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An Efficient ANN-Based MPPT Optimal Controller of a DC/DC Boost Converter for Photovoltaic Systems

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Original scientific paper

In this paper, a simulation study of the maximum power point tracking (MPPT) for a photovoltaic system using an artificial neural network is presented. Maximum power point tracking (MPPT) plays an important role in photovoltaic systems because it maximizes the power output from a PV solar system for all temperature and irradiation conditions, and therefore maximizes the power efficiency. Since the maximum power point (MPP) varies, based on the PV irradiation and temperature, appropriate algorithms must be utilized to track it in order maintain the optimal operation of the system. The software Matlab/Simulink is used to develop the model of PV solar system MPPT controller. The system simulation is elaborated by combining the models established of solar PV module and a DC/DC Boost converter. The system is studied using various irradiance shading conditions. Simulation results show that the photovoltaic simulation system tracks optimally the maximum power point even under severe disturbances conditions.

Key words: Artificial Neural Network , Boost Converter Control, Matlab/Simulink, MPPT, Optimization, Solar Photovoltaic Energy

Učinkoviti optimalni regulator uzlaznog DC/DC pretvarača za sustav fotonaponskih ćelija za praćenje točke maksimalne snage temeljen na umjetnim neuronskim mrežama. U ovom je radu prikazana simulacijska studija postupka traženja točke maksimalne snage za sustav fotonaponski ćelija korištenjem umjetne neuronske mreže. Traženje točke maksimalne snage važno je za sustave fotonaponskih ćelija zato što maksimizira izlaznu snagu fotonaponskih ćelija za sve temperature i osunčanosti te na taj način maksimizira učinkovitost. Točka maksimalne snage varira s promjenom osunčanosti i temperature te je potrebno koristiti prikladne algoritme za praćenje kako bi se osiguralo optimalno funkcioniranje sustava. Za razvoj modela regulatora za praćenje točke maksimalne snage, koji upravlja sustavom fotonaponskih čelija, koristio se Matlab/Simulink. Simulacija je provedena kombinacijom modela modula solarnih fotonaponskih ćelija i DC/DC uzlaznog pretvarača. Sustav se promatrao tijekom različitih uvjeta osunčanosti i zasjenjenosti. Simulacijski rezultati pokazuju da simulacijski sustav fotonaponskih ćelija optimalno prati točku maksimalne snage i u uvjetima većih poremećaja.

Ključne riječi: umjetna neuronska mreža, upravljanje uzlaznim pretvaračem, Matlab/Simulink, traženje točke maksimalne snage, optimizacia, energija iz solarnih fotonaponskih ćelija

1 INTRODUCTION

Photovoltaic (PV) generation is becoming increasingly attractive as a renewable energy source [1-2]. In order to overcome the ever-increasing power needs in many industrial applications such as artificial satellites, the best available solution is to use of renewable energy sources such as solar and wind. It is inexhaustible and free of pollution. It has the advantages of low running and maintenance cost and also noiseless operation.

The voltage power characteristic of a photovoltaic (PV) array is nonlinear and time varying because of the changes caused by the atmospheric conditions. As the photovoltaic (PV) cell exhibits nonlinear behavior, while interfacing the ac load to photovoltaic modules DC-DC converters and inverters are needed.

The proposed scheme here uses a boost DC/DC converter to generate a utility voltage to a constant desired value. When the solar radiation and temperature varies the output power of the PV module also changes. In order to obtain the maximum efficiency of the PV module it must operate at the maximum point of the PV characteristic [3].

Therefore it is necessary to operate the PV module at its maximum power point for all irradiance and temperature conditions. To obtain maximum power from photovoltaic array, photovoltaic power system usually requires maximum power point tracking controller (MPPT).

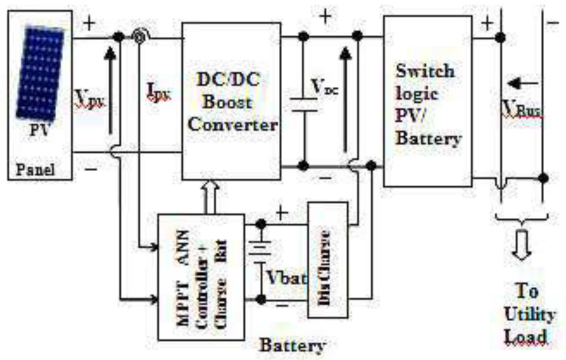

Fig. 1. Block diagram of proposed system

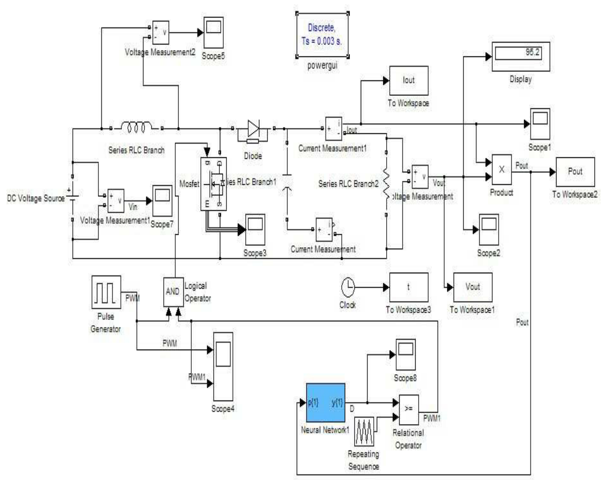

Fig. 2. The simulink electrical circuit model of the boost converter

Figure 2. shows the global model of the electrical circuit of a boost converter using Matlab/Simulink. The power switch is responsible to modulate the energy transfer from the input source to the load by varying the duty cycle D [6]. The classical relationship between input and output voltages of a boost converter operating at steady state condition is given by:

$$\frac{V_0}{V_i} = \frac{1}{1-D} \tag{1}$$

The method needs to calculate dP/dV periodically in order to determine the maximum power point (MPP). Though it is relatively simple to implement, it cannot track the MPP when the irradiance changes rapidly and it oscillates around the MPP instead of tracking it. The incremental conductance method can track MPP rapidly but increases the complexity of the algorithm, which employs the calculation of dI/dV. The constant voltage method which uses 76% open circuit voltage as the MPP voltage and the short-circuit current method are simple, but they do not always accurately track MPPs. Artificial intelligence (AI) based methods are increasingly used in renewable energy systems due to the flexible nature of the control offered by such techniques. The AI techniques are highly successful in nonlinear systems due to the fact that once properly trained they can interpolate and extrapolate the random data with high accuracy. The presented technique utilizes the environment information as the input to ANN.

