Improving efficiency of Photovoltaic System with Neural Network Based MPPT Connected To DC Shunt Motor

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ABSTRACT: *A photovoltaic generator exhibits nonlinear voltage-current characteristics and its maximum power point varies with solar radiation. A boost converter is used to match the photovoltaic system to the load of dc shunt motor and to operate the pv cell array at maximum power point. This paper presents an application of a neural network for the identification of the optimal operating point of pv module maximum power tracking control. The output power from the modules depends on the environmental factors such as solar insolation, cell temperature, and so on. Therefore, accurate identification of optimal operating point and continuous control of boost converter are required to achieve the maximum output efficiency. The proposed neural network has a quite simple structure and provides a highly accurate identification of the optimal operating point and also a highly accurate estimation of the maximum power from the PV modules. This model is simulated in matlab/simulink and results are obtained.*

Keywords: *photovoltaic (PV) module, solar radiation, neural network, solar insolation maximum power point tracking (mppt) , boost converter, maximum output efficiency*

I. INTRODUCTION

Recently, as the fossil fuel exhaustion and environmental pollution are aggravated, the concern of the development of alternative energy systems, which are renewable and pollution free, has been increased continuously. Among them the photovoltaic (PV) power generation systems standout as an important solution because they produce electric power without inducing environmental pollution, by directly transforming solar irradiation into electricity. The main drawbacks of PV systems are high fabrication cost and low energy-conversion efficiency, which are partly caused by their nonlinear and temperature dependent *V–I* and *P–I* characteristics. To overcome these drawbacks, three essential approaches can be followed:

1. *Improving manufacturing processes of solar arrays*: many research efforts have been performed with respect to materials and manufacturing of PV arrays.
2. *Controlling the insolation input to PV arrays*: the input solar energy is maximized using sun-tracking solar collectors.
3. *Utilization of output electric power of solar arrays*: the main reasons for the low electrical efficiency are the nonlinear variations of output voltage and current with solar radiation levels, operating temperature, and load current. To overcome these problems, the maximum power operating point of the PV system (at a given condition) is tracked using online or offline algorithms and the system operating point is forced toward this optimal condition.

Many MPPT techniques have been proposed, analyzed, and implemented. They can be categorized as:

A) Look-up table method -- The nonlinear and time-varying nature of pv cells and their great dependency on radiation and temperature levels as well as degradation (aging, dirt) effects, make it difficult to record and store all possible system conditions.
B) Perturbation and observation (P&O) method-- Measured cell characteristics (current, power) are employed along with an online search algorithm to compute the corresponding maximum power point independent of insolation, temperature, or degradation levels.
C) Computational method -- The nonlinear *V–I* characteristics of PV panel is modeled using mathematical equations or numerical approximations. Based on the modeled *V–I* characteristics, the corresponding maximum power points are computed for different load conditions as a function of cell open-circuit voltages or cell short-circuit currents.

This paper presents an alternative method to identify the optimal operating point to achieve the maximum output efficiency of the PV modules using a neural network. The input signals are solar irradiance and the cell temperature. The Block diagram of the photovoltaic system with a neural network based maximum power tracking is shown in Fig.1.

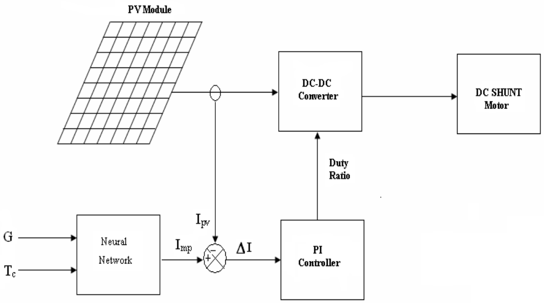


Figure 1. Block diagram of PV system

II. MODELING OF PHOTOVOLTAIC CELL

Fig.2 shows the typical equivalent circuit of PV-cell. The typical I_{pv}-V_{pv} output characteristics of PV-cell are represented as following Eq. 1.

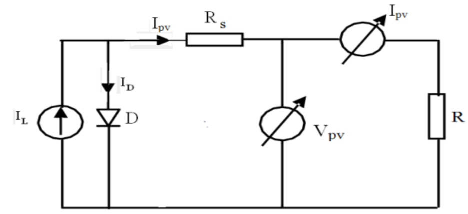


Figure.2 Equivalent model of photovoltaic cell

$$I_{PV} = I_L - I_0 \left(\exp\left(\frac{V_{PV} + I_{PV} R_S}{\propto} \right) - 1 \right) \ldots (1)$$

Where,

$$I_L = \frac{G}{G_{ref}} \left(I_{Lref} + \mu_{Isc} (T_C - T_{Cref}) \right) \ldots (2)$$

$$I_o = I_{Oref} \left(\frac{T_{Cref} + 273}{T_C + 273} \right)^3 exp\left(\frac{e_{gap}\, q}{N_s \propto_{ref}} \left(1 - \frac{T_{Cref} + 273}{T_C + 273} \right) \right) . (3)$$

I_{PV} and V_{PV} =Cell output current and voltage; I_L= Light-generated current; Io= Cell saturation current at T_r; Tc = Cell Temperature; Tref = 273K reference temperature; q = Charge of an electron; Rs = Series Resistance; e_{gap} = Band gap of the material; α = Thermal voltage timing completion factor; μ_{Isc} = Temperature coefficient of the short-circuit current.

