

# Improving Efficiency of Photovoltaic System by Using Neural Network MPPT and Predictive Control of Converter

Mahdi Heidari\*<sup>‡</sup>

\*Department of Electrical Engineering, Faculty of Engineering, University of Zabol, Bonjar Road, Zabol, Iran, Postal code: 9861335856

(m.heidari@uoz.ac.ir)

<sup>‡</sup>Corresponding Author; Mahdi Heidari, Department of Electrical Engineering, University of Zabol, Bonjar Road, Zabol, Iran, Postal code: 9861335856, Tel: +98 54 31232020, Fax: +98 54 31232020, m.heidari@uoz.ac.ir

*Received: 18.07.2016 Accepted: 22.09.2016*

**Abstract-** This paper proposes a new method to extract maximum energy from Photovoltaic (PV) systems. The artificial neural network (ANN) is used to track the maximum power based on the irradiance level and temperature. By using this algorithm the current in which the PV operates at its maximum power is extracted. In addition to ANN, a predictive controller is used to maximize the efficiency of the boost converter. The simulation results verify the suitable performance of the proposed method and this method maximizes the photovoltaic system energy extraction.

**Keywords** Photovoltaic system, MPPT, neural network, predictive controller.

## 1. Introduction

In recent years, the use of renewable energy has attracted more interests in developed countries. The major advantages of the renewable energies such as solar energy are: renewability and compatibility with the environment. Also they are economically beneficial.

One of the most useful renewable energies is solar energy that is converted to the electrical energy by using the photovoltaic cells. The input energy of the photovoltaic cells is affected by some factors such as panel angels, weather condition, irradiance, temperature and etc. To obtain the maximum power from the photovoltaic cells, one of the main cost-effective approaches is maximum power point tracking.

Because of the non-linearity of the Voltage-current and power-current curves of solar arrays, the maximum power depends on the operation point. The purpose of the MPPT is to apply suitable voltage to get the maximum current from the array. So far for optimization of maximum power point tracking (MPPT) systems, many techniques have been proposed in literatures. Some of these techniques are based on using the gradient of the P-V curve to locate the maximum power point (MPP) [1-3]. A comprehensive analysis and experimental evaluation of the reference voltage

perturbation and direct duty ratio perturbation techniques for implementing the P&O MPPT algorithm is presented in [4]. With reference voltage perturbation, the system has a faster response to temperature and irradiance transients. However, it loses stability if it operates at a high perturbation rate.

A modified variable-step incremental conductance MPPT technique has been proposed in [5]. This technique simplifies the structure implementation and shows minimal steady-state power oscillations around the MPP in addition to improved transient performance under sudden irradiance changes.

The Fractional  $V_{OC}$  and Fractional  $I_{SC}$  methods have shown themselves to be the most suitable algorithms for use with a Thermo-electric generator as they deliver the most consistent steady state performances [6].

Ripple correlation control is a dynamically rapid method used for the maximum power point tracking of photovoltaic arrays. The ripple is interpreted as a perturbation from which a gradient ascent optimization can be realized [7].

MPPT method that is based on the offline characterization of the MPP locus of a PV module is presented in [8]. This method requires only the measurement of the input voltage and current. As any other estimation

method, its effectiveness can be impaired by variations in the operating conditions.

The adaptive extremum seeking control (AESC) scheme is presented in [9] in order to track the maximum power point of PV. The convergence of the system for the placement to an adjustable neighbourhood of the optimum is guaranteed by utilizing a Lyapunov-based adaptive control method.

A PC-based maximum power point tracker for a PV system using neural networks has been developed in [10]. By using the artificial neural networks for detecting the optimal operating point under different operating conditions, the control algorithm has been developed.

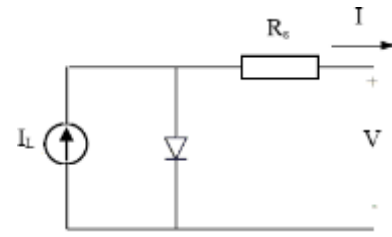
Neural fuzzy is presented in [11-12] for controlling PV system output voltage to operate at maximum power point Despite the irradiation and temperature changes. Applications of neural fuzzy controller on MPPT of PV showed a good performance. A complete fuzzy logic solar array maximum power tracking controller is proposed in [13] that shows fast convergence to the MPP and minimal fluctuation about it. Since the proposed approach requires only output current and voltage of the PV array, not the measurement of solar irradiation level and temperature, it needs the less number and cost of equipment despite the design complexity.