The neural network is a powerful technique for mapping the input-output nonlinear function.

2 PV CELL EQUIVALENT CIRCUIT

A solar panel cell is basically a p-n semiconductor junction. When exposed to the light, a DC current is generated. The generated current varies linearly with the solar irradiance. The equivalent electrical circuit of an ideal solar cell can be treated as a current source parallel with a diode shown in figure 3.

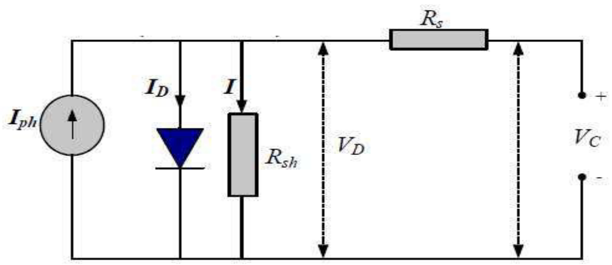

Fig. 3. Equivalent electrical circuit of a solar cell

The current through diode is given by:

$$I_D \;\; = I_0 \left\{ exp\left(\frac{\alpha V_D}{A}\right) - 1 \right\} \tag{2}$$

where: $\alpha = \frac{e^0}{KT}$.

$$I_c = I_{ph} - I_d - I \tag{3}$$

where:

Ic : Cell current (A).

Iph: Light generated current (A).

Io: Reverse saturation Current.

e0: Charge of electron = 1.6 x 10-19 (coulomb)

K: Boltzmann constant (j/K).

A: dimensionless of the solar panel.

T: cell temperature (K).

Rs, Rsh: cell series and shunt resistance (ohms).

3 PV ARRAY CHARACTERISTICS

As it is crucial to operate the PV energy conversion systems at or near the maximum power point to increase the PV system efficiency, the study of the PV array characteristics became of great importance. The nonlinear nature of PV system is apparent from Fig.3. In addition, the maximum power operating point varies with solar radiation level and PV panel temperature. Therefore the tracking control of the maximum power point is a complicated problem. Hence, the use of intelligent control techniques such as Artificial Neural Networks (ANNs) has gained great popularity to solve this problem [10]. There are many techniques to adapt the load impedance value in order to obtain the optimal solar panel output voltage [6-7] and [8]. A general diagram is presented in Fig. 4. which consists of an MPPT computing system and a DC/DC converter. The DC/DC converter acts as an impedance matching unit. The MPPT computing system measures the input voltage and the input current and computes the power in order to control the DC/DC converter. The storage device can be either a battery or a super capacitor [7].

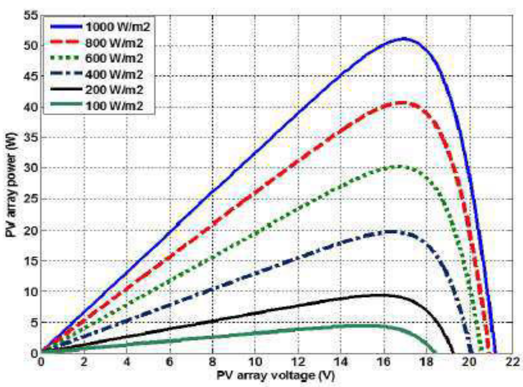

Fig. 4. Power-voltage characteristics of photovoltaic module at different irradiance levels with constant temperature (25 0C).

4 BATTERY MATHEMATICAL MODEL

The battery model is based on a lead acid battery model

Lead acid battery cells consist of two plates' .positive and negative plate. Immersed in a dilute sulfuric acid solution. The positive plate or anode is made of lead dioxide (PbO2) and the negative plate, or cathode .is made of lead (Pb).The battery model has two modes of operation: charge and discharge. The battery is in charge mode when the battery input current is positive while the discharge mode is in case of the current is negative. The terminal voltage (Vb) of the battery is given by:

$$V_b = V_l + I_b.R_l \tag{4}$$

where, V_l, I_b and R_l are the battery open circuit voltage (V), battery current (A) and the internal resistance of the battery respectively . V_l and R_l are governed by a set of equations depending on which mode of operation the battery is in [6].

4.1 Charge mode

The battery voltage and state of charge (*SOC*) during charging mode can be described using the following equation [6]:

$$V_1 = V_{ch}N = [2 + 0.184.SOC(t)]\,.ns \tag{5}$$

$$\mathrm{R_1{=}R_{ch}{=}}\frac{0.758+\frac{0.1309}{[1.06.\mathrm{SOC(t)}].\mathrm{ns}}}{\mathrm{Q_m}} \tag{6}$$

4.2 Discharge mode

During battery discharge, the voltage V_b–SOC relationship is given by:

$$V_1 = R_1.I_b = [1.926 + 0.124.SOC(t)]\,.ns \tag{7}$$

$$R_1 = R_{dch} = \frac{0.19 + \frac{0.1307}{[SOC(t)-0.14].ns}}{Q_m} \tag{8}$$

where $SOC(t)$ is the current state of charge, ns is the number of 2V battery cells in series and Q_m is the maximum battery capacity (Wh). The $SOC(t)$ is the ratio between the present capacity and the nominal capacity and can be estimated using the following equation [6]:

$$SOC\,(t) = SOC\,(t-1) + \int_{t-1}^{t} \left(\frac{K_b.V_l.I_b}{Q_m} - SOC\,(t-1)\,.D \right) dt \tag{9}$$

where, K_b is the battery charge/discharge efficiency. The $SOC(t)$ can be found by knowing the previous condition .Since $SOC(0) = SOC(1)$ =initial state of charge, $SOC(1)$ can be found.