Fig.3 shows the typical I_{pv}-V_{pv} and P-V_{pv} output characteristic curve of PV-module for a particular irradiation and cell temperature. In case the irradiation and temperature are varied, respectively from Fig. 3, we observe that the output characteristics of PV-module are nonlinear and each curve only has one MPP. Additionally, the output current of PV module is mainly affected by Solar irradiation variation, whereas the output voltage of PV-module is mainly affected by temperature variation. Therefore, to efficiently use PV module, in case the atmospheric conditions are varied, the MPP tracking of PV-module should be implemented.

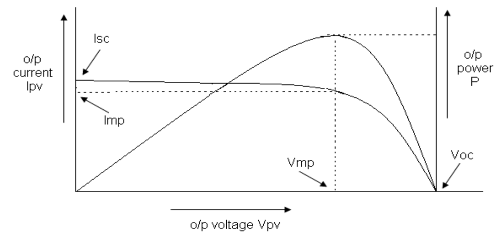


Figure 3 I_{pv}-V_{pv} & P-V_{pv} characteristics of a PV cell

III. THE NEURAL NETWORK BASED MAXIMUM POWER POINT TRACKING FOR PV-SYSTEM

The block diagram for identifying the optimal operating point is shown in Fig.4.

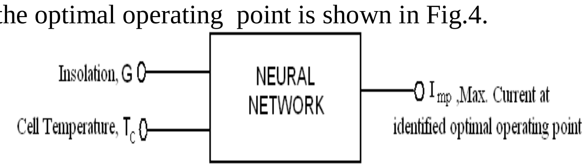


Figure.4 Block Diagram for the identification of optimal operating point

The configuration of 3-layer feed-forward neural network is shown in Fig.5. The network has 3 layers with 3 neurons in input, 4 neurons in hidden, and 1neuron in output layers [8].

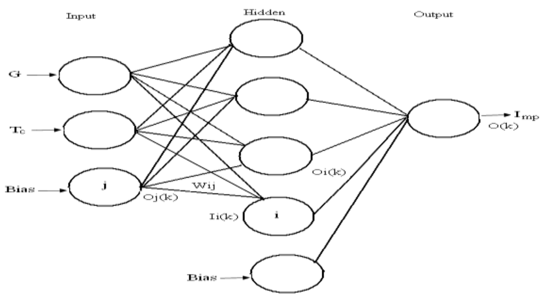
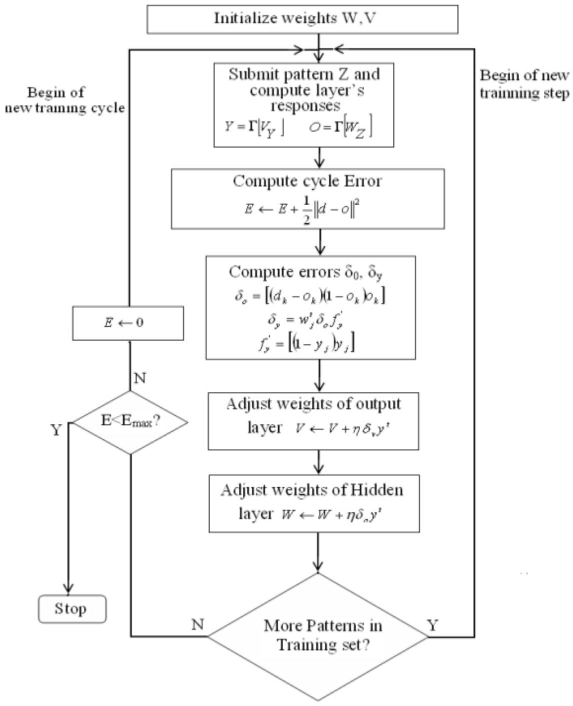


