DIU Journal of Science and Technology Volume 1,Issue 1,July 2006

2006-07-01

PERFORMANCE EVALUATION OF A MAXIMUM POWER POINT TRACKER (MPPT) FOR SOLAR ELECTRIC VEHICLE USING ARTIFICIAL NEURAL NETWOR

Kaiser, M. Shamim

Daffodil International University

Notice:
This paper has high similarity with the reference paper [2]. The readers are advised to cite the reference article [2]

PERFORMANCE EVALUATION OF A MAXIMUM POWER POINT TRACKER (MPPT) FOR SOLAR ELECTRIC VEHICLE USING ARTIFICIAL NEURAL NETWORK

M. Shamim Kaiser, Subrata Kumar Aditya, Rezaul Karim Mazumder†
Department of Electronics and Telecommunication Engineering,
Daffodil International University, Dhaka1207, Bangladesh
†Department of Applied Physics, Electronics & Telecommunication Engineering,
University of Dhaka, Dhaka-1000, Bangladesh
Email: shambd-diu@daffodilnet.com

Abstract—*In this paper, the performance of an Artificial Neural Network (ANN) based maximum power point tracker (MPPT) for solar electric vehicles has been evaluated. The core component of a MPPT is boost converter with insulated gate bipolar transistor (IGBT) power switch. The reference voltage for MPPT is obtained by ANN with gradient descent algorithm. The tracking algorithm changes the duty-cycle of the converter so that the PV-module voltage equals the voltage corresponding to the MPPT at any given irradiance, temperature, and load conditions. For fast response, the system is implemented using digital signal processor (DSP). The overall system stability is improved by including a proportional-integral-derivative (PID) or proportional-integral (PI) controller, which is also used to match the reference and battery voltage levels. The controller, based on the information supplied by the ANN, generates the boost converter duty-cycle. The energy obtained is used to charge the lithium ion battery stack for the solar vehicle. The experimental and simulation results show that the proposed scheme is highly efficient.*

Keywords—*Artificial Neural Network (ANN), Maximum Power Point Tracker (MPPT), and Solar Vehicles.*

1. Introduction

Photovoltaic (PV) generation is gaining increased importance as a renewable source of energy. The undesirable rapid changes of solar power, which usually occur in a running vehicle, arise as a result of shade from buildings, large trees, and clouds in the sky. Conventional PV systems have difficulties in responding to rapid variations due to shade. The main drawbacks of PV systems are that the initial installation cost is considerably high and the energy conversion efficiency (from 12% to 29%) is relatively low. Furthermore, in most cases, PV systems require a power conditioner for load interface. Therefore, the overall system cost could be reduced drastically by using highly efficient power conditioners, such as the maximum power point tracker power applications [1-12]. Among the hill climbing methods [1-5], the perturb and observe (P&O) method tracks maximum power point (MPP) by repeatedly increasing or decreasing the output voltage at MPP of the PV module. This method requires calculation of dP/dV to determine the MPP [1], [2], [4]. Though the method is relatively simple to implement, it cannot track the MPP when the irradiance changes rapidly. Also, the method oscillates around the MPP instead of directly tracking it. The incremental conductance technique (ICT) is the most accurate [6], [7] among the other methods. This method gives good performance under rapidly changing conditions. However, the complex calculation of dI/dV and the complicated algorithm require use of a digital signal processor (DSP), which will usually increase the total system cost. The MPP tracking method using the short circuit current of the PV module utilizes the fact that the operating current at MPP of the PV module is linearly proportional to the short circuit current of the PV module [9]. Under rapidly changing atmospheric conditions, this method has a fast response speed of tracking the MPP, but the control circuit is complicated. The MPP tracking method using open circuit voltage of the solar panel [11] utilizes the fact that the operating voltage at MPP is almost linearly proportional to open circuit voltage at MPP of the PV module (using 76% of open circuit voltage as the MPP voltage). This method is very simple and cost-effective, but the reference voltage does not change between samplings. MPPTs using the fuzzy logic [13], [14] and the artificial neural network (ANN) [15] have been reported. These studies show that such modern control algorithms are capable of improving the tracking performance as compared to the conventional methods[2].