Figure 5. shows the Lithium-Ion battery subsystem implementation in the Simulink toolbox. There is only one input h this subsystem (I_b) and the outputs of the system are battery voltage V_b , the battery power (Pb) and the battery state of charge (SOC).

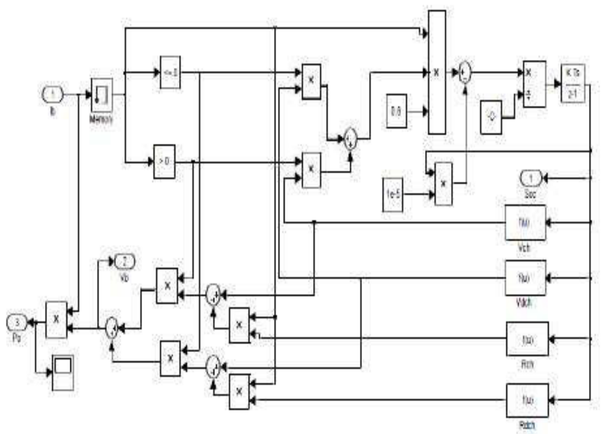

Fig. 5. The battery model in MALTAB/Simulink

5 DESCRIPTION OF THE PROPOSED TECHNIQUE

The MPPT strategy proposed here consists of a combination of a neural network and MPPT techniques for the implementation of the duty cycle regulator. When solar radiation changes slowly, the system controls the DC-DC converter using the P& O, and the neural network learns simultaneously the MPP found by the P& O. However if the solar radiation varies too rapidly, the neural network controller tracks the MPP rapidly and adjusts the duty cycle of the DC-DC converter. Neural networks usually require independent and identically distributed samples to ensure successful on-line learning. Here, however, similar training samples are used by the artificial neural network (ANN). To deal with these training samples, we have used an MLP [8-9] in order to ensure fast and correct learning. The main idea is that the neural network learns each sample online because it is difficult to store all learning samples in small devices. In Figure 6. the ANN learning technique is a memory-based one and allows estimating at any instant the required optimal duty cycle 'D'. Even with sparse data in a multidimensional measurement space, the algorithm provides smooth transitions from one estimated value of D to another. The ANN consists of an input layer ($P_{pv} = x(t)$), a pattern layer, a summation layer and an output layer. The output of the ANN is the duty cycle $D(x) = y(t)$ in the Fig. 7.

The obtained training error of the ANN is very small and is about $10.0e - 25$ as depicted in Fig. 7.

6 THE OPTIMAL DUTY CYCLE DETERMINATION

The MPPT technique proposed differs from other techniques [3-4] and [5] in that the duty cycle of the switching

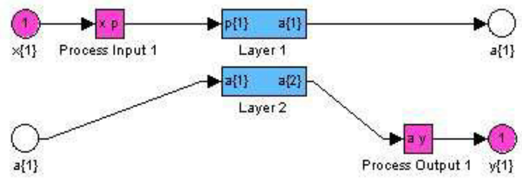

Fig. 6. Neural network

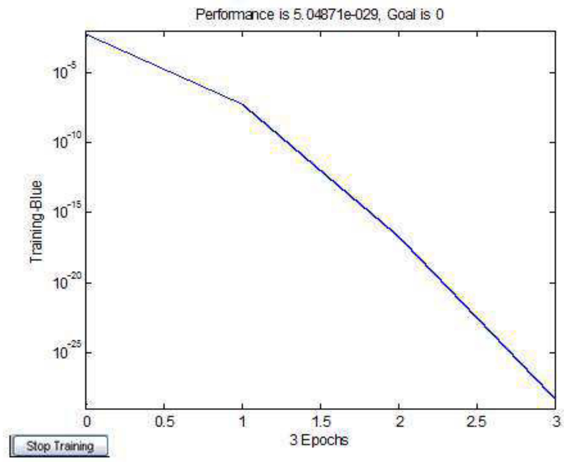

Fig. 7. Training error using the neural network

of the DC/DC buck converter is optimally calculated online. The algorithm of the three-point weights comparison is run periodically by perturbing the solar array terminal voltage and comparing the PV output power on three points of the P-V curve. The three points are the current operation point (A), a point B, perturbed from point A, and a point C, with doubly perturbed in the opposite direction from point B. Figure 8. depicts the three possible cases. In these cases, for the points A and B, if the power corresponding to the point B is greater than or equal to that of point A, the status is assigned a positive weighting. Otherwise, the status is assigned a negative weighting. Amongst the three measured points, if two are positively weighted, the duty cycle of the converter should be increased. On the contrary, when two are negatively weighted, the duty cycle of the converter should be decreased. In the other cases with one positive and one negative weighting, the MPP is reached or the solar radiation has changed rapidly and the duty cycle is not to be changed. Figure 8. shows the idea of the MPP detection algorithm

By monitoring voltage V and current I, the P& O algorithm determines whether generated power has increased. If so, the next change in voltage should be the same as the last V. If not, the next change in voltage should be

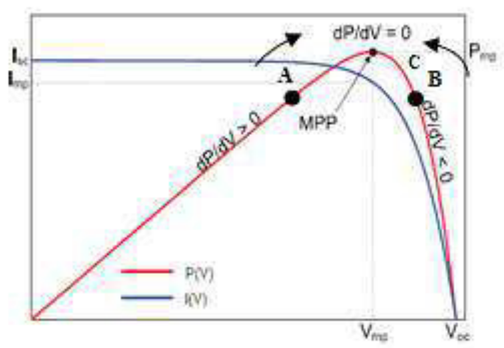

Fig. 8. Sign of dP/dV at different positions on the power Characteristic of a PV module.

negative P& O achieves the function of an MPPT [8] easily, but it cannot track MPP rapidly when solar radiation changes quickly. In order to eliminate this drawback, our MPP technique utilizes an ANN to achieve learning and maximum power point tracking. The MPP tracker operates by periodically incrementing or decrementing the estimated solar panel voltage V_{pv}. If a perturbation occurs on the PV output, then the subsequent perturbation is generated in the opposite direction. The weights of the neurons are changed subsequently to the presence and severity of a perturbation. They are maintained constants in stable working conditions

7 SIMULATION RESULTS

Figure 9. Shows the overall simulation circuit under MATLAB/Simulink In order to validate the on-line learning ANN, many simulations tests have been implemented.

