating conditions. A co-simulation methodology, combining Matlab/Simulink™ and Cadence/Pspice™, has been used to verify the effectiveness of Bee's algorithm to track the MPP of serially connected PV modules subject to various shading patterns. In addition, a performance comparison with Particle Swarm Optimization (PSO) based MPPT algorithm is also presented. The experimental resuls have shown the validity of the developed heuristic algorithm and its good tracking capabilities under shading conditions.

Keyword:

Highlights

1. Introduction

Photvotaic energy sources are becomming a mature technology where their applications are spreading, ranging from supplying small electronic devices to a large power plants connected to medium and low voltage ditribution electric systems. But some problems remain a challenge for photovoltaic systems as improving the overall efficiency, maximizing the available power, minimizing the return period of the installation cost, fault detection and diagnosis... etc [Swider et al., 2008 ; Elasser et al., 2010 ; Lorente et al, 2014, Silvestre et al, 2013, Thomas et al, 2014,]. Several research works and reports have addressed the issue of low yields and power losses in PV systems facilities and all have approved the use of a power optimizer known as maximum power point traking (MPPT).

Most of the tracking techniques of maximum power point are based on the assumption that all cells in the same module and all modules in the same string receive the same irradiance. Perturb and observe (P&O) and incremental conductance are the most popular algorithm implemented in comercial battery regulator and grid connected inverter and can accuratelly track the MPP under uniforrm illuminating conditions (Lin,2011; Trishan Esram et al, 2007; Salas et al, 2006). However in real conditions of operation, PV modules are subject to partial shading which is a real issue responsible of the most power lowering and mismach [Woyte et al, 2003; Armstrong and Hurley, 2010]. In such conditions the power voltage curves are caraterized by the apparition of multiple locall peaks caused by the activation of bypass diodes avoiding shaded cells from dammage by overheating [Patel and Agarwal, 2008 ; Silvestre et al, 2009, Solórzano and Egido, 2014]. Conventional MPPT algorithm are not designed for such senario and may converge at the first local maxima wich may not be the global maximum. Consequently, a significant usefull power can be wasted where overall system yield could significantly lowered.

To deal with the consequences of shading on the P-V curves, various improvements of the conventional algorithms have been proposed. Some of them are topology based where extra aditional power circuits are neede to perform GMPPT serach [Velasco et al, 2009; Kobayashi et al, 2006; Walker and Pierce ,2006]. Thus, the overall efficiency is reduced and total cost will be increased. Some other techniques are algorithm based, such as artificial neural netwark [Kassem, 2012], fuzzy logic with polar controller [Syafaruddin et all, 2009], sequential extremum seaking control **[Lei et al, 2011]**, dividing rectangle (DIRECT) serach control [Nguyen and Low, 2010]. Two main disadvantages are atributed to th ofermentioned techniques: Time machine consumming and complexe hardware implementation.

Recently, swarm intelligence-based optimization algorithms have gained much attention due to its ability to find near-optimal solutions to difficult optimization problems such as multimodal objective functions. Since the *P-V* curves exhibit multimodal characteristics during PSC, the swarm intelligence-based methods seem to be well suited to track the GMPP. Among the swarm intelligence-based optimization algorithms, the particle swarm optimization (PSO) **[Kashif et al, 2012; Yi-Hwa et al, 2012; Chun-Liang, 2012]** and ant colony optimization (ACO) **[Lian Lian et al, 2013]** offer significant benefits as: no requirement for prior knowledge of internal system parameters; reduction in computational effort and a compact solution for multivariable problems. However, both of PSO and ACO have five parameters to be determined, which makes these algorithms inflexible and complex. In addition PSO convergence significantly depends on the initial place of the agents.

Artificial Bee Colony (ABC) is a relatively new member of swarm intelligence. It was proposed by Karaboga in 2005 [Karaboga, 2005], based on foraging behaviour, learning, memorizing and information sharing characteristics of honeybees. At present, the ABC algorithm has been successfully applied in distinct science fields such as electrical engineering [Ulas and Kürs, 2013; Ahmed et al, 2013], image processing [Cuevasa, 2013], mathematics [Karaboga and Akay, 2009], mechanical engineering [Ahin et al, 2009], civil engineering [Sonmez, 2011] and many others. However, it has not been still applied to MPPT in PV systems. In this work, the ABC algorithm was applied to this field. We propose a novel ABC-based MPPT with direct control for PV systems working under partial shadowing conditions. With this MPPT control scheme the duty cycle is adjusted directly by the algorithm without the need of using a linear controller. In addition, it features an excellent tracking capability, good accuracy, convergence independent of the initial conditions, no requirement of knowledge about the characteristics of PV array and uses just two control parameters.

The rest of this paper is organized as follows: in Section 2 an overview of partial shading on PV modules and its impact on MPP location is given. Section 4, briefly presents the principle of the ABC algorithm and how it is applied to MPPT in PV systems. Section 5 provides simulation results and a discussion of the proposed approach. Comparisons with other methods are also presented in this section. Finally, Section 6 presents the conclusions and directions for future work.

2. PV systems working under partial shading conditions

The overall electrical characteristic of a PV array consisting of set of series and parallel connected modules is obtained by the composition of the individual characteristic of each module. Thus, in series connection whith a uniform illumination, the whole I-V characteristic is obtained by summing point by point voltages for the same currents, while in parallel connection it is obtained by summing currents for the same voltages. However, when a group of PV modules serially connected are partially shaded, the overall I-V characteristic shows steps caused by the activation of bypass diodes preventing the shaded cells from reverse biasing and overheating.

These steps in the I-V characteristic reveals the presence of local mxima in the power-voltage curve where significant power reduction can be noticed. In addition, local maxima will always lead to the failure of the MPPT control especially with classical algorithms such as Perub and Observe or Incremenrtal inductance. In Fig1, it is illustrated the qualitative total power reduction of two PV modules connected in series with one shaded module compared to the total power obtained in case of uniform illumination.

