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Neural Network based Maximum Power Point Tracking Technique for PV Arrays in Mobile Applications

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***Abstract.* – Maximum power point tracking (MPPT) of photovoltaic (PV) arrays is an essential concern to enhance the efficiency of the whole PV system. Under partially shaded conditions (PSC) that all modules do not receive uniform illumination, the tracking turns out to be challenging, due to the output power-voltage characteristic of the PV array exhibits multiple peaks. In mobile applications, PSC becomes more troublesome since the partial shading patterns change very fast. Therefore the tracking of the MPP should be quick and precise. In this paper a two-stage MPPT Method that combines Artificial Neural Network (ANN) and Hill Climbing (HC) is presented. In the first stage an ANN estimates the vicinity of the MPP and in the second stage, HC is performed to obtain the exact MPP. The approach is very fast which makes it suitable for mobile applications and is able to extract maximum power under uniform irradiation and PSC. The validity of the proposed method is investigated by simulations in MATLAB/Simulink environment. The simulation results show that the proposed method provides a quick and accurate tracking.**

Index Terms – Photovoltaics, MPPT, Solar Vehicle, Partially Shaded Condition, ANN

I. Introduction

Over the last few decades, solar energy has received a great deal of attention due to depletion of fossil fuel sources and environmental concerns. Transportation systems as one of the greatest fossil fuel consumers play an important role in greenhouse gas emissions [1]. The electric vehicle (EV) is a solution to this problem. Recently some car manufacturers start to employ PV panels on the rooftop of vehicles as an extra source of power, and yet they face difficulties such as solar cell low conversion efficiency and the limitation of space for PV installation. These limitations reveal the necessity of an effective maximum power point tracker (MPPT). MPPT of a PV array in any environmental condition is significantly important to improve the overall PV system efficiency.

The output power-voltage (P-V) characteristic of a PV array is nonlinear and dependent upon illumination level and temperature. Consequently, the tracking of the MPP at various environmental conditions can be a challenging problem. Mostly, the MPP is achieved by current or voltage regulation of a DC-DC converter. An extensive amount of study has been conducted and many MPPT methods have been proposed so far [2-4]. The most well-known methods include Perturbation and Observation (P&O), Hill Climbing (HC) and Incremental Conductance (IC), which benefit from simplicity and low cost. However, under partially shaded conditions (PSC) which the output P-V characteristic displays multiple peaks, these methods are unsuccessful since they cannot distinguish between global and local peaks.

Many MPPT Methods using fuzzy logic (FL) [5], artificial neural networks (ANN) [6], evolutionary computation (EC) [7, 8] and other techniques [9, 10] have been applied to PV systems under PSC. These methods appear to be competent but they differ in many aspects such as speed of tracking, cost, required number of sensors, ease of implementation, and application they suit. In mobile applications, the speed of tracking is considered to be in priority since the shading patterns change very fast.

ANNs highlight some advantages such as non-linear mapping, less computational burden, no requirement for knowledge on internal parameters, and fast response. In MPPT applications, the input signals to the ANN can be electrical inputs such as PV array voltage and current, non-electrical inputs such as temperature and irradiance, or any combination of these. The output is usually the voltage of MPP or the corresponding duty cycle. ANN-based MPPT techniques that are presented in [11-14] require solar irradiance and/or temperature sensors, which result in higher cost. Commonly, electrical inputs are preferred to non-electrical inputs from cost and robustness points of view [6]. Thus authors of [15] proposed an ANN-based modified IC algorithm that utilizes the voltage and current measured at a single point of the PV characteristic to estimate the global maximum power point (GMPP). However, the performance of the method is satisfactory under a limited number of PS patterns. In [16], the inputs to ANN include the voltage and current of several points of PV characteristic and the output signal is estimated GMPP. This method has good accuracy but suffers from slow tracking and heavy computational burden. Ref. [17] proposed a direct neural control scheme consists of a single adaptive neuron and a combined on-line and off-line learning rule. Every PV panel has its own converter and MPPT, which is not cost-effective.

Considering the criteria to access MPPT in mobile applications, the existing methods have several shortcomings such as slow tracking, too much complexity, inability to track GMPP under complicated PS patterns and high cost. This paper proposes an ANN-based MPPT method that tracks GMPP under uniform irradiation conditions (UIC) and PSC quickly and precisely and is appropriate to solar vehicles. The remainder of the paper is organized as follows: Section II describes the PV model and effects of PSC on its characteristic. Section III presents basic concepts of ANN. The proposed MPPT Method is discussed in Section IV. Section V briefs the simulation results and discussions. Conclusions are presented in the last section.