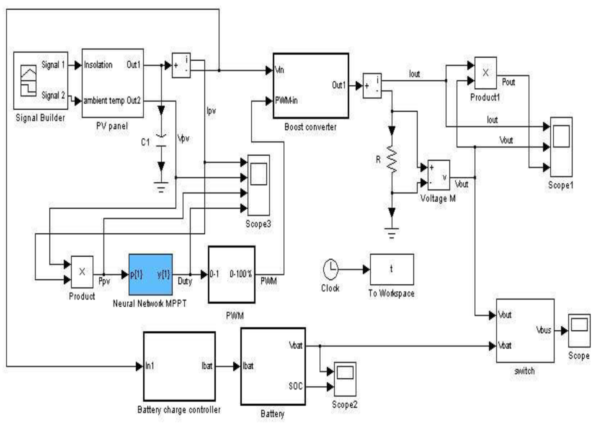

Fig. 9. The system simulation in MATLAB/Simulink.

Based on the above models and control methods, the grid-connected hybrid PV/Battery generation system can be implemented in MATLAB/Simulink. In this paper, three simulation cases are suited namely:

Case 1: Simulation without disturbance

Case 2: Simulation with disturbance

Case 3: Simulation with changes of solar irradiance.

These cases are discussed as follows:

Case 1: PV Operation simulation without disturbances, the solar irradiance is 1000W/m2, and temperature is 25°C.

The simulation interval time considered is 0.1 s. And the simulation step is .0001s.

The simulation results are depicted in Figures 10-19. At the start, the system undergoes a short transient period of about 10 ms. It can be noticed that the PV panel output voltage, current and power present a small voltage overshoot, hence better damped oscillations during this period than those obtained in [3-4]. The MPP tracking control guarantees maximum output bus power of 220W and the duty cycle D witch the main control parameter of the DC-DC buck converter varies between 0 at the start then increases to a steady value of 0.45. Figures 13, 14 and 15 show respectively the bus voltage, the load current and the DC-DC boost converter output power which feeds a resistive load $R = 6\Omega$.

The voltage across the inductor presents high frequency oscillations [8] due to the transfer of the energy between the load and the source during the on-off state of the MOSFET switch (Figure 18).

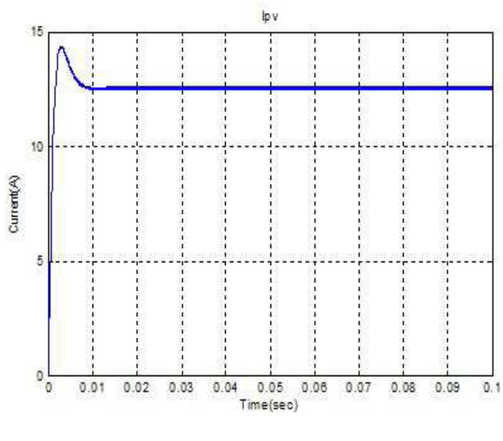

Fig. 10. The output PV panel current

Case 2: In the simulation with disturbances:

In Figures 20-21-22–29, two different disturbances are assumed as input in the irradiance of PV panel (using signal builder bloc of Simulink). The first one 'd1'correponds to a sudden step increase of 100w/m2 in the irradiance

