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An Adaptive PSO-Based Approach for Optimal Energy Harvesting in PV Systems

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Motivation

Energy harvesting for PV systems must be done efficiently, accurately and fast under continuous and sometimes rapid changes in ambient environmental conditions like irradiation and temperature fluctuations. There exist a number of methods for energy harvesting of PV systems in literatures. Amongst the widely used methods is maximum power point tracking (MPPT). Two important issues in energy harvesting are efficiency and speed of the implemented method.

Research Goal

A PSO-SG (particle swarm optimization – sub-gradient) MPPT algorithm is proposed in this study, which is shown to work accurately and fast. This PSO-based algorithm shortens the MPP tracking time by using the sub-gradient method to update the algorithm parameters at each iteration.

Test object system

The algorithm is tested under dynamic and static conditions of testing for a small PV system that includes three series-connected PV modules. The validation of the model has been carried out using MATLAB/Simulink software.

Introduction

The objective of PSO-based MPPT methods is to adjust the duty cycle for the converter such that the corresponding output power from the PV module is maximized. Duty cycles are considered as candidate solutions moving in the search space with velocity of:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1\left(dbest_i^k - d_i^k\right) + c_2 r_2\left(G - d_i^k\right)$$

The weight of the particles (Ω) and design parameters (c_1 and c_2) are tuned such that the algorithm converges in a finite number of iterations. $r_1, r_2 \in (0,1)$ are random numbers used to guarantee covering all the search space. $dbest_{i\in\mathbb{N}}^k$ and G are the best candidate solutions at iteration k and over all iterations from *1,…,k*, respectively. At any iteration *k*, the performance (*P*) of a duty cycle candidate for the corresponding MPP is computed based on the hill-climbing principle:

$$P(d_i^{k+1}) > P(d_i^k)$$

The performance of PSO-based MPPT methods depends on the following factors (i) the number of particles used, (ii) tuning of the design parameters, ω, c1 and c2, and (iii) sampling time (Tsamp), which is calculated considering the system model and settling time.

Mathematical Proof for: Concavity of PV cell

To have a better understanding of PV cell characteristics let us consider one PV cell. The extracted power from one cell is

$$P_{PV} = I_{PV} \times V_{PV} \qquad (*)$$

One of the most important issues about one PV cell (Ns = 1) is to proof whether the above-mentioned function is concave?

$$V = V_{PV} \ge 0 \qquad I = I_{PV} \ge 0 \qquad R = R_s \ge 0$$

$$\alpha = \frac{q}{K \times T \times n} > 0$$

$$\Psi = V + I \times R \ge 0$$

$$I_{PV} = I_{ph} - I_s \times (e^{\alpha\Psi} - 1)$$

$$\partial\Psi/\partial V = 1 + R\,\partial I/\partial V$$

$$\partial I/\partial V = -\alpha I_s \times e^{\alpha\Psi}(\partial\Psi/\partial V)$$

$$\partial I/\partial V = -\alpha I_s/(e^{-\alpha\Psi} + \alpha I_s R)$$

$$P = V \times [I_{ph} - I_s \times (e^{\alpha\Psi} - 1)]$$

$$\partial P/\partial V = I_{ph} + I_s - I_s e^{\alpha\Psi}[1 + V\,\alpha(\partial\Psi/\partial V)]$$

$$\partial^2 P/\partial V^2 = -I_s e^{\alpha\Psi} \times \Phi$$

$$\Phi = V\,\alpha[{}^2/_V\,(\partial\Psi/\partial V) + \alpha(\partial\Psi/\partial V)^2 + (\partial^2\Psi/\partial V^2)$$

As $I_s e^{\alpha\Psi} > 0$, so if Φ has a positive sing the function in (*) is concave.

$$\Phi = V(\alpha(\partial\Psi/\partial V) + 1/V)^2 - 1/V + V\alpha(\partial^2\Psi/\partial V^2)$$

$$\partial^2\Psi/\partial V^2 = -\alpha R(\partial I/\partial V)(\partial\Psi/\partial V)^2 \ge 0$$

