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An Intelligent MPPT controller based on direct neural control for partially shaded PV system

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ABSTRACT

The development of an effective maximum power point tracking (MPPT) algorithm is important in order to achieve maximum power operation in a photovoltaic system (PV). In this study, a direct neural control (DNC) scheme is developed. The intelligent MPPT controller consists of a hybrid learning mechanism; an on-line learning rule based on gradient decent method and an off-line learning rule based on Big Bang–Big Crunch (BB–BC) algorithm. The effectiveness of the proposed system is tested under partial shading conditions by applying the cascaded converter topology. The feasibility of the DNC is evaluated by the simulation results and compared to the conventional perturbation and observation (P&O) method.

1. Introduction

In recent years, electricity and environmental protection demands are motivating research in the direction of exploiting green energy sources like solar energy, wind energy, water energy, biomass energy, etc. Low cost reliable solar energy is widely used in buildings and industrial applications such as hybrid electric vehicles and aerospace applications.

Photovoltaics (PV) are a major part of solar systems that directly convert solar irradiance into electricity. In order to reduce the cost of energy, it would be ideal to maintain the PV at its maximum power operation at all times. This becomes complicated by uncertain nonlinear current–voltage (*I–V*) and power–voltage (*P–V*) characteristics due to the changes in intrinsic and atmospheric conditions. The maximum power point (MPP) is a unique point on the *P–V* curves depending on the above conditions; at this point the PV system produces its maximum output power. Although, there are many factors influencing energy conversion efficiency, the maximum power point tracking (MPPT) is the most vital aspect of control design in a PV system.

MPP tracker is a buck converter associated with the control unit (DNC) usually employed to interface the power flow from the PV system to the load in order to extract the maximum power from the PV system. DNC constitutes a switch control method for buck converters.

MPPT is a nonlinear control problem and therefore an MPP tracker is designed to control a nonlinear process. The unpredictable change of the environmental conditions influences the PV characteristics and parameters considerably. Kanarachos and Geramanis [1] developed a multi layer feedforward NN as a direct controller based on a back propagation learning law, which can be easily implemented in practice in order to test hydronic heating systems for temperature control. Utomo [2] designed an enhanced NN controller for buck-boost DC/DC converter by applying back propagation algorithm. Also, in the literature many researchers were introduced solutions in control problems by adopting a single neuron controller. A direct neural network (NN) controller for energy saving and high comfort level in HVAC systems was studied by Liang and Du [3]. Varghese et al propose a control method for speed BLDC Motor by using a Single neuron PI controller [4]. Tang et al. design an adaptive single neuron PID method for controlling the liquid level [5].

Furthermore, a significant number of MPPT algorithms have been presented such as the perturb and observe method (P&O)

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and the incremental conductance method [6,7]. MPPT controllers based on artificial intelligence techniques have been proved more beneficial than classical models, regarding efficiency and accuracy [8]. Computational intelligence based methods using fuzzy logic, neural networks, particle swarm optimizers (PSO) and genetic algorithms (GA) have been applied in order to improve the tracking efficiency [6,8–11]. Dounis et al. [12] proposed a methodology to track the MPP using feedback control based on a proportional integral-derivative (PID) controller tuned by fuzzy gain scheduling and online adaptation of the scaling factors. Results show that the designed adaptive approach achieves a good maximum power operation under any conditions such as different levels of solar irradiance and/or PV cell temperature for various PV sources. Furthermore, partial shaded condition is an important issue in PV operation as many local maxima come up in the P-V curve. Many algorithms have been introduced in order to overcome this problem. Tajuddina et al. [13] introduce a technique using a differential evolution algorithm, Murtaza et al. [14] study the methodology on bypass diode mechanism, Jiang et al. [15] introduce ant colony technique for partial shaded conditions while Shaiek et al. [16] developed a GA technique suitable for partial shaded conditions.

The main contribution of this paper is to develop a methodology using a single neuron in order to achieve MPPT control. A direct neural control (DNC) scheme is proposed for MPPT control in order to improve the performance of the buck converter and to achieve the maximum power point operation. The DNC consists of a single adaptive neuron and a hybrid learning mechanism combining an on-line learning rule based on gradient decent method and an off-line learning rule based on Big Bang–Big Crunch (BB–BC) algorithm [17]. The on-line learning scheme is usually implemented by using error back-propagation algorithms but it suffers from convergence towards a local minimum caused by the initial weights and the setting of learning parameters. To overcome this problem, an off-line learning scheme is employed, based on a Big Bang–Big Crunch optimization algorithm. The initial value of parameters such as the weights of the neuron (w_1, w_2, w_3), the slope of the sigmoidal function (a) and the learning rate (η) are optimized off-line by the BB–BC algorithm. The optimum initial values can be used as a starting point for the gradient-based method that is able to ameliorate the solution of extracting maximum power from a PV system. These values can also be found by the trial and error method, but this is a five dimension problem and the finding of the optimal solution is a very hard and time consuming procedure. Simulation results demonstrate the effectiveness of the proposed control system and show that this methodology has a better performance on a PV system in transient operations. The effectiveness of the proposed system is also tested under partial shading conditions by applying the cascaded converter topology [18].