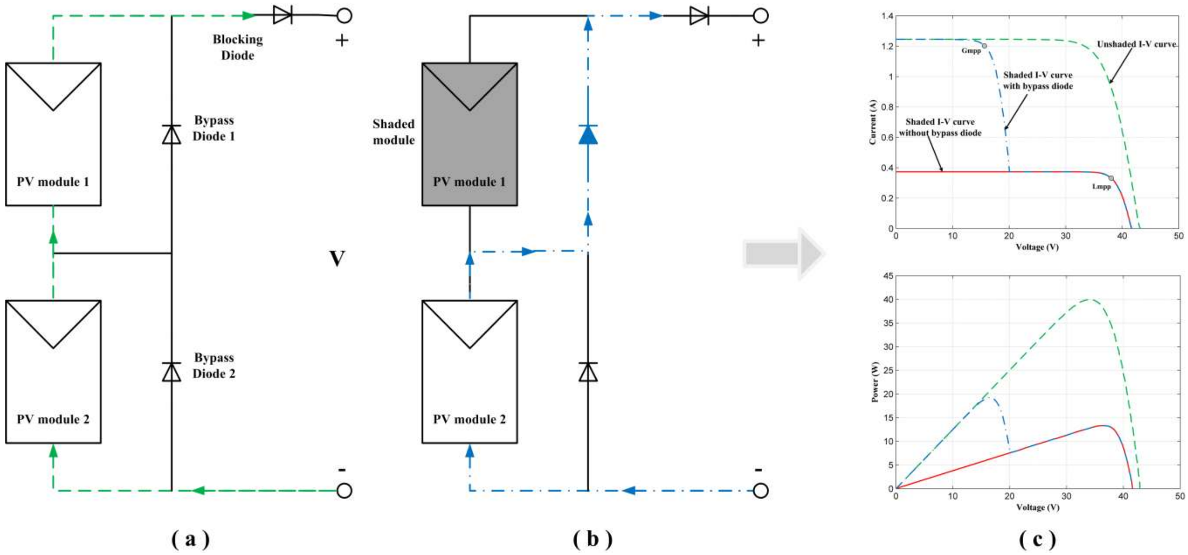

Fig. 1. Operation of PV array: (a) under uniform irradiation, (b) under PSC, (c) the resulting *I-V* and *P-V* curve for (a) and (b).

Thus, it is clearly shown (Fig.1.c) that in order to achieve optimal energy harvesting from the PV array, the system should be operated at the global maximuum power point (GMPP) which need an efficient MPPT method.

3. ABC optimization applied to direct control of MPPT

3.1. Fundamental of ABC optimisation algorithm

The Artificial Bee Colony (ABC) algorithm is a swarm based meta-heuristic algorithm that was introduced for solving multidimensional and multimodal optimisation problems. The algorithm is specifically based on the model proposed by Tereshko and Loengarov [Tereshko, 2000, Tereshko, 2002; Tereshko and Loengarov, 2005] for the foraging behaviour of honeybee colonies.

In the ABC algorithm, the artificial bees are classified into three groups: employed bees, onlooker bees and scouts. A bee that is currently searching for food or exploiting a food source is called an employed bee. A bee waiting in the hive for making decision to choose a food source is named as an onlooker. Employed bees whose food sources cannot be improved through a predetermined number of trials become scouts and their food sources are abandoned. The number of food sources is equal to the number of employed bees and also equal to the number of onlooker bees. Analogously, in the optimization context, the position of a food source represents a candidate solution of the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution.

At the initialisation phase, the ABC generates a randomly distributed initial population of SN solutions. Each solution is produced within its limits according to the equation below:

$$x_i^j = x_{\min}^j + rand[0,1](x_{\max}^j - x_{\min}^j) \quad i = 1,2,...,SN \quad j = 1,2,...,D \tag{1}$$

where $x_{\min}^j$ and $x_{\max}^j$ represent the minimum and the maximum of the parameter j and D is the number of optimization parameters.

After initialization, the population of the solutions is subject to repeated cycles $C = 1,2,...,MCN$, of the search processes of the employed bees, the onlooker bees and the scout bees.

For each cycle, every employed bee produces new solution v_{ij} according to Eq. (2) and then evaluates its fitness fit_i.

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{2}$$

where $k \in \{1,2,...,SN\}$ and $j \in \{1,2,...,D\}$ are randomly chosen indexes. Although k has to be different from i. ϕ_{ij} is a random number between [-1, 1].

After the information is shared by the employed bees, each onlooker finds new solution v_{ij} within the neighbourhood of x_i by using Eq. (2), based on the probability P_i defined as:

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (3)$$

where fit_i is the fitness value of the solution x_i.

After each candidate solution v_{ij} is produced and then evaluated by the artificial bee, its fitness is compared with that of its old one. If the new solution has an equal or better fitness than the old solution, it replaces the old one in the memory. Otherwise, the old one is retained in the memory. In other words, a greedy selection mechanism is employed in the selection operation between the old and the candidate one.

At the end of each search cycle, if the fitness of a solution cannot be improved and the predetermined number of trials, which is called ‘‘*limit*”, is exhausted, then the solution will be abandoned by scout bee and a new solution is randomly searched. The new solution x_i will be generated using the Eq. (1).

It is clear, from the above explanation, that there are three control parameters in the basic ABC: The number of candidate solutions which is equal to the number of employed and onlooker bees *SN*, the value of “*limit*” and the maximum cycle number *MCN*.

A detailed pseudo-code of the ABC algorithm for one-dimensional optimisation problem is given below:

1: Begin
2: Generate the initial solutions $x_i, i = 1, 2, ..., SN$ using Eq. 1
3: Evaluate the fitness (fit_i) of the population
4: Set cycle to 1
5: Repeat
6: **For** each employed bee **{**
Produce new solution v_i using Eq. 2
Calculate the value fit_i
Apply the greedy selection process }

7: Calculate the probability values P_i for the solutions x_i by Eq. 3
8: **For** each onlooker bee **{**
Select a solution x_i depending on p_i
Produce new solution v_i by using Eq. 2
Calculate the value fit_i
Apply the greedy selection process }

9: **If** there is an abandoned solution for the scout
Then replace it with a new solution which will be randomly produced using Eq. 1
10: Memorize the best solution achieved so far
11: cycle = cycle + 1
12: until cycle = *MCN*

3.2. Application of ABC to the MPPT problem

The ABC-based optimization described in section 4.1 is now applied with a slight change made in the scout bees' phase, to realize the MPPT algorithm for photovoltaic generation system (PGS) operating under PSC with direct control technique.

To realize the direct control ABC-based MPPT, each candidate solution is defined as the duty cycle value d of the *DC-DC* converter, so the optimization problem has one parameter to be optimized ($D = 1$). Thus, equations (1) and (2) become:

$$d_i = d_{\min} + rand\left[0,1\right](d_{\max} - d_{\min}) \tag{4}$$

$$new\_d_i = d_i + \phi_i(d_i - d_k) \tag{5}$$

The fitness of each solution (duty cycle) is chosen as the generated power Ppv of the PGS. Equation (3) becomes:

$$P_i = \frac{Ppv_i}{\sum_{n=1}^{SN} Ppv_i} \tag{6}$$

To evaluate the duty cycles, the digital controller successively outputs the PWM signal according to the value of d_i, and then the PV voltage Vpv_i and current Ipv_i can be measured and the corresponding power (Ppv_i) of each duty cycle d_i can be calculated. It should be noted that in order to acquire correct samples, the time interval between two successive duty cycle evaluations (*Ts*) has to be greater than the power converter's settling time.