II. Modeling of PV Arrays

A well-known electrical model for PV modules is the single diode model [18], which is shown in Fig. 1. According to this model, the output current of a PV module can be expressed as a function of the output voltage as follows:

$$I = I_{pv} - I_0 \left[\exp\left(\frac{q(V + R_s I)}{akT} \right) - 1 \right] - \frac{V + R_s I}{R_p} \tag{1}$$

where the parameters in the above equation denote:

V	output voltage of the module (V)
I	output current of the module (A)
I_{pv}	photovoltaic current of the module (A)
I_0	equivalent saturation current (A)
k	Boltzmann constant (J/K)
T	temperature of the p-n junction (Kelvin)
q	electron charge (C)
a	diode ideality constant
R_s	equivalent series resistance (Ω)
R_p	equivalent parallel resistance (Ω)

Since the effects of R_s and R_p are negligible, the photovoltaic current (I_{pv}) can be approximated to short-circuit current (I_{sc}). Considering the effects of irradiance and temperature on photovoltaic current, the photovoltaic current can be illustrated as:

$$I_{pv} = (I_{pv,n} + K_I (T - T_n)) \frac{G}{G_n} \tag{2}$$

where the parameters in the above equation denote:

$I_{pv,n}$	photovoltaic current at nominal condition (A)
T	actual temperature (Kelvin)
T_n	nominal temperature (Kelvin)
G	irradiation on the module surface (watts/m^2)
G_n	nominal irradiation (watts/m^2)
K_I	short circuit current/temperature coefficient

Fig. 2(a) and Fig. 2(b) show the plots of photovoltaic current versus photovoltaic voltage for various irradiance levels and various temperatures, respectively. It can be seen that the short-circuit current is directly proportional to the solar irradiance and the temperature varies the open-circuit voltage of the photovoltaic module significantly. The relationship of temperature and open-circuit voltage of the module ($V_{oc,module}$) can be described as follows:

$$V_{oc,module} = V_{oc,n} + K_V (T - T_n) \tag{3}$$

where $V_{oc,n}$ is the open-circuit voltage of the module at nominal conditions and K_V is the open-circuit/temperature coefficient.

When the entire array receives uniform insolation, the P-V characteristic of the array exhibits a single MPP. When the entire array does not receive uniform insolation, the generated current of the shaded and unshaded modules are different that may cause hotspot problem. In order to protect shaded modules from the hotspot problem, one or two bypass diodes are connected in parallel with each PV module. Consequently, the P-V characteristic displays multiple peaks, with several local and one global peak as shown in Fig. 3.

III. Artificial Neural Networks

Artificial neural networks (ANN) are biologically inspired computational models, used in various engineering fields to solve a variety of problems such as function approximation,

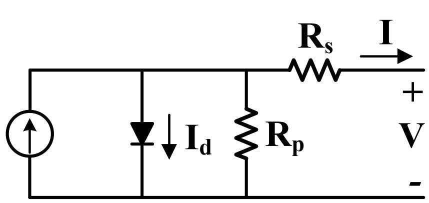

Fig. 1 Single diode model of a PV module

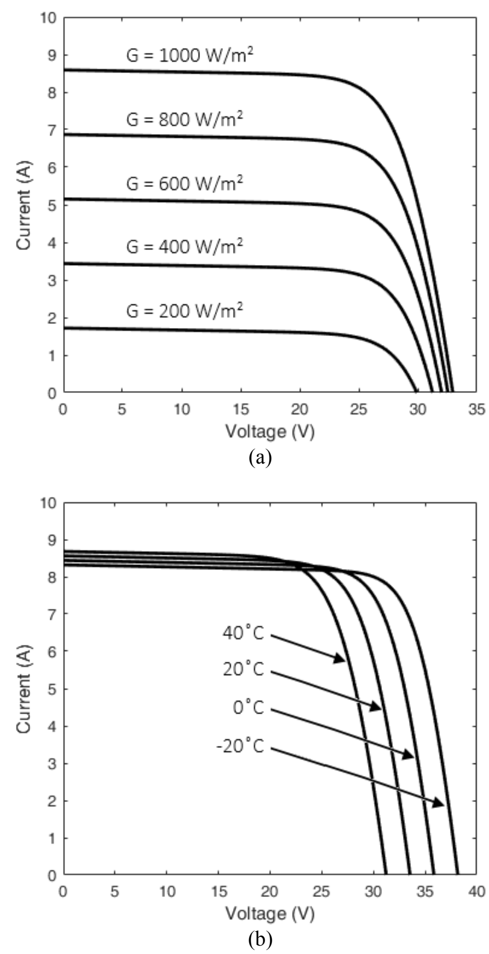

Fig. 2. (a) Insolation effect on I-V characteristics (b) Temperature effect on I-V characteristics