To proof $\Phi \ge 0$, considering the positive first part, only the following polynomial is required to be proved positive, which is

$$-1/V + V\alpha\,(\partial^2\Psi/\partial V^2)$$

$$-V\alpha^2[1/V^2\alpha^2 - R(\partial I/\partial V)(\partial\Psi/\partial V)]^2$$

According to the calculations the function presented in (*) is a concave function

Conclusion

A PSO-SG method as an adaptive MPPT algorithm developed in this study. The algorithm implemented on both static and dynamic conditions to test the accuracy and speed of the method. Refer to simulations, (i) in static condition the PSO-SG algorithm found global maximum in all possible cases within less than 0.15(ms) and with average efficiency of 99.4% and also never stopped at a local optimum, (ii) in dynamic condition the algorithm followed the variation of irradiation.

Sub-gradient method

For a convex function of $f : \mathbb{R}^n \rightarrow \mathbb{R}$ to find the maximum point of f , the following iterative algorithm is used:

$$x^{k+1} = x^k - \beta_k S_g^k$$

where x^k is the k_{th} iterate, S_g is sub-gradient of f at x^k, and $\beta_k > 0$ is the kth sub-gradient step size.

$$\beta_k > 0, \lim_{k\rightarrow\infty} \beta_k = 0$$

$$\sum_{k=1}^{\infty} \beta_k = \infty\,, \quad \beta_k = \frac{a}{b + \sqrt{k}}$$

Regarding the sub-gradient method:

$$\forall k: f_{best}^k = \max\{f_{best}^{k-1}, f(x^k)\}$$

$$\lim_{k\rightarrow\infty} f_{best}^k - f^* < \varepsilon\,, \quad f^* = inf_x f(x)$$

PSO-SG MPPT Algorithm

Inertia weight for each particle: $\Omega = [\omega_1^k, \ldots, \omega_i^k, \ldots, \omega_N^k], i \in N$

where N is the number of particles and k is the number of iteration.

Each element of the matrix Ω updates at each iteration

$$\omega_i^k = \sum_{i=1}^{N} \omega_i^{k-1} \Big/ N - \beta_k S_g^k$$

The implemented sub-gradient in this work is

$$S_g^k = (\partial P_{PV}/\partial V_{PV})_i^k$$

$$\partial P_{PV}/\partial V_{PV} = \Delta P_{PV}/\Delta V_{PV}$$

$$(P_{PV}^t - P_{PV}^{t-Tsamp})/(V_{PV}^t - V_{PV}^{t-Tsamp})$$

velocity (v_i^{k+1}) is now derived as:

$$v_i^{k+1} = \omega_i^k v_i^k + c_1 r_1\left(dbest_i^k - d_i^k\right) + c_2 r_2\left(G - d_i^k\right)$$

Results

Static- Three possible case studies (three different partial shading patterns) are shown in Figure (1) global maximum (GM) is located in three different places. PV outputs and updating inertia weights are shown in Figure(2) and Figure(3) respectively. Results shows that in all three cases the MPPT algorithm track the GM and does not stick at local maximum.

Dynamic- A trapezoidal irradiance is used to simulate a dynamic irradiation variation. Figure (4) b shows PV outputs while the proposed method is used under the dynamic irradiance variation. It shows tracking is fast and accurate in dynamic irradiation variation.