In the original algorithm, at the end of each search cycle the abandoned solution that has not improved its fitness over a predetermined number of cycles (limit) is replaced by a new, randomly chosen, solution. If this strategy is used in the MPPT algorithm, the stopping criterion stops the search process before using the scout bees, because the power Ppv remains unchanged. Thus, a very important phase that gives ability to the algorithm to escape from local minima is eliminated. To remedy this problem, a different strategy for the scout bees' phase, which consists in replacing the duty cycle giving less power at the end of each search cycle, by another randomly chosen value, is proposed in this work.

The application procedure of the proposed method can be divided in four phases:

- *Initialisation phase:*

Set the algorithm parameters. This, includes the number of candidate solutions SN, maximum cycle number MCN and the sampling time Ts. Then, generate a randomly distributed initial SN duty cycles using Eq. 4 and evaluate them.

$$d_i \quad (i = 1, 2, \ldots, SN)$$

- *Employed bees phase:*

Update employed bees' duty cycles using Eq. 5 end evaluate them. Then, apply the greedy selection process and calculate the probability value P_i for each duty cycles d_i using Eq. 6.

- *Onlooker bees phase:*

Using the roulette wheel selection, recruit the onlooker bees for local searching around the chosen duty cycle value which is depending on the calculated probability P_i. Evaluate the new duty cycles and then apply the greedy selection process.

- *Scout bees phase:*

Using Eq.4, replace the duty cycle that gives less power with the new randomly chosen duty cycle and then evaluate it.

At the end of each search cycle, the algorithm memorizes the best solution achieved so far and repeats the procedure from the employed bees phase until the maximum cycle number (*MCN*) is reached or until the power value remains unchanged within a specified number of cycles.

Usually, the real working environment of the PV system is always changing due to the varying weather, and as a result, the global MPP is always changing. This requires the MPPT algorithm to have the ability to search for a global MPP for the new weather condition. For this purpose, the search process has to restart with a total re-initialization whenever the weather conditions are changed. Here, we use the following strategy to detect these changes:

$$\frac{|Ppv_{new} - Ppv_{last}|}{Ppv_{last}} \geq \Delta Ppv(\%) \tag{7}$$

The search process of a new MPP will be executed again whenever the inequality, given above, is satisfied. This ensures that the MPPT algorithm can always find the global MPP under various working environmental conditions.

The flowchart of the proposed ABC-based MPPT algorithm of PV systems is shown in Fig. 3.

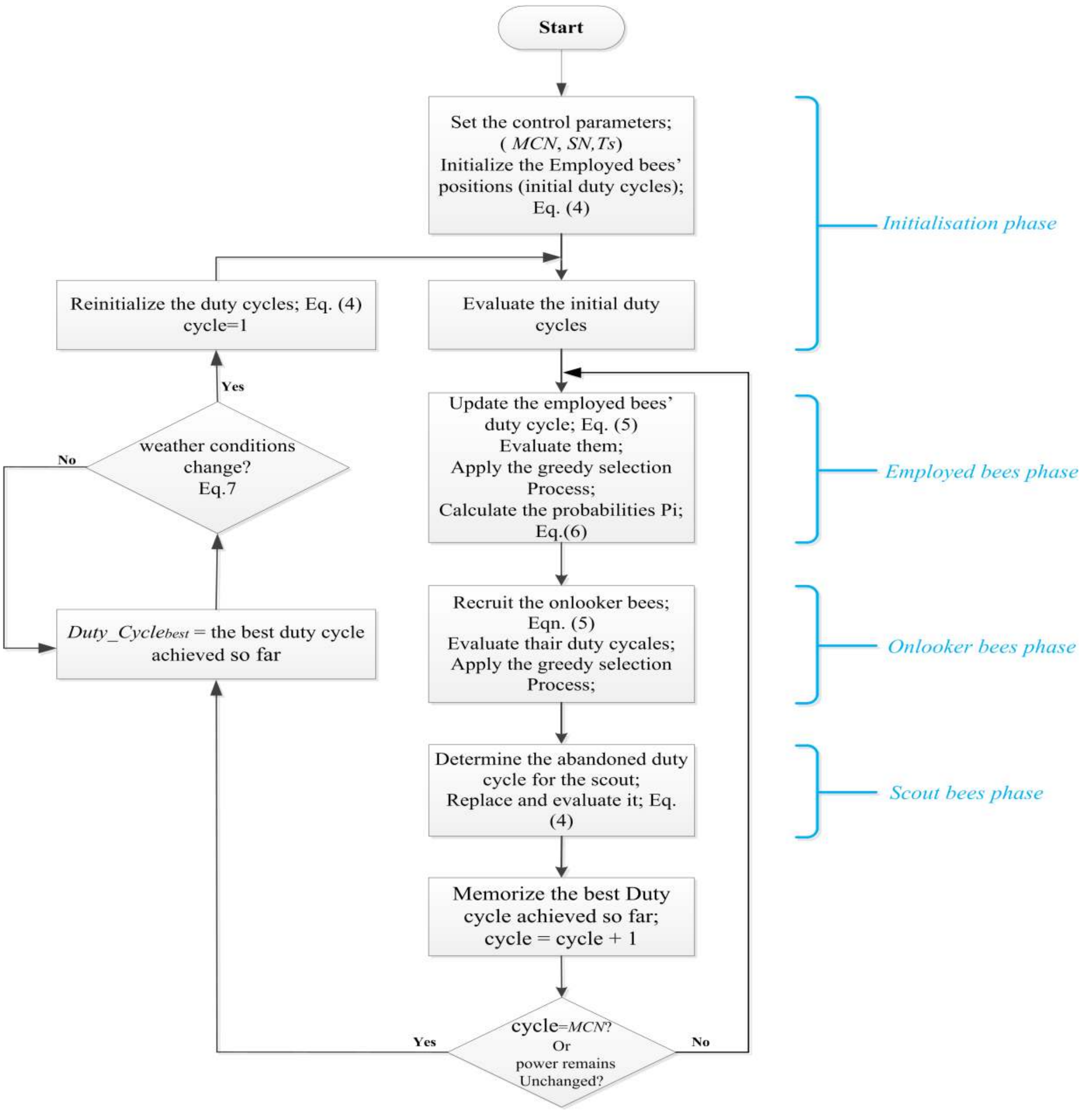

Fig. 3. Flowchart of the proposed ABC-based MPPT with direct control technique for PV system.

