Solar Energy 137 (2016) 189–200

Contents lists available at ScienceDirect

Solar Energy

journal homepage: www.elsevier.com/locate/solener

Maximum power point tracking using a variable antecedent fuzzy logic controller

Trevor Hocksun Kwan *, Xiaofeng Wu

School of Aerospace, Mechanical and Mechatronics Engineering (AMME), University of Sydney, University of Sydney, Darlington 2006, NSW, Australia

ARTICLE INFO

Article history:
Received 22 February 2016
Received in revised form 1 August 2016
Accepted 4 August 2016
Available online 15 August 2016

Keywords:
SEPIC converter
Fuzzy logic control (FLC)
Maximum power point tracking (MPPT)
Solar panel

ABSTRACT

Maximum power point tracking (MPPT) techniques are popularly used for maximizing the output of solar panels by continuously tracking the maximum power point of their *P-V* curves, which depend both on the panel temperature and the input insolation. Various MPPT algorithms have already been studied in literature, including perturb and observe (P&O), hill climbing, incremental conductance and neural networks. In particular, fuzzy logic control (FLC) is an another popular technique which achieves a significantly improved performance in MPPT in terms of response speed and no oscillations about the maximum power point (MPP). Unfortunately, a major issue that arises in classical FLC based MPPT algorithms is the lack of versatility to rapidly changing environmental conditions such as the applied irradiance. This paper presents an alternative design of an adaptive MPPT fuzzy logic controller which utilizes simple formulae instead of complex learning algorithms to adjust the antecedents. To verify the proposed MPPT system, a customized off the shelf solar panel is connected to a SEPIC converter and the overall system is both simulated on Simulink and experimentally verified. The resulting response is shown to be fast and stable in comparison to previous designs which used fixed fuzzy logic antecedents that need to be manually modified whenever the environmental conditions change or if a different solar panel is used.

1. Introduction

Renewable energy sources have been a major research topic in recent years, especially because of environmental issues such as pollution and global warming. Amongst the various existing concepts, solar photovoltaic (PV) arrays have attracted the most attention because of their higher conversion efficiency. Moreover, ongoing research is also being undertaken to find new configurations and materials to further enhance the efficiency of the PV array (Xing et al., 2013; Guter et al., 2009; Crisp et al., 2004; Isomura et al., 2002). Indeed, solar energy can be considered as a potential prospective solution for the energy crisis.

All solar panels have power characteristic curves such that when an impedance of a unique size is connected, maximum power is obtained. This unique impedance varies considerably with both the input irradiance and the temperature of the module. Subsequently, a maximum power point tracking (MPPT) algorithm is utilized to emulate the impedance such that the power system is always operating at the maximum power point (MPP). Various MPPT techniques already exist (Esram and Chapman, 2007; De Brito et al., 2013) including perturb & observe (P&O) Yu and Chau, 2009; Femia et al., 2005; Hsiao and Chen, 2002; Abdelsalam et al., 2011; Chen et al., 2007 or hill climbing (Xiao and Dunford, 2004; Liu et al., 2008), incremental conductance (Safari and Mekhilef, 2011; Lee et al., 2006; Yan et al., 2008; Liu et al., 2007, 2008; Mei et al., 2011), fractional short circuit current or open circuit voltage (Mutoh et al., 2006) and neural networks (Lin et al., 2011).

In particular, the fuzzy logic controller (FLC) was first introduced in Won et al. (1994) for the MPPT application where the authors aimed to tackle the commonly known issues in the P&O and hill climbing algorithms such as the trade-off between response speed and steady state oscillations. In Won et al. (1994), the FLC takes two inputs, the slope of the *P-I* curve ($\frac{dP}{dI}$, Eq. (1)) and the change in its value (Eq. (2)). The output is then the change in the DC-DC converter's duty cycle (ΔD). The main idea is to drive $\frac{dP}{dI}$ toward zero since this is the location of the MPP. The second input ($cE[n]$) is then used to effectively damp the duty cycle so that it settles at the MPP rather than oscillate around it.

$$E[n] = \frac{dP}{dI} = \frac{P[n] - P[n-1]}{I[n] - I[n-1]} \tag{1}$$

* Corresponding author.
E-mail address: tkwa1498@uni.sydney.edu.au (T.H. Kwan).

http://dx.doi.org/10.1016/j.solener.2016.08.008
0038-092X/

$$cE[n] = E[n] - E[n-1] \tag{2}$$

FLC based MPPT has ever since evolved into a very popular topic where many variations of the FLC for MPPT have been introduced by many researchers. For instance, various papers have considered using $\frac{dP}{dV}$ as the input to the FLC rather than Eq. (1) since it typically achieves a more stable response (Hajighorbani et al., 2014; Cheikh et al., 2007; Lalouni et al., 2009). Specifically, Hajighorbani et al. (2014) studied and evaluated the performances of several different fuzzy rule bases and hence determined the optimal rule base amongst the selected candidates. Lalouni et al. (2009) and Al Nabulsi and Dhaouadi (2012) have also proposed using the reference output voltage as the output of the FLC and a 2nd control loop is subsequently used to select the appropriate duty cycle. This method is essentially a modified perturb and observe (P&O) algorithm involving FLC. Alajmi et al. (2011) and Alajmi et al. (2013) proposed using the change in power (dP) and the change in current (dI) as the two inputs to the FLC instead of $\frac{dP}{dI}$ since this would increase the FLC's stability under rapidly changing irradiances. Moreover, the fuzzy PID concept has also been applied to the MPPT problem in Dounis et al. (2013) and Salem et al. (2005).