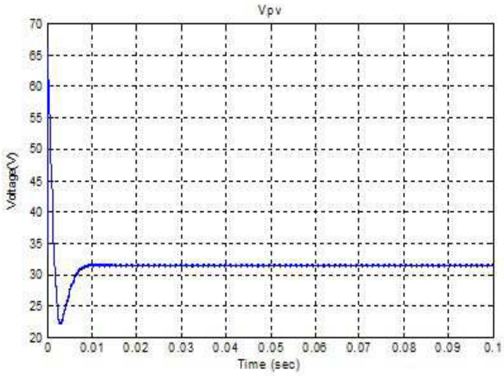

Fig. 11. The output PV panel voltage

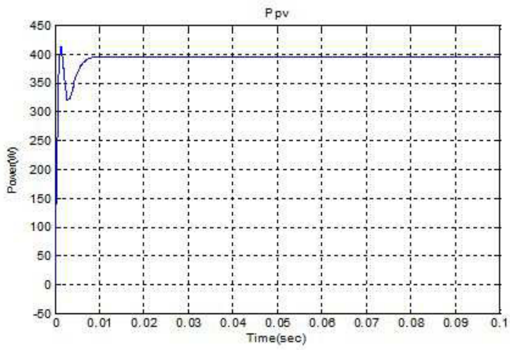

Fig. 12. The output PV panel power

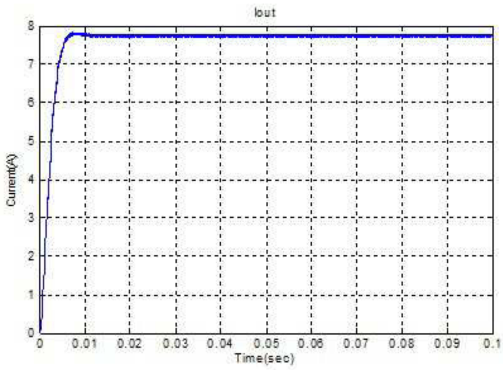

Fig. 13. The Boost converter output current

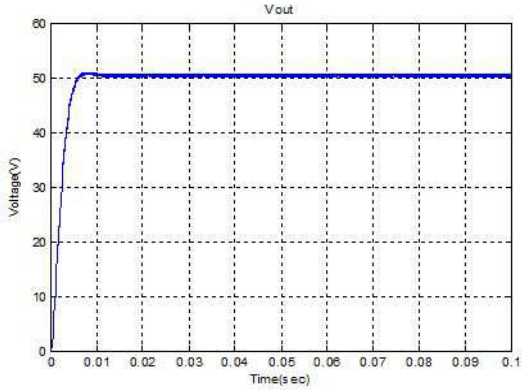

Fig. 14. The Boost converter output voltage

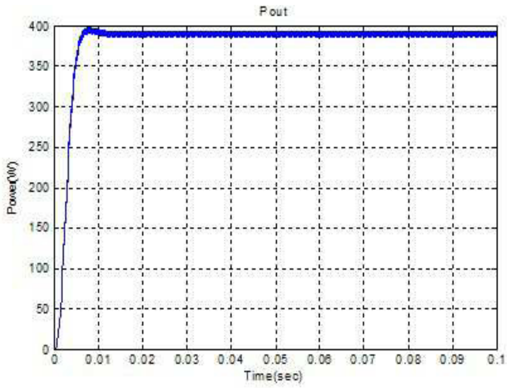

Fig. 15. The Boost converter output power

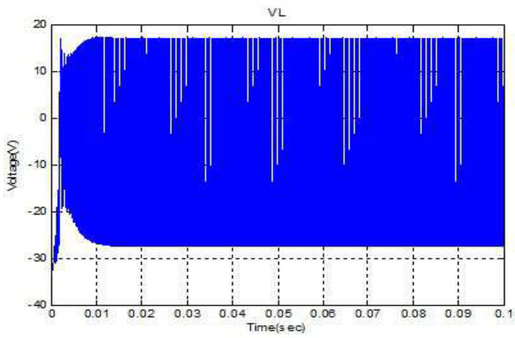

Fig. 16. The output self voltage

which occurs at 0.028s and the second one ‘d2‘ is a sudden step decrease of 100w/m2 which happens at 0.068s. The ANN controller adjusts the duty cycle of the dc-dc boost converter to produce maximum power to charge the battery that is shown in Fig.14 (k). The response time of the system at the start is short about 10ms, while it is about 60ms for other systems [1].

Case 3: Simulation with rapid step changes of solar radiance

Moreover, in order to prove the efficiency of the ANN-MPPT on-line controller, we have simulated in figures 30 - 27 a continuous step increase of solar radiance. The ANN controller shows that it tracks the maximum power point reliably, in order to avoid having to move rapidly the operation point, when the solar radiation is varying quickly or when a disturbance or data reading error occurrence. The figures above mentioned show that the MPP control

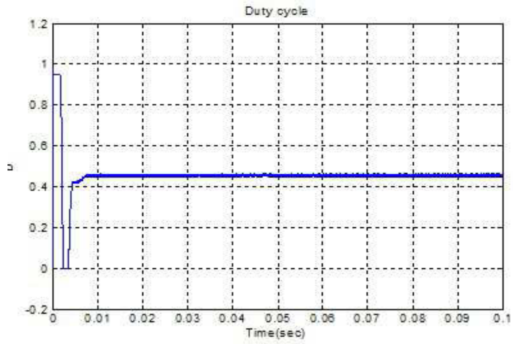

Fig. 17. Duty cycle

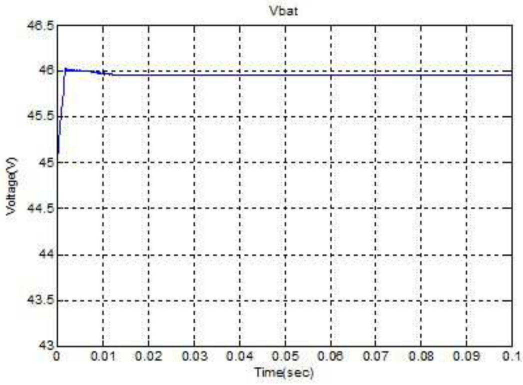

Fig. 18. The output battery voltage during Charging Period

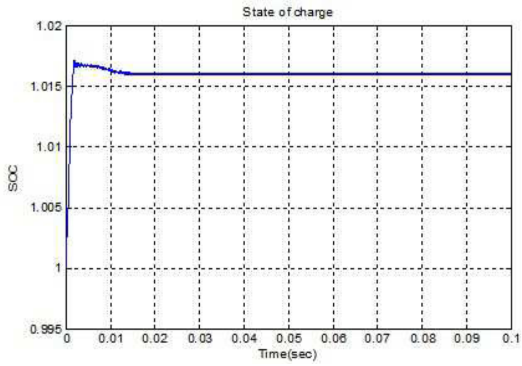

Fig. 19. The battery state of charge (SOC).