In addition to maximum power point tracking problem, the optimization of converters efficiency is the other important issue that attracts many of the researchers. A DC-DC converter is required to operate as an interface between PV panels and loads [14]. The DC-DC boost converter is used to fix the output voltage of the PV system [15]. Researchers have proposed control methods in order to increase the efficiency of the converters. Some of these methods include using PID controller, fuzzy controller, and the other control methods. As a case in point, a novel smart-PID controller for optimal control of DC-DC boost converter is used in [16] as voltage controller in PV systems.

In this paper, the MPPT algorithm is based on the I-V curve and solar parameters include solar irradiance and temperature is used as input parameters. The maximum power point is tracked by neural-network. Moreover, the efficiency of the dc/dc converter is improved by using a predictive controller. In section 2, the Photovoltaic model and its characteristics are described. In section 3 the proposed method is illustrated. Simulation and results are summarized in section 4. Finally, section 5 concludes the paper.

## 2. Description of Photovoltaic Systems

In this paper, a simplified method is used for PV cell modelling as it is presented in [17-18]. Figure 1 shows the equivalent circuit of a solar cell. Solar arrays are formed by series and parallel combination of these cells.



**Fig. 1.** The circuit diagram of the PV model.

$I_L$  is directly proportional to the irradiance. The diode is used to determine the I-V characteristics of the cell.  $R_s$  is the series resistance which gives a more accurate relation between the maximum power point and the open circuit voltage. The Equations of I-V characteristics of the PV cell are described as bellow. Throughout this paper the Solarex MSX60 60W array is used to illustrate the proposed model.

By using the model of figure 1, Eq. 1 gives the current Equation. The I-V curve is offset from the origin by photo generated current  $I_L$ :

$$I = I_L - I_0 \left( e^{q(V+IR_s)/nkT} - 1 \right) \tag{1}$$

As it is shown in (2), the relationship between the photo-current and temperature is linear.

$$I_L = I_{L(T_1)} (1 + K_0 (T - T_1)) \tag{2}$$

Where  $K_0$  is defined as bellow:

$$K_0 = (I_{SC(T_2)} - I_{SC(T_1)}) / (T_2 - T_1) \tag{3}$$

As it can be seen from (4),  $I_L$  is directly proportional to irradiance  $G$  ( $Wm^{-2}$ ). By considering  $I_{SC}=3.68A$  at 1 Sun ( $1sun= 1000Wm^{-2}$ ) and  $T_1=25^\circ C$  ( $298^\circ K$ ), we have  $I_L (T_1) = 3.8 A/Sun$ .

$$I_{L(T_1)} = G * I_{SC(T_1,nom)} / G_{(nom)} \tag{4}$$

Eq. 5 determines the relationship between  $I_0$  and temperature:

$$I_0 = I_{0(T_1)} * (T/T_1)^{3/n} * e^{-qV_g/nk*(1/T-1/T_1)} \tag{5}$$

In (5),  $I_0$  at  $25^\circ C$  is calculated by using the open circuit voltage and short circuit current at this temperature:

$$I_{0(T_1)} = I_{SC(T_1)} / \left( e^{qV_{OC(T_1)}/nkT_1} - 1 \right) \tag{6}$$

The Equations 7 and 8 give the series resistance of the panel. For the MSX60,  $R_s=8m\Omega$ .

$$R_s = -dV / dI_{V_{OC}} - 1 / X_V \tag{7}$$

$$X_V = I_{0(T_1)} * q / nkT_1 * e^{qV_{OC(T_1)}/nkT_1} \tag{8}$$

The module of the MSX60 has 36 series connected cells. This array has Open circuit voltage of 21 V, and short circuit current of 3.74A at  $T=25^\circ C$ . Figure 2 shows I-V curve for

different irradiation levels and Figure 3 shows the I-V curve for different temperatures.

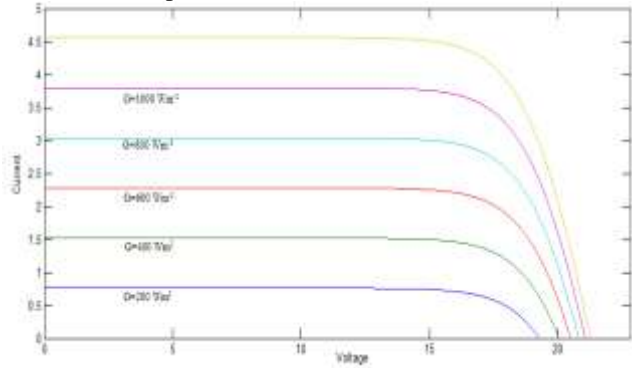


Fig. 2. I-V curve for different irradiation levels at constant temperature.