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or scan the QR code
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Static

Figure (1) Three case studies for static condition

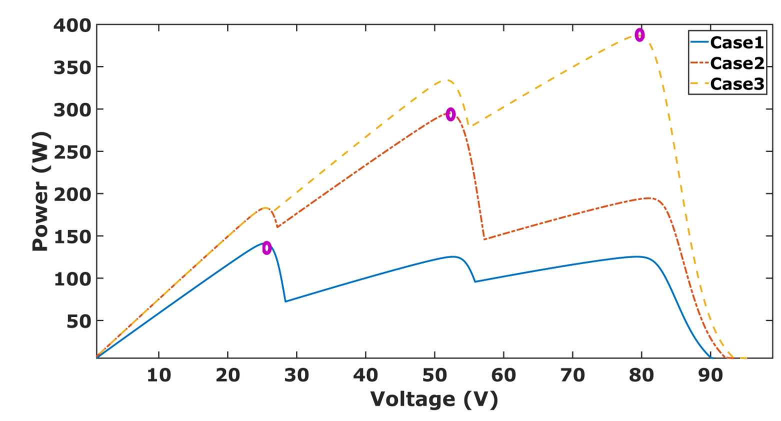


Figure (2) PV output power, voltage and current

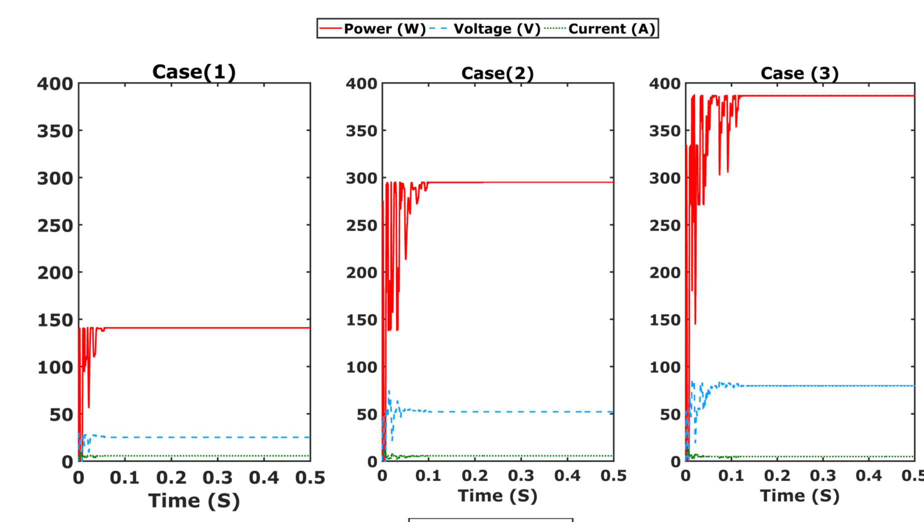
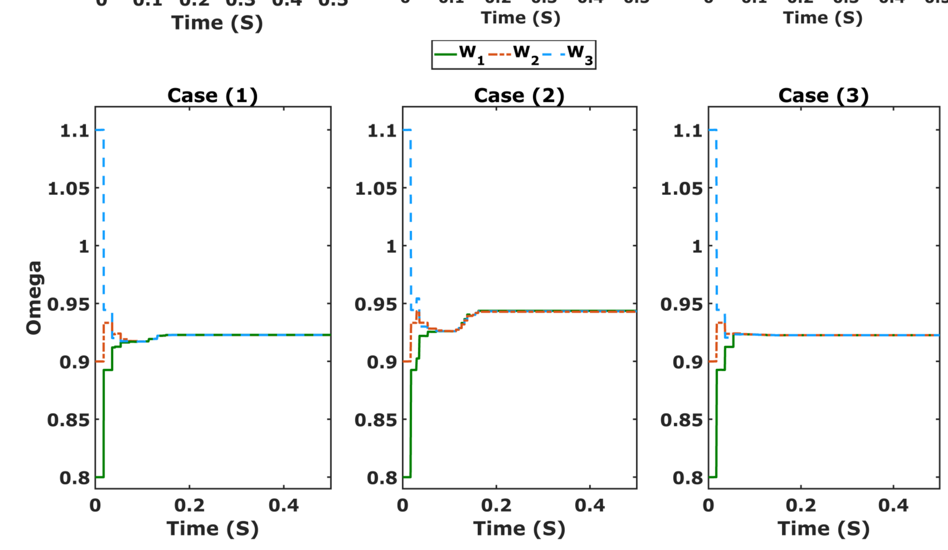


Figure (3) Ω values under PSC and static condition.



