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Evolutionary based maximum power point tracking technique using differential evolution algorithm

Mohammad Faridun Naim Tajuddin[a,b,*], Shahrin Md Ayob[b],
Zainal Salam[b], Mohd Sazli Saad[c]

[a] School of Electrical Systems Engineering, Universiti Malaysia Perlis, Malaysia
[b] Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Malaysia
[c] School of Manufacturing Engineering, Universiti Malaysia Perlis, Malaysia

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ABSTRACT

This paper presents a maximum power point tracking (MPPT) technique for photovoltaic (PV) system using a modified differential evolution (DE) algorithm. The standard DE is modified to deal with dynamic objective function problem to suit with the nonlinear time-varying MPPT nature. Using this approach, a fast and accurate convergence to MPP can be achieved. The performance of the algorithm is evaluated under large and rapid fluctuations of irradiation. For benchmarking, comparison to the conventional hill climbing (HC) technique is carried out. The results show that it outperforms the HC in terms of convergence speed and accuracy. In addition, the power oscillation at steady state is significantly diminished. The effectiveness of the proposed technique in handling partial shading conditions is also demonstrated. With this capability, the proposed technique can be suitably used for building integrated PV (BIPV) system.

1. Introduction

Solar photovoltaic (PV) has grown to be one of the most important renewable energy (RE) sources because of its environmental friendliness and long-term benefits. However, the low energy conversion efficiency of the PV module and high initial costs of PV system have been recognised as the major hindrance in its widespread acceptance [1]. One of the most economical ways of increasing the efficiency of PV system that should not be overlooked is to enhance the system by improving its maximum power point tracking (MPPT) capability. Generally, the voltage–current characteristics of a PV module/array are nonlinear in nature; the maximum power point (MPP) varies according to the amount of solar irradiance that hits the module and its temperature. Since these two parameters change continuously, the MPP on the *P–V* characteristic curve is not consistent. This MPP tracking process becomes more challenging during partial shading, a condition where the modules in an array do not receive a uniform solar irradiation. Such occurrences are quite common for building integrated PV (BIPV) systems (which are commonly installed in dense urban areas) due to the shadows from the nearby structures such as adjacent buildings, poles and trees. The main consequence of partial shading is the complexity of the *P–V* characteristic curve; it becomes multi-modal (multiple peaks curve), making it more difficult to locate the true global MPP.

Based on literature, the MPPT techniques can be categorised into two types. The first is known as the conventional MPPT, which includes perturb and observe (P&O), hill climbing (HC), incremental conductance (IncCond), fractional open circuit voltage and short circuit current. The second type is based on soft computing (SC), which includes fuzzy logic controller (FLC), artificial neural networks (ANN) and evolutionary algorithm (EA).

Most of the conventional MPPT techniques demonstrate a good steady-state and dynamic performance under normal irradiance condition. However, they typically exhibit high oscillation around the operating point and unable to properly track the MPP under rapid fluctuation of solar irradiance [2]. Furthermore, none of the conventional techniques are capable of dealing with partial shading (PS) conditions [3]. Multimodality of the *P–V* curve due to PS results in the conventional MPPT techniques to be trapped at the local maximum peak, causing huge amount of power losses.

To alleviate the problems, SC based MPPT techniques have been proposed, i.e. FLC, ANN, EA, etc. The FLC and ANN are proven to be

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[*] Corresponding author at: School of Electrical Systems Engineering, Universiti Malaysia Perlis, Malaysia. Tel.: +60 75536187; fax: +60 75566272.

E-mail addresses: faridun@unimap.edu.my (M.F.N. Tajuddin), shahrin@fke.utm.my (S.M. Ayob), zainals@fke.utm.my (Z. Salam), sazlisaad@unimap.edu.my (M.S. Saad).

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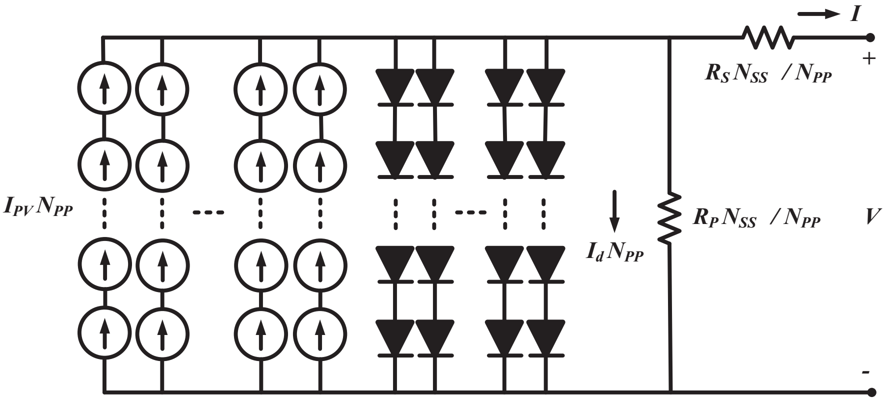

Fig. 1. Series parallel (SP) connected PV modules ($N_{SS} \times N_{PP}$).

effective and exhibit better steady-state and dynamic performance as compared to the conventional MPPT techniques [4–7]. However, the optimised design is difficult to be achieved for both techniques. FLC needs expert's knowledge and experience while ANN requires large amount of training data [8]. Due to these limitations, EA techniques have gained much attention due to their attractive features as the global optimisers. It is envisaged to be the best candidate in dealing with MPPT problem. Currently, several EA-based MPPT techniques have been proposed such as genetic algorithm (GA) [9], particle swarm optimisation (PSO) [10], ant colony optimisation (ACO) [11] and differential evolution (DE) [12]. The results are quite promising and encouraging.

