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A New Neural Networks MPPT controller for PV Systems

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***Abstract*—In this paper, an Artificial Neural Network (ANN) MPPT controller has been proposed. The data required to generate the ANN model are obtained from the principle of Perturbation and Observation (P&O) method. The neural network MPPT controller is developed in two modes: the offline mode required for testing different set of neural network parameters to find the optimal neural network controller (structure, activation function, and training algorithm) and the online mode which the optimal ANN MPPT controller is used in PV system. The inputs variables for ANN are the output power derivate (dP) and voltage derivate (dV) corresponding to a given insolation and operating cell temperature conditions, which they have significant influence on the ANN response ; the output variable of ANN is the corresponding normalized increasing or decreasing duty cycle (+1 or -1). The proposed neural network MPPT is tested and validated using Matlab/Simulink model for different atmospheric conditions. Results and analysis are presented, many contribution have been demonstrated (response time, MPPT tracking, Overshoot).**

Keywords— Artificial neural network MPPT controller; Perturbation and observation MPPT algorithm; Photovoltaic Cell modelling; ANN Training and testing.

I. INTRODUCTION

Nowadays, Photovoltaic energy conversion systems have become one of the most important topics of renewable energy systems. This has become possible due to its rapid advances in PV cell technology, the energy conversion efficiency, size of Photovoltaic array, as well as the developments in power electronics and their wide control for maximum power point tracking [1-4].

Photovoltaic (PV) has been continuously growing at a rapid pace over the recent years, which it is used in many applications such as water supply in rural areas, battery charging, mountain cabins, meteorological measurement systems, light sources, island electrification, water pumping, highway/traffic conditions, satellite power systems [2-5]. Photovoltaic offers various significant advantages such as: their fuel is abundant and free, the photovoltaic processes are completely self-contained, the photovoltaic solar panel contributes to the evolution of consciousness towards nature conservation, quiet in operation, long life, low maintenance cost[2-5].

Despite the widespread use of PV systems, but their low efficiency present a great disadvantage. Therefore, maximum power point tracking (MPPT) controller is required to improve the efficiency of the PV system [3-6]. A variety of MPPT methods have been developed and improved continuously. These methods include perturb and observe (P&O) [7-9], Incremental Conductance (IC) [10-12], Hill Climbing (HC) [13-15], fractional open-circuit voltage [16-17], fractional short-circuit current [18-19], neural network [20], fuzzy logic methods [21], and genetic algorithms [12]. These techniques differ in many aspects such as required sensors, complexity, cost, range of effectiveness, oscillation around the MPP, convergence speed, correct tracking when irradiation and/or temperature change and hardware implementation.

Recently, artificial neural network technique has provided new interest in PV systems. The ability of ANN to estimate unknown parameters inspired its application for MPP tracking. These networks can be trained off-line for non-linear mapping and can then be used in an efficient way in the on-line environment [23].

In this work, ANN (artificial neural network) MPPT controller is proposed to provide the duty cycle under different atmospheric conditions, since trained neural network can quickly map nonlinear relationship between input data and the output. The data required to generate the ANN model are obtained from the principle of Perturbation and observation (P&O) method, which it's transformed into logic table using sign function. The neural network MPPT controller is developed in two modes: the offline mode required for testing different set of neural network parameters to find the optimal neural network controller (structure, activation function, and training algorithm) and the On-line mode which the optimal ANN MPPT controller is used in PV system. The proposed neural network MPPT controller is tested and validated using Matlab/Simulink model for different conditions.

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II. Modeling of Photovoltaic Cell

Photovoltaic effect is the process of converting sunlight directly into electricity using solar cells. The first photovoltaic device was demonstrated in 1839 by Edmond Becquerel. A solar cell is a non-linear device and can be represented as a current source model as shown in Fig. 1[2-4]. It consists of a light generated current source, a single diode representing p-n junction cell, a series resistance Rs and a shunt resistance R_{sh} describing an internal resistance of cell to the current flow [2]. This PV generator exhibits a nonlinear voltage–current characteristic that depends on the insolation.

The solar cell terminal current can be expressed as a function of photo-generated current, diode current and shunt current as given by

$$I_o = I_{ph} - I_d - I_{sh} \tag{1}$$

Where:

I_{ph} is the current generated by the incident light (it is directly proportional to the Sun irradiation),
I_d is the current through the diode;
I_{sh} is the current through the parallel resistor R_{sh}.

