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A Solar-powered Battery Charger with Neural Network Maximum Power Point Tracking Implemented on a Low-Cost PIC-microcontroller

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Abstract **– This paper presents the development of a maximum power point tracking algorithm using an artificial neural network for a solar power system. By applying a three layers neural network and some simple activation functions, the maximum power point of a solar array can be efficiently tracked. The tracking algorithm integrated with a solar-powered battery charging system has been successfully implemented on a low-cost PIC16F876 RISC-microcontroller without external sensor unit requirement. The experimental results with a commercial solar array show that the proposed algorithm outperforms the conventional controller in terms of tracking speed and mitigation of fluctuation output power in steady state operation. The overall system efficiency is well above 90%.**

I. INTRODUCTION

In present, as the problem of fossil energy depletion becomes more severe, photovoltaic has received much interest to be used as a secondary energy source. The term photovoltaic refers to the phenomenon involving the conversion of sunlight into electrical energy via a solar cell [1]. Performance of a photovoltaic-based system strongly depends upon the capability to determine an optimal operating point of the solar array at which the maximum power can be drawn for any given load. Under certain temperature and light intensity, there is only single maximum-power point in a normal cell. Therefore, maximum power point tracking (MPPT) of the solar cell is essential as far as the system efficiency is concerned.

There are a number of MPPT techniques have been proposed in the past decades. They range from conventional methods, such as the Hill-Climbing Method [2] and the Perturbation and Observation Method (P&O) [3], to much more sophisticated artificial intelligent methods, such as Fuzzy Logic Control (FLC) [3], Adaptive Neural Fuzzy Inference System (ANFIS) [4] and Genetic Algorithm Trained Radial Basis Function Neural Network (GA-RBF) [5]. Comparatively, conventional methods can give poorer performances, but easier to implement.[3-5] Artificial Intelligent methods, on the other hand, perform better, but their structure are generally more complicated and require relatively high performance processor. The implementation of an inference engine for FLC, for instance, is time-consuming and occupies a large memory space [6]. It, therefore, may not be suitable for some applications where cost is a prime concern.

The Artificial Neural Network (ANN) algorithm has also been applied widely for MPPT. In [5], for example, the ANN for MPPT in a grid-connected system is presented. The application of ANN together with FLC for MPPT of a coupled-inductor interleaved-boost-converter-supplied PV system has been presented in [7]. These algorithms, however, requires complicated data training procedure to initialize the operation. The ANN proposed in [8] employs external sensory units, i.e. light intensity and load current sensors, for the initialization and identification of the operating point.

In this paper, we propose an implementation of MPPT. The algorithm is based on the Hill-Climbing method co-operated with ANN. A low-cost PIC16F876 RISC controller is employed for the algorithm processing, and it is integrated to a boost converter to form a solar-powered battery charging system. There is no external sensory unit required to be added into the system. Despite of its cost-effectiveness, we shall demonstrate that the system performance is outstanding.

The remainder of the paper is organized as follows. A typical solar power system is reviewed in Section II. The system configuration of the proposed SPBC is addressed in Section III. The design of ANN for MPPT is described in section IV. In Section V, the development of Artificial Neural Network Solar-Power Battery Charging System (ANN-SPBC) is discussed. The experimental results are shown in this section. Finally, conclusion is drawn in Section VI.

II. SPBC SYSTEM

The configuration of the solar-powered battery charging system (SPBC) used in this research is shown in Fig. 1, a key of which is PIC16F876 RISC microcontroller [9]. The boost converter circuit used in the battery charging mechanism comprises of one inductor (L=15mH), two capacitors (C_1 = 2200μF, C_2=100μF), and two Schottky diodes D_1 and D_2. A power MOSFET BUZ11 operating at 46 kHz is used as a switching device S. A commercial-grade battery bank with rated at 12V, 5Ahr is used for the power storage. It is selected corresponding to the solar array [10].

In our design, the controller performs two main functions. First, it determines duty ratio D for the operation of switch S in such a way that the operating point of the solar array can be controlled toward the maximum power point. The controller also has to consistently detect the battery voltage to avoid battery overcharging. When the battery is fully charged, the controller will switch off the switch S.

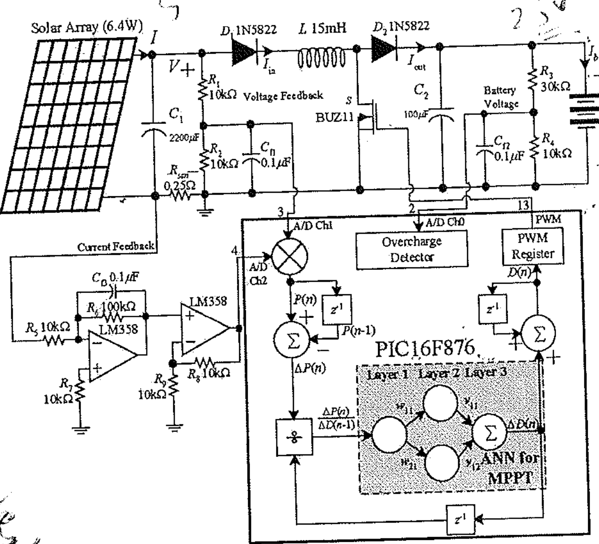

Fig. 1. The proposed ANN-SPBC system.