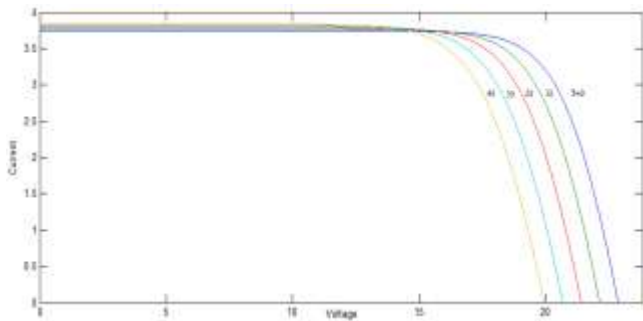


Fig. 3. I-V curve for different temperatures at constant irradiation

3. Proposed Photovoltaic System

As it can be seen from figures 2 and 3, I-V characteristics change by variation of temperature and irradiance level. So these two parameters have great impact on the output power. In order to obtain the maximum power, these two parameters should be evaluated.

Figure 4 shows the proposed photovoltaic system. This system includes PV arrays, artificial neural network block, boost converter and its predictive controller. Firstly, based on the temperature and irradiance level, ANN predicts the output current which corresponds the maximum power point. Then, arrays work based on the obtained current. Finally, the predictive controller is used to obtain the maximum efficiency.

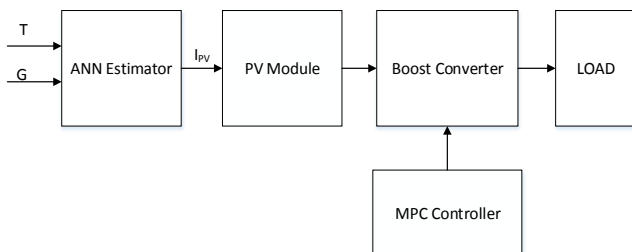


Fig. 4. The proposed Photovoltaic system and its controller

3.1. Maximum Power Point Tracking by Using Neural Network

In this paper, neural network is used to obtain the maximum power by using irradiation levels and temperature. The method of back propagation with Levenberg-Marquardt back propagation training function and Mean Square Error (MSE) is implemented. In order to train the neural network, 5000 samples of temperature and irradiation are used. Also, output power samples are used as target of ANN training as shown in figure 5.

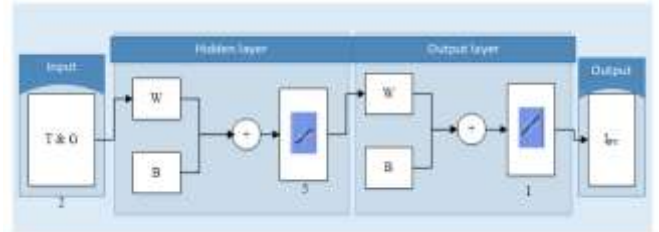


Fig. 4. The proposed artificial neural network

3.2. Predictive Controller Design of Boost Converter

The predictive model of controller is implemented to estimate the future behaviour of the controlled variables so that proper control actions could be determined [19]. A DC/DC boost converter is used to control the voltage in order to extract the maximum power from the system. As it can be seen from the figure 5, the operation of the converter can be described as follows when the switch is opened (S=1).

$$\begin{aligned} \frac{di_L}{dt} &= \frac{v_{pv}}{L} \\ \frac{dv_{pv}}{dt} &= -\frac{i_L}{C_1} + \frac{i_{pv}}{C_1} \\ \frac{dv_o}{dt} &= -\frac{v_o}{RC_2} \end{aligned} \tag{9}$$

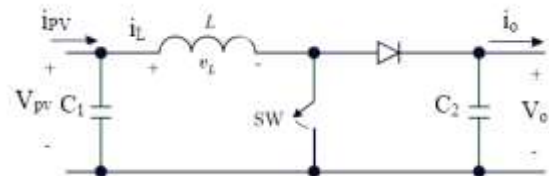


Fig. 5. Boost converter

When the switch is closed (S=0), then we have:

$$\begin{aligned} \frac{di_L}{dt} &= \frac{v_{pv}}{L} - \frac{v_o}{L} \\ \frac{dv_{pv}}{dt} &= -\frac{i_L}{C_1} + \frac{i_{pv}}{C_1} \\ \frac{dv_o}{dt} &= \frac{i_L}{C_2} - \frac{v_o}{RC_2} \end{aligned} \tag{10}$$