4. Results and discussion

4.1. Simulation results

In this section, the feasibility and the effectiveness of the proposed ABC-based MPPT algorithm with direct control are verified using a co-simulation methodology. The photovoltaic array and the BOOST converter are implemented in the Pspice environment while the control algorithm is implemented in The Matlab/Simulink environment. The tested PV array configuration consists of one string of two modules, as shown in Fig. 4. Fig. 5 shows the simulink model of the MPPT algorithm, and Fig.6 shows the Pspice circuit of the PV array and the boost converter.

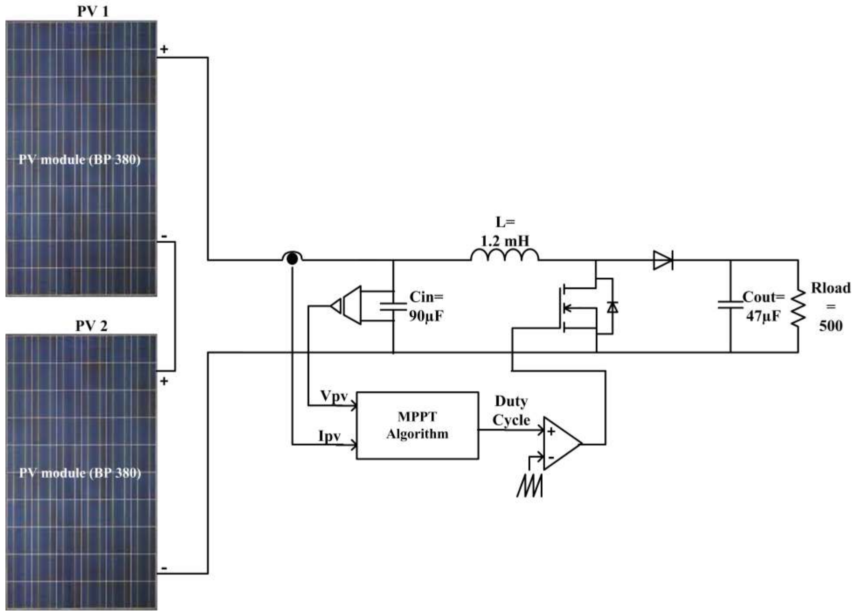

Fig. 4. System block diagram.

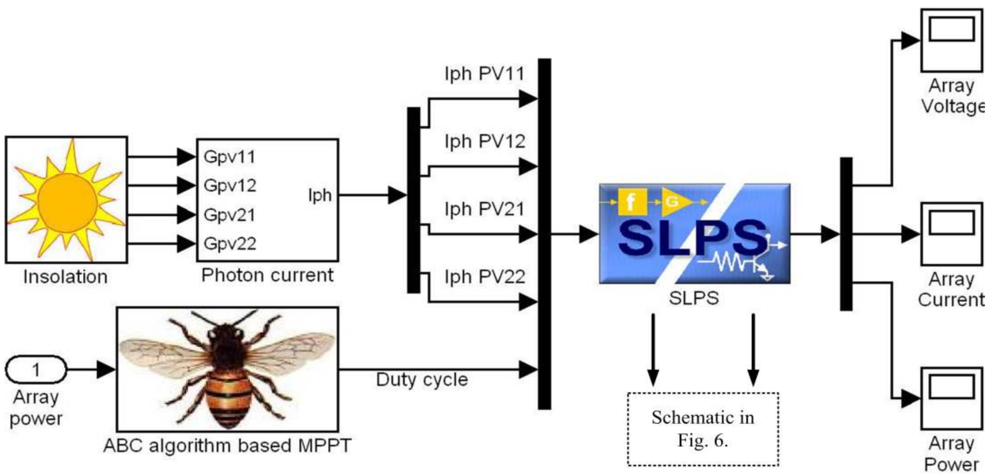

Fig. 5. Simulink model of the proposed MPPT algorithm.

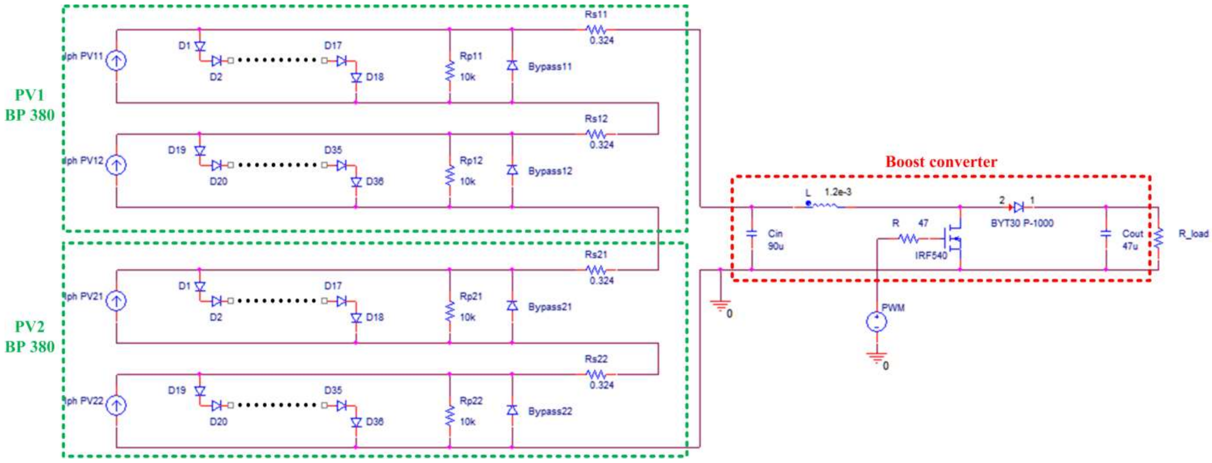

Fig. 6. Pspice schematic of PV array and boost converter.

