Journal Homepage: http://dergipark.gov.tr/ejens
EJENS
European Journal of Engineering and Natural Sciences
DergiPark AKADEMİK
CODEN: EJENS

An Investigation of Intelligent and Conventional Maximum Power Point Tracking Techniques for Uniform Atmospheric Conditions

Ekrem Kandemir[1,2,*], Numan Sabit Cetin[2], Selim Borekci[3]
[1]*TUBITAK National Observatory, Research & Development Department, 07058, Antalya, Turkey.*
[2] *Ege University, Solar Energy Institute, 35100, Izmir, Turkey.*
[3] *Akdeniz University, Electrical – Electronics Engineering Department, 07058, Antalya, Turkey.*
**Corresponding Author email: ekrem.kandemir@tubitak.gov.tr*

Abstract

In recent years, power generation from photovoltaic (PV) system has received great attention compared to other renewable sources. Due to nonlinear characteristics of PV cells, the maximum allowable power level from PV panel changes with atmospheric parameters which are solar irradiance and temperature. In this context, maximum power point tracking (MPPT) algorithms are essential to maximize the output power of PV panel for any solar irradiance and temperature values. In the literature, various MPPT techniques have been studied to deliver maximum power from PV systems. Hence, this study discusses intelligent control techniques, which are called fuzzy logic controller (FLC) and neural network controller (NNC), and compares efficiency performance and convergence speed to conventional perturb & observe (P&O) and incremental conductance (Inc. Cond.) tracking techniques for MPPT of PV system.

In this paper, 150W PV panel model is investigated for different atmospheric conditions in MATLAB. Results of simulation show that NNC based and FLC based MPPTs have 4.66% better tracking accuracy than conventional P&O and Inc. Cond. under standard test condition (STC). NNC based MPPT has best iteration response rate among the other MPPTs under uniform atmospheric conditions. Therefore, the NNC based MPPT presents best superior quality in terms of efficiency and convergence speed for PV systems among the other MPPTs.

Key words

PV Model, Maximum Power Point Tracking, Perturb & Observe, Incremental Conductance, Fuzzy Logic Control, Neural Network Control

1. INTRODUCTION

For a long term and sustainable supply of energy, it is essential to exploit and utilize the renewable sources at a much larger scale [1]. Compared to other renewable sources, photovoltaic energy (PV) has proven to be more pollution – free, noise – free and has limitless source of energy [2]. In addition, PV power has commonly used for industrial, commercial, residential and military purposes [3]. However, PV power is environment dependent such as solar irradiance and ambient temperature because of nonlinear electrical characteristics of PV cells. The development for improving the efficiency of the PV system is still a challenging field of research and the maximization of extracted PV power from PV systems is a matter concern as its conversion efficiency is low [4], [5].

In general, PV panels have only one maximum power point (MPP) on its power – voltage curve where PV panel produces its maximum power under uniform solar irradiance condition and this point changes with solar irradiance and temperature [6]. The position of MPP on the corresponding power – voltage curve varies depending on solar irradiance, temperature and also electrical load. Therefore, to make the PV power generation efficient, a capable maximum power point tracking (MPPT) techniques are used to estimate and to track the actual MPP against any environmental parameters changes such as solar irradiance and temperature [7].

Numerous MPPT techniques have been investigated in the literature such as Perturb & Observe (P&O), incremental conductance (Inc. Cond.), fuzzy logic controller (FLC) and neural network (NN) [1], [3], [8], [9]. The quality of an MPPT technique is evaluated in terms of its complexity, cost, tracking speed, accuracy and number of sensors required for its implementation [10]. Because of being simplicity and easy to implement, P&O and Inc Cond. MPPT techniques, which are known as a few of conventional MPPTs, are ones of the most preferred algorithms in the literature. Although, these methods present some drawbacks in its design such as convergence and oscillation problems around MPP region. To remove these drawbacks and enhance the performance of PV panels, intelligent or soft – computing MPPTs such as fuzzy logic and/or neural network based techniques are widely preferred in the literature [11].

In this paper, conventional MPPTs such as P&O and Inc. Cond. and intelligent MPPTs such as FLC and NN based MPPTs are investigated and compared in terms of tracking accuracy and convergence speed. Related analysis and simulation results are discussed separately for each MPPT technique and comparison tables for conventional and intelligent MPPTs are provided in detail.