Nevertheless, the aforementioned FLC based MPPT algorithms all involve setting certain constants for the curves of both the input and the output truth membership functions. These constants quantify the inputs and outputs into their relevant members and their values for optimal performance rely not only on the choice of the solar panel, but also on the environmental conditions (irradiance and temperature). Obviously, this means that such FLC designs lack versatility and adaptability. Subsequently, a FLC involving variable input and output memberships are desired. In this aspect, Patcharaprakiti et al. (2002) introduced the adaptive FLC for MPPT where the antecedents are adjusted based on a learning algorithm to optimize the response of the tracker. Alternatively, Larbes et al. (2009) and Messai et al. (2011) also proposed using genetic algorithms to train the FLC. Although such algorithms can achieve the desired versatility and adaptability, they are typically very computationally intensive. Subsequently, these algorithms often require that the fuzzy rule base optimization process be conducted offline. This has the obvious disadvantage of requiring external computers who need to periodically update the fuzzy rules and hence update the software in the microcontroller. Alternatively, in a recent publication (Guenounou et al., 2014), an online adaptive FLC is proposed which involves two FLCs; The first is simply the conventional FLC MPPT algorithm and the second is used to evaluate the appropriate gain to be multiplied with the "normalized" duty cycle perturbation. Unfortunately, as mentioned in the paper, their proposed algorithm still requires fine tuning via trial and error and thus has the same issue as the conventional FLC based MPPT algorithms.

This paper takes a different approach in that the antecedents and the consequences of the FLC are varied in ratios w.r.t. the measured current. A customized function $\left|V\frac{dI}{dV}\right|$ (Eq. (14)) is used as the input to the FLC and its basis for achieving MPPT is based on the conventional condition of $\frac{dP}{dV} = 0$ (Eq. (3)). By comparing this function to the operating current, a relative or variable antecedent based FLC is achieved. In doing so, the trial and error process that is otherwise used in conventional FLC designs to determine the critical points of the membership functions is eliminated. More importantly, because the customized function $\left|V\frac{dI}{dV}\right|$ is effectively compared in ratios to the measured current, a high degree of online flexibility is obtained. Thus, even without modifying the proposed FLC algorithm's membership functions, a high tracking performance is maintained when the irradiance is significantly changed or even when a different solar panel is used. Furthermore, unlike FLC designs that require training via genetic or other learning algorithms, the proposed FLC is simple in terms of computational intensity and, as demonstrated experimentally in this paper, can be directly implemented into a typical microcontroller.

$$J = \frac{dP}{dV} = V\frac{dI}{dV} + I \rightarrow \begin{cases} < 0 & \text{Right of MPPT} \\ = 0 & \text{At MPPT} \\ > 0 & \text{Left of MPPT} \end{cases} \tag{3}$$

It is noted that as solar panels in satellites are a prime interest to the authors, the operation of solar panels in outer space is conducted in this research. Unlike ground based applications, the space environment involves larger ranges in possible irradiance and also larger temperature differences upon changes in irradiances.

The remainder of the paper is organized as follows. Section 2 describes the PV circuit model. Section 3 shows the proposed FLC based MPPT algorithm and the underlying principles used to design them. Section 4 presents the simulation and its results. Section 5 provides an experimental verification of the proposed algorithm and Section 6 concludes this paper.

2. PV modeling

This paper adopts the single diode equivalent circuit model which includes a series (R_s) and parallel resistor (R_p). The mathematical model is given in Eqs. (4)–(7) and the equivalent circuit model is given in Fig. 1.

$$I = I_{PV} - I_0\left(e^{\frac{V+IR_s}{aV_t}} - 1\right) + \frac{V+IR_s}{R_p} \tag{4}$$

$$I_{PV} = I_{SC} = n_p(I_{scN} + K_i\Delta T)\frac{G}{G_N} \tag{5}$$

$$I_0 = \frac{I_{sc}}{e^{\frac{V_{OC}}{aV_t}} - 1} \tag{6}$$

$$V_{OC} = n_s(V_{ocN} + K_v\Delta T) \tag{7}$$

The parameters in Eqs. (4)–(7) are given as follows:

I_{PV} – The photovoltaic current that is generated by the solar panel.
I_{SC} – The short circuit current of the solar panel.
I_{scN} – The short circuit current of a single cell of the solar panel under the specified nominal conditions.
K_i – A co-efficient that approximates linearly the change in I_{SC} with respect to the operating temperature.
V_{OC} – The open circuit voltage of the solar panel.
V_{ocN} – The open circuit voltage of a single cell of the solar panel under the specified nominal conditions.
K_V – A co-efficient that approximates linearly the change in V_{OC} with respect to the operating temperature.
n_s – Number of solar cells in the solar panel that are in series.
n_p – Number of solar cells in the solar panel that are in parallel.
R_s – The resistance of the internal series resistor.
R_p – The resistance of the internal parallel resistor.

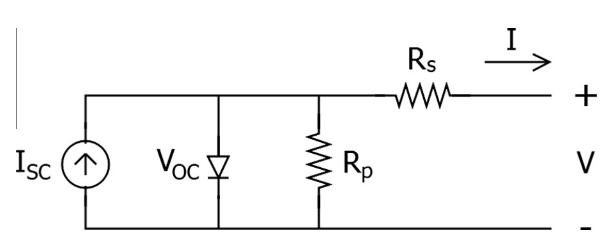

Fig. 1. The equivalent circuit model of a solar panel.