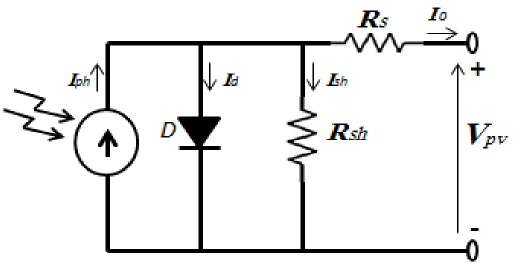

Fig. 1. Simpli• ed equivalent circuit of a photovoltaic cell

The current–voltage characteristic of a PV array is described by the by following equation:

$$I_0 = N_p I_{ph} - N_p I_{rs}\left[e^{\frac{q(V+R_s I_o)}{AkTN_s}} - 1\right] - N_p \frac{q(V+R_s I_o)}{N_s R_{sh}} \tag{2}$$

Where:

I_{rs} is the cell reverse saturation current;
V is the cell output voltage (V);
A is the diode ideality constant;
T is the reference cell operating temperature,
q is the electron charge ($1.60217646 \times 10^{-19}$ C),
k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K),
R_s and R_p are the series and shunt resistors of the cell, respectively.

The generated photocurrent I_{ph} is related to the solar irradiation by the following equation:

$$I_{ph} = \frac{G}{1000}\left(I_{sc} + k_i(T - T_r)\right) \tag{3}$$

Where:
I_{sc}: cell short circuit current at reference temperature and irradiation;
G: Solar irradiation in W/m^2;
T_r: Cell reference temperature;
k_i: Short-circuit current temperature coefficient .

III. Conventional Perturb & Observe (P&O) Method

At present, photovoltaic (PV) has received much interest as a secondary energy source. Due to nonlinear characteristics and low efficiency of photovoltaic arrays, tracking the maximum power point (MPP) of a photovoltaic array is an essential part of a PV system. The Perturbation and observation is one of the most commonly used MPPT methods for its simplicity and ease of implementation [2, 7-9]. In this method, the array voltage is slightly disturbed (increase or decrease) then the actual value of the power P(k) is compared to the previous obtained value P(k-1). If the power panel is increased due to the disturbance, the following disturbance will be made in the same direction. If the power decreases, the new perturbation is made in the opposite direction. The flowchart of the Perturbation and observation method is illustrated in Fig.2.

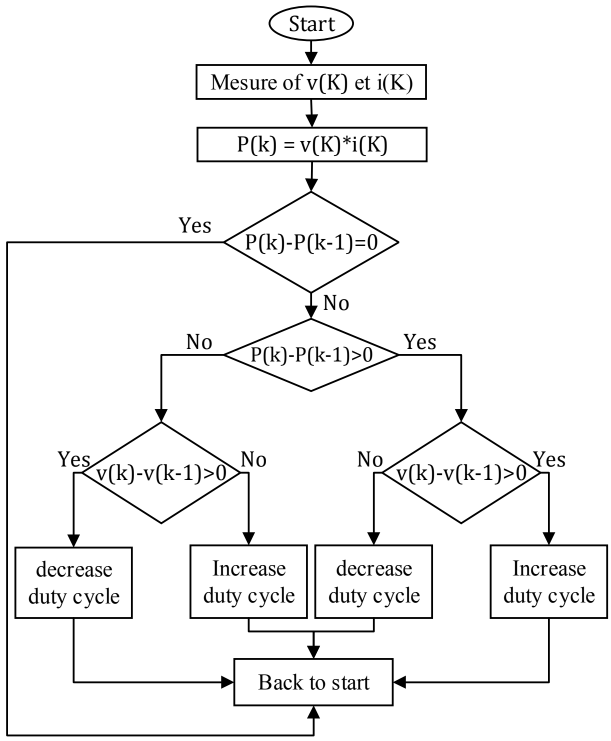

Fig. 2 Flowchart of the conventional P&O algorithm

IV. PROPOSED NEURAL NEWORKS MPPT ALGORITHM

Artificial neural networks are widely accepted as a technology offering an alternative way to solve complex problems. An artificial neural network is a mathematical model that tries to simulate the structure and functionalities of biological neural networks. A neural network is an information processing system [24-26]. It consists of a number of simple highly interconnected processors (units) known as neurons similar to biological cells of the brain. These neurons are interconnected by a large number of weighted links, over which signals can pass. Each neuron receives many signals over its incoming connections, and produces a single outgoing response. Such networks have exceptional pattern recognition and learning capabilities. Recent applications of ANN have shown that they have considerable potential in overcoming the difficult tasks of data processing and interpretation. Four major steps are necessary in ANN applications [26-28]:

1-Data generation : This step constitutes an off-line computation. It consists on obtaining a set of training patterns that covers the possible operating conditions.