2. PV CELL AND EQUIVALENT CIRCUIT MODEL

PV cells are the main components of the PV systems and they consist of p – n junction semi – conductor materials that sunlight exposure causes to release electrons around a closed circuit. Typically, they are modelled either as single diode or double diode equivalent circuits but single diode model is more preferred because of simplicity and easy to implement [11], [12].

PV panel consists of several series and/or parallel connected PV cells in order to generate higher level electrical power. Figure 1 depicts single diode equivalent circuit model of a PV cell, which transforms directly sunlight into electrical current.

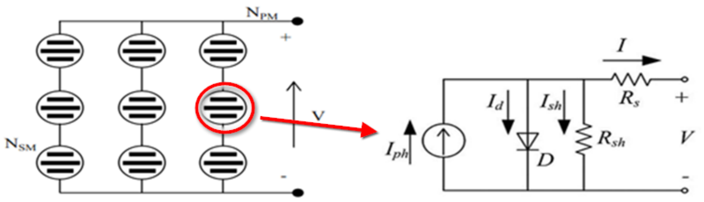

Figure 1. PV panel and single diode circuit model of a PV cell [11]

The output current of the PV cell can be expressed in Eq. (1) as,

$$I = I_{ph} - I_o\left(e^{\frac{q(V+R_S I)}{AkT}} - 1\right) - \frac{V+R_S I}{R_{sh}} \tag{1}$$

where I and V represent PV cell output current and voltage. R_s and R_{sh} are the PV cell series and shunt resistances respectively. I_{ph} is the PV cell photo current, I_o is the diode saturation current, A is the diode quality factor ($\cong 1.2$), k is Boltzmann's constant ($1.38 \times 10^{-23}\ J/K$) and T is the PV cell temperature in kelvins [6].

By solving Eq. (1) or using equivalent circuit model as shown in Figure 1, electrical characteristic curve of the related PV panel can be obtained for any environment condition in the simulations, MATLAB i.e. During uniform environment conditions where the solar irradiance is equally distributed among the PV panels, only single maximum power point is available in the PV panel's power – voltage curve as shown in Figure 2. And this MPP point changes with solar irradiance and temperature [6]. As shown in Figure 2, PV panel power is almost proportionally with the variation of solar irradiance. Hence, when solar irradiance increases, the maximum PV panel power also increases. In addition, the variation of temperature affects PV panel power inversely that PV power increases if temperature decreases.

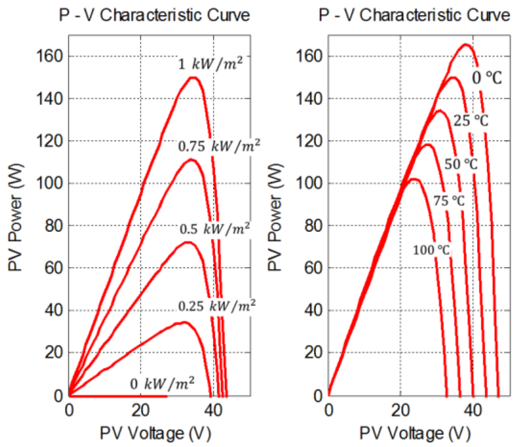

Figure 2. Voltage and power curves of PV panel for different solar irradiance and temperature conditions [6]

3. CONVENTIONAL AND INTELLIGENT MPPT TECHNIQUES

PV cells and panels operates on different power level depended on different environment condition and electrical load. Because of that, generation of maximum power is not guaranteed at all electrical loads [13]. Hence, MPPTs provide to ensure that at any environmental condition, i.e. any solar irradiance or temperature, maximum achievable power is extracted from PV system [12].

The MPPTs can be classified in many different groups depending on several parameters i.e. MPPT strategy, tracking speed, complexity, PV panel dependency, etc. In general, MPPT techniques are classified into two types [6]:

- Conventional techniques,
- Intelligent techniques.

The most popular conventional techniques are perturb & observe (P&O) and incremental conductance (Inc. Cond.) in the literature. These algorithms are widely used in commercial products due to their simplicity and robustness. On the other hand, intelligent MPPTs such as fuzzy logic control (FLC) and neural network (NN) tend to be more versatile, efficiency and better steady state performance [1].