The tracking algorithm changes the duty ratio of the converter so that the PV module voltage equals the voltage corresponding to the MPP at that atmospheric condition. This adjustment is carried out by using the back-propagation ANN. The reference voltage to the MPP is obtained by an off-line trained ANN. The controller generates the boost converter duty-cycle[1], [2].

2. The Photovoltaic Array

The solar array characteristics significantly influence the design of the converter and the control system, so the PV characteristics will be briefly reviewed here. The solar array is a nonlinear device and can be represented as a current source model, as shown in Figure 1. The traditional *I-V characteristics* of a solar array, when neglecting the internal shunt resistance, are given by the following equation [2]:

$$I_o = I_g - I_{sat}\{\exp[\frac{q}{AKT}(V_o + I_o R_s)] - 1\} - \frac{V_o + I_o R_s}{R_{sh}} \quad (1)$$

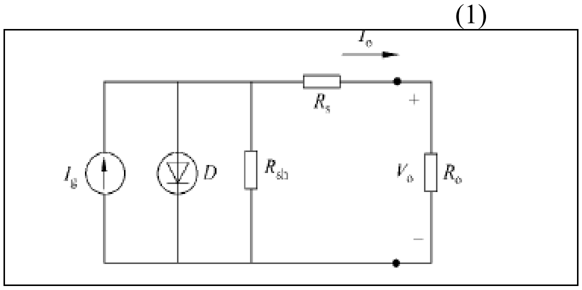

Figure 1: Equivalent circuit of the solar cell.

where, I_o and V_o are the output current and voltage of the solar array respectively. I_g is the generated current under a given insolation; I_{sat} is the reverse saturation current; q is the charge of an electron; k is the Boltzmann constant; A is the ideality factor for a P-N junction; T is the array temperature, R_s and R_{sh} are the intrinsic series and shunt resistances of the solar array respectively . The saturation current of the solar array varies with temperature according to the following equation

$$I_{sat} = I_{or}\left[\frac{T}{T_r}\right]^3 \exp\left[\frac{qE_{GO}}{Ak}(\frac{1}{T_r} - \frac{1}{T})\right] \quad (2)$$

$$I_g = \left[I_{sc} + K_t(T - 25)\frac{\lambda}{100}\right] \quad (3)$$

where T_r is the reference temperature; E_{GO} is the band-gap energy of the semiconductor used in the solar array; A is also an ideality factor; I_{sc} is the short circuit current at 25°C; K_t is the short-circuit current temperature coefficient and λ is the insolation in W/m². Equations (1)-(3) are used in the development of computer simulations for the solar array. The Matlab programming language is used. Figure 2 show the simulated current-voltage and power-voltage curves for the solar array at different insolations and different temperatures. These curves show that the output characteristics of the solar array are nonlinear and greatly affected by the solar radiation, temperature, and load condition. Each curve has a maximum power point (P_{max}), which is the optimal operating point for the efficient use of the solar array.[2]