2. Model of PV sources

2.1. A PV source

The equivalent circuit of the Photovoltaic (PV) source is illustrated in Fig. 1 and its characteristics are presented in Table 1. The output current equation in respect to solar irradiance G, temperature T and voltage across the PV source Vpv is:

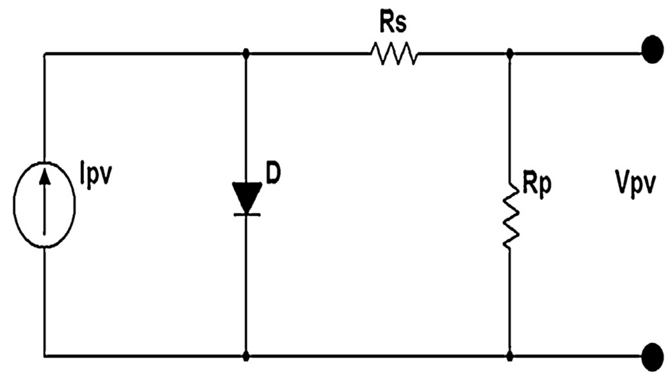

Fig. 1. Equivalent circuit of photovoltaic power source.

Table 1
Parameters of the PV source.

Parameters	Description	Value
n_p	Number of cells connected in parallel	1
n_s	Number of cells connected in series	30
R_s	Series resistance at reference conditions	0.008 (Ω)
R_p	Parallel resistance	1000 (Ω)
I_{scr}	The short circuit current of a PV cell at the reference conditions	7.34 (A)
V_{ocr}	The open circuit voltage of a PV cell at the reference conditions	0.6 (V)
P_{mppr}	The maximum power that the PV cell can produce at the reference conditions	3.48828 (W)
n_{pmpp}	Coefficient factor of the power at the MPP	−0.0044
n_{scT}	Temperature coefficient	0.00004
Io	Reverse saturation current	10^{-6} (A)
q	Electron charge	1.6×10^{-19} (C)
A	Quality factor	1.3
k	Boltzmann constant	1.38×10^{-23} m^2 kg s^{-2} K^{-1}
G	Solar irradiance	Variable ($\frac{W}{m^2}$)
T	Temperature	Variable (°C)

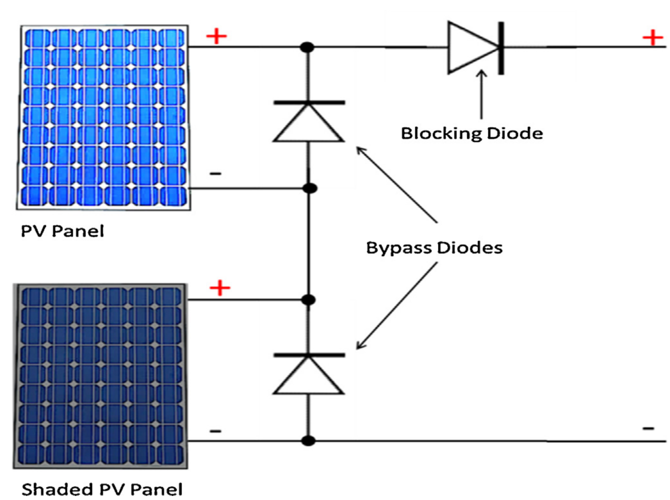

Fig. 2. PV module in series topology.

this model the parallel resistance is external, thus it is not contained into Eq. (1) The relation between the reverse saturation current I_o

$$I_{pv}[G,T,V_{pv}] = I_o[T]n_p + I_{sc}[G,T]n_p - \frac{An_sV_{th}}{R_s[G,T]}\text{Product Log}\left[\frac{e^{\frac{1}{An_sV_{th}}[IO[T]n_sR_s[G,T]+ISC[G,T]n_pR_s[G,T]V_{pv}]}}{An_sV_{th}} I_O[T]n_pR_s[G,T]\right] \quad (1)$$

Where V_{th} is the thermal voltage and equals to $V_{th} = kT/q$, Product Log is the Lambert W function, the inverse function of $f(W) = We^{W}$. In

versus the temperature T, the series resistance R_s versus the temperature T and solar irradiance G, the short circuit current I_{sc}