3.1. Perturb & Observe (P&O) Technique

This technique is commonly preferred by the researchers to implement MPPT operation for the PV systems because of simplicity and exhibiting enough convergence accuracy. In this technique, a perturbation is applied to PV panel voltage and PV panel output power is observed. The aim of this technique is to adjust PV panel voltage to the voltage of MPP of PV panel (V_{mpp}) to extract maximum power from the PV panel for the actual environment condition. This is done by applying small and constant perturbation to the PV voltage a step by step. After each perturbation, the output PV power variation (dP) is observed according to the variation of the PV voltage (dV) [5]. If the sign of (dP/dV) is positive, the actual point is in the left side of the MPP and the PV voltage should be increased to reach MPP; else the sign of (dP/dV) is negative, the actual point is in the right side of MPP and the PV voltage should be decreased to reach MPP [6]. This process is performed until (dP/dV) equals to zero. This mechanism is also defined as below.

$$\frac{dP}{dV} = 0 \Rightarrow at\ MPP \quad (2)$$

$$\frac{dP}{dV} > 0 \Rightarrow Left\ Side\ of\ MPP \quad (3)$$

$$\frac{dP}{dV} < 0 \Rightarrow Right\ Side\ of\ MPP \quad (4)$$

The disadvantage of this method is that at vicinity of MPP, it oscillates around MPP and this causes steady state error. Low values of perturbation size reduces steady state error at the cost of reduction in tracking speed [12]. In addition, this technique sometimes fails to track the MPP under rapid changing environment conditions.

3.2. Incremental Conductance (Inc. Cond.) Technique

This technique basically uses similar way but different relationship of PV characteristic curve from P&O technique to determine MPP. In this method, derivative of PV current and PV voltage are used to determine the movement of the actual operating point [6]. After each perturbation of PV voltage, the output PV current is observed to determine MPP. If the $(\Delta I/\Delta V)$ is greater than negative sign of the actual PV conductance value, the actual point is in the left side of MPP and the PV voltage should be increased to reach MPP; else the $(\Delta I/\Delta V)$ is lower than the negative sign of actual PV conductance value, the PV voltage should be increased. And this process is performed until the $(\Delta I/\Delta V)$ equals to negative sign of the actual PV conductance value. This mechanism is also defined as below.

$$\frac{\Delta I}{\Delta V} = -\frac{I}{V} \Rightarrow at\ MPP \tag{5}$$

$$\frac{\Delta I}{\Delta V} > -\frac{I}{V} \Rightarrow Left\ Side\ of\ MPP \tag{6}$$

$$\frac{\Delta I}{\Delta V} < -\frac{I}{V} \Rightarrow Right\ Side\ of\ MPP \tag{7}$$

As the tracking of MPP is done rapidly it helps to overcome the disadvantage of the P&O technique which fails to track the MPP control under fast varying conditions and it can be easily implemented in a simple microcontroller [6], [7]. The main disadvantage of this technique is its perturbation size, which causes oscillations and steady state error around MPP, and complexity.

3.3. Fuzzy Logic Control (FLC) Based Technique

Fuzzy logic control (FLC) based MPPT is one of the most used intelligent method to perform MPPT task for any PV system in any environment condition [4], [14]. FLC is operated by using membership functions instead of mathematical model. It consists of three stages: fuzzification, fuzzy inference engine, rule tables and defuzzification as shown in Figure 3.

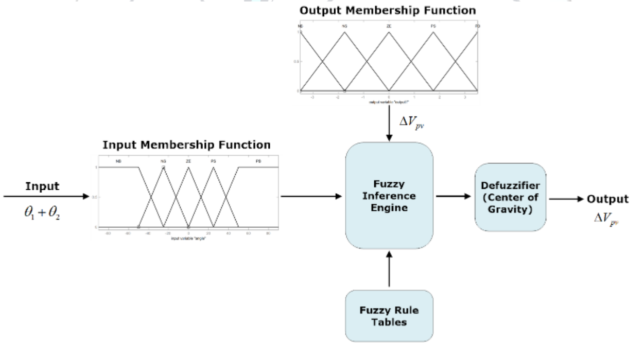

Figure 3. Block diagram of the FLC based MPPT

In the proposed FLC system, the input of FLC is sum of angle conductance and angle of increment conductance. The input variables are expressed in Eq. (8) and the MPPT determination condition is illustrated in Figure 4.

$$\theta_1 + \theta_2 = \tan^{-1}\left(\frac{dI_{pv}}{dV_{pv}}\right) + \tan^{-1}\left(\frac{I_{pv}}{V_{pv}}\right) = 0° \tag{8}$$