Figure.5 Configuration of a Neural Network

The node in the input layer gets the input insolation, G and Cell temperature, Tc. These signals are directly passed to the nodes in the hidden layer. The node in the output layer provides the identified maximum Imp. The nodes in the hidden layer get signals from the input layer and send their output to the node in the output layer. For each node in the hidden and the output layer, the output $O_i(k)$ is given as follows:

$$O_i(k) = \frac{1}{1 + exp(-I_i(k))} \dots (4)$$

Where the sigmoid function is utilized for the I/P-O/P characteristics of the nodes. The term $I_i(k)$ is the input signal given to the node I at the K^{th} sampling. The input $I_i(k)$ is given by the weighted sum from the previous nodes as follows:



$$I_i(k) = \sum_j W_{ij}(k) O_j(k) \dots (5)$$

Figure.6: Error back propagation training algorithm flowchart

.In the training process, we need a set of I/P-O/P patterns for the neural network as shown later. All the computations are performed off-line during the training process. With the training patterns, the connection weights W_{ij} recursively until the best fit is achieved for the I/P-O/P patterns in the training data. A commonly used approach is the *generalized delta rule*, where the sum of the squared error described below is minimized during the training process.

$$E = \sum_{k=1}^{N} (T(k) - O(k))^2 \dots (6)$$

Where N is the total number of training patterns. T(k) is the target output from the output node and O(k) is the computed one. Fig.6 illustrates the flowchart of the error back-propagation training algorithm for a basic two-layer network as shown in Fig.5.

IV. STATE SPACE MODEL OF BOOST CONVERTER

PV cells have relatively low conversion efficiency and the improvement of overall system efficiency is an important factor in the area of PV systems. This can be partly achieved by using high efficiency intermediate converters. In this paper, a boost converter coupled with PV array is presented.

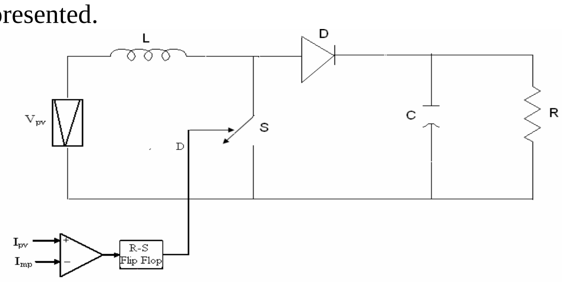


Figure.7 Circuit Diagram for Boost Converter

A state space averaging technique is used to develop linear state space models for dc-dc boost converter. The average state space model for the boost dc/dc converter can then be obtained as follows:

$$\begin{bmatrix} \frac{di_L}{dt} \\ \frac{dv_c}{dt} \end{bmatrix} = \begin{bmatrix} 0 & -\frac{(1-D)}{L} \\ \frac{1-D}{C} & -\frac{1}{RC} \end{bmatrix} \begin{bmatrix} i_L \\ V_c \end{bmatrix} + \begin{bmatrix} \frac{1}{L} \\ 0 \end{bmatrix} [v_c] \ldots (7)$$

$$V_o = [0 \quad 1] \begin{bmatrix} i_L \\ V_c \end{bmatrix} \ldots (8)$$

Where D = Duty ratio of the switch

V. MOTOR MODEL

The schematic diagram of a dc shunt motor is illustrated in fig.8. The fundamental equations governing the operation of the shunt dc motor are as follows:

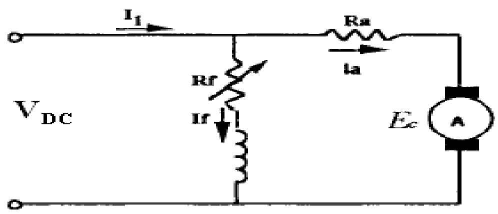


Figure.8 schematic diagram of dc shunt motor

$$V_1 = V_f = V_a = E_c + I_a R_a \ldots .(9)$$

$$I_1 = I_a + I_f \ldots \ldots (10)$$

$$E_c = k\emptyset n \ldots (11)$$

Where, V_{DC}= Terminal voltage; V_f = field voltage; V_a= armature voltage; E_c= counter emf; k=design constant; Φ= mutual air-gap flux per pole; n=rotational speed, r /min; R_a= armature resistance; $I_{1=}$ line current; I_f= field current; I_a= armature current

V. SIMULATION RESULTS

Based on the mathematical equations discussed before, a dynamic model for a PV module consisting of 153 cells in series has been developed using matlab/Simulink. The input quantities (solar irradiance G and the ambient temperature Ta) are used to determine the characteristics of a PV module.

A.PV Model Performance

The model I_{pv}-V_{pv} characteristic curves under different irradiances are given in Fig.9 at 25 °C. It is noted from the figure that the higher is the irradiance, the larger are the short-circuit current (I_{sc}) and the open-circuit voltage (V_{oc}). Obviously, the larger will be the maximum power (P), shown in Fig.10.