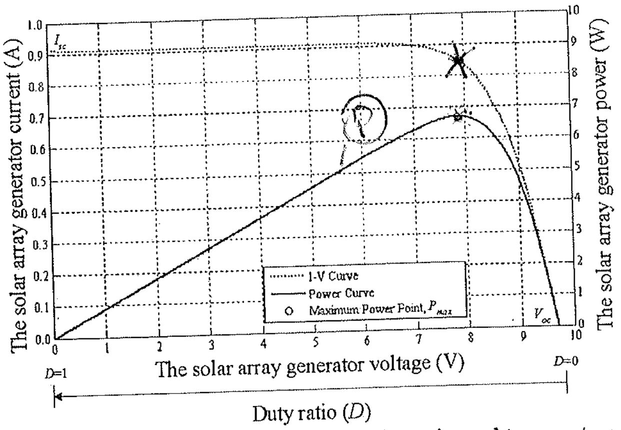

Fig. 2. I-V and Power curve under light intensity and temperature.

TABLE I

SORAY ARRAY SPECIFICATION (25°C, 100mW/cm^2)

Parameters	Definitions
Maximum power, $P_{\max}$	6.70W
Voltage at Maximum power point, V_m	7.90V
Current at Maximum power point, I_m	0.81A
Short circuit current, I_{sc}	0.91A
Open circuit voltage, V_{oc}	9.70V
Model size	275×270×26mm

III. SOLAR-POWERED SYSTEM

A. Characteristic of a solar array

Typically, a solar array comprises of a number of solar cells connected in series and/or parallel. Its mathematical model may be given as [5] :

$$P_T = n_p I_{ph} V - n_p I_o \left(\exp\left(K_o \left(\frac{V}{n_s} + I_T R_{sT} \right) \right) - 1 \right) V - \left(V/n_s + I_T R_{sT} \right) V / R_{shT} \quad (1)$$

, where P_T denotes the output power (W), V denotes the output voltage of the solar array (V), I_{ph} denotes the current of the solar array that is proportional to light intensity (A), I_T denotes the output current proportional to temperature (A), I_o denotes the array's reverse saturation current (A), R_{sT} and R_{shT} are defined as the equivalent series and parallel resistance (Ω) respectively, n_s is the number of series string in the solar array , n_p is the number of parallel string in the solar array and K_o is a constant.

Generally, the characteristic of a solar array can be comprehensively described by its operating curve known as I-V curve. This specific curve is usually supplied by the manufacturers. It shows the relationship between output voltage and current of the solar array as depicted in Fig. 2. It can be observed that, under a certain light intensity and temperature, there is a unique point on the I-V curve at which the maximum power can be generated from the solar array. Thus, a mechanism is required to track this specific point, so that the optimal operation of the overall system can be achieved. Table I shows the specification of a commercial solar array used in this research works.

B. MPPT by hill climbing algorithm

Probably, one of the simplest methods for tracking the maximum power point is the so-called Hill-Climbing Method [2], in which MPPT is obtained by comparing the output power at two different operating points, and then, the duty ratio ($D(n)$) can be determined from

$$D(n) = D(n-1) + \operatorname{sgn}(\Delta P) \cdot \Delta D(n) \quad (2)$$

, where sgn(•) is the signum function, $\Delta P(n)$ is the change in output power and $D(n)$ is the duty ratio at consecutive time interval n. $\Delta D(n)$ is the step size of change in duty ratio.

In this algorithm, the ΔD is generally fixed, and the tracking performance closely depends on the ratio $\Delta P/\Delta D$ as shown in Fig. 3. We can see that larger ΔD needs smaller number of operation step to reach the maximum power point, the derivative $\Delta P/\Delta D$ is equal to zero. It, however, results larger fluctuations around the maximum power point. Smaller ΔD, on the other hand, takes longer to reach the target, but it can give smoother tracking performance. Therefore, trade-off between performance indexes, i.e. the tracking time and the suppression of fluctuation of generating power in steady-state condition, must be carefully considered in the determination of such fixed ΔD.