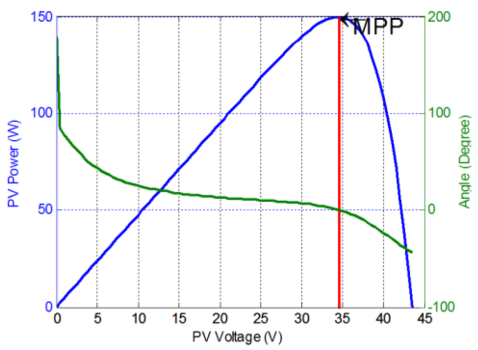

Figure 4. PV power – voltage and the angle ($\theta_1 + \theta_2$) MPPT relation for the proposed FLC based MPPT

During fuzzification process, input variables are converted into some defined linguistic variables according to chosen membership functions. For that purpose, the linguistic variables of the input are defined as NB (Negative Big), NS (Negative Small), ZE (Zero), PS (Positive Small) and PB (Positive Big). In fuzzy inference stage, the linguistic variables get manipulated based on the fuzzy rule base which defines the behavior of the controller as shown in Figure 5. In the defuzzification process, the FLC output is converted to a numerical value from the linguistic variable using membership function for the output [7].

$\theta_1 + \theta_2$	NB	NS	ZE	PS	PB
ΔV_{pv}	NB	NS	ZE	PS	PB
Region Area	Region 1		Region 2	Region 3	

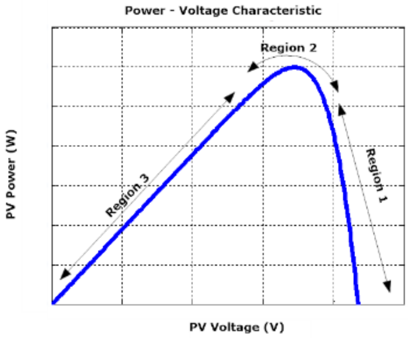

Figure 5. Fuzzy rule table and MPPT process in inference stage of the proposed FLC

The main advantages of FLCs are: no requirement of exact mathematical model of system to implement, capable of working with indefinite inputs, ability of handling non – linearity, fast and accurate convergence and tracking efficiency etc. The main disadvantages are: necessary to be tuned periodically, more complex structure, dependency to system and requiring prior knowledge of the behavior of PV system [5], [7], [12].

3.4. Neural Network (NN) Based Technique

The neural networks (NN) are becoming popular for system identification and non – linear system modelling applications. This technique is used to solve the difficult problems using parameter approximation. In recent days, NN control techniques are rising incrementally for the optimization and MPPT application of renewable power systems instead of conventional techniques [7], [9].

For MPPT operation, multi – layer feed forward neural network structure is commonly preferred and this NN structure consists of three layers: input, hidden and output layers as shown in Figure 6.

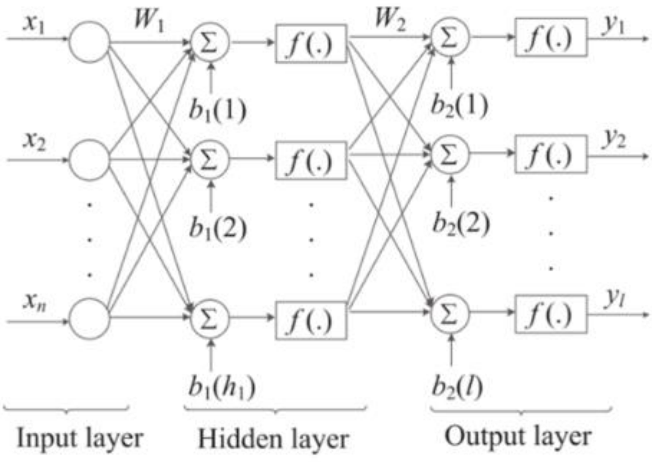

Figure 6. Architecture of multi-layer feed forward neural network [15]

The input layer receives input environmental data such as solar irradiance and temperature; second layer called as hidden layer contains 10 hidden neurons to estimate MPP value and sends to third layer. The third layer called as output layer contains single neuron to provide output to system. For MPPT purpose, 104 training data including MPP values for different solar irradiance and temperature values are applied 1000 times to train the designed NN structure. In addition, 10 different validation data, which also contains MPP values for different solar irradiance and temperature values, are used to verify and analyze performance of the trained neural network. After training the neural network 1000 times with the training data, the error of the neural network is approx. 1.5×10^{-4} according to the verification data. The performance analysis of the neural network is shown in Figure 7.

