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Evaluation of Improved MPPT-Based ANN Controller for PV Standalone System

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Abstract: This study presents an improved Maximum Power Point Tracking (MPPT) controller using Artificial Neural Network (ANN) which is evaluated under different condition of solar irradiance and cell temperature. This intelligent method is compared with Perturbation and Observation (P&O) method which is the most popular and commonly used conventional MPPT controller. The transient and steady state responses are presented and compared for both high and low solar irradiations as well as the dynamic responses. The control system is implemented on eZdsp TMF28335 Digital Signal Processor (DSP). Experimental results are provided for both high and low irradiations, at the same condition of cell temperature and solar irradiation applied in simulation work. The results show that ANN MPPT has smaller tracking time and provides higher efficiency than P&O with different step-sizes, under both high and low solar irradiations. In addition, in term of dynamic responses, the ANN MPPT controller is much faster than P&O MPPT at locating and tracking the Maximum Power Point (MPP), in case of changing solar irradiation condition.

Key words: Maximum Power Point Tracking (MPPT), Photovoltaic (PV), DC-DC boost converter, Artificial Neural Network (ANN), Perturbation and Observation (P&O), Digital Signal Processor (DSP)

INTRODUCTION

Recently, energy crisis along with environmental issues such as global warming and air pollution, has taken the researchers attention towards the renewable energy resources (Askarzadeh and Rezazadeh, 2013). Solar energy especially has widely been investigated and used all around the world, since it is plentiful source of energy which has no pollution and noise and needs little maintenance. PV module has nonlinear characteristic which is affected by the solar irradiance and cell temperature (Putri and Rifai, 2012; Cha and Lee, 2008). For each solar irradiance and cell temperature, there is a unique voltage-power or current-power curve at which the power of the PV module has a unique maximum value, named Maximum Power Point (MPP) (Houssamo *et al*., 2010). In order to compensate high installation cost and low efficiency of the PV module, it is essential to make work at its related MPP (Pandey *et al*., 2008; Ngan and Tan, 2011). In order to achieve this goal, MPPT methods have been developed (Ngan and Tan, 2011; Leyva *et al*., 2006; Jordehi, 2015a, b; Jordehi *et al*., 2015; Jordehi, 2014). Among different MPPT controllers, Perturbation and Observation (P&O) method is frequently used as reported in literatures, mainly because of its simplicity and generalization to different PV modules. In this method, there should be a trade-off between tracking speed and power oscillation. With large step-size, it will take less time for this method to track the MPP from one steady-state to another, leading to high power oscillation around MPP and consequently power loss in long term. On the other hand, power loss caused by perturbation in the steady-state can be improved by choosing smaller step-size but it will slow down the system in tracking the MPP (Kumar *et al*., 2011; Ahmed and Shoyama, 2011). Intelligent methods have been brought up by researchers as a solution for problems associated with conventional MPPT methods (Hajighorbani *et al*., 2014). Artificial Neural Network (ANN) seems appropriate approach in this context, since it can handle the uncertainty and variation of atmosphere related parameters as well as the non-linearity nature of the PV module characteristics (Ramaprabha and Mathur, 2011).

Most of the previous ANN MPPT algorithms use an ANN to trace the optimum points of voltage and current or maximum power at the first step, then by using a PI controller in the next step and adjusting the duty cycle of the converter, make the PV module to work at its maximum power point. With these algorithms, although, the performance of the MPPT has improved as compared to traditional methods of P&O and Incremental Conductance (INC) methods, the controller gain

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parameters need retuning for different loads and different conditions of irradiation and consequently cell temperature (Ramaprabha *et al*., 2012; Veerachary *et al*., 2003; Mohamed *et al*., 2012).

In this research, an improved MPPT using Artificial Neural Network (ANN) has been presented which by applying two sensors of irradiance and temperature for finding optimum points, then using two sensors of voltage and current for delivering the instant duty cycle to the boost converter, covers a wide range of load, instead of just defining a fixed duty cycle for each weather condition and a constant load. Furthermore, the second step of the controller eliminates the need for PI controller which needs retuning for different conditions of loads and solar irradiances.