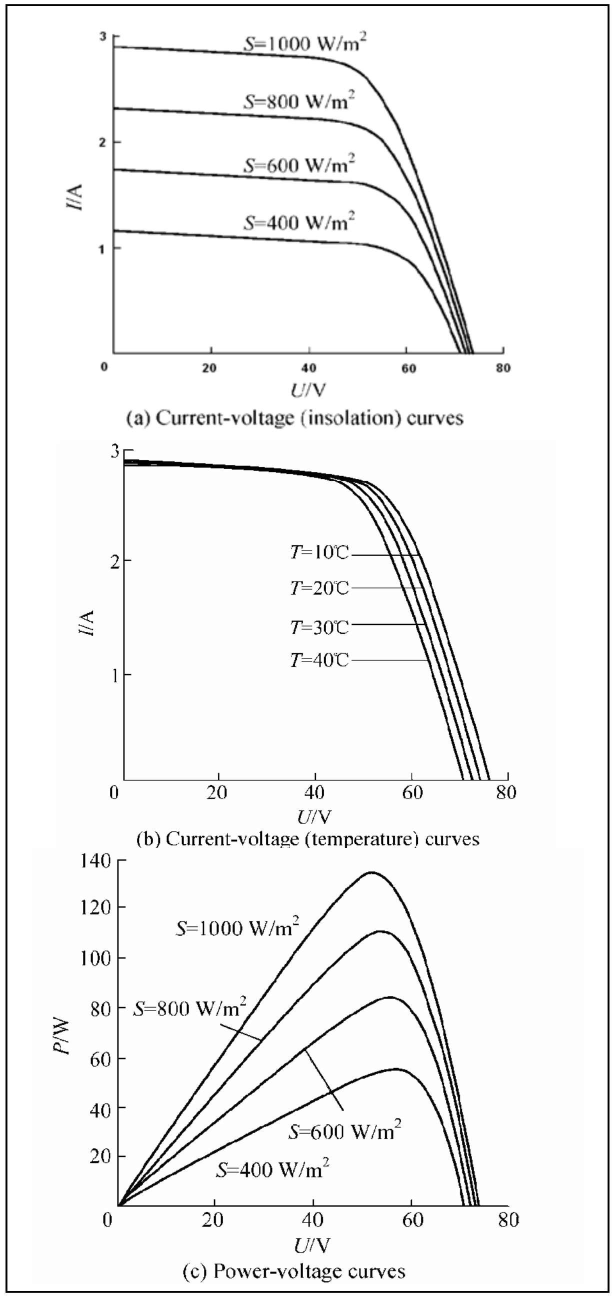

Figure 2: Current-voltage and power-voltage curves for the solar array at different insolations, S, and different temperatures[2].

3. Artificial Neural Network

ANN technology has been successfully applied to solve very complex problems. Recently, its application in various fields is increasing rapidly [2], [16], [17].

The instantaneous sum of error squares or error energy at iteration is given by

$$\xi(n) = \frac{1}{2}\sum_{j\in C} e_j^2(n) \tag{4}$$

where neuron ***j*** lies in a layer to the right of neuron ***i,*** and neuron ***k*** lies in a layer to the right of neuron ***j*** when neuron ***j*** is a hidden unit; $\xi(n)$ is the error signal at the output of neuron ***j*** for iteration ***n***; and the set **C** includes all the neurons in the outer layer of the network. The correction $\Delta w_{ji(n)}$ to the synaptic weight w_{ji} is given by[2]

$$\Delta w_{ji(n)} = \alpha \Delta w_{ji}(n-1) + \eta \delta_j(n) y_i(n) \tag{5}$$

where ***α*** is the momentum constant; ***η*** is the learning-rate parameter of the back-propagation algorithm; $\delta_j(n)$ is the local gradient. The error signal at the output is defined as[2]

$$e_j(n) = d_j(n) - y_j(n) \tag{6}$$

where $d_j(n)$ is the desired response or wanted targets and $y_j(n)$ is the output signal. Adjustment of the weights for these layers is given by

$$w_{ji}(n+1) = w_{ji}(n) + \alpha . w_{ji}(n-1) + \eta \delta_j(n) y_j(n) \tag{7}$$

From Equations. (4), and (6), the mean squared error performance index can be rewritten as

$$\xi(n) = \frac{1}{2}\left(V_{ref}(n) - V_A(n)\right)^2$$

The network training is performed repeatedly until the performance index $\xi(n)$ falls below a specified value, ideally to zero. In other words $\xi(n) \to 0$ implies $\xi(n) = \frac{1}{2}\left(V_{ref}(n) - V_A(n)\right)^2 \to 0$, and then the connecting weights of the network are adjusted in such a way that the array voltage V_A is identically equal to the maximum power point voltage V_{mp} . At this stage the reference voltage V_{ref} becomes equal to the maximum power point voltage V_{mp} .

The configuration of the proposed three-layer feed forward neural network function approximator is shown in Figure 3. The neural network is used to obtain the voltage of the maximum power $V_{mp}(n)$ of the solar panel. The network has three layers an input, a hidden, and an output layer. The numbers of nodes are two, four, and one in the input, the hidden and output layers, respectively. The reference-cell open circuit voltage $V_{oc(n)}$ and the time parameter $T(n)$ are supplied to the input layer of the neural network [2].