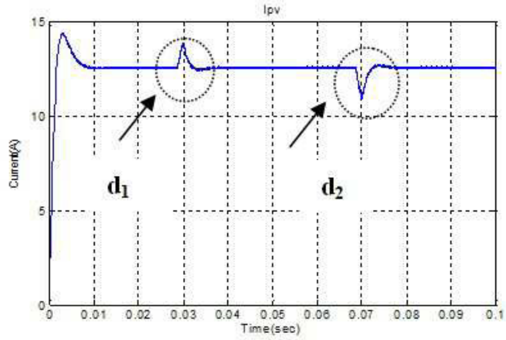

Fig. 20. The output PV panel current with two disturbances

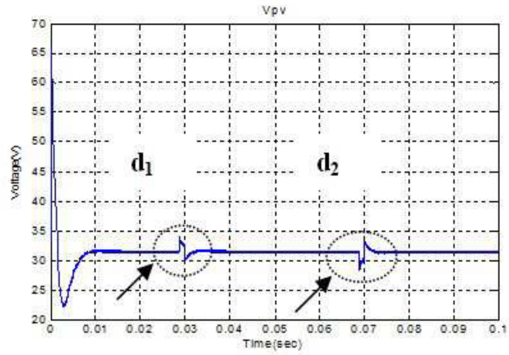

Fig. 21. The output PV panel voltage with two disturbances

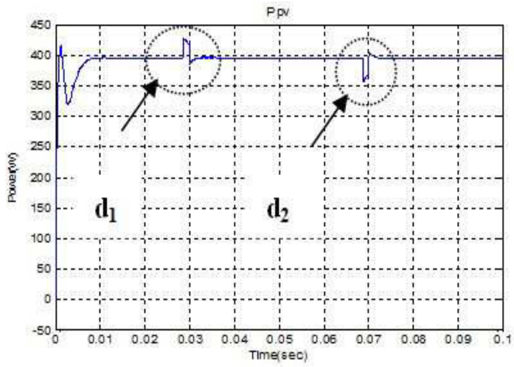

Fig. 22. The output PV panel power with two disturbances

tracks the charging and discharging of the back-up battery quickly when the shading of the PV panel changes considerably [4] and quickly, and has high control precision and stability in charging and discharging from the state of charge of the battery (39).

Figure 39 shows the commutation between the battery and the bus, when the PV voltage suddenly drops, a swith logic inserted an interface between the bus on one hand, and the battery and the boost converter on the other hand, acts to reestablish the bus voltage to the required level of 50V which feeds a load.

8 CONCLUSION

In this research work, an MPPT technique is presented to the control of a boost DC-DC converter applied to the power supply of stand-alone utilities such artificial communications satellites. An Artificial Neural Network is

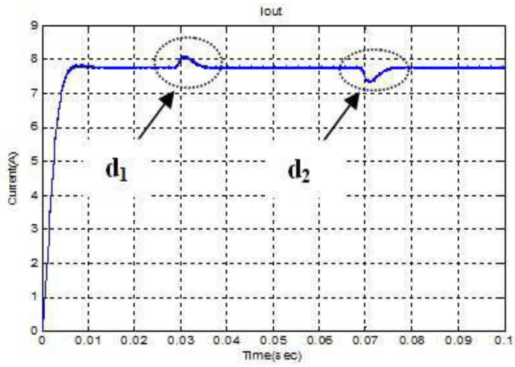

Fig. 23. The Boost converter output current with two disturbances

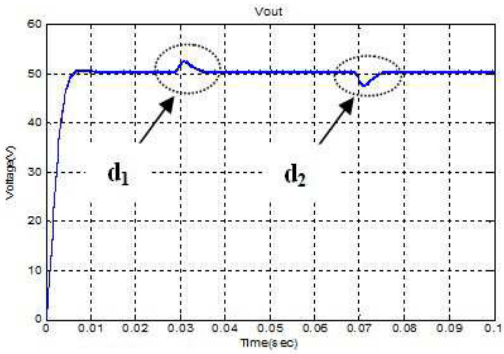

Fig. 24. The Boost converter output voltage with two disturbances

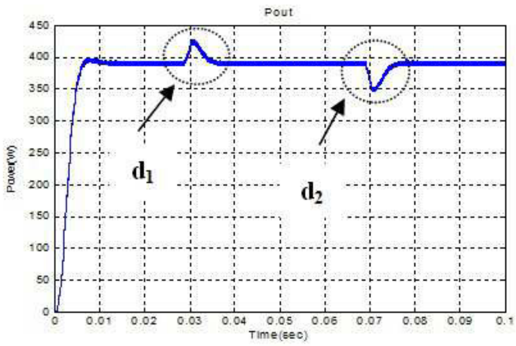

Fig. 25. The Boost converter output power with two disturbances.

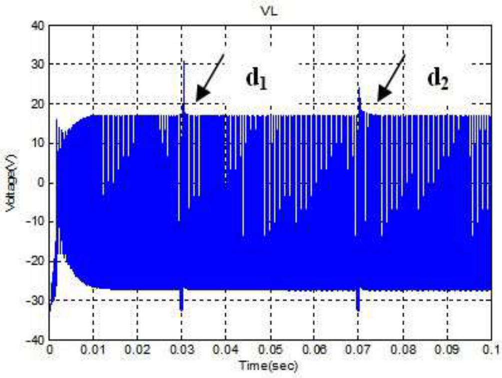

Fig. 26. The output self voltage with two disturbances

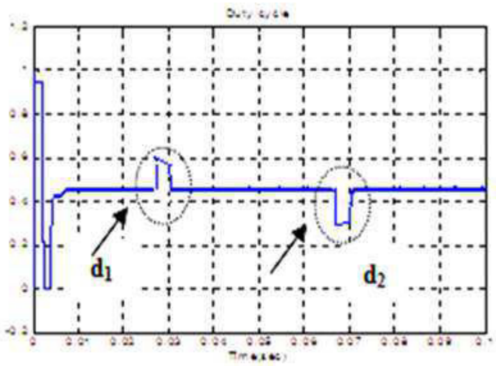

Fig. 27. Duty cycle with two disturbances

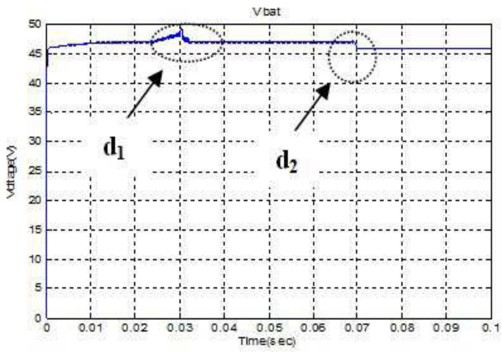

Fig. 28. The output battery voltage with Presence of a radiation disturbance during the Charging Period

used to achieve the decision for the logic switching between the PV output bus and the battery. The MATLAB/Simulink software has been used for the simulation of the power and control circuits. This improved MPPT algorithm extracts the maximum power point from the PV panel module corresponding with a load resistance in terms of solar radiation and ambient temperature which vary according to the position of the satellite relatively to the sun. Simulation results concerning major and minor disturbances of radiation showed that the response is within satisfactory response times and waveforms amplitudes. Moreover, the efficiency of the developed technique is better than the classical MPPT algorithm. An on-line ANN controller, in conjunction with the well-known P&O technique [7], and using the back-propagation algorithm