Discrete form of the system can be written as follows:

$$i_L(k+1) = i_L(k) + \frac{T_s}{L} v_{pv}(k) - \frac{T_s}{L} v_o \tag{11}$$

$$v_{pv}(k+1) = -\frac{Ts}{C_1} i_L(k) + v_{pv}(k) + \frac{Ts}{C_1} i_{pv}(k)$$

$$v_o(k+1) = -\frac{Ts}{C_2} i_L(k) + \left(1 - \frac{Ts}{RC_2}\right) v_o(k)$$

$$i_L(k+1) = i_L(k) + \frac{Ts}{L} v_{pv}(k)$$

$$v_{pv}(k+1) = -\frac{Ts}{C_1} i_L(k) + v_{pv}(k) + \frac{Ts}{C_1} i_{pv}(k)$$

$$v_o(k+1) = \left(1 - \frac{Ts}{RC_2}\right) v_o(k)$$

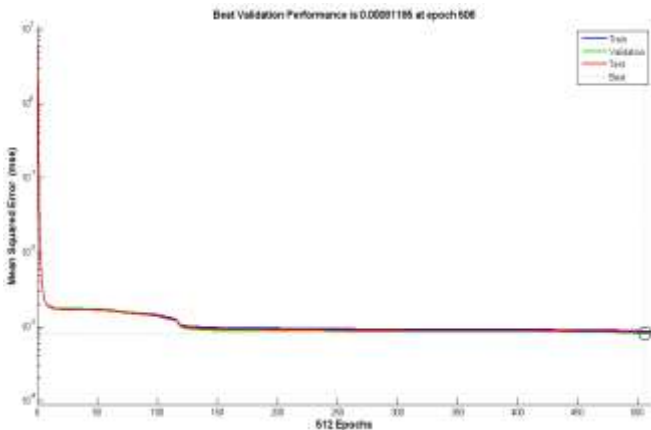
The cost function for states of open and close switch is defined in the bellow Eq.:

$$J_{S=0,1}^1 = w_A |v_o(k+1)_S v^*|^2 + w_B |i_L(k+1)_S - i^*|^2 \quad (12)$$

The cost function will be calculated for all the switching states; for the next step the proper control action will be applied.

**4. Simulation Results**

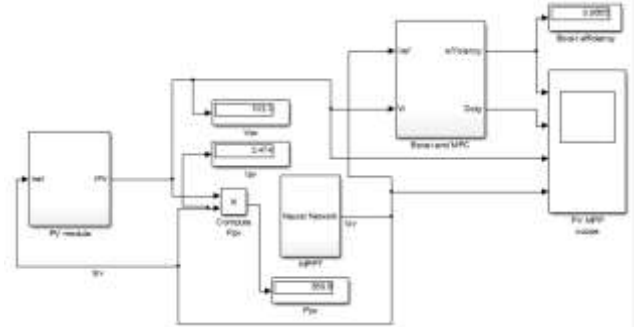
The proposed photovoltaic system is implemented by using MATLAB/SIMULINK. As it has been explained in previous sections, firstly the ANN estimates the maximum output power. The performance of the neural network is shown in figure 6.



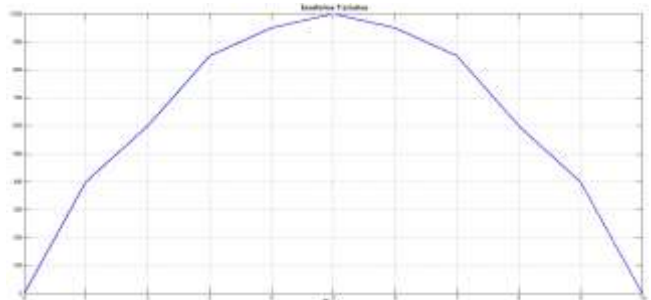
**Fig. 6.** Performance of the ANN

After training and running the ANN, as it is shown in figure 7, the proposed Photovoltaic system and its controller is implemented in MATLAB/SIMULINK. In this paper, 6 modules are used. The simulation results are shown in figures 8 to 12. Figure 8 shows the insolation variation during 10 hours. The maximum power point tracker changes its reference by insolation variation. Figure 9 shows the current in which the photovoltaic works under its maximum power. Figure 10 shows the PV power and output power. Figure 11 shows the duty cycle of the boost converter in which the desired output voltage is obtained. Figure 12 shows the efficiency of the boost converter. By analyzing