In the proposed MPPT algorithm, the number of candidate solutions (SN) influences the convergence speed and the tracking performance of the algorithm. More bees means that it is easier to find the global MPP with a good accuracy, but more time will be required. Fewer bees gives a better convergence speed, but the convergence rate could be unsatisfactory. Therefore, the trade off between fast convergence speed and the convergence rate should be made when choosing the number of candidate solutions SN. Fig.7 shows the relationship between the number of candidate solutions (SN) and the convergence rate for all the cases investigated in the simulations. The relationship between the number of candidate solutions (SN) and the average convergance time, when Ts is choosen equal to 0.05s, is shown in Figs.8. Since our objective for the MPPT algorithm is to get fast convergence with a high convergance rate, SN has been choosen equal to 3.

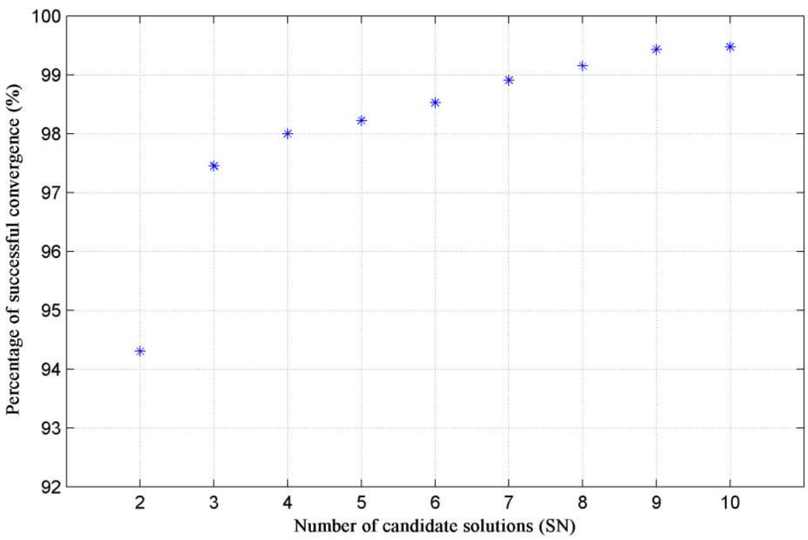

Fig. 7. Relationship between the number of candidate solutions (SN) and the convergence rate.

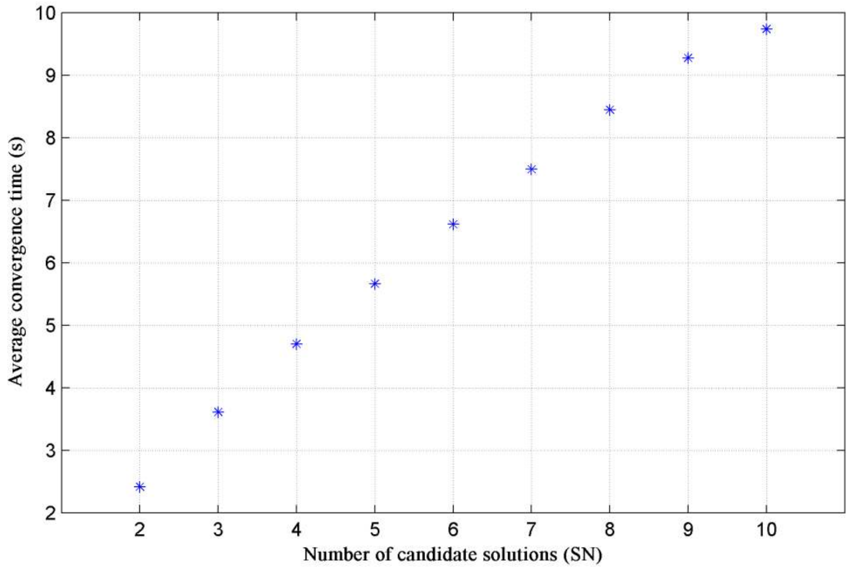

Fig. 8. Relationship between the number of candidate solutions (SN) and the average convergance time.

a. Power Tracking with Various Shading Patterns: Simulation study

This study demonstrates the ability of the proposed ABC-based MPPT to track the global MPP under steady and transient shading patterns. The parameters of the used PV modules are listed in Table, where two bypass diodes protecting eighteen cells in each module are considered. Since it is very difficult to test all the non-uniform irradiance conditions, only some shading patterns are considered in the study. The four used shading patterns (SPs) are listed in Table 2. For SP1, the irradiance on all the PV sub-modules is uniform; as a result, only one peak exists in the *P-V* characteristic curve. For SP2 there are two peaks, while for SP3 and SP4 there are three peaks. According to the design guidelines given in section 3.2, the parameters values of the implemented ABC-based MPPT algorithm are given in Table 3.

Table 1
Parameters of the used PV modules (BP SX 80).

Parameter	Value
maximum power	80W
open circuit voltage	22.1 V
maximum power voltage	17.6 V
short circuit current	4.8 A
maximum power current	4.6 A
temperature coefficient	-0.080 V/°C
configuration	2s1P (2 bypass diodes)

Table 2
Considered shading patterns.

Pattern N°.	Shading pattern [Gpv11, Gpv12, Gpv21, Gpv22] (W/m^2)
SP1	[1000, 1000, 1000, 1000]
SP2	[1000, 500, 1000, 1000]
SP3	[1000, 700, 100, 1000]
SP4	[1000, 500, 100, 1000]

Table 3
ABC Algorithm parameters used in the study.

Parameter	Symbol	Value
Number of candidate solutions	*SN*	3
maximum cycle number	*MCN*	30

Table 4
Performance of the proposed ABC-based MPPT under various shading patterns.

Pattern N°.	Ideal power (W)	Extracted power (W)
SP1	159.652	159.380
SP2	117.896	116.568
SP3	88.948	88.377
SP4	74.140	73.976

For each of the above four cases, the ABC-based MPPT algorithm is executed 1000 times. The ideal power values and the average values of the extracted power are shown in Table 4. It shows that the proposed ABC-based MPPT can track the global MPP. In fact, the extracted power is very close to the ideal power in all cases. The distribution of the average values of the extracted power from the PV module, over the shading patterns, is shown in Fig. 9. The obtained result indicates that the efficiency of the proposed method is not affected by the initial conditions of the searching process. The ability to find the global MPP for the new weather conditions is very important. In order to illustrate the tracking ability of the proposed ABC-based MPPT algorithm under transient irradiance conditions, we have considered three cases – Case 1: SP changes from SP1 to SP2; Case 2: SP changes from SP1 to SP3, and Case 3: SP changes from SP1 to SP4. The power, the voltage and the current transient characteristics and the corresponding duty cycle for Case 1, Cases 2 and 3 are shown in Figs. 10–12, respectively. The sampling period Ts of the MPPT algorithm is set to 0.05 s and $\Delta Ppv(\%)$ (the weather conditions change detection) value is set to 2 %. It can be seen that when the shading pattern changes from a uniform condition to a partially shaded condition at 8 s, the proposed MPPT algorithm can find the global MPP for the new shading pattern.