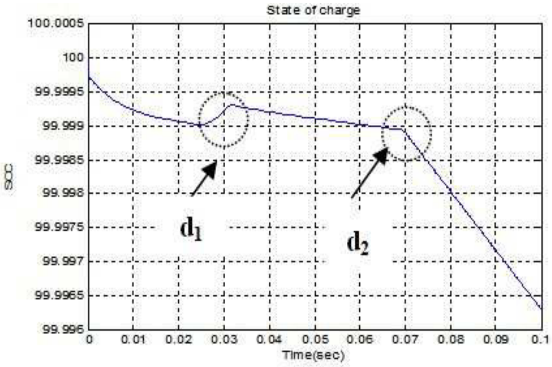

Fig. 29. Variation of the state of charge

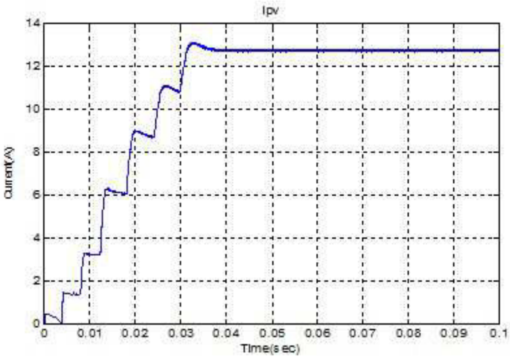

Fig. 30. The output PV panel current with a step change of irradiance

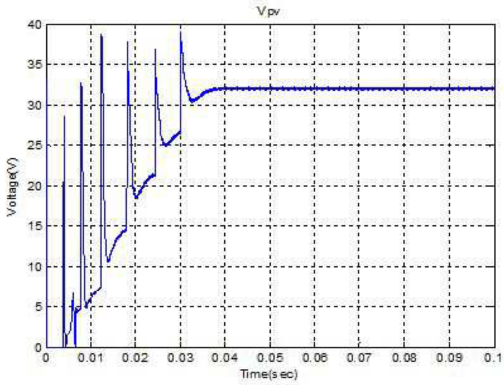

Fig. 31. The output PV panel voltage with a step change of irradiance

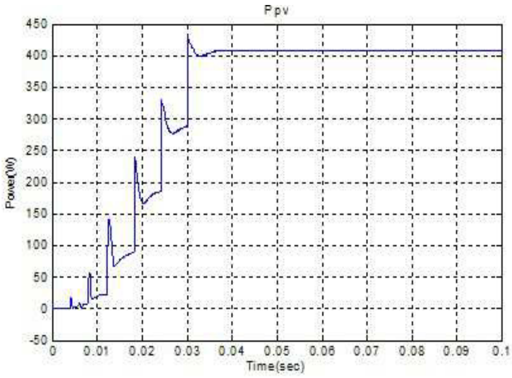

Fig. 32. The output PV panel power with a step change of irradiance

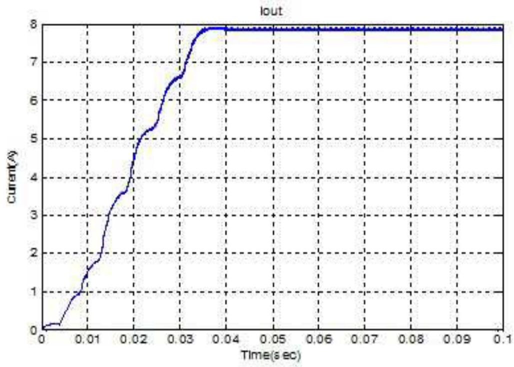

Fig. 33. The Boost converter output current with a step change of irradiance

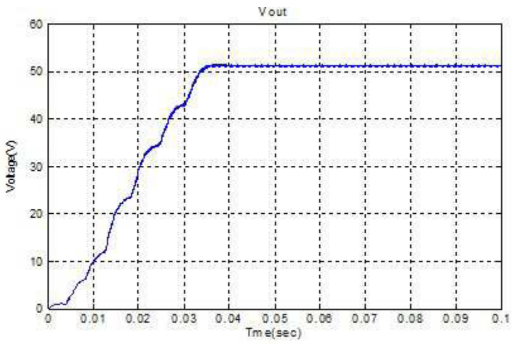

Fig. 34. The Boost converter output voltage with a step change of irradiance

in order to minimize the controlled error, has been utilized for online estimation of the reference voltage in the feed-forward loop. The simulated results using the on-line training of the ANN show that the efficiency of the MPPT and the effectiveness of this control method are higher than the classical ones [5-9]. This strategy has several advantages, particularly in that there is no need for voltage and current sensors, and it avoids a complex calculation of power. Finally, the maximum output power of photovoltaic battery is realized under sudden shading conditions [4] of the PV panel and there is continuous impedance matching of the PV source and the system battery-load. Other hybrid approaches using the PSO and ANN techniques could be

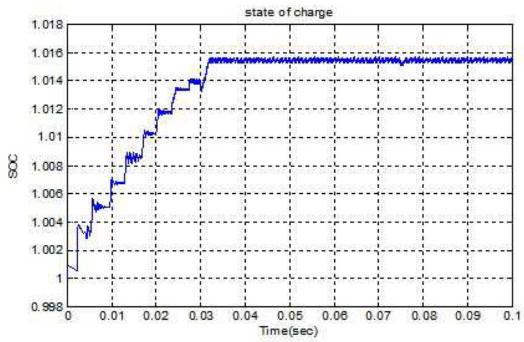

Fig. 38. Variation of the battery state of charge ***(SOC)***

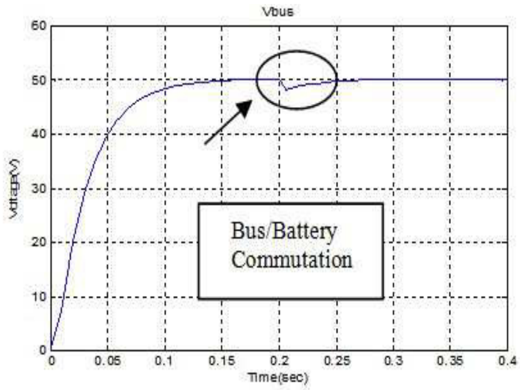

Fig. 39. The output load voltage transient during bus/battery commutation.