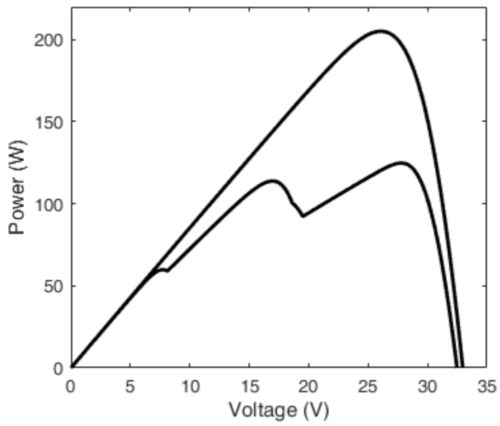

Fig. 3. The P-V characteristic of a PV array under UIC and PSC

pattern recognition, prediction, and optimization. The configuration of a feed-forward artificial neural network is shown in Fig. 4. The network has three layers: an input, a hidden, and an output layer. The number of neurons are two input layer neurons, three hidden layer neurons, and one output layer neuron. The connections between neurons have weights. By applying a nonlinear function (activation function) to the weighted sum of the inputs of a neuron, the output signal of the neuron is computed. The activation function introduce nonlinear properties to the network.

ANNs model the input-output relationship of a dataset. They gather their knowledge through the training process. During training, weights are adjusted to minimize the difference between the network outputs and the desired values. Commonly the mean squared error (MSE) is considered as the cost function. There is a plethora of algorithms for training a neural network. Most of them employ some form of gradient descent algorithm. Once the network is trained properly, it is able to predict the output from any input pattern.

IV. THE PROPOSED MPPT METHOD

Fig. 5 depicts the flowchart of the proposed method, which comprises two stages. A sudden change in the output power of the array is used as an indicator that the PS pattern has changed. Once a variation in the PS pattern is detected, the two-stage method is initiated. In the first stage, an ANN is used to initially determine the neighborhood of the new GMPP. The ANN estimates the GMPP only by taking measurements at few predetermined points of the I-V curve. In the second stage, HC is performed to obtain the exact GMPP.

In order to clarify how the ANN predicts the GMPP, a PV array consists of two parallel connected strings of three series connected modules is considered. Fig. 6 shows the I-V characteristic of the PV array under various PS patterns. According to Section II, the ambient conditions of solar irradiance level and cell temperature significantly affect MPPs and the output characteristics of a PV module. Cell temperature and solar irradiance level are the main factors that vary open-circuit voltage and short-circuit current of a PV module, respectively.