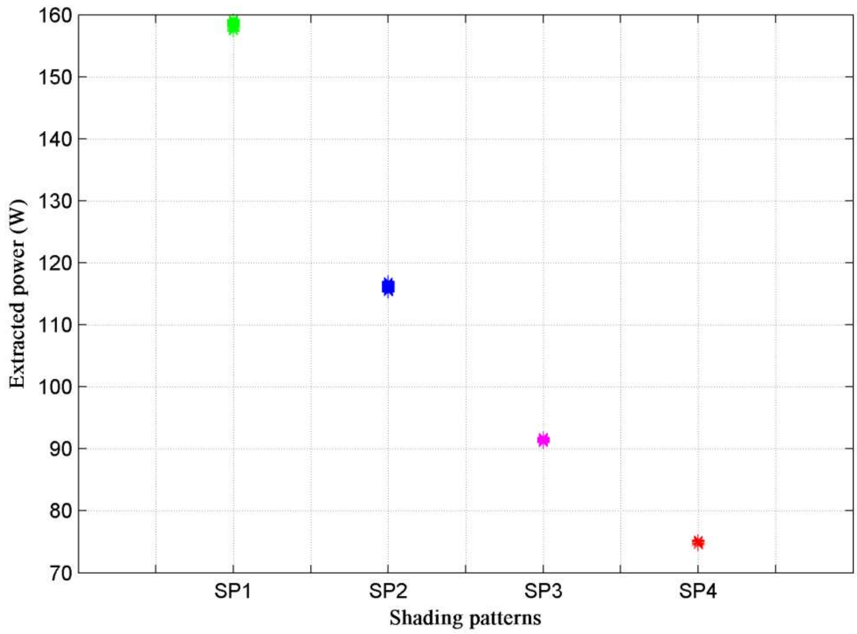

Fig. 9. Power extracted by the ABC-based MPPT algorithm under four different shading patterns.

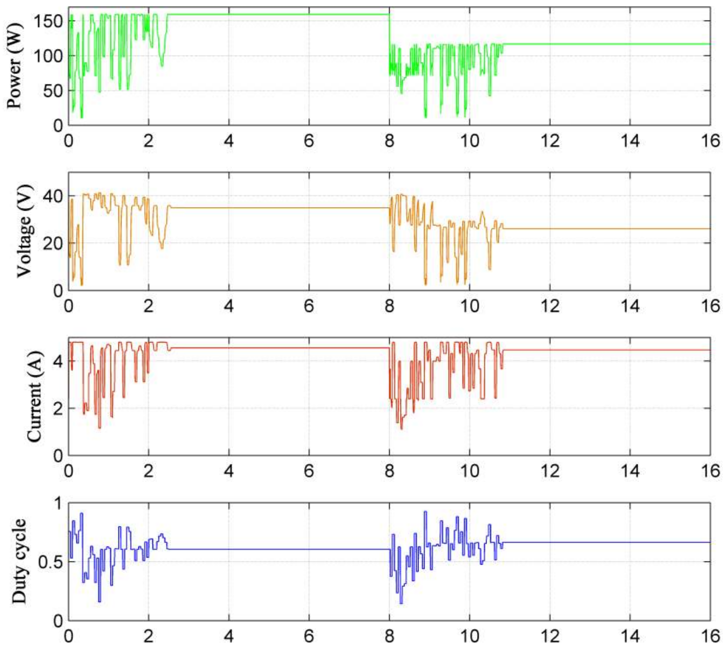

Fig. 10. Shading pattern SP1 to shading pattern SP2.

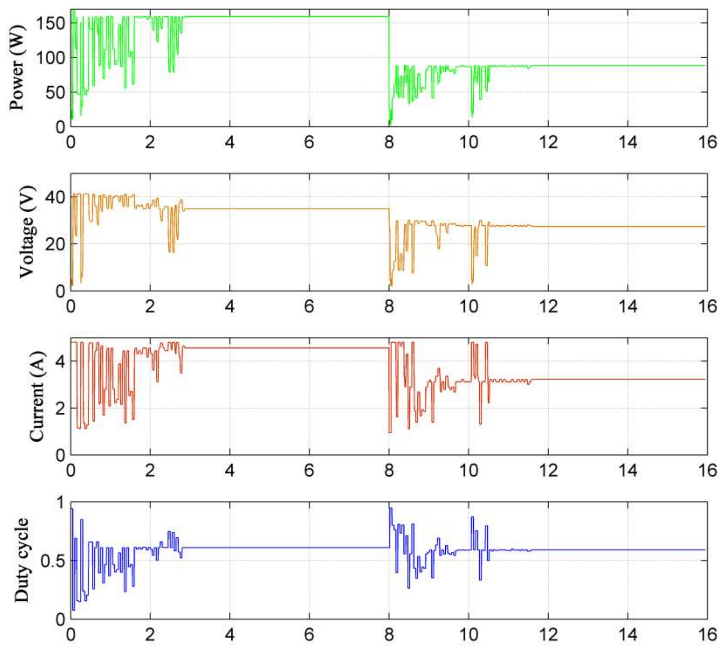

Fig. 11. Shading pattern SP1 to shading pattern SP3.

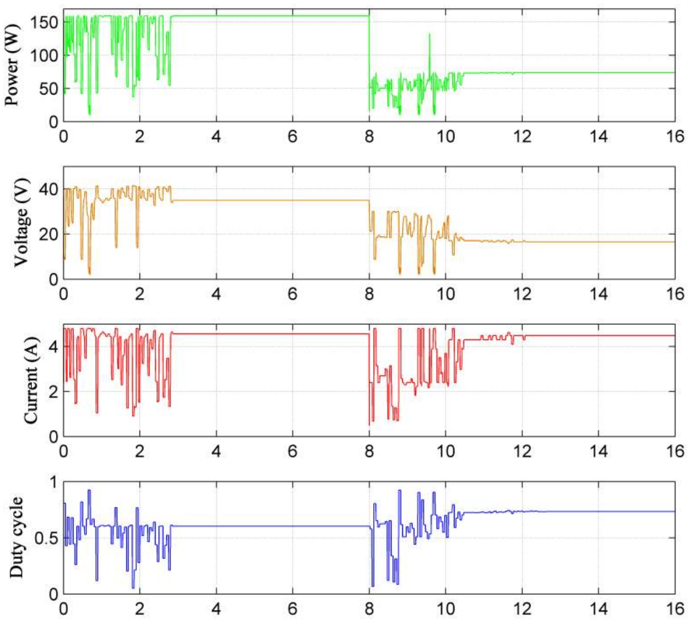

Fig. 12. Shading pattern SP1 to shading pattern SP4.