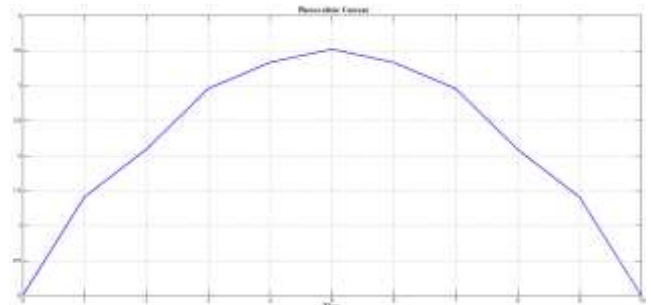
these figures it can be observed that the PV system operates at its optimal value. Moreover, the efficiency of the boost converter is maximized, so the maximum energy is extracted.



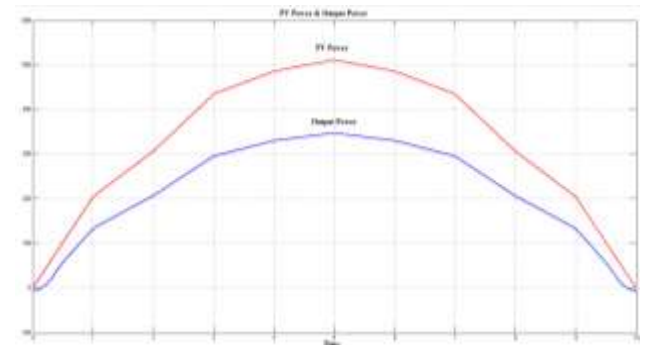
**Fig. 7.** View of implemented system in MATLAB/Simulink



**Fig. 8.** Insolation variation



**Fig. 9.** Photovoltaic current



**Fig. 10.** PV & Output Power

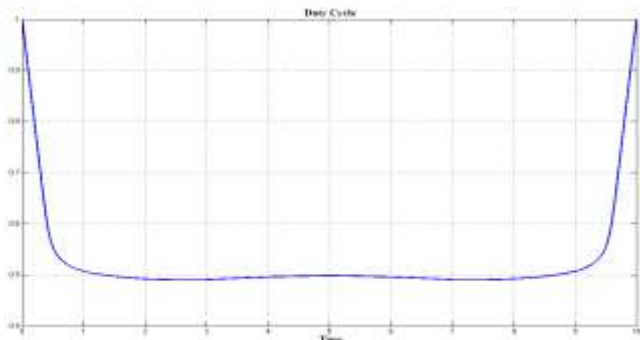


Fig. 11. Duty cycle of boost converter

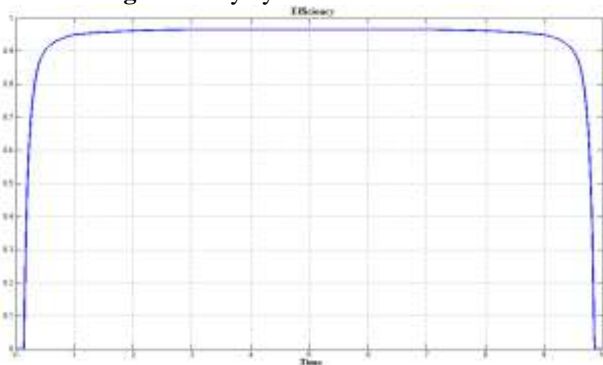


Fig. 12. Efficiency of Boost converter

## 5. Conclusion

In this paper a neural network based control is used to track the maximum power of photovoltaic system. The neural networks inputs are irradiance level and temperature. The PV optimal current is the output of the ANN. Moreover, predictive controller is used to maximize the efficiency of the boost converter. The simulation results proved the suitable performance of the proposed method. Compared to the previous control strategies, the proposed method has a higher performance for extraction of power.

## References

[1] A. K. Abdelsalam, A. M. Massoud, S. Ahmed, and P. N. Enjeti, "High-performance adaptive perturb and observe MPPT technique for photovoltaic-based microgrids," *IEEE Transactions on Power Electronics*, vol. 26, pp. 1010-1021, 2011.