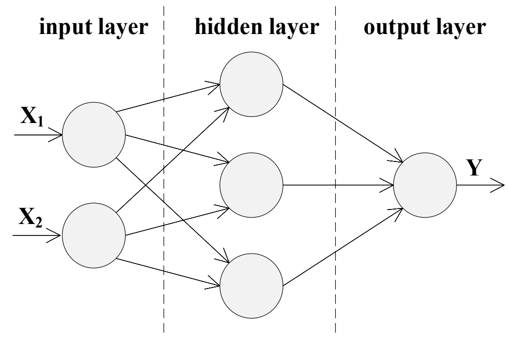

Fig. 4. Configuration of a feed-forward neural network

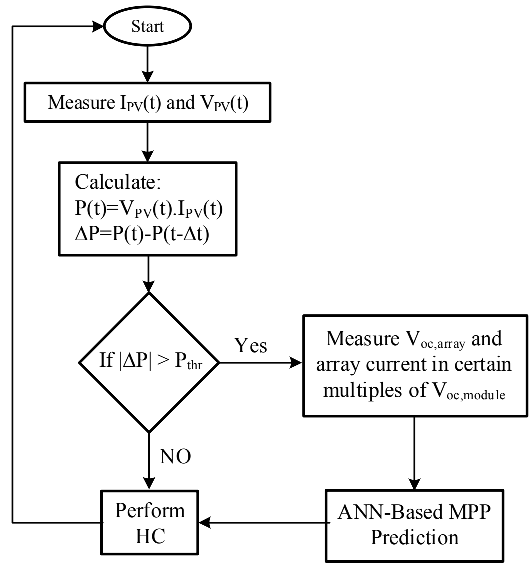

Fig. 5. Flowchart of proposed MPPT method

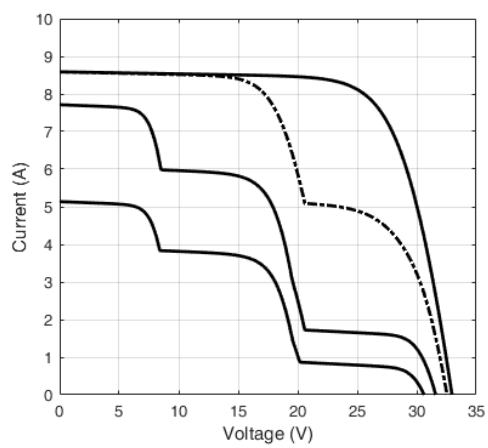

Fig. 6. The P-V characteristic of a PV array under UIC and PSC

On the other hand, as thoroughly elaborated in [19] the voltage values in the starting points of current steps, are in near left side neighborhood of certain integer multiples of open-circuit voltage of a module ($V_{oc,module}$) and the value of current in each step is almost constant up to the end of that step. As a result, in order to sample the PV output characteristic, the PV current is measured at integer multiples of $V_{oc,module}$. The current measurements at these points are regarded as input signals to

ANN. to avoid the boost converter operating at zero voltage point, the current is measured at 0.5 $V_{oc,module}$ instead of zero voltage. Moreover, in order to consider the effect of temperature variations on the PV characteristic, the open-circuit voltage of the array ($V_{oc,array}$) is regarded as another input to ANN. Consequently, for a PV system consists of N series connected PV modules in each string, the number of input signals to ANN is calculated as N+1. Therefore the ANN controller of the discussed PV system has four input layer neurons: one neuron is associated with the open-circuit voltage of the array and three neurons belong to the PV currents measured at $0.5\times V_{oc,module}$, $1\times V_{oc,module}$, and $2\times V_{oc,module}$. The output signal is the MPP voltage.

V. Simulation Results and Discussion

To investigate the performance of the proposed method a PV system has been simulated using MATLAB/Simulink environment. Fig. 7 depicts the configuration of the simulated PV system, which is composed of a 3×2 PV array (two strings of three series connected modules), a DC-DC boost converter and a battery. The parameters of the PV system and the PV modules considered in this study are given in Table I and Table II, respectively.

In this study, a three-layered feed-forward network with four input neurons, 10 hidden layer neurons, and one output neuron is employed. The number of neurons in the hidden layer is acquired by trial and error. The hidden layer neurons have Rectified Linear Unit (ReLU) as the activation function and the output neuron has a linear activation function.

In order to involve a wide range of PS patterns in the dataset, five solar irradiance levels (200, 400, 600, 800 and 1000 W/m^2) have been considered for each PV module. Therefore for the aforementioned PV system, there are 5^6 (= 15625) different combinations of solar irradiance levels over six PV modules in the array. In an effort to extract the dataset from the simulations, the PV modules are modeled based on the single diode model, and the I-V curves for all shading patterns are logged. Then the $V_{oc,array}$ and the PV current in the certain multiples of $V_{oc,module}$ are collected as the input dataset. The GMPPs form the target dataset as well.

The neural network has been trained, validated and tested offline by using 15625 data patterns. To adjust the weights and biases, the Levenberg-Marquardt algorithm has been adopted. In order to achieve the desired network performance, in this study the acceptable MSE is considered to be less than 0.2.