b. Proposed MPPT algorithm versus PSO-based MPPT (simulation study)

The purpose of this study is to compare the proposed ABC-based MPPT algorithm with PSO-based MPPT algorithm proposed in [22], the parameter settings of the implemented PSO-based MPPT algorithm are listed in Table 5. This comparison is carried out using three criterions and executing the both MPPT algorithms 1000 times for each of the shading pattern given in Table 2. From this table, it can see that the ABC algorithm is a good choice, in terms of the number of successful convergence, for the MPPT purpose under partial shading conditions. There is a slight difference in the accuracy and the average convergence cycle values obtained by these two methods as shown in Table 6.

Table 5
PSO Algorithm parameters used in the study.

Parameter	Symbol	Value
number of particles	N	6
maximum cycle number	max_generation	30
inertia weight	w	0.4
cognitive coefficient	c1	1.2
social coefficient	c2	1.6

Table 6
Comparison between the ABC and the PSO based MPPT algorithms under different shading patterns.

Pattern N°/ Algorithm		Number of successful convergence (%)	Accuracy (%)	Average convergence cycle
SP1	ABC	99.80	99.83	9.39
	PSO	99.20	99.66	7.95
SP2	ABC	97.70	99.72	9.57
	PSO	90.20	99.06	8.41
SP3	ABC	96.70	99.36	10.32
	PSO	87.10	98.22	9.22
SP4	ABC	95.60	99.78	10.27
	PSO	78.40	98.56	9.17

4.2. Experimental results

For hardware implementation, both ABC and PSO-based MPPT control programs were developed in a C++ environment and is compiled and downloaded on to the DSP board. The DSP used is eZdsp TMS320F28112 from Texas Instruments. In the experiment, the components of the BOOST converter have the same value as in the simulation and the converter is driven at a 20 kHz switching frequency. The output voltage and current are sampled after every 0.05 s (Ts). Fig. 13. shows the experimental setup. The PV array which is considered for experimental setup is shown in Fig. 14. It has the same configuration as in the simulation studies. The module parameters are also listed in Table 1.

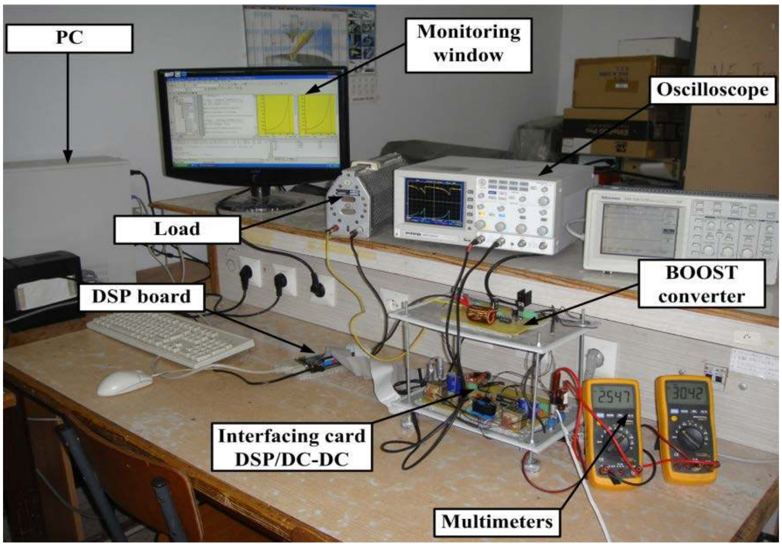

Fig. 13. Experimental setup of MPPT system.

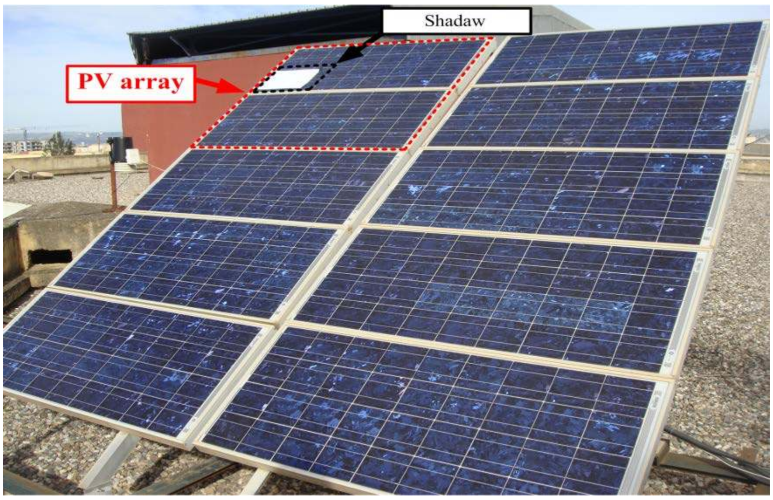

Fig. 14. PV array (Making artificial shade with sheets for observing response).

To verify the performance of the new MPPT algorithm three tests were performed. In the first experiment, the PV array was under uniform insolation condition and the corresponding *I–V* and *P-V* curves were recorded and demonstrated in Fig. 15a and Fig. 15b, respectively. According to these figures, the corresponding voltage and current of MPP point were 23.8 V and 3.66 A. To confirm the validity of the proposed algorithm, the obtained results for the corresponding voltage and current waveforms of the PV array were demonstrated in Fig. 14. It is seen that the generated voltage and current in Fig. 14 are around 23.5V and 3.6 A and have good agreement with the result of Fig. 16. This result confirms the correct operation of new MPPT algorithm under uniform insolation conditions.