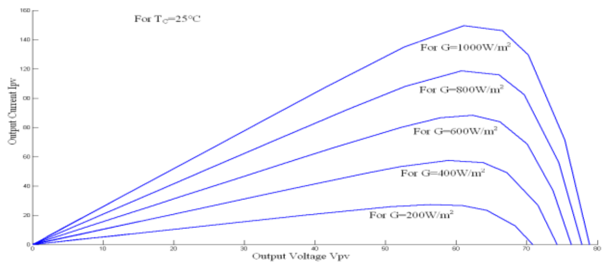


Figure.9 V_{pv}-I_{pv} characteristics for constant T_c and Varying G

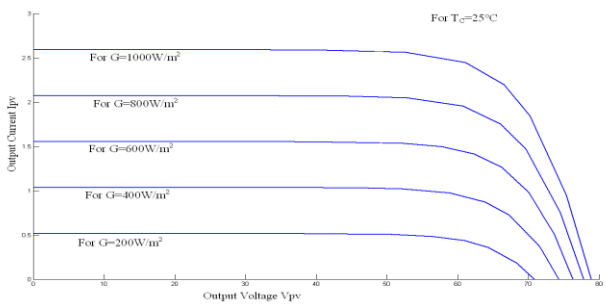


Figure 10.P-V_{pv} characteristics for constant Tc and Varying G

B. Training of a Neural Network

The training of a neural network consists of solar irradiance and cell temperature as the input patterns. The target pattern is given by measured I_{mp} for training the neural network. This calculated I_{mp} values is given as a training data to the neural network. Fig.12 shows the convergence of error during training process. During the training process, the convergence error is taken as 0.01.

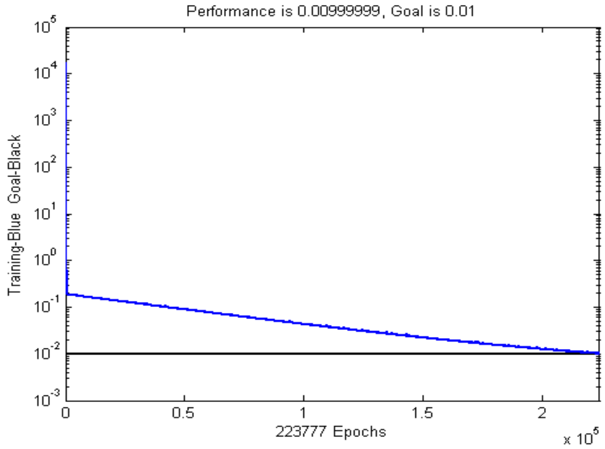


Figure.12 Training of a Neural Network

The training function used is TRAINGDX (Gradient descent w/momentum & adaptive linear backpropagation). The graphs for the I_{mp} of the neural network and the calculated values of the PV model are are combined to show the error between the two:

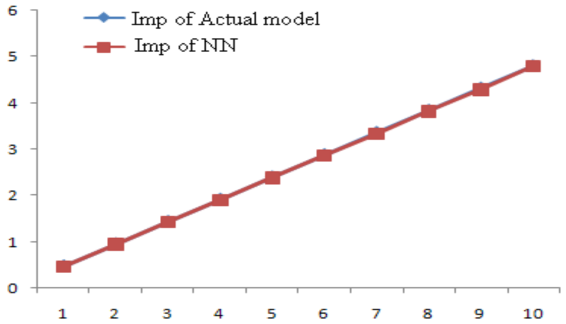


Figure 13: Combined graph of I_{mp} for both neural network and calculated

C. Optimal power point tracking for Boost converter And DC shunt motor

A Boost converter supplied by PV system has been shown in fig(1). Comprehensive simulation studies were made to investigate the influence of a boost converter as an intermediate maximum power point tracker for the PV supplied system. The PV array is simulated using a neural network as shown in figs. 4&7. **As** the studies mainly concentrate on maximum power operation of the PV module**,** a simulated modeling was developed in the matlab environment, for the PV supplied converter system employing the mathematical models developed in the preceding sections. The simulated dynamic maximum power point tracking characteristics are shown in fig.14&15 . The converter parameters considered in this paper are : L=0.06mH, C=0.4mF and R(equivalent load) =50Ω.

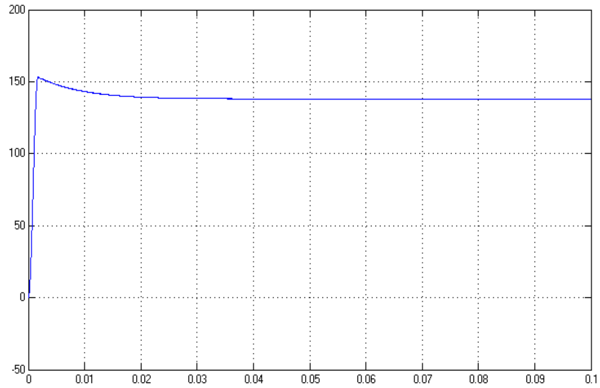


Figure.14 Simulated Dynamic characteristics of capacitor voltage to reach maximum power point