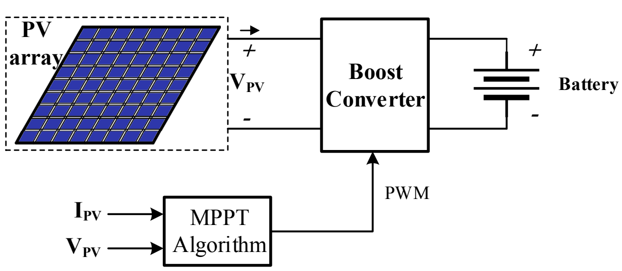

Fig. 7. Configuration of the MPPT for the PV system

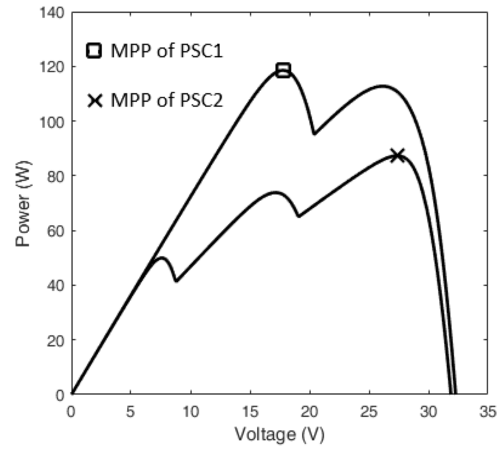

Fig. 8. The PV characteristic under PSC1 and PSC2

TABLE I
PARAMETERS OF THE PV SYSTEM

Parameter	Value
L	0.6 mH
C_{in}	2 μF
C_{out}	48 μF
f_{sw}	40 KHz
$V_{battery}$	36 V

TABLE II
ELECTRICAL PARAMETERS OF THE PV MODULE UNDER STANDARD TEST CONDITIONS

Parameter	Value
P_{MPP}	35 W
$V_{oc,n}$	11 V
$I_{sc,n}$	4.3 A
V_{MPP}	8.75 V
I_{MPP}	4 A

TABLE III
PERFORMANCE EVALUATION OF THE PROPOSED METHOD UNDER PSC1 AND PSC2

	Actual MPP	Tracked MPP	Tracking Time
PSC1	118W	118W	11ms
PSC2	87W	87W	11ms

This is accomplished by setting the number of hidden layers and hidden layer neurons. After training the network, the GMPP of the array can be estimated even for the PS patterns that are not included in the training dataset.

The performance of the proposed method is evaluated under the conditions that the PS pattern changes rapidly: initially, the solar irradiance level is set to 1000 W/m^2 for all modules. At t=0.2sec and t=0.3sec PSC1 and PSC2 occur, respectively. Fig. 8 shows the PV characteristics under PSC1

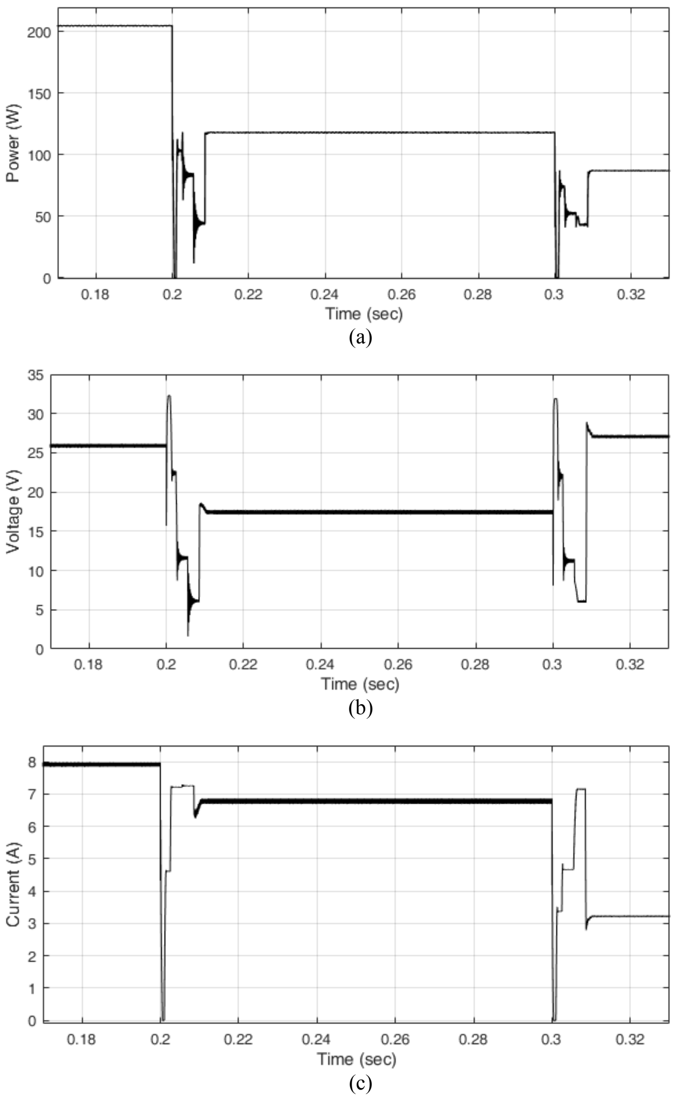

Fig. 9. Performance of the proposed method under PSC1 and PSC2
(a) PV power (b) PV voltage and (c) PV current