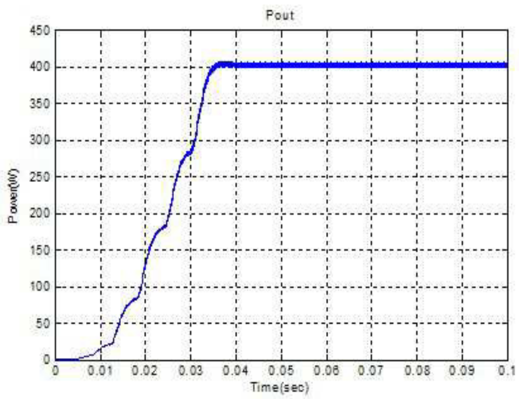

Fig. 35. The Boost converter output power with a step change of irradiance

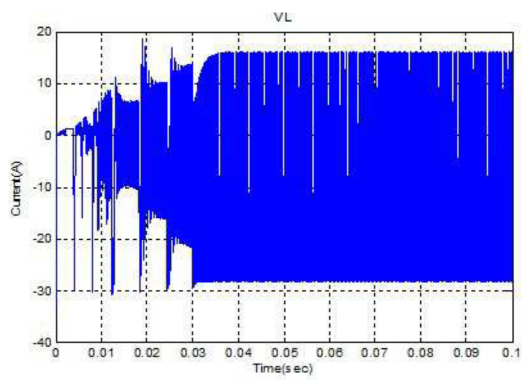

Fig. 36. The output self voltage with step changes of irradiance

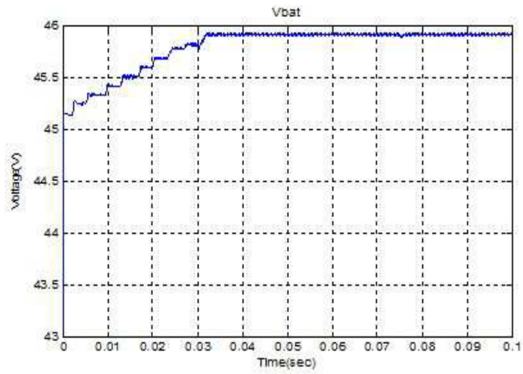

Fig. 37. The output battery voltage with a step change of irradiance during the Charging Period

used for further enhancement of the MPP tracking of stand-alone PV systems.

REFERENCES

[1] Y.-H. Chang and C.-Y. Chang, "A Maximum Power Point Tracking of PV System by Scaling Fuzzy Control," presented at international Multi-Conference of Engineers and Computer Scientists, Hong Kong, 2010.

[2] E.I and O. Rivera, "Maximum Power Point Tracking using the Optimal Duty Ratio for DC-DC Converters and Load Matching in Photovoltaic Applications," IEEE, pp. 987-991, 2008.

[3] T. Hiyama, S. Kouzuma, and T. Imakubo, "Evaluation of neural network based real time maximum power tracking controller for PV system,", IEEE Trans. Energy Conversion, vol. 10, pp. 543-548,1995.

[4] D. Sera, R. Teodorescu, J. Hantschel, and M. Knoll, "Optimized Maximum Power Point Tracker for Fast- Changing Environmental Conditions," Industrial Electronics, IEEE Transactions on, Vol. 55, No. 7, pp. 2629 – 2637, July 2008.

[5] Tamer T. N. Khatib, A. Mohamed, N. Amin, K. Sopian,"An Efficient Maximum Power Point Tracking Controller for Photovoltaic Systems Using New Boost Converter Design and Improved Control Algorithm",WSEAS Transactions on power systems, Issue 2, Vol. 5, pp. 53-6, April 2010.

[6] T. DenHerder, "Design and Simulation of Photovoltaic Super System Using Simulink", Report of a Senior Project, Electrical Engineering Department, California Polytechnic State University, San luis Obispo, 2006.

[7] Emad M. Ahmed and Masahito Shoyama "Variable Step Size Maximum Power Point Tracker Using a Single Variable for Stand-alone Battery Storage PV Systems"Journal of Power Electronics, Vol. 11, No. 2, March 2011.

[8] M. Veerachary, T. Senjyu, and K. Uezato, "Neural Network Based Maximum Power Point Tracking of Coupled Inductor Interleaved Boost Converter Supplied PV System using Fuzzy Controller," IEEE Transactions on Industrial Electronics, Vol. 50, No. 4, pp. 749-758, August 2003.

[9] Bin, G.; Jason, D.; Lai, J.-S.; Zheng, Z.; Chung, L. High boost ratio hybrid transformer DC-DC converter for photovoltaic module applications. IEEE Trans. Power Electronics, Vol. 28, pp. 2048–2058, 2013.

[10] Tseng, K.-C.; Huang, C.-C.; Shih, W.-Y. "A high step-up converter with a voltage multiplier module for a photovoltaic system", IEEE Trans. Power Electron., 28, 3047–3057. 2013

[11] Saurav Satpathy, "photovoltaic power control using MPPT and Boost converter", Department of Electrical Engineering National Institute of Technology, Rourkela , May 2012.

[12] H. Lee, L. M. Phuong, P. Q. Dzung, N. T. Dan Vu, and L. D. Khoa, "The new maximum power point tracking algorithm using ANN-based solar PV systems," in Proceedings of the IEEE Region 10 Conference (TENCON '10), pp. 2179–2184, Fukuoka, Japan, November 2010.

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