2-Selection of inputs : This step constitutes the most important factor in the successful use of ANN and therefore needs a special attention. The state variables candidates for ANN inputs should be independent variables which have significant influence on the ANN response.

3-Selection of ANN architecture:Multilayered feedforward backpropagation ANN is the most popular type used by many applications. It consists of an input layer, one or more hidden layers, and an output layer.

4-Training the ANN and testing: Training is the process of determining the weights which are the key elements of an ANN. The training algorithm is used to find the weights that minimize some overall error measure such as the sum of squared errors (SSE) or mean squared errors (MSE) [27].

A. Model and training of ANN tracker

To extract the maximum power from the PV module, an ANN model with three layer feedforward is selected as shown in Fig. 3.

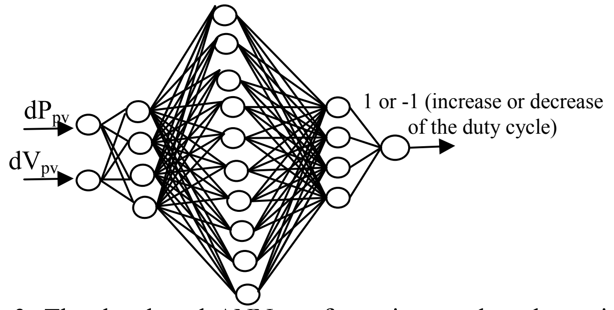

Fig .3. The developed ANN configuration used to determine duty cycle at MPP

The ANN inputs variables are the PV array output power derivate (dP) and the voltage derivate (dV) corresponding to a given solar radiation and operating cell temperature conditions. The output variable of ANN is the corresponding duty cycle.

In this work, a feed-forward backpropagation ANN is used with three hidden layers having a logsig, purelin and purelin activation functions. The first one has four neurons, the second has ten neurons and the third has four neurons. The output layer consists of one output neuron having poslin activation function (Fig. 3). The optimum number of neurons in hidden layer and the number of hidden layer is determined on a heuristic basis so that the prediction accuracy is acceptable.

The proposed artificial neural network MPPT controller is based on the same principle of Perturbation and observation (P&O) method, where the decreasing or increasing of duty cycle depends on the sign of (dP/dV). The basic principle of neural network MPPT controller is summarized in the following table:

Table I. Basic training for the ANN MPPT controller

dP_{pv}	dV_{pv}	dP_{pv}/ dV_{pv}	Duty cycle
1	1	+1	D(k)= D(k-1)+step
1	-1	-1	D(k)= D(k-1)-step
-1	1	-1	D(k)= D(k-1)-step
-1	-1	+1	D(k)= D(k-1)+step

The system operates in two steps:

1) The offline step: required for the training of different set of neural network parameters to find the optimal neural network controller in term of structure, activation function and training algorithm.

2) The online step: uses the found optimal ANN MPPT controller in PV system to track the MPP point.

Fig. 4 shows the ANN MPPT controller developped using Simulink.

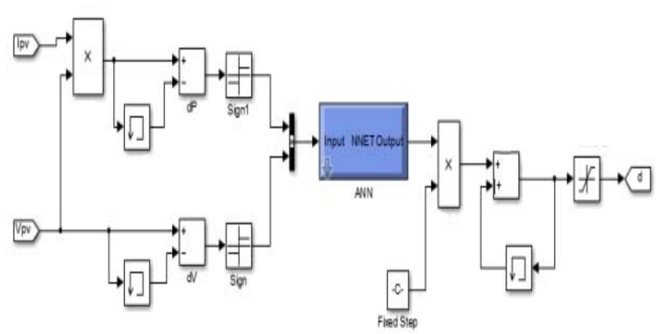

Fig. 4. Fixed step ANN MPPT controller Simulink model.