Dynamic

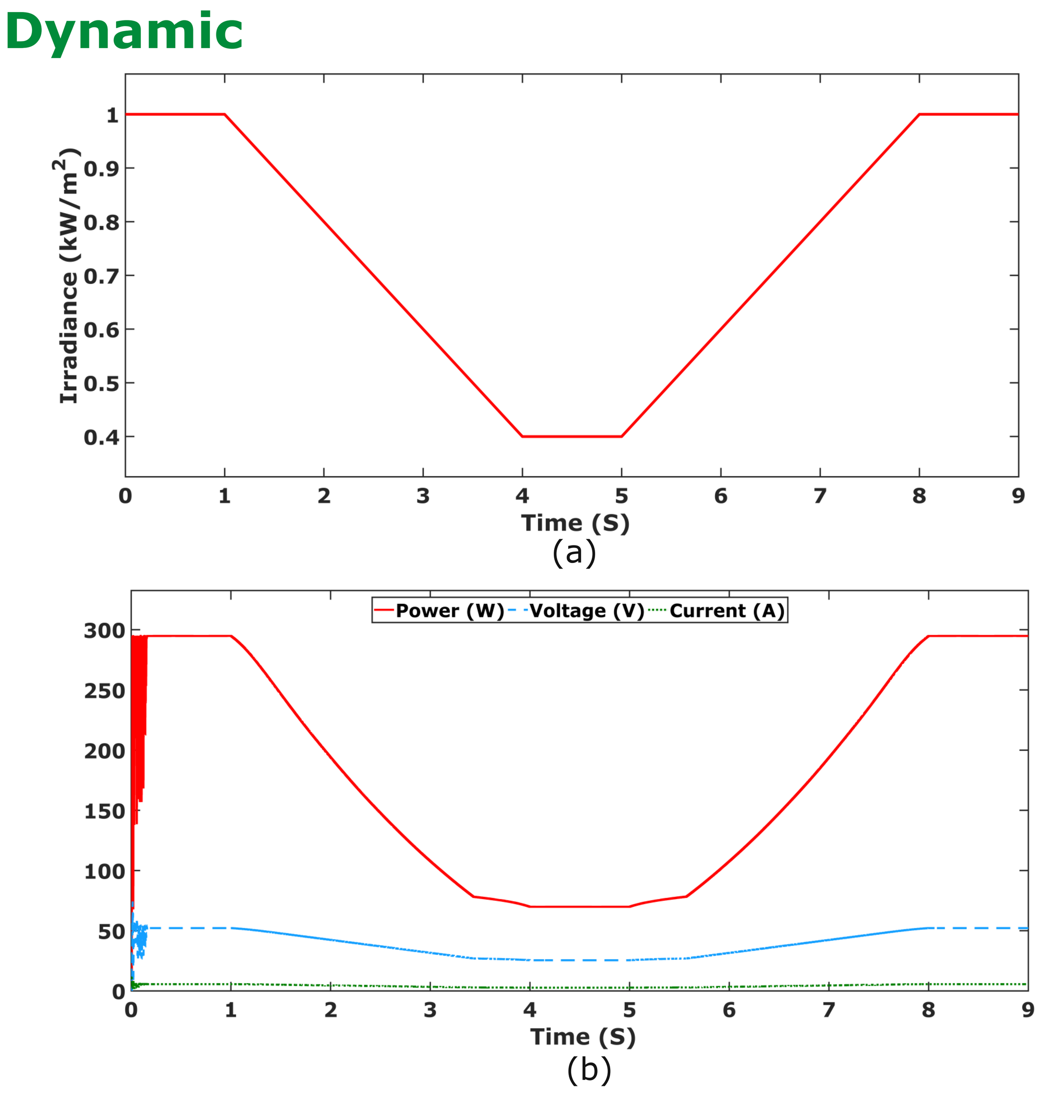


Figure (4) (a) Dynamic Irradiance variation (b) PV output power, voltage and current