IV. MPPT USING ANN

In our research, we applied an artificial neural network to the conventional Hill-Climbing MPPT so that the duty ratio can be dynamically adjusted accordingly to the ratio of P/ D. The configuration of ANN is shown in the shaded box of Fig. 3. It comprises of three layers, the input, hidden and output layers. The structure of each layer can be described as follows:

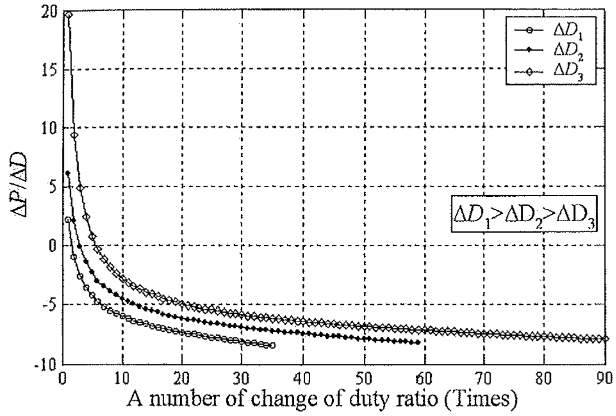

Fig. 3. The characteristic of change of power (ΔP) with change of duty ratio (ΔD).

Layer 1: The single node in this layer receives the ratio $\Delta P/\Delta D$ as its input, and gives two outputs to the next layer. The weight functions of this layer, w_{11} and w_{21}, are assigned as +1 and −1, respectively. The output from this layer is given as:

$$f_i = w_{i1}\frac{\Delta P(n)}{\Delta D(n-1)} \tag{3}$$

Layer 2: Two nodes in this layer calculate the output using a ramp function as the activation function as shown in Fig. 4 (a). Mathematically, this activation function is described by

$$a(f_j) = \begin{cases} 1 & \text{if } f > 0 \\ f_j & \text{if } 0 \le f < 1 \\ 0 & \text{if } f < 0 \end{cases} \tag{4}$$

, where f is the node's input. The weight functions of this layer, v_{11} and v_{12}, are chosen so that the network's output, the change in duty ratio, cover the designed range as shown in Fig. 4 (b).

Layer 3: The single fixed node in this layer computes the output by summing the contribution from each node in layer 2:

$$\Delta D = \sum_j v_{1j} a(f_j) \tag{5}$$

Note that the proposed ANN structure for MPPT requires only data measured from the solar array. There is no need for any external sensory.

V. EXPERIMENTAL RESULTS

For performance evaluation, the ANN software was developed using C-programming language with an associated cross-compiler for PIC16F876. Using the solar array whose characteristics described above, tracking performance of MPPT obtained from the proposed ANN and the conventional hill climbing algorithm [2] was examined. It should be noted that a sampling time for both algorithms was selected to be 10ms.

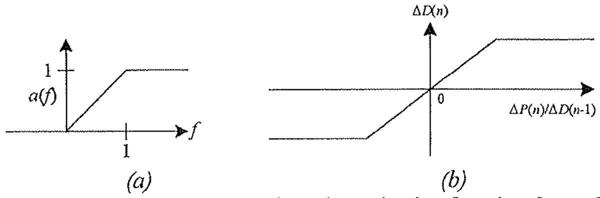

Fig. 4. Graph represented (*a*) the activation function for each node in layer 2 and (*b*) the output characteristic of the proposed ANN

In the experiment, the light source was turned on at $t = 0$s under a light intensity of 80mW/cm^2 and temperature of 40°C. The maximum power point at this environment is 5.1W. Fig. 5 (a) and (b) show the power tracking results obtained from the Hill-Climbing method with the change in duty ratio, ΔD, of 0.02 and 0.04, respectively. It can be seen that the settling time (t_s) when $\Delta D = 0.02$ is 250ms whereas it takes only 110ms when $\Delta D = 0.04$. The larger ΔD, however, gives larger fluctuations in output power.

Fig. 6 shows the results obtained from the proposed ANN algorithm. We can obviously see that the settling time is substantially reduced, only 36 ms, and the power fluctuations are very small throughout the course.

The system performance has also been tested under more practical scenarios. The light intensity is set to be varying with the values of 25, 90 and 50mW/cm^2 at 0 to 2s, 2 to 4s, and 4s onward, respectively. This environment results in three maximum power points of 1.8W, 6.1W and 3.3W, respectively. The results obtained from our proposed system are depicted in Fig. 7. Again, the maximum power point can be tracked relatively fast and with small fluctuations, even under such dynamic environment.

In order to verify the efficiency of the overall system, the steady state power received by the battery has been measured. The DC-link current flowing through the battery at steady state is shown in Fig. 8. It is observed that the battery voltage, V_{bat}, measured after the boost converter is 12.9V, and the battery current is 0.43A. Hence, the output power fed into the battery becomes 5.0W. This means the overall efficiency of the proposed system is more than 91% given that the output power solar array is 6.1W.

VI. CONCLUSIONS

In this paper, the development of a maximum power point tracking for photovoltaic systems has been presented. The experimental results obviously show that the artificial neural network algorithm we proposed can give significantly faster tracking speed than the conventional Hill-Climbing method. Furthermore, the power fluctuation in steady state condition is substantially mitigated. We have demonstrated that the proposed algorithm can be easily implemented on a low-cost PIC16F876 RISC microcontroller-based system to form a high performance solar-powered battery charging system. Although without any external measuring unit, the maximum power point of the solar cell can be efficiently tracked with fast and smooth reaction to the environment changes. The efficiency of the whole system is well above 90%.