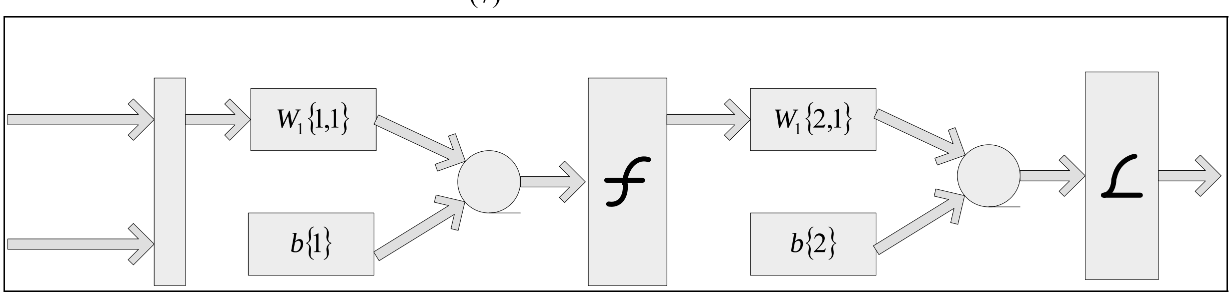

Figure 3: Feed forward neural network function approximator.

These signals are directly passed to the nodes in the next hidden layer. The node in the output layer provides the identified maximum power point voltage $V_{mp}(n)$. The nodes in the hidden layer get signals from the input layer and send their output to the node in the output layer. The sigmoid activation function is utilized in the layers of the network. The training program calculates the connecting weights $W_1\{1,1\}$ with the bias $b\{1\}$ for the input to hidden layer mapping, the connecting for the input to hidden layer mapping, the connecting weights $W_1\{2,1\}$ with bias $b\{2\}$ for the hidden layer to output layer mapping. During the training the connecting weights are modified recursively until the best fit is achieved for the input-output patterns in the training data. The training of the net was accomplished off-line using Matlab. The diagrammatic representation of the proposed system is shown in Figure 4.