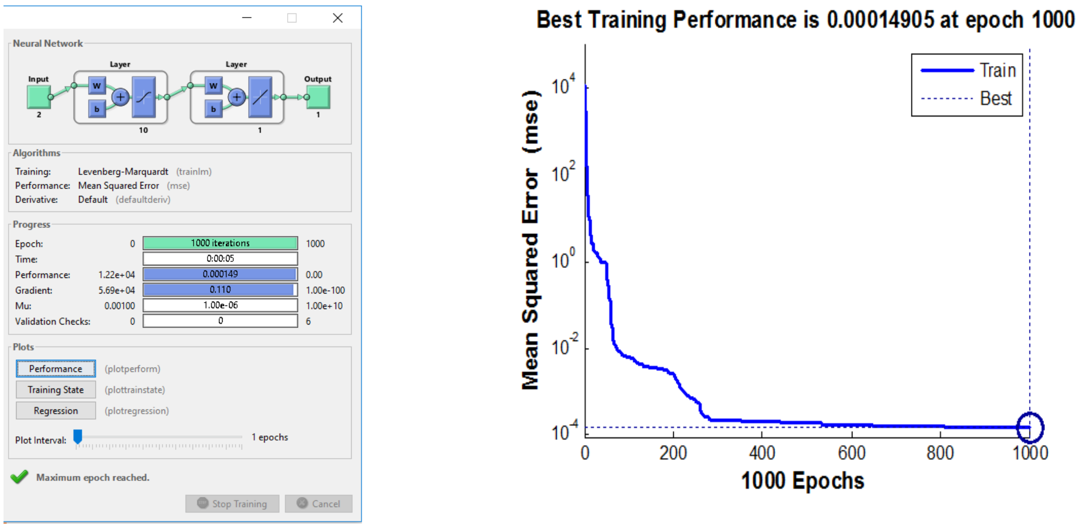

Figure 7. (a) Training result of the designed neural network *(b) Performance result and error of the neural network*

The main advantage of NN based MPPT technique is that it can provide satisfactory tracking accuracy of MPP and higher convergence speed without the exact information of the model parameters. However, its disadvantage is that it has to be specifically trained for the PV system on which it has to be implemented. In addition, the neural network requires to train in regular intervals of time to ensure accurate and efficient tracking of MPP when considering that the electrical characteristic of PV panel is time varying [5].

4. COMPARISON RESULTS OF CONVENTIONAL AND INTELLIGENT MPPTS

This study investigates a comparison between conventional P&O and Inc. Cond. MPPTs and intelligent FLC and NN based MPPTs in MATLAB. The performance of P&O, Inc. Cond. MPPT techniques with 3.5 V derivation parameter, fuzzy logic and neural network based MPPT techniques performance results are given in Figure 8 for standard test condition (1 kW/m^2, 25℃).

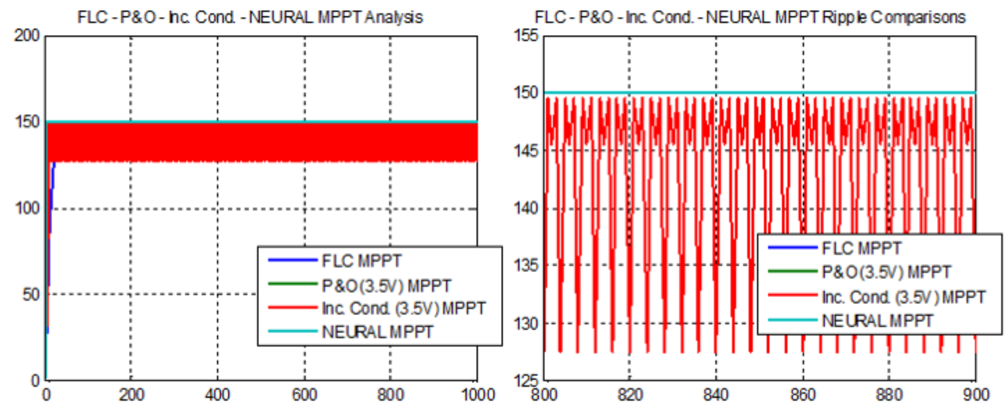

Figure 8. Conventional and intelligent MPPTs simulation results for standard test condition (1 kW/m2, 25℃)

As shown in Figure 8, intelligent FLC and NN based MPPTs are 4.66% more efficient than conventional P&O and Inc. Cond. MPPTs. Especially, neural network based MPPT has best iteration rate and also tracking accuracy among the other MPPTs. The conventional MPPTs have 4.45 times faster convergence speed but 4.66 % less tracking accuracy than FLC based MPPT due to oscillations around MPP. The overall simulation results in terms of iteration rate and tracking accuracy performance are given in Table 1.