V. Simulation Results

To illustrate the efficiency of the proposed neural network MPPT controller, a boost converter connected to a Solarex MSX-60 model is used. Fig.5 and Fig.6 show the P-V characteristics and I-V characteristics of the PV cell which are given from a typical PV panel Solarex MSX-60 formed by 36 solar cells. Electrical parameters are listed in table II [28]:

TABLE II
Electrical Characteristics of Solarex MSX -60 (1kW/m², 25°C)

Description	MSX-60
Maximum Power (P_m)	60W
Voltage Pmax (V_m)	17.1 V
Current at Pmax (I_m)	3.5 A
Short Circuit current (I_{sc})	3.8 A
Open Circuit voltage (V_{oc})	21.1
Temperature coeff of Voc	-(80±10)mV/°C
Temperature co-eff of Isc	(0.065±0.01)%/°C
Temperature co-eff of power	(-0.5±0.05)%/°C
Nominal operating cell temperature NOCT2	47±2°C

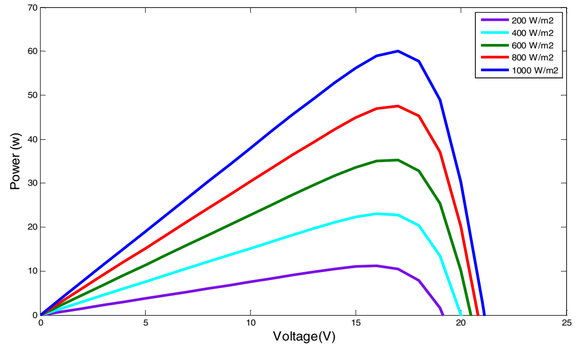

Fig. 5 PV characteristics under various insolation levels

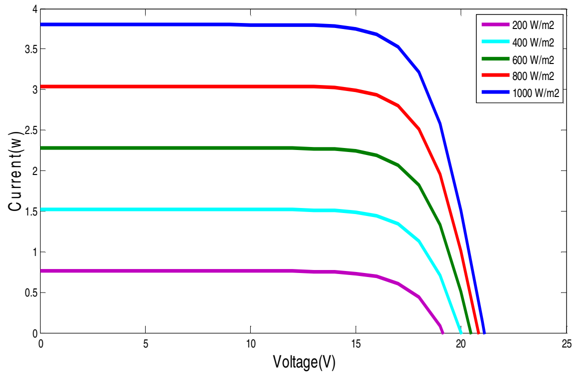

Fig. 6 IV characteristics under various insolation levels

The proposed neural network MPPT controller is tested and validated using Matlab/Simulink model under constant and variable insolation levels, results are shown in the following figures:

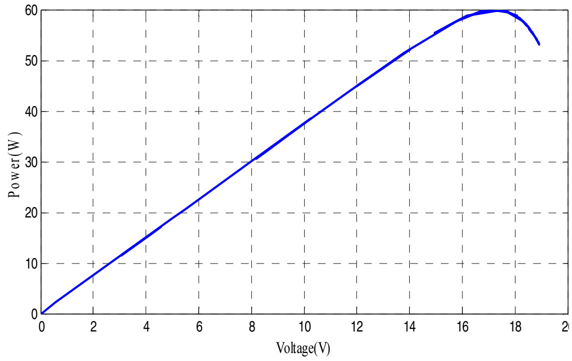

Fig. 7. P-V array output power with ANN MPPT controller under constant insolation G = 1000 W/m^2

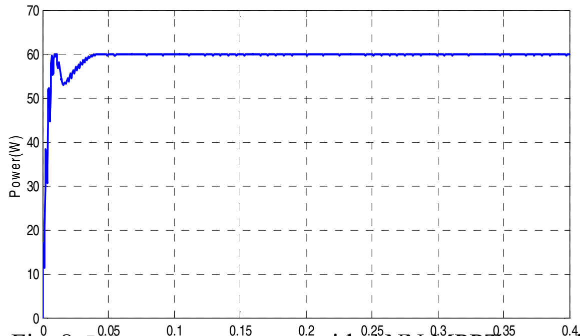

Fig. 8. PV array output power with ANN MPPT controller under constant insolation G = 1000 W/m^2

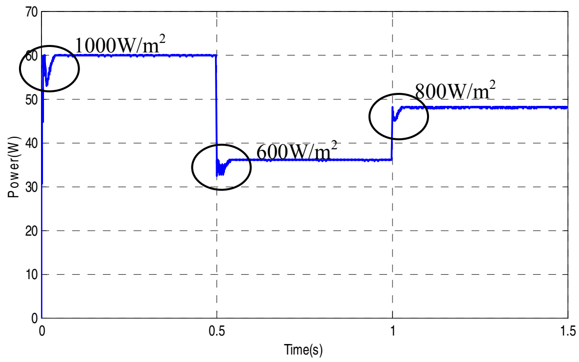

Fig. 9. PV array output power with ANN MPPT controller under variable insolation G = 1000, 600, 800 W/m^2)

- *MPPT tracking*

Fig. 8 and Fig.9 show maximum power point tracking neural network MPPT controller for constant and variable insolation levels. We can see that in both cases, the power values given by ANN MPPT controller are very close to the theoretical value corresponding to irradiation levels. Therefore, the MPPT algorithm discussed in this paper has considerable accuracy.

- *Response time*

From Fig. 10, we can observed that response time of proposed neural network MPPT controller is very less than those given in many papers (0.035s) . Therefore, the proposed ANN algorithm has a good tracking rapidity especially around the MPPT point.

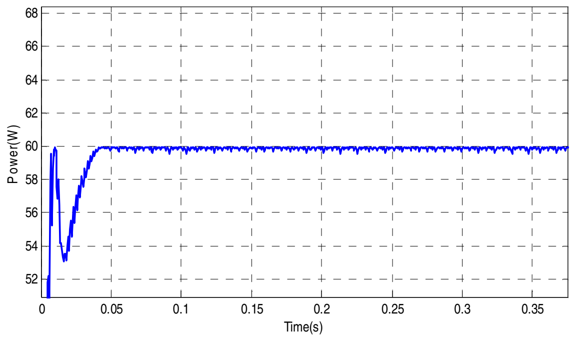

Fig. 10. PV array output power response time with ANN MPPT controller

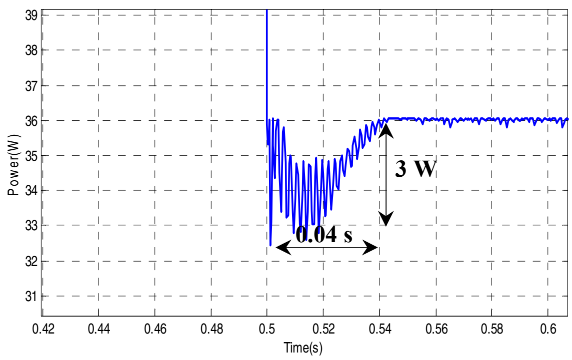

Fig. 11. Output power Overshoot with ANN MPPT controller in the case of sudden decrease in insolation (1000 to 600 W/m^2)

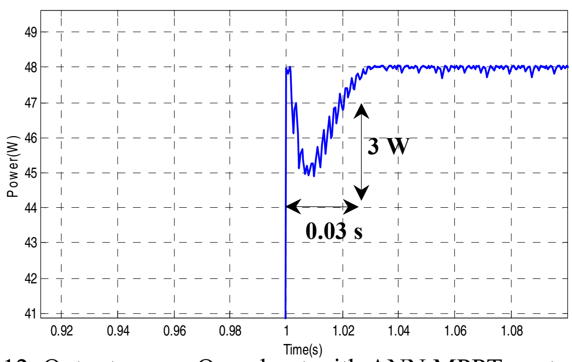

Fig. 12. Output power Overshoot with ANN MPPT controller in the case of sudden increase in insolation (600 to 800 W/m^2)

- Overshoot

From Fig. 11 and 12, it can be observed that the quality of the output power P_{PV} (overshoot) in case of suddenly decreasing or increasing insolation with neural network MPPT algorithm is presents a very good performances in both terms: response time and overshoot power (0.04 s , 3W).

VI. CONCLUSION

In this paper, a new neural network MPPT controller has been proposed and investigated. The neural network MPPT controller is developed in two modes: the offline mode required for testing different set of neural network parameters to find the optimal neural network controller (structure, activation function, and training algorithm) and the online mode which the optimal ANN MPPT controller is used in PV system. The proposed artificial neural network MPPT controller is based on the same principle of Perturbation and observation method, where the decrease or increase of duty cycle depends on the sign of (dP/dV). Simulation results demonstrate the high performances of neural network MPPT controller under fast changing insolation; many contributions have been demonstrated especially tracking accuracy, response time, and overshoot. Therefore, the MPPT algorithm discussed in this paper has high performance and a considerable accuracy.

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