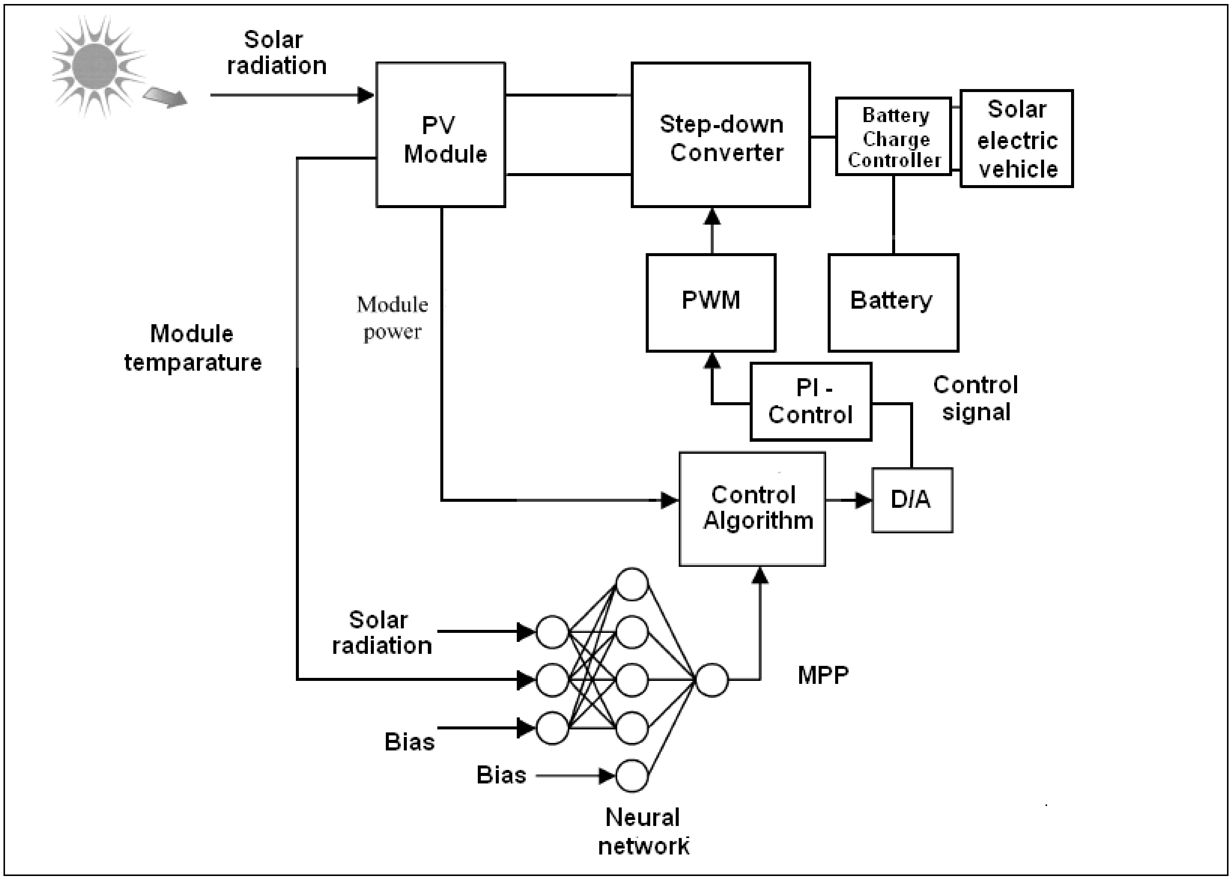

Figure 4: Diagrammatic view of the proposed MPPT.

4. Experimental Results

A PV array used for the collection of the experimental data is Siemens SM50 (Germany) type modules. The module has a maximum power output of 45 W and a 20-V open-circuit voltage at an irradiation of 1000 W/m2 and a 25 C ° temperature. The PV module specifications provided by the manufacturer in Table 1.

Table 1: Electrical specification for the Siemens SM50 Module.

Maximum power, Pm	**50W**
Short circuit current, I_{sc}	**3.04A**
Open circuit voltage, V_{oc}	**21.4V**
Voltage at max power point, V_{mp}	**18V**
Current at max power point, I_{mp}	**3**

The feed-forward back-propagation ANN, as shown in Fig.3 was trained with values obtained from experimental data of the reference cell. Gradient descent algorithm was used in training as it improves the performance of the ANN, reducing the total error by changing the weights along its gradient. The training parameters are as follows learning rate parameter η=0.1; momentum factor α=0.9; number of training iterations=10 000; error goal=0.000 001. The convergence errors for the training process and performance of ANN based MPPT are shown in Figures 5 and 6 respectively. The parameters used for the training of the ANN and the output values given by the ANN after the training can be found in Table 2. Various sets of reference cell open circuit voltage Voc and a time parameter T are supplied as the input to the ANN. In order to validate the learning capability of the ANN, other sets of Voc different from the one in Table 2 were also supplied to the ANN, which gave out values of V_{mp} as expected. The software Matlab was used in the training of the ANN. The results are matched with the results of [2].

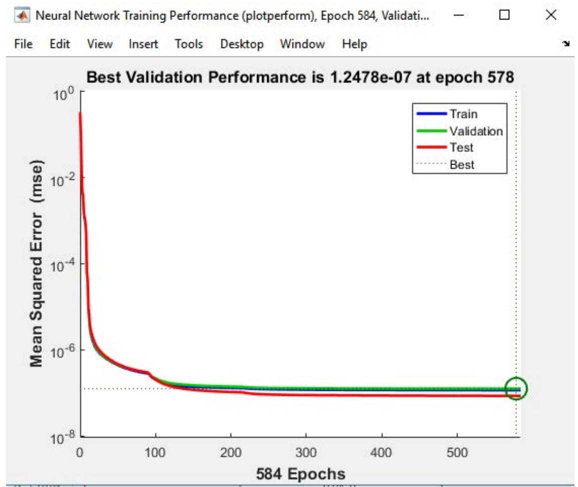

Figure 5: Convergence of error for the neural network training process.