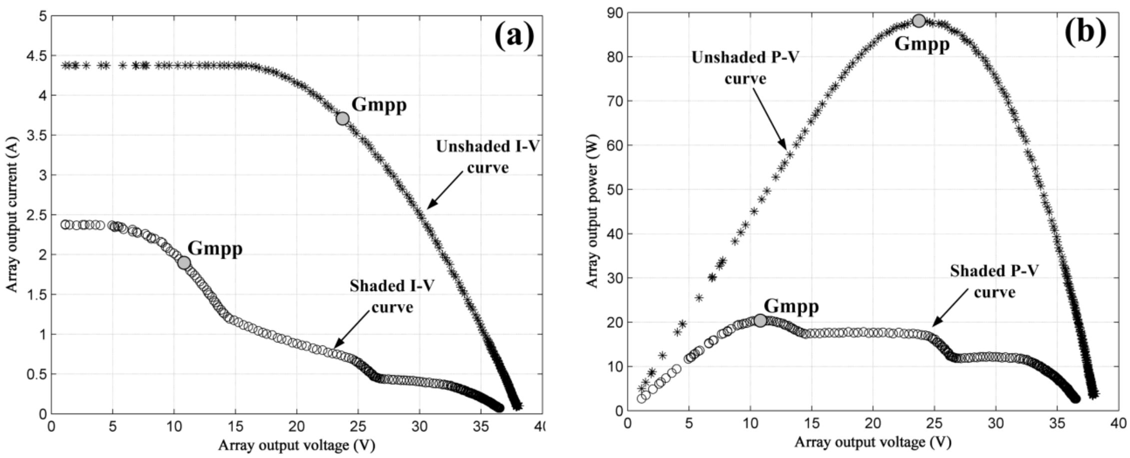

Fig. 15. I–V and P-V curves of the PV array under uniform insolation condition and partially shaded conditions.

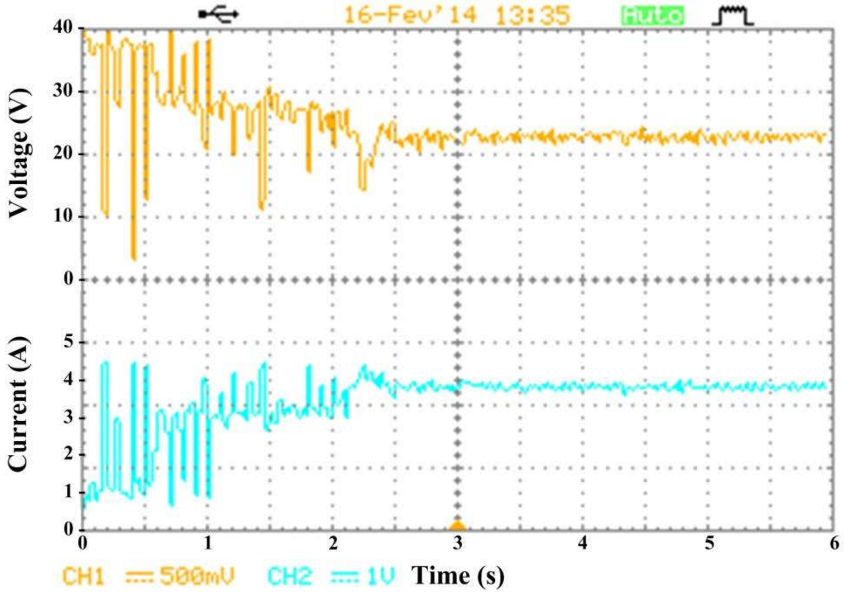

Fig. 16. Corresponding array voltage, and current waveforms under uniform insolation condition.

In the second experiment, the PV array was under uniform insolation condition for 6 s. Then, at t = 6 s, a partial shadow was made intentionally as depicted in the *I–V* and *P-V* curves shown in Fig. 15. The behavior of MPPT algorithm before and during the partial shadow is shown in Fig. 17. It is clearly shown that the generated PV power is almost 20 W which is close to maximum achievable power, according to Fig. 15b.

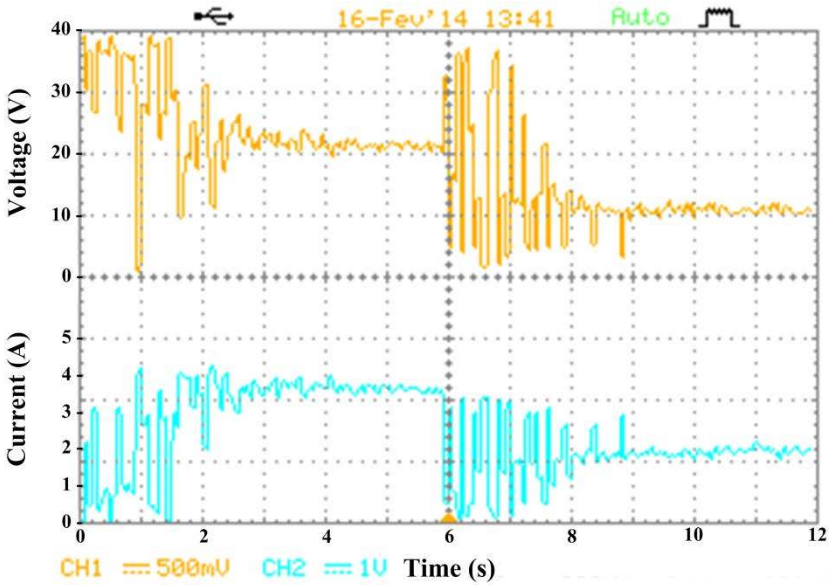

Fig. 17. Behavior of the new MPPT algorithm before and during the occurence of partial shadow.

In the last experiment a comparison between the proposed ABC-based MPPT algorithm and PSO-based MPPT algorithm proposed in [Chun-Liang et al, 2012] was carried out under three shading patterns (SP1: 1 peak; SP2: 2 peaks; SP3: 3 peaks). This comparison is carried out by executing the both MPPT algorithms 200 times for each pattern. The obtained result given in Table 7 confirms better performance of ABC-based MPPT, especially , in term of number of successful convergence.

Table 7
Comparison between the ABC and the PSO based MPPT algorithms under different shading patterns.

Pattern N°/ Algorithm		Number of successful convergence (%)	Accuracy (%)	Average convergence cycle
SP1	ABC	98.50	99.22	10.1
	PSO	97.50	98.53	8.9
SP2	ABC	96.00	98.52	10.3
	PSO	89.5	98.26	9.1
SP3	ABC	93.50	98.76	10.4
	PSO	76.00	97.83	9.3

5. Conclusion

In this work we proposed and presented a novel ABC-based MPPT by using direct duty cycle control method for PV systems under partially shaded conditions. The feasibility of the proposed algorithm has been verified with various shading patterns on a PV system. The simulation results have shown that the proposed ABC-based MPPT algorithm provides better tracking performance to find the global MPP under partially shaded conditions than PSO-based MPPT algorithm. In addition, the proposed control algorithm requires only two control parameters and its convergence is not dependent on the initial conditions. The experimental results have shown the ability of the algorithm to track the MPP in normal and shaded conditions with good performances.

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