In aspect of evaluation of MPPT performance, to take into account dependency of the MPP on solar irradiance and cell temperature, it is important to evaluate performance of the MPPT controller under different weather conditions. However, depending on the application, required precision and issues concerned with system performance and energy efficiency, one can decide between simple traditional or saying somewhat complex intelligent MPPTs.

Hence, in order to contribute a technical point of view in this area, this work provides a simulation and experimental performance comparison of a well-known conventional P&O and an improved intelligent ANN-based MPPT controllers. Since speed of the controller for tracking the MPP and PV MPPT efficiency are two main factors in evaluating MPPTs and because of high dependency of these factors to solar irradiance, for both high and low solar irradiance conditions, the transient and steady state responses of proposed ANN MPPT controller are evaluated and compared with P&O method of different step-sizes as well as the dynamic response under changing solar irradiance condition.

Figure 1 shows the equivalent circuit of a solar cell which is approximated by a current source paralleled with a diode (Samrat *et al*., 2014).

The output current of solar cell can be delivered by using Kirchhoff's Current Law (KCL) in Fig. 1, as shown in Eq. 1 (Mohammed, 2011; Farhat and Sbita, 2011):

$$I_{pv} = I_{ph} - I_D - I_{sh} \tag{1}$$

Where:

I_{PV} = The PV output current
I_{ph} = Photocurrent and
I_d and I_{sh} = The current of diode and shunt resistor respectively

In practice, instead of solar cells, we deal with PV modules which consist of solar cells connected in series and parallel to provide the voltage and the current requirement of load. Thus for a PV module with N_s cells in series and N_p cells in parallel, the characteristic equation is stated as (Golder, 2006; Zegaoui *et al*., 2011):

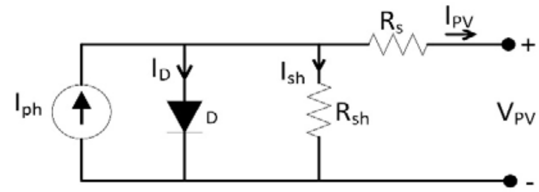

Fig. 1: A solar cell equivalent circuit model

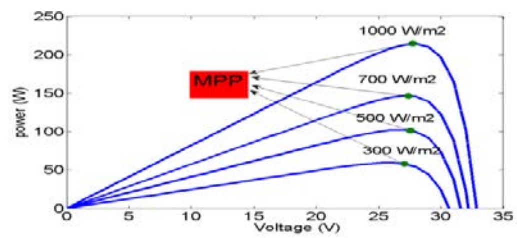

Fig. 2: The P-V curve for different irradiations at 25°C

$$I_{pv} = N_p I_{ph} - N_p I_o \left[\exp\left(\frac{q(V_{pv} + R_s I_{pv})}{N_s AKT} \right) - 1 \right] - \frac{V_{pv} + R_s I_{pv}}{R_{sh}} \tag{2}$$

Where:

I_o = Reverse saturation current
V_{PV} = PV output voltage
R_s and R_{sh} = Series and parallel resistance, respectively
T = Cell temperature
q, A and K = The electron charge (1.602×10^{-19}C), diode ideality factor and Boltzmann constant (1.38×10^{-23} J K^{-1}), respectively

The values of power, voltage and current for KYOCERA KD210GH-2PU PV module at MPP for irradiation of 1000 W/m^2 and temperature of 25°C are 210 W, 26.6 V and 7.9 A, respectively. The open-circuit voltage and short-circuit current values also are 33.2 V and 8.58 A, respectively (Fig. 2).

MATERIALS AND METHODS

DC-DC boost converter: The DC-DC converter acts as MPP-tracker which by adjusting the output voltage of the module at optimum point, makes the PV module to operate

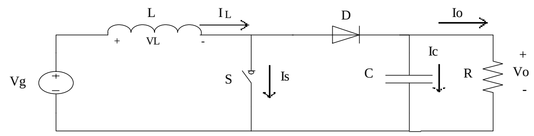

Fig. 3: DC-DC boost converter circuit diagram

at its MPP (Santos *et al*., 2006). The converter used in thiswork is a boost converter which by stepping up the input voltage, delivers desired value in its output. The simulation model of the boost converter is shown in Fig. 3. Equation 3 expresses the relationship between the input voltage, output voltage and duty cycle of the boost and Eq. 4 states the relation between the input impedance, output impedance and duty cycle of the boost as below (Erickson, 1997; Veerachary *et al*., 2002):

$$\frac{V_o}{V_g} = \frac{1}{1-D} \tag{3}$$

Where:

V_g and V_o = Input and output voltages, respectively
D = Duty cycle of the converter

$$D = 1 - \sqrt{\frac{R_{in}}{R_o}} \tag{4}$$

where, R_{in} is input impedance and R_o is output impedance of the converter. In this research in order to design the boost converter, the working frequency was configured at 22 kHz to ensure the low switching loss and the inductor and capacitor values were calculated as 360 μH and 200 μF, respectively which ensure the Continuous Conduction Mode (CCM) operating of the converter and maximum allowed voltage ripple of 1% for output capacitor, for a resistive load of 33 Ω-210 W.

Maximum power point tracking

Perturbation and Observation (P&O) MPPT: P&O MPPT algorithms are based on the fact that the variation of the PV power to the PV voltage is zero at MPP, positive at the left and negative at the right side of the voltage-power characteristic of each PV module. By using this fact, the PV voltage is sampled to locate the module operating point on the PV voltage-power curve and then perturbed to move the operating point towards the MPP (Sera, 2009). Figure 4 presents the flowchart of the PandO algorithm used in this work at which the control variable is direct duty cycle.

Artificial neural network MPPT: ANN is a model developed by imitating the structure and function of human brain. Its structure is composed of several inter-connected processing units named as neurons. The neurons are connected to each other through weighted links. ANN needs to be trained to solve the problems given to it. Training is by continuously adjusting the weights of the links between neurons. Once ANN is trained, it is ready to solve associated problem (Negnevitsky, 2005).

ANN is usually comprised of three layers of input, hidden and output as shown in Fig. 5. However, it is possible to have more than two layers of hidden. Inputs are given to the input layer and then the output of each layer is calculated by neurons by using activation function. Common architectures for ANN are: Multilayer Perceptron (MLP), Radial Basis Function (RBF) and Recurrent Neural Networks (RNN) (Mellit *et al*., 2009).

ANN architecture used in this research is a MLP network, a feed-forward network at which the inputs are propagated forward layer by layer. In MLP, by applying a good range of data as inputs and defining outputs as targets, training can be done through back propagation learning algorithm. This algorithm employs usually sigmoid or sigmoid tangent function in hidden layer and linear one in the output layer for training. During the training, each output of any layer is calculated by using the related weights of links and activation function defined for each layer, then comparing with targets. After that, by calculating error using Mean Squared Error (MSE) and back propagating it to the network, link weights are manipulated to decrease the error.

ANN-based MPPT controller used in this work has two steps. The first step is an ANN which by sensing the solar irradiance and cell temperature as inputs, gives the PV voltage and PV current at which maximum power happens; i.e., voltage optimum point V_{pm} and current optimum point I_{pm}. Then, the second part of the controller, by using the Eq. 4 and developing the mathematical equation related to the duty cycle, input impedance (V_{pm}/I_{pm}) and output impedance of the boost converter, computes the required duty cycle of the boost. To assume that at time t the PV module is working at ($V_{pv}(t)$, $I_{pv}(t)$) with duty cycle d(t), the output impedance is delivered as below:

$$\begin{aligned} R_o(t) &= \frac{R_{in}(t)}{(1-d(t))^2} = \frac{V_{in}(t)/I_{in}(t)}{(1-d(t))^2} \\ &= \frac{V_{PV}(t)/I_{PV}(t)}{(1-d(t))^2} \end{aligned} \tag{5}$$