Table 1. Comparison results for conventional and intelligent MPPTs at standard test condition (1 kW/m^2, 25°C)

MPPT Type	MPPT Technique	Iteration Rate	MPP Power (W)	Tracking Accuracy (%)
Conventional	P&O (3.5 V)	11	142.988	95.33 %
	Inc. Cond. (3.5 V)	11	142.988	95.33 %
Intelligent	Fuzzy Logic Control	49	149.987	99.99 %
	Neural Network	2	149.987	99.99 %

To observe tracking accuracy and convergence speed for different environment condition, the following simulation results are discussed for different solar irradiance values (1, 0.8, 0.6, 0.4 kW/m^2) at a constant temperature (30°C) in Figure 9. The intelligent MPPTs have better tracking accuracy than conventional ones for different solar irradiance values due to no oscillations around MPP for fuzzy logic and neural network based MPPTs. According to the simulation results, neural network based MPPT technique is better than conventional MPPTs in terms of tracking efficiency and convergence speed and also faster than fuzzy logic based MPPT for standard and different environment conditions.

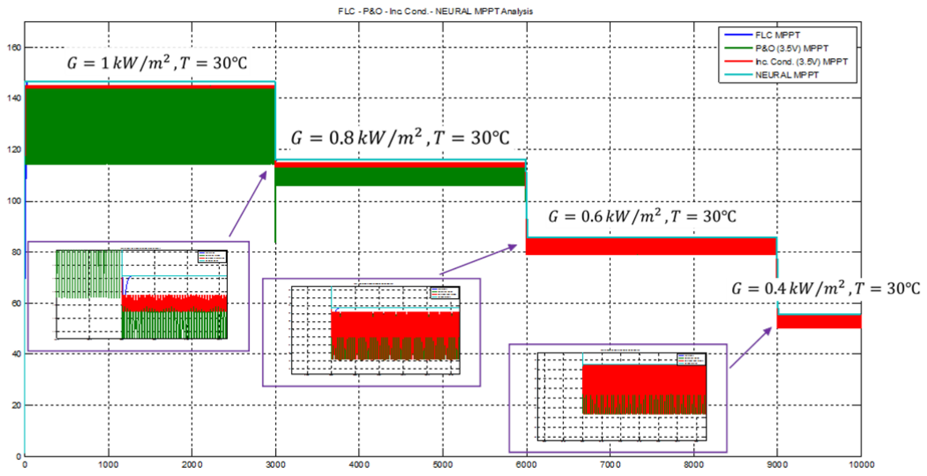

Figure 9. PV output power for conventional and intelligent MPPTs for different environment condition

Additionally, a characteristic comparison table in terms of panel dependency, tuning, tracking rate, complexity and required inputs for conventional and intelligent MPPT types, which are discussed in this paper, is presented in Table 2.

Table 2. Characteristic comparison for the MPPT techniques

MPPT Technique	PV Panel Dependency	Periodic Tuning	Tracking Rate	Complexity	Required Inputs
P&O	No	No	Variable	Low	Current, Voltage
Inc. Cond.	No	No	Variable	Moderate	Current, Voltage
Fuzzy Logic Control	Yes	Yes	High	High	Variable
Neural Network	Yes	Yes	High	Very High	Variable

Although, intelligent MPPTs are more difficult to implement and require additional PV panel information and periodic tuning; they have more efficient, robust and higher tracking rate features than conventional MPPTs.

5. CONCLUSIONS

In the last decade, PV energy generation has become one of the most used renewable energy choice instead of the fossil fuels. Compared to the other renewable sources, PV energy is more environmentally friendly, noise-free, low-cost and readily available universally. Hence, power generation from PV systems becomes important issue for the researchers. Due to non-linear characteristics of PV cells, the maximum allowable power level of PV systems is dependent on atmospheric parameters such as solar irradiance and temperature. Therefore, maximum power point tracking has turned out to be compulsory task to make energy conversion efficiently for the PV systems.