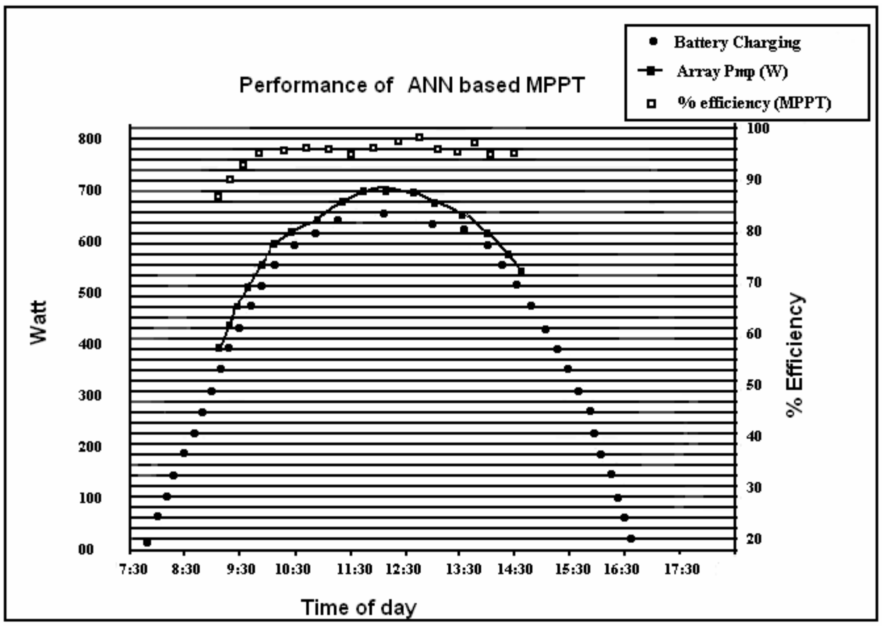

Figure 6: Performance of ANN based Maximum Power Point Tracker.

The weights to the hidden layer 1 from input 1 are as follows

$$W_1\{1,1\} = \begin{bmatrix} 2.1706 & -5.3856 & -3.2326 & -5.1766 \\ 109.8309 & -27.943597 & -97.725 & -8.564 \end{bmatrix}$$

The weights to the output layer 2 are

$$W_1\{2,1\} = [-0.2039 \quad 0.0065 \quad 0.0561 \quad -0.3029]$$

The bias to layer 1 is

$$b\{1\} = [-60.0887 \quad 12.996 \quad -54.4753 \quad -1.5969]$$

The bias to layer 2 is $b\{2\} = [-0.0397]$

Table 2: Results of the trained data given by ANN [2].

	Hours of the day										
	900	930	1000	1030	1100	1130	1200	1230	1300	1330	1400
Time Parameter	-1	-0.9	-0.8	-0.7	-0.6	-0.5	-0.4	-0.3	-0.2	-0.1	0
V_{oc} measured	0.555	0.519	0.516	0.529	0.517	0.514	0.516	0.510	0.511	0.509	0.508
V_{mp} measured	0.422	0.394	0.392	0.402	0.393	0.391	0.392	0.388	0.388	0.387	0.386
V_{mp} given by ANN	0.421	0.379	0.388	0.416	0.395	0.394	0.392	0.388	0.388	0.386	0.385

5. Conclusion

An artificial neural network MPPT for charging the battery stack of a solar (hybrid) vehicle has been proposed in this paper. An off-line ANN, trained using a back-propagation with gradient descent momentum algorithm, is utilized for online estimation of reference voltage for the feed-forward loop. Experimental data is used for the offline training of the ANN, and software Matlab is used in the training of the net. The precision of the estimation has been verified by the graph of the convergence error. The proposed method has several advantages over the conventional methods, particularly in that there is no need for voltage and current sensors, and in that it avoids a complex calculation of power. The experimental and simulation results show that the proposed scheme is highly efficient.

6. References

[1] C. Hua , J. Lin, C. Shen., Implementation of a DSP-controlled photovoltaic system with peak power tracking. *IEEE Trans. Ind. Electron*., 1998, Vol. 45(1), pp,11-24.

[2] T A Ocran and C Junyi, C Binggang and S. Xinguha "Artificial Neural Network Maximum Power Point Tracker for Solar Electric Vehicle", *Tsinghua Sc & Tech. Conversion*, 2005, Vol. 10 (2), pp. 204-208.

[3] T. Hiyama, K. Kitabayashi, "Neural Network Based Estimation of Maximum Power Generation" *IEEE Trans. On Energy Conversion*, 1997, Vol. 10(3).

[4] J.H.R. Enslin, D.B. Snyman, "Combined Low-cost, High-Efficient Inverter, Peak Power Tracker and Regulator for PV Applications", IEEE Trans. on Power Electronics, 1998, Vol 6(1).