Amongst the EAs, DE is one of the most powerful global optimisation algorithms and highly potential for solving MPPT problem due to its simplicity, fast computational speed and capable of finding the true global optima for a multi-modal search space [12]. DE-based MPPT was first introduced in [12] and further applied to a PV-grid connected system in [13] by the same author. However, the proposed DE in [12,13] is designed based on static objective function technique, i.e. pre-determined *P–V* curves. Hence, it is not practical for real-time MPPT since the *P–V* characteristic curve will always change with temperature and solar irradiance

This paper proposes a modified DE optimisation for MPPT application. Modifications to the standard DE algorithm are done to ensure its effectiveness in dealing with nonlinear time-varying MPP problem, i.e. dynamic objective function. It is shown that the proposed technique is able to deal with large and rapid fluctuations of solar irradiation and reaching the global MPP under various PS conditions. In addition, the steady-state oscillation around the MPP is significantly reduced once the correct MPP is reached. To further justify its viability, a comparative study with the conventional HC is also carried out.

The remainder of the paper is organised as follows: next section discusses the modelling of a PV array simulator used in this work. Section 3 presents a brief introduction to the standard implementation of DE algorithm followed by how it is modified for MPPT application. Section 5 provides the tracking results of the proposed technique and comparatively studies its performance with HC technique. The conclusion is made in the last section.

2. PV array model

Single diode model is used to model the characteristics of PV arrays in this work because its offers a good compromise between simplicity and accuracy. This model is suitable for a qualitative prediction of partial shading and mismatch modules effect. Furthermore, for a large PV array system, it is quite impossible to determine a very precise model for every single cell due to inherent variations of the cell parameters [14,15]. Hence, the single-diode model is sufficient and more preferable in MPPT strategy design.

A large PV array normally composes of several PV modules interconnected in a series-parallel (SP) configuration as shown in Fig. 1. The output current equation of an array formed by SP connection of identical modules using single-diode model can be written as:

$$I = N_{PP}\left\{I_{PV} - I_0\left[\exp\left(\frac{V + (N_{ss}/N_{PP})R_S I}{aV_T N_{SS}}\right) - 1\right]\right\} - \frac{V + (N_{SS}/N_{PP})R_S I}{R_P} \tag{1}$$

where I_{PV} is the current generated by incident light, I_0 is reverse saturation current, R_S is the series resistance, R_P is the parallel resistance, N_{SS} is the number of series modules, N_{PP} is the number of parallel modules, a is the diode ideality constant, and $V_T = N_S kT/q$ is the thermal voltage of the PV module having N_S cells connected in series. Other variables are defined as follows: q is the electron charge ($1.60217646 \times 10^{-19}$), k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K).The light-generated current which is linearly proportional to the solar irradiance and temperature can be written as:

$$I_{PV} = (I_{PV\_STC} + K_i(T - T_{STC}))\frac{G}{G_{STC}} \tag{2}$$

where I_{PV_STC} is the light-generated current at the Standard Test Condition (STC), T and T_{STC} are the actual and temperatures at STC respectively (in Kelvin, $T_{STC} = 298$ K), G is the irradiance on the device surface, and G_{STC} is the irradiation at STC (1000 W/m^2). The constant K_i is the temperature coefficient of short-circuit current provided by the manufacturer. The diode saturation current, I_0 can be expressed as:

$$I_0 = I_{0\_STC}\left(\frac{T_{STC}}{T}\right)^3 \exp\left[\frac{qE_g}{ak}\left(\frac{1}{T_{STC}} - \frac{1}{T}\right)\right] \tag{3}$$

where E_g is the band gap energy of the semiconductor ($E_g = 1.12$ eV for the polycrystalline Si at 25 °C), and I_{0_STC} is the diode saturation current at STC:

$$I_{0\_STC} = \frac{I_{SC\_STC}}{\exp(V_{OC\_STC}/aV_{t\_STC}) - 1} \tag{4}$$

with V_{t_STC} is the thermal voltage of Ns series-connected cells at the STC temperature T_{STC}. The only unknowns of Eq. (1), R_S and R_P are calculated by iteratively fit the *I–V* and *P–V* curve of the calculated model and actual model from manufacturer datasheet [16]. The electrical parameters of MSX60 module from Solarex at STC used in this work are tabulated in Table 1.