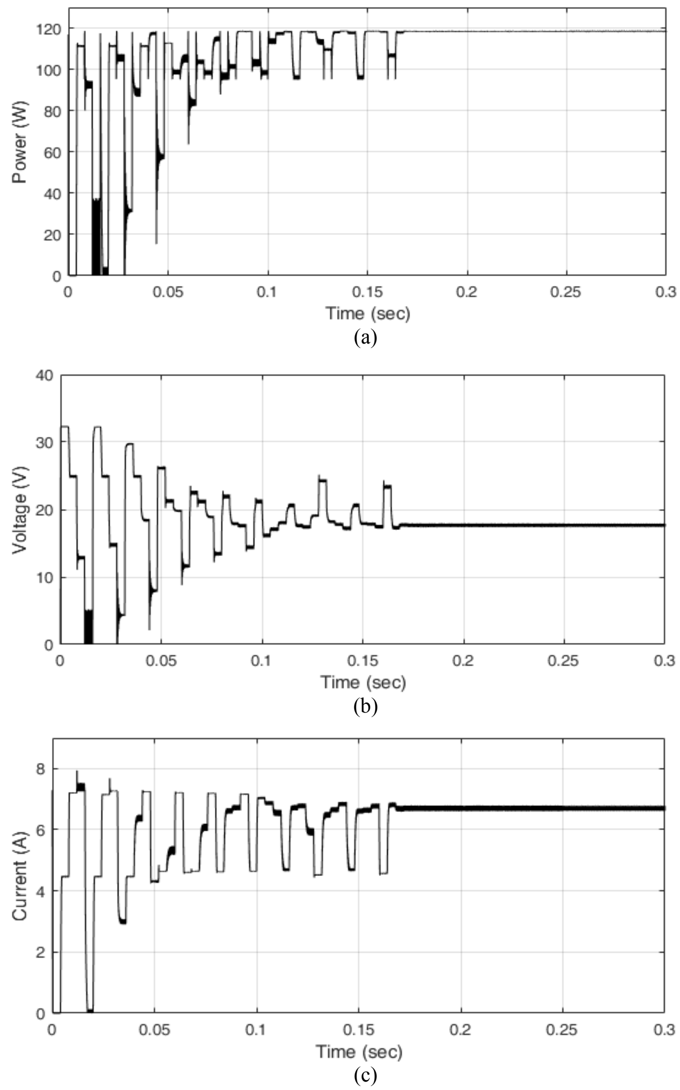

Fig. 10. Performance of the PSO based method under PSC1
(a) PV power (b) PV voltage and (c) PV current

and PSC2. The PV array power, voltage, and current waveforms are shown in Fig. 9(a), Fig. 9(b), and Fig. 9(c), respectively. Table III presents the performance of the method under the test. As it can be seen, in both shading patterns the proposed method tracks the GMPP rapidly within 11ms.

To confirm the superiority of the new approach, a performance comparison between the proposed method and a PSO based method is conducted. Fig. 10 depicts the performance of the PSO-based tracker under PSC1. The PV power, voltage, current, and duty cycle waveforms are shown in Fig. 10(a), Fig. 10(b), and Fig. 10(c), respectively. As can be observed, the accuracy of the PSO based MPP tracker is acceptable but the tracking is very slow compared to the proposed method.

VI. Conclusion

This paper introduced a new two-stage ANN-based MPPT method, which operates satisfactorily under UIC and PSC. First, the open-circuit voltage of the array and the PV current measured data, the vicinity of the GMPP is estimated by an ANN. Finally, a HC approach is performed to reach the exact GMPP. The configuration of the neural network is simple with a low computational burden and there is no need for irradiation or temperature sensors. The effectiveness of the approach was confirmed by simulations in terms of speed of tracking and accuracy. The simulation results showed that the new method tracks the GMPP quickly within 11ms. It can be concluded that the method is well suited to mobile applications.

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