[2] S. B. Kjær, "Evaluation of the "hill climbing" and the "incremental conductance" maximum power point trackers for photovoltaic power systems," *IEEE Transactions on Energy Conversion*, vol. 27, pp. 922-929, 2012.

[3] A. Safari and S. Mekhilef, "Simulation and hardware implementation of incremental conductance MPPT with direct control method using cuk converter," *IEEE Transactions on Industrial Electronics*, vol. 58, pp. 1154-1161, 2011.

[4] C. Haithem and A. Sakly, "Comparison between P&O and PSO methods based MPPT algorithm for photovoltaic systems," 2015 16th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA), IEEE, 2015, pp. 694-699.

[5] R. Faraji, A. Rouholamini, HR. Naji, R. Fadaeinedjad, MR. Chavoshian, "FPGA-based real time incremental conductance maximum power point tracking controller for photovoltaic systems," *IET Power Electronics*, vol. 7, pp. 1294-1304, 2014.

[6] I. Laird and D. D. Lu, "Steady state reliability of maximum power point tracking algorithms used with a thermoelectric generator," in 2013 IEEE International Symposium on Circuits and Systems (ISCAS2013), 2013, pp. 1316-1319.

[7] T. Esrām, J. W. Kimball, P. T. Krein, P. L. Chapman, and P. Midya, "Dynamic maximum power point tracking of photovoltaic arrays using ripple correlation control," *IEEE Transactions on power electronics*, vol. 21, pp. 1282-1291, 2006.

[8] V. V. Scarpa, S. Buso, and G. Spiazzi, "Low-complexity MPPT technique exploiting the PV module MPP locus characterization," *IEEE transactions on industrial electronics*, vol. 56, pp. 1531-1538, 2009.

[9] X. Li, Y. Li, J.E. Seem, "Maximum Power Point Tracking for Photovoltaic System Using Adaptive Extremum Seeking Control," *IEEE Transactions on Control Systems Technology*, vol. 21, pp. 2315-2322, 2013.

[10] A. Bahgat, N. Helwa, G. Ahmad, and E. El Shenawy, "Maximum power point tracking controller for PV systems using neural networks," *Renewable Energy*, vol. 30, pp. 1257-1268, 2005.

[11] B. Tarek, D. Said, and M. Benbouzid, "Maximum power point tracking control for photovoltaic system using adaptive neuro-fuzzy," in ANFIS," in Eighth International Conference and Exhibition on Ecological Vehicles and Renewable Energies (EVER), Monte Carlo, 2013.

[12] A. Gupta, P. Kumar, R. K. Pachauri, Y. K. Chauhan, "Performance analysis of neural network and fuzzy logic based MPPT techniques for solar PV systems," In Power India International Conference (PIICON), 2014 6th IEEE, pp. 1-6.

[13] J. Li and H. Wang, "Maximum power point tracking of photovoltaic generation based on the fuzzy control method," in 2009 International Conference on Sustainable Power Generation and Supply, 2009, pp. 1-6.

[14] J. L. Santos, F. Antunes, A. Chehab, and C. Cruz, "A maximum power point tracker for PV systems using a high performance boost converter," *Solar Energy*, vol. 80, pp. 772-778, 2006.

[15] A. Kotsopoulos, J. Duarte, and M. Hendrix, "A predictive control scheme for DC voltage and AC current in grid-connected photovoltaic inverters with minimum DC link capacitance," in *Industrial Electronics Society, 2001. IECON'01. The 27th Annual Conference of the IEEE*, 2001, pp. 1994-1999.

[16] M. Elshaer, A. Mohamed, and O. Mohammed, "Smart optimal control of DC-DC boost converter in PV systems," in *Transmission and Distribution Conference and Exposition: Latin America (T&D-LA)*, 2010 IEEE/PES, 2010, pp. 403-410.

[17] G. Walker, "Evaluating MPPT converter topologies using a MATLAB PV model," *Journal of Electrical & Electronics Engineering*, vol. 21, pp. 49-56, 2001.

- [18] A. Sarwar, M. Hasan, AQ. Ansari, "Five parameter modelling and simulation of solar PV cell," In Energy Economics and Environment (ICEEE), IEEE, 2015, pp. 1-5.
- [19] S. Kouro, P. Cortés, R. Vargas, U. Ammann, and J. Rodríguez, "Model predictive control—A simple and powerful method to control power converters," IEEE Transactions on Industrial Electronics, vol. 56, pp. 1826-1838, 2009.