[5] M.A.S. Masoum, H. Dehbonei, E.F. Fuchs, "Theoretical and Experimental Analyses of Photovoltaic Systems with Voltage and Current–Based Maximum Power Point Tracking", Accepted for publication in IEEE Trans. on Energy Conversion.

[6] M Shamim Kaiser, A Anwar, S K Aditya, and R K Mazumder, Design and simulation of Fuzzy Based MPPT, *Renewable Energy Prospect and Progress,*2005, pp 19-21.

[7] M Shamim Kaiser, S A Sharna, A Anwar, S K Aditya, and R K Mazumder, Artificial Neural Network based grid connected inverted for photovoltaic system, The Journal of the Bangladesh Electronics Society, 2005, Vo l5(2), pp. 21-26.

[8] Jeannette Lawrence, *Introduction to Neural Networks,* 5th edition, January, California Scientific, Nevada City. 1993.

[9] T. Noguchi, Togashi S, Nakamoto R, Short current pulse based MPPT for multiple photovoltaic and converter module system, *IEEE Ind. Electron conf.,* 2002. Vol. 49(1), pp 217-223.

[10] D Y Lee, Noh H J, Hyun D S, Choy I. An improved MPPT converter using current compensation method for small scaled PV applications. In Proc. IEEE Applied Power Electron. Conf., Dalas, TX, USA, 2002 pp. 540-545.

[11] Enslin J H R, Wolf M S, Snyman D B, Sweigers W. Integrated photovoltaic maximum power point tracking converter. *IEEE Trans. Ind. Electron.*, 1997, Vol.44(6), pp.769-773.

[12] Y. Chen, Smedley K, Vacher F, Brouwer J. A new maximum power point tracking controller for photovoltaic power generation. In Proc. IEEE Applied Power Electron. Conf., Miami Beach, FL, USA, 2003 pp.56-62.

[13] A. Nafeh, Fahmy F H, El-Zahab E M A. Evaluation of a proper controller performance for maximum power point tracking of a stand-alone PV system. *International Journal of Numerical Modelling*, 2002, Vol.15(4) pp.385-398.

[14] M. Veerachary, Senjyu T S, Uezato K. Feedforward maximum power point tracking of PV systems using fuzzy controller. *IEEE Trans. Aerosp. and Electron. Syst.*, 2002, Vol.38 (3) pp.969-981.

[15] T. Hiyama, S. Kouzuma, Evaluation of neural network based real time maximum power point tracker for PV system, *IEEE Energy Conv*. 1995. Vol 10(3), pp.543-548.

[16] Bose B K, ANN application in power electronics, *IEEE Ind. Electron conf.*, Denver CO, USA, 2001, pp 1631-1638.

[17] S. Haykin, *Neural Networks—A Comprehensive Foundation,* 2nd Edition. New York Prentice Hall Inc.,1999.

M. Shamim Kaiser is currently a Lecturer in the Electrical and Telecommunication Engineering Department at the Daffodil International University. Mr. Kaiser received his B.Sc. (Honors), M.S. degrees from University of Dhaka in 2001 and 2002 respectively. He is currently doing his Ph.D. in the Department of Applied Physics, Electronics and Communication Engineering, University of Dhaka. Mr. Kaiser's areas of interest include Artificial Intelligence System, Renewable Energy Engineering, and Digital Signal Processing. He is a member of International Solar Energy Society, Bangladesh Solar Energy Society Bangladesh Electronics Society.

Subrata Kumar Aditya is currently working as a Professor in the Department of Electronics and Telecommunication Engineering, Daffodil International University. Mr. Aditya received his B.Sc. (Honors) and M.Sc.. degree from University of Dhaka. He did his Ph. D. from IIT Kharagpur, India. Mr. Aditya's areas of interest include Artificial Intelligence System, Renewable Energy Engineering, and Digital Signal Processing.

Rezaul Karim Mazumder is currently a Professor in the Department of Applied Physics, Electronics & Telecommunication Engineering, University of Dhaka. Mr. Mazumder received his M.Sc and Ph.D. degrees from University of Dhaka. Mr. Mazumder's areas of interest include Renewable Energy Engineering and Power Electronics.