In this study, conventional P&O, Inc. Cond., intelligent FLC and NN based MPPT techniques performances are investigated and compared in terms of tracking efficiency and convergence speed for 150W PV panel under uniform environment conditions in MATLAB. According to the simulation results, intelligent MPPTs increased tracking efficiency 4.66% compared to the conventional MPPTs for the examined PV panel. Especially, NN based MPPT have best tracking and convergence performances among the other MPPTs. In addition, a characteristic comparison table for the investigated conventional and intelligent MPPT techniques is provided in this paper.

REFERENCES

[1]. J. Ahmed and Z. Salam, “A Modified P&O Maximum Power Point Tracking Method With Reduced Steady-State Oscillation and Improved Tracking Efficiency,” IEEE Trans. Sustain. Energy, vol. 7, no. 4, pp. 1506–1515, Oct. 2016.

[2]. A. B. . Bahgat, N. . Helwa, G. . Ahamd, and E. . El Shenawy, “Estimation of the maximum power and normal operating power of a photovoltaic module by neural networks,” 2004.

[3]. J.-K. Shiau, Y.-C. Wei, and B.-C. Chen, “A Study on the Fuzzy-Logic-Based Solar Power MPPT Algorithms Using Different Fuzzy Input Variables,” Algorithms, vol. 8, no. 2, pp. 100–127, Apr. 2015.

[4]. P. Takun, S. Kaitwanidvilai, and C. Jettanasen, “Maximum Power Point Tracking using Fuzzy Logic Control for Photovoltaic Systems,” in Proceedings of the International MultiConference of Engineers and Computer Scientists, 2011.

[5]. A. Gupta, Y. K. Chauhan, and R. K. Pachauri, “A comparative investigation of maximum power point tracking methods for solar PV system,” Sol. Energy, vol. 136, pp. 236–253, 2016.

[6]. E. Kandemir, N. S. Cetin, and S. Borekci, “A comprehensive overview of maximum power extraction methods for PV systems,” Renew. Sustain. Energy Rev., vol. 78, pp. 93–112, 2017.

[7]. S. Saravanan and N. Ramesh Babu, “Maximum power point tracking algorithms for photovoltaic system – A review,” Renew. Sustain. Energy Rev., vol. 57, pp. 192–204, 2016.

[8]. M. A. G. de Brito, L. Galotto, L. P. Sampaio, G. de A. e Melo, and C. A. Canesin, “Evaluation of the Main MPPT Techniques for Photovoltaic Applications,” IEEE Trans. Ind. Electron., vol. 60, no. 3, pp. 1156–1167, Mar. 2013.

[9]. K. Karabacak and N. Cetin, “Artificial neural networks for controlling wind–PV power systems: A review,” Renew. Sustain. Energy Rev., vol. 29, pp. 804–827, Jan. 2014.

[10]. D. Gonzalez Montoya, C. A. Ramos Paja, and R. Giral, “Maximum power point tracking of photovoltaic systems based on the sliding mode control of the module admittance,” Electr. Power Syst. Res., vol. 136, pp. 125–134, 2016.

[11]. E. Kandemir, N. S. Cetin, and S. Borekci, “A Comparison of Perturb & Observe and Fuzzy-Logic Based MPPT Methods for Uniform Environment Conditions,” Period. Eng. Nat. Sci., vol. 5, no. 1, pp. 16–23, 2017.

[12]. A. R. Jordehi, “Maximum power point tracking in photovoltaic (PV) systems: A review of different approaches,” Renew. Sustain. Energy Rev., vol. 65, pp. 1127–1138, 2016.

[13]. S. Borekci, E. Kandemir, and A. Kircay, “A Simpler Single-Phase Single-Stage Grid-Connected PV System with Maximum Power Point Tracking Controller,” Elektron. ir Elektrotechnika, vol. 21, no. 4, pp. 44–49, Aug. 2015.

[14]. C. S. Chiu, “T-S Fuzzy Maximum Power Point Tracking Control of Solar Power Generation Systems,” IEEE Transactions on Energy Conversion, vol. 25, no. 4. pp. 1123–1132, 2010.

[15]. L. L. Jiang, D. R. Nayanasiri, D. L. Maskell, and D. M. Vilathgamuwa, “A hybrid maximum power point tracking for partially shaded photovoltaic systems in the tropics,” Renew. Energy, vol. 76, pp. 53–65, 2015.