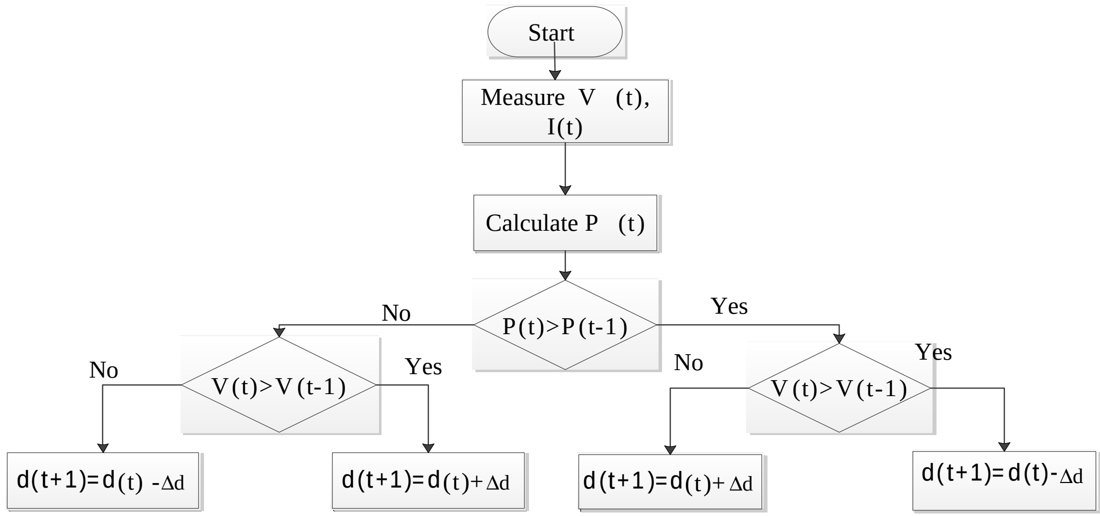

Fig. 4: Flow chart of the P&O algorithm

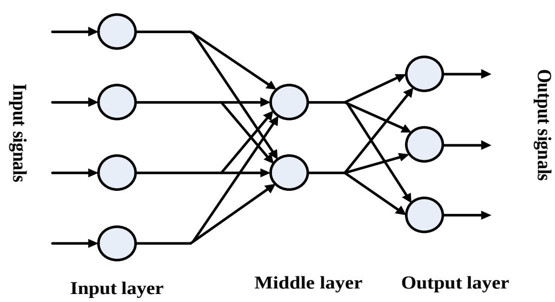

Fig. 5: Architecture of a typical artificial neural network

RESULTS AND DISCUSSION

The whole PV MPPT system for two P&O and ANN MPPT controllers which is comprised of a PV module as current source, a DC-DC boost converter as MPP tracker, a controller and a resistive load is simulated in MATLAB. For both high and low solar irradiance conditions, transient and steady-state responses of two P&O and ANN methods are evaluated and compared in aspects of tracking time and MPPT efficiency. Furthermore, dynamic response comparison is provided to compare the speed of two controllers in tracking the MPP in case of rapid changes in solar irradiance.

For transient and steady-state response comparison, since P&O controller performance is affected by the step-size of the perturbation (Δd), the results are provided for three different step-sizes of 0.01, 0.0075 and 0.0050. Furthermore, both high and low solar irradiance conditions are considered for comparison as P&O MPPT controller acts in different ways under different solar irradiances.

For performance comparison under rapidly changing of solar irradiance, an irradiance scheme is given as input to the PV module and for constant temperatures of 40°C, PV voltage, current and power responses are delivered.

Transient and steady state: Figure 6 presents the comparison of PV output power of ANN MPPT and PandO under irradiance of 930 W/m^2 and constant temperature of 42°C which tracking time of the MPP with ANN method is 2 msec while with P&O method is 8 msec. Furthermore, the PV module with ANN MPPT delivers more average power and consequently higher efficiency than P&O MPPT with different step-sizes.

Figure 7 displays the comparison of PV output power for ANN and PandO MPPTs with different step-sizes of 0.01, 0.0075 and 0.005, under irradiance of 300 W/m^2 and constant temperature of 40°C. As shown in Fig. 7, the PV module with ANN MPPT method has the minimum tracking time of 3.3 msec while the smallest tracking time for P&O method is 25 msec for step-size of 0.01. In addition, ANN MPPT has delivered more average power and subsequently higher efficiency than P&O MPPT with different step-sizes.

Dynamic responses: Since, PV output current is a function of solar irradiance and solar irradiance is changing during the day, it is important to evaluate the performance of a MPPT under changing solar irradiance. Figure 8 shows the irradiance signal applied to ANN and P&O MPPT controllers with step-size of 0.0075 and Fig. 9 and 10 represent the PV output power, voltage and current responses for two methods, under constant temperature of 40°C.

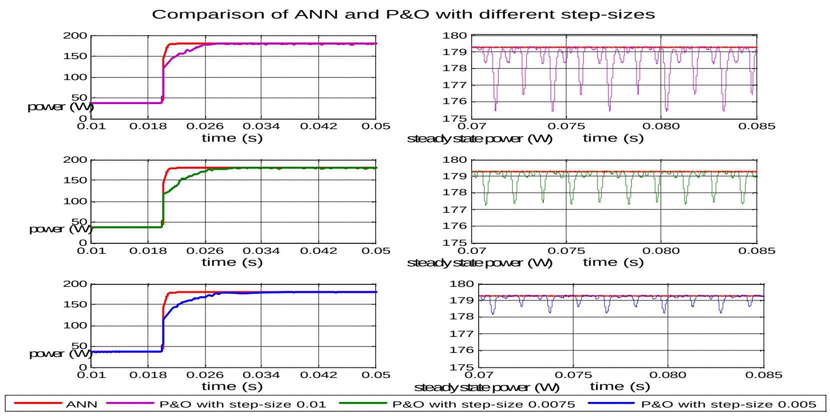

Fig. 6: Simulation result of maximum power point for ANN and P&O MPPT controllers with different step-sizes (irradiance: 930 W/m^2, temperature: 42°C)

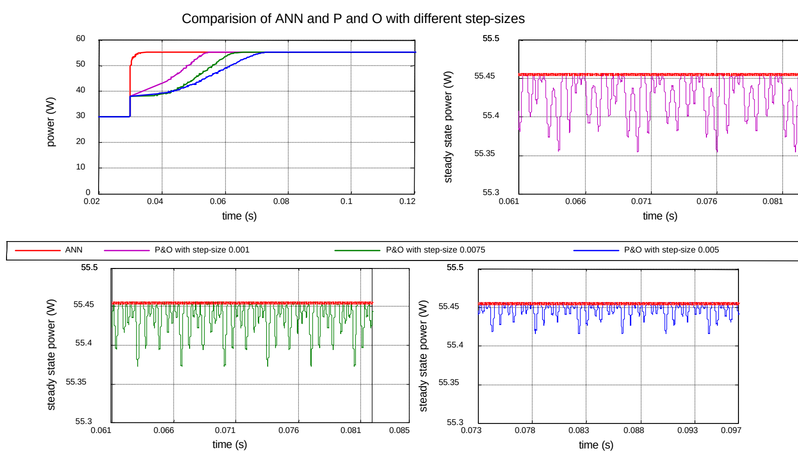

Fig. 7: Simulation result of ANN and P&O MPPT controllers with different step-sizes (irradiance: 300 W/m^2, temperature: 40°C)

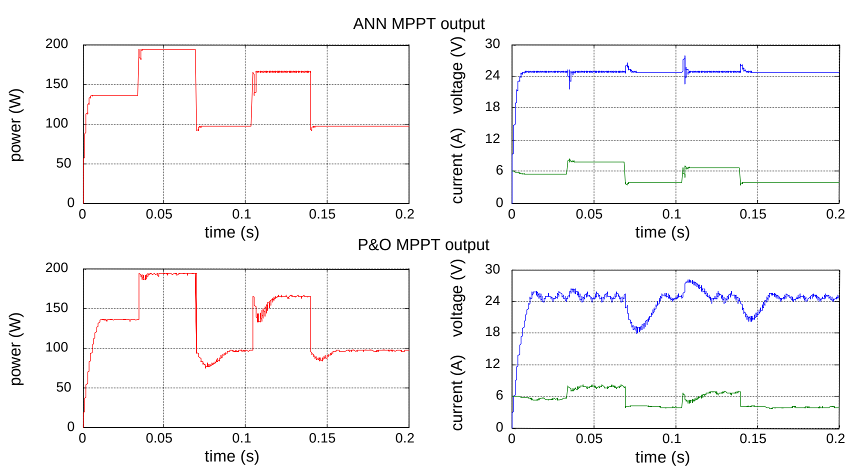

Fig. 8: Simulation results of ANN and P&O MPPT controllers under changing irradiance with constant temperature of 40°C

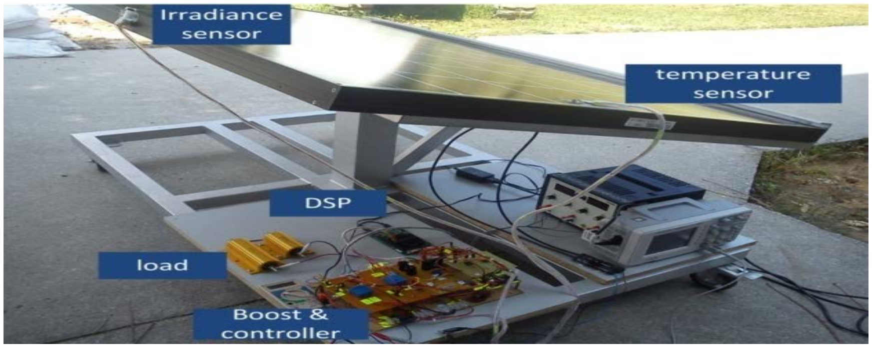

Fig. 9: Overall hardware setup

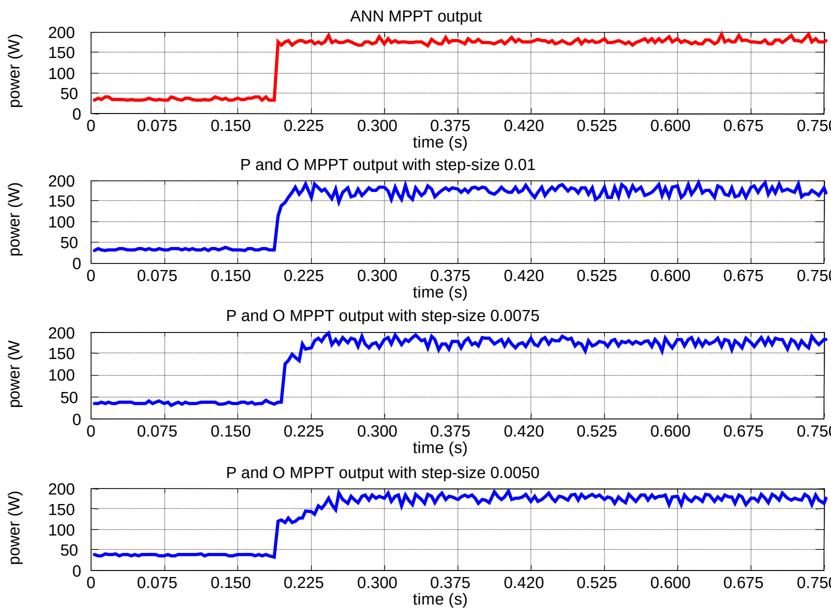

Fig. 10: Experimental results for ANN and P&O MPPT controllers with different step-sizes (irradiance: 930 W/m^2, temperature: 42°C)

As Fig 8 shows, ANN MPPT gives more stable output as compared to PandO method and the power oscillation in static irradiance parts is much less than P&O method. Furthermore, ANN MPPT controller could rapidly track the fast changes of solar irradiance with small oscillation and it can maintain the voltage of the PV module almost constant. On the other hand, in the same condition, P&O MPPT fails to follow the fast changes of solar irradiance. Indeed, ANN method has much better performance in changing weather condition, since it is a fast and precise model which can locate the exact MPP in a short time, leading to short tracking time and more stable output as compared to P&O method. According to results, when solar irradiance changes from one level to other level, it takes maximum 4 msec for proposed ANN-based MPPT to find and track the new MPP while the maximum tracking time for P&O method is 26 msec. Thus, ANN method can track the changes of solar irradiance much faster than P&O method.

Experimantal results: Laboratory prototype is developed to evaluate and compare two above-mentioned MPPT controllers. The specification and the values of the PV module, fabricated boost converter and the load are the same as simulation work. To implement and perform the control algorithm, eZdspTMF28335 board from SPECTRUM Digital INC is selected which provides PWM signals for the control gate of the converter. Figure 9 shows the overall hardware setup.

Figure 10 presents the experimental results for ANN and P&O methods with different step-sizes, under high irradiance of 930 W/m^2 and constant temperature of 42°C.

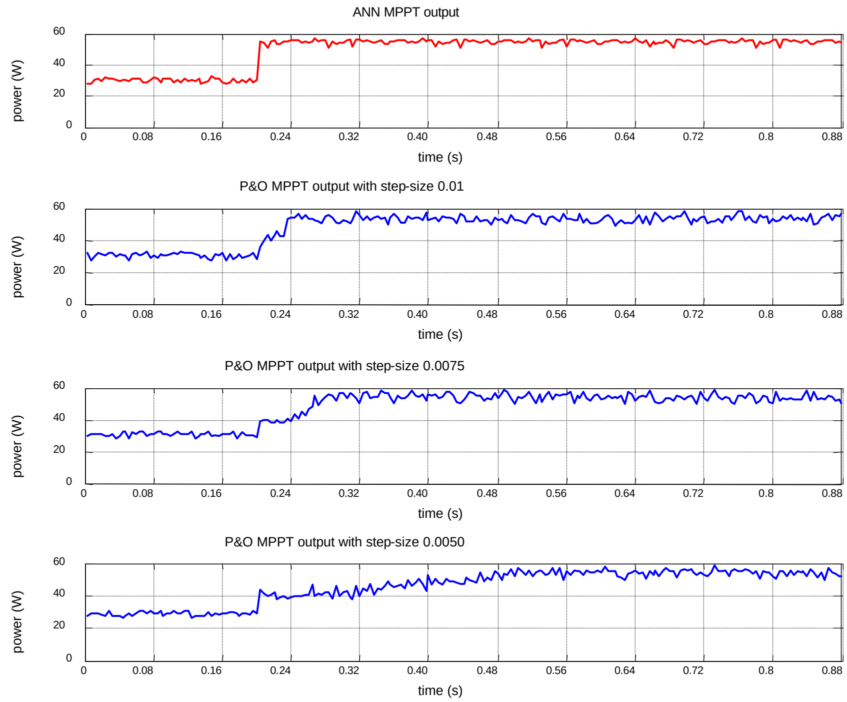

Fig. 11: Experimental results for ANN and P&O MPPT controllers with different step-sizes (irradiance: 300 W/m^2, temperature: 40°C)

The results show that under high solar irradiance, ANN can track the MPP with small tracking time of 4 ms, while tracking time with P&O method is 24, 48 and 80 msec for step sizes of 0.01, 0.0075 and 0.0050, respectively. In addition, ANN MPPT has provided efficiency of 4, 3.33 and 2.71% more than P&O with step-size of 0.01, 0.0075 and 0.005, respectively. Among different step-sizes of P&O method, step-size of 0.005 has delivered the highest efficiency which on the other hand has the longest tracking time, leading to slow response to the changes of solar irradiance.

Figure 11 depicts the experimental results for ANN and P&O methods with different step-sizes, under low irradiance of 300 W/m^2 and constant temperature of 40°C. Table 1presents the comparison of results in brief.

The results show that under low solar irradiance, ANN method tracks the MPP with small tracking time of is 6 msec while tracking time with P&O method is 40, 84 and 250 msec for step sizes of 0.01, 0.0075 and 0.0050, respectively. In addition, ANN MPPT has provided efficiency of 2.44, 1.27 and 0.96% more than P&O with step-sizes of 0.01, 0.0075 and 0.005, respectively. Among different step-sizes of P&O method, step-size of 0.005 has delivered the highest efficiency which on the other hand has the longest tracking time, leading to slow response to the changes of solar irradiance.

CONCLUSION

In order to provide a technical vision and practical assessment in deciding between traditional and intelligent MPPT controllers for a desired application, this study has presented an analytical comparison of two well-known ANN and P&O MPPT controllers, in aspects of tracking time and MPPT efficiency, under different conditions of solar irradiance.

For transient and steady-state response comparison, evaluation is carried out for both high and low solar irradiances.

The simulation and experimental results show that for both high and low solar irradiances, the tracking time, average power and MPPT efficiency have been improved as compared to P&O with different step-sizes. Furthermore, the dynamic response comparison shows that ANN-based MPPT method could track the rapid changes of irradiance with small tracking time of maximum 4 msec as compared to P&O method with maximum tracking time of 26 msec. The results validate the high performance of the ANN MPPT controller as compared to P&O with different step-sizes, under varying condition of solar irradiance.

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