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HYBRID MPPT ALGORITHM FOR PV SYSTEMS UNDER PARTIALLY SHADED CONDITIONS USING A STOCHASTIC EVOLUTIONARY SEARCH AND A DETERMINISTIC HILL CLIMBING

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Abstract: A hybrid maximum power point tracking method has been proposed for the photovoltaic system using a stochastic evolutionary search and a deterministic hill climbing algorithm. The proposed approach employs the particle swarm optimizer (PSO) to solve a dynamic optimization problem related to the control task in a *PV* system. The position of the best particle is updated by the hill climbing algorithm, and the position of the rest of the particles by the classic PSO rule. The presented method uses the re-randomization mechanism, which places five consecutive particles randomly, but in specified intervals. This mechanism helps track the maximum power point under partially shaded conditions.

Keywords: *maximum power point tracking, photovoltaic system, hybrid part–stochastic part–deterministic search rule, particle swarm optimization, partial shading, hill climbing*

1. INTRODUCTION

Solar energy is one of the fastest growing fields of renewable energy [1–3]. The main advantages of photovoltaics include its applicability in most regions of the world, both in industrial and household applications. In order to achieve an optimum efficiency of photovoltaic modules, it is necessary to use the MPPT control algorithm of the inverter circuit connected to the panel. If the load current of a module is subjected to a change, the voltage on the electrodes is likewise affected. The MPPT algorithm controls the load current to yield maximum power (Fig. 1) [4]. Classical algorithm methods of MPPT such as Hill Climbing (HC) or Perturb and Observe (P&O) allow one to effectively track the maximum power point of the module provided with idealized characteristics [5]. The problem occurs when an uneven solar irradiance distributes along a string (modules wired in series). Classical methods of MPPT set the system in the area of a local maximum which may be lower than the global maximum power point. One

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way to solve this is to use an unconventional method, e.g., a stochastic MPPT algorithm like the adaptive HC method using PSO [6], or to remove the random number in the acceleration factor of the conventional PSO velocity equation [7].

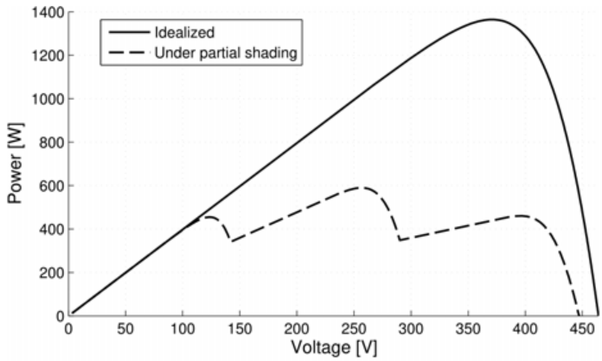


Fig. 1. *P–U* curve in PV system under idealized and partially shaded conditions

A pure PSO can work as MPPT and set a direct duty cycle [8]. An example of the stochastic method is also described in [9], detailing an algorithm where PSO is activated to search the area of the global peak, and then the algorithm is switched to the conventional incremental conductance (INC) algorithm to track the maximum output power of the photovoltaic system. The next method uses PSO for the current search and it needs a periodical acquisition of the *P–U* curve of the PV strings [10]. A different example is the algorithm based on a PSO using the reinitialization of the swarm to track the global maximum [11]. The next method uses PSO to tune the parameters of the fuzzy logic controller [12]. In [13–15], the grouping idea of the shuffled frog leaping algorithm (SFLA) is introduced to the basic PSO algorithm to perform searches of the global extremum area. In the algorithm described in [16], the PSO algorithm will trigger the optimisation with an initial value close to the MPP, which is determined by the Lagrange interpolation formula. In this paper, the main aim is to present a novel hybrid MPPT algorithm that employs the synergy between a classic HC and a stochastic search for a maximum power point based on the particle swarm algorithm (PSO), where the best particle of the swarm in the given iteration is updated using the HC algorithm.

2. HILL CLIMBING MPPT

The hill climbing method is based on the change of the reference *PV* system voltage by module voltage control and the observations of the resulting power change. In the first step, the voltage and current of the PV system are measured (Fig. 2). Then the power generated by the system is calculated according to

$$P(i) = V_{PV}(i) I_{PV}(i) \tag{1}$$

where $P(i)$ denotes the power of the PV system in the i-th iteration and $V_{PV}(i)$ and $I_{PV}(i)$ are the voltage and load current of the PV system in the i-th iteration. In the next step, $P(i)$ is compared with $P(i-1)$ and then the reference voltage of the *PV* system in the next iteration is set according to

$$V_{PV}^{\mathrm{ref}}(i+1) = \begin{cases} V_{PV}^{\mathrm{ref}}(i) + dl & \text{if} \quad P(i) \geq P(i-1) \\ V_{PV}^{\mathrm{ref}}(i) - dl & \text{if} \quad P(i) < P(i-1) \end{cases} \tag{2}$$

where $V_{PV}^{\mathrm{ref}}(i)$ denotes the reference voltage of the *PV* system in the i-th iteration and d is the constant factor, which is a slope multiplier where the slope is $l = P(i)/P(i-1)$. The step of the reference voltage value can be either fixed or determined on the basis of the *P–U* curve slope. The algorithm is shown in Fig. 2.

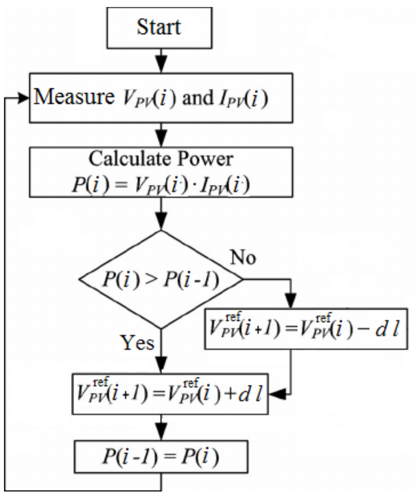


Fig. 2. Hill climbing MPPT algorithm

3. PARTICLE SWARM OPTIMIZER (PSO)

The method presented in the article uses the PSO algorithm, which is a stochastic optimization algorithm based on a quasi-random search of the solution space. PSO describes the position of individual particles in the optimization by the position (which represents $V_{PV}^{\mathrm{ref}}(i)$) and velocity vectors. The equations that define the position and velocity for a one-dimensional search space are:

$$v_j(i+1) = c_1 v_j(i) + c_2 r^{p\,\text{best}} \delta_p \left(q_j^{p\,\text{best}} - q_j(i)\right) + c_3 r^{g\,\text{best}} \delta_p \left(q^{g\,\text{best}} - q_j(i)\right) \tag{3}$$

$$q_j(i+1) = q_j(i) + \min\left\{\max\left\{-v_{\text{clmp}}, v_j(i+1)\right\}, v_{\text{clmp}}\right\} \tag{4}$$

where v_j and q_j are the velocity and the position of the j-th particle, $q_j^{p\,\text{best}}$ stores the best solution proposed so far by the j-th particle, $q^{g\,\text{best}}$ denotes the best solution found so far, c_1, c_2, c_3 are the inertia, cognitive and social weights, respectively. Velocity clamping is implemented and the maximum speed is v_{clmp}. The random numbers $r^{p\,\text{best}}$ and $r^{q\,\text{best}}$ are uniformly distributed in the unit interval. In all the experiments described in this paper, the c_1, c_2 and c_3 factors were calculated using the constricted PSO formula [17, 18] and their values are 0.73, 0.73×2.05 and 0.73×2.05, respectively. The direction variable δ_p (–1 or 1) enables the swarms to switch between attract and repel modes and is chosen to be dimension-wise (p-wise), i.e. individual control of diversity is possible in each search dimension [19]. For each particle in each iteration, the objective function is calculated according to:

$$\Im(i) = P(i) \tag{5}$$

In the case of the MPPT algorithm, we define the dynamic optimization problem (DOP), which is related to using the evaporation factor during objective function updating. The DOP is considered in the case of the MPPT algorithm due to varying solar irradiance, where the optimum $V_{PV}^{\text{ref}}(i)$ value can differ with the irradiance. An absence of the evaporation factor would retain the MPPT at the point of the highest power found so far, because after a decrease in solar irradiance, the algorithm would not be able to update the best solution. In each swarm iteration, the value of the objective function is compared with the product of the evaporation rate and the highest particle of the objective function so far. If the value of the objective function from the current iteration is greater than said product, the position of this particles becomes the current personal optimum ($p$best) and the objective function of $p$best becomes the current optimum personal value according to

$$Q_j = \Im\left(q_j^{p\,\text{best}}\right) \tag{6}$$

where Q_j stores the best personal fitness value so far of the j-th particle. Otherwise, Q_j becomes the product of the optimum particle from the previous iteration and the rate of evaporation.

4. HC-PSO HYBRID MPPT

The method presented in the article is a hybrid of the HC and PSO. Each subsequent PSO particle in each swarm iteration is evaluated by the objective function. If a given particle is the current leader, the voltage $V_{PV}^{\text{ref}}(i)$ represented by that particle in the next iteration is determined by the HC method according to

$$q_j(i+1)=\begin{cases} q_j(i)+dl & if \quad P(i)\geq P(i-1) \\ q_j(i)-dl & if \quad P(i)<P(i-1) \end{cases} \tag{7}$$

A particle that is not a leader operates on the principle of the classical PSO described in section 3, taking into account the position of the current particle leader, which is determined on the basis of HC. The position of such a particle is updated according to (3) and (4). The algorithm presented in this article is based on the method presented in [20] and [21]. The presented method uses two mechanisms to help locate the global maximum. The first is the growth of the evaporation rate mechanism, used for the first time in [22], which aims to accelerate the finding of a new solution after a quick change of the global maximum power point, which manifests itself in a quick change of system performance. In this case, the use of the nominal value of the evaporation factor may delay the process of finding the global maximum. In the case of a relatively rapid decline in the average power for all particles (when the power in the i-th iteration is lower than 75% of the power in one of the past 7 iterations), the rate of evaporation grows exponentially in accordance with the formulas

$$F(i+1)=\begin{cases} 0 \text{ if } \Im\left(q_j(i)\right)>p(i)Q_j(i-1) \\ F(i+1) \text{ if } F(i)>0 \text{ or } \sum\limits_{j=1}^{N_{\text{swarm}}} P(j,i)<0.75\sum\limits_{j=1}^{N_{\text{swarm}}} P(j,i-k), k=1,2,...,7 \end{cases} \tag{8}$$

$$p(i)=p_{\text{base}}^{1+F(i)} \tag{9}$$

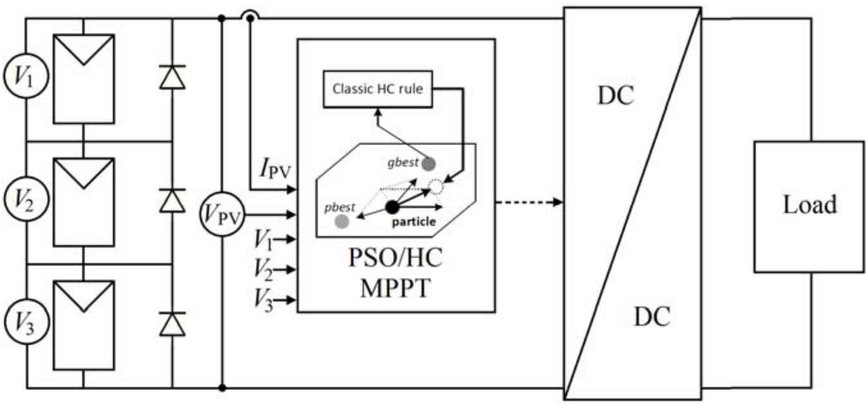


Fig. 3. A schematic diagram of the HC-PSO MPPT control system where PV modules with parallel diodes are connected in series

where $P(j, i)$ is the power of the PV system of the j-th particle in the i-th swarm iteration, $\Im(q_j(i))$ is the current fitness of the j-th particle, N_{swarm} is the number of particles, $F(i)$ is a component of the exponent of the evaporation rate in the i-th swarm iteration, $p(i)$ denotes the evaporation rate in the i-th swarm iteration and p_{base} is the base value of the evaporation rate. The condition for launching the mechanism was chosen as a compromise with the aim of not introducing a faster rate of forgetting the best solution found in cases of a low variation in irradiance. This mechanism is supposed to work in cases such as a bird landing on one of the panels. The rate of evaporation returns to its primary form the moment any particle becomes the new Q_j. The second mechanism is re-randomization. If the growth of the evaporation rate mechanism is activated for three iterations and an uneven voltage on individual modules occurs (the difference between the highest and the lowest voltage measured like in the Fig. 3 is greater than 15%), five consecutive particles (excluding the current leader) are located randomly at specified intervals (in this case for model simulation, at 80 V intervals). Other particles in this particular case operate according to a conventional PSO (+ a classic HC MPPT for the leader). This solution provides a chance to locate the global maximum. The advantages of the presented method include a fast convergence obtained using HC and a greater probability of finding the global maximum in case of a partial shading phenomenon than for conventional P&O and HC methods.

5. NUMERICAL RESULTS

The simulation studies have been performed in Matlab/Simulink with the PLECS Blockset tool. The PV string model based on the BP365 65W module provided by the PLECS tool has been implemented in the main model [23]. The developed simulation model assumes the power electronic converter to be an ideal linear amplifier. A controlled current source is then used to load the PV string. The load current is set by the PV string voltage (V_{PV} in Fig. 3) controller of a PI type.

Table 1. Parameters of swarm

Parameter	Value
Swarm size	10
Particle dimension	1
Base value of evaporation rate	0.9

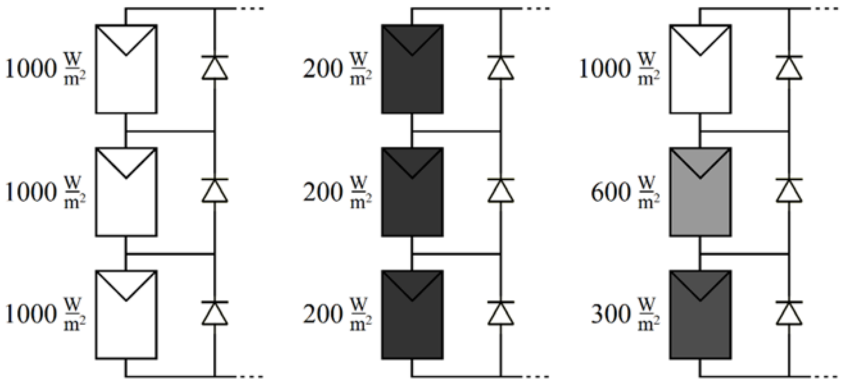
The reference voltage is shaped directly by the optimizer. For the purpose of this survey, four simulation scenarios were adopted:

1) sudden change in irradiation, from sunshine conditions (Fig. 4a) to partial shading conditions (Fig. 4c), which is shown in Fig. 5a,

2) smooth and steady decline in solar irradiance, which simulates a cloud covering (Fig. 5b), with the target irradiance value as in Fig. 4b,

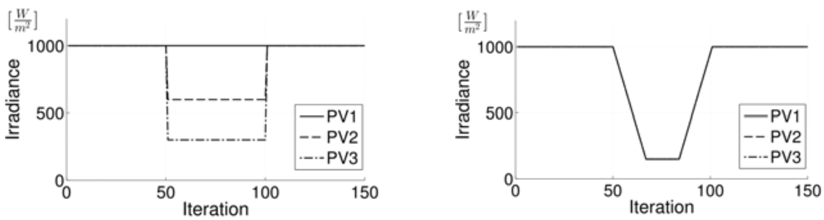
3) slow variable shadow cast by an obstacle, which causes a smooth change of irradiation shown in Fig. 5c,

4) irradiation change to the exact target values as in the first and third scenario (Fig. 4c), with a smooth change – the difference with respect to the third scenario is the rate of the change of irradiation, Fig. 5c and 5d are to be compared.

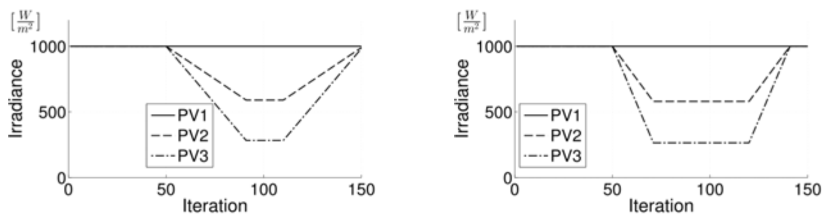


a) sunshine b) clouds c) partial shading

Fig. 4. Irradiance on PV panels in test scenarios



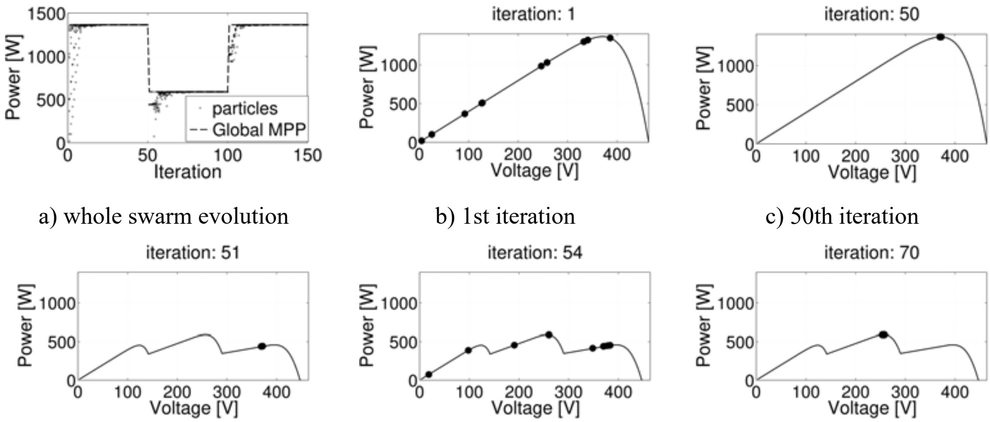
a) first scenario b) second scenario



c) third scenario d) fourth scenario

Fig. 5. Comparison of irradiance on PV panels in test scenarios during 150 iterations

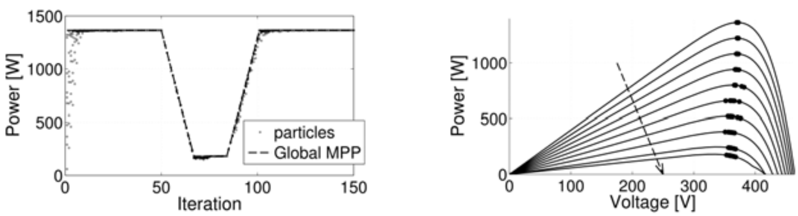
The swarm parameters are shown in Table 1. In the case of a step change in the parameters, which occurred in the 51st swarm iteration, the system is trapped in the zone of the local maximum area which it cannot exit by the means of the classical MPPT HC method. A hybrid MPPT HC-PSO in such a case, where a large concentration of particles lies around the local maximum (Fig. 6d), is also unable to jump into the area of global maximum. The presence of local the maximum area on the objective function discloses different voltage levels of individual modules. After taking this and the sudden cumulative power drop of the PV system in the MPPT algorithm into account, the re-randomization module for five consecutive particles activates, which occurs in the 54th swarm iteration (Fig. 6e).



a) whole swarm evolution b) 1st iteration c) 50th iteration

d) 51st iteration e) 54th iteration f) 70th iteration

Fig. 6. Comparison of numerical results in the first test scenario
(the change in irradiance occurs as a result of a jump in the 51st iteration of the swarm)



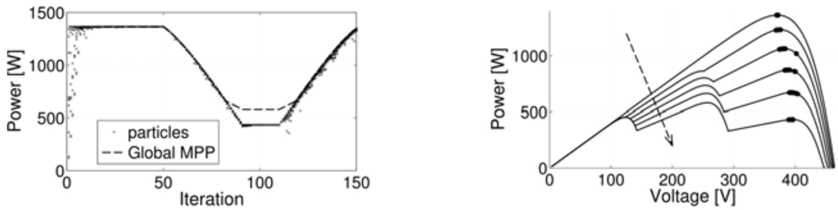
a) whole swarm during 150 iterations with marked global MPP

b) particles on the P–U curve during selected iterations between 50 and 67

Fig. 7. Numerical results in the second test scenario (smooth and steady decline in solar irradiance)

At this point, the swarm has its representative in each area of the local maximum, which results in the coincidence of all particles in the area of global maximum (Fig. 6f). After returning to the rated conditions with one function maximum, the algorithm quickly converges to a global maximum (Fig. 6a), where the hybridization of HC (the best particle) and PSO (the other particles) assists the system.

The second case simulates a cloud that covers modules at an appropriate speed to trigger the re-randomization mechanism. This does not happen at a uniform irradiance change that occurs over all modules, thus the voltages of all the connected modules are similar. Figure 7 shows that the re-randomization mechanism is not necessary because the HC-PSO MPPT algorithm copes precisely with solar irradiation changes. The use of re-randomization in this case would decrease the speed of convergence to the global maximum.

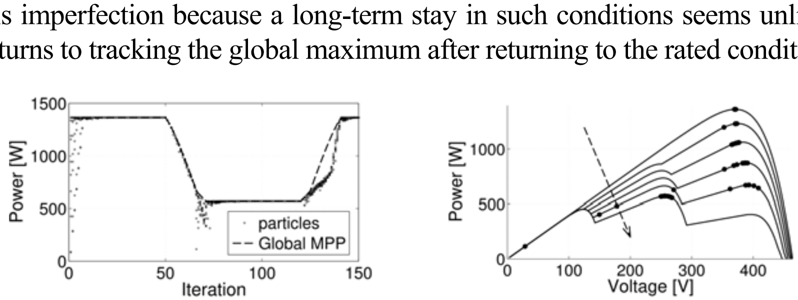


a) whole swarm during 150 iterations with marked global MPP

b) particles on the P–U curve during selected iterations between 50 and 91

Fig. 8. Numerical results in the third test scenario (smooth change in irradiance)

The third case simulates a shadow cast by an obstacle, covering modules unevenly. Subsequently, uneven voltages appear on individual modules and the objective function has three local maxima (Fig. 8). This case represents the compromise adopted for the needs of the algorithm. A slower rate of irradiance, compared to the second scenario, causes a lack of response from the re-randomization mechanism (Fig. 8b). The irradiation rate of change condition was introduced, especially at slow rates (Fig. 8a), not to trigger the re-randomization mechanism. As the result of slow solar irradiance changes, the system converges to a lower local maximum instead of the global one. Without the re-randomization mechanism, the HC-PSO MPPT algorithm is unable to find the global maximum in such conditions. We accept this imperfection because a long-term stay in such conditions seems unlikely. The system returns to tracking the global maximum after returning to the rated conditions.



a) whole swarm during 150 iterations with marked global MPP

b) particles on the *P–U*curve during selected iterations between 50 and 71

Fig. 9. Numerical results in the fourth test scenario
(faster change in irradiance than in the third scenario)

The fourth scenario presents the change of parameters to target values, identical as in the third scenario, but with the change occurring more rapidly, which triggers the re-randomization mechanism (Fig. 9), and as a result the HC-PSO MPPT algorithm finds the global maximum. In the case of deploying the traditional HC method in such conditions, the maximum power point would not be found, as in scenario 3, on the other hand in HC-PSO MPPT, the new leader (one of the particles that has been re-randomized) indicates the area of the global maximum power point for the remaining particles. The traditional HC method would not be able to find this area.

6. SUMMARY

A new method for the search algorithm of a *PV* system maximum power point has been developed. This method is based on the combination of the classical hill climbing algorithm with a stochastic optimization method based on the particle swarm optimization algorithm. The *PV* system voltage is represented by the PSO particle position. The best swarm particle in a given iteration is updated based on the HC method, and the remaining ones on the basis of the PSO method. The effectiveness of the new method has been confirmed in simulation studies in the case of partial shading conditions, where a global maximum power point has been located. The computational complexity of the proposed algorithm is fairly low and thus suitable for an implementation using low cost microcontrollers. The requirement is to measure the voltages in at least two places in the PV string (used to trigger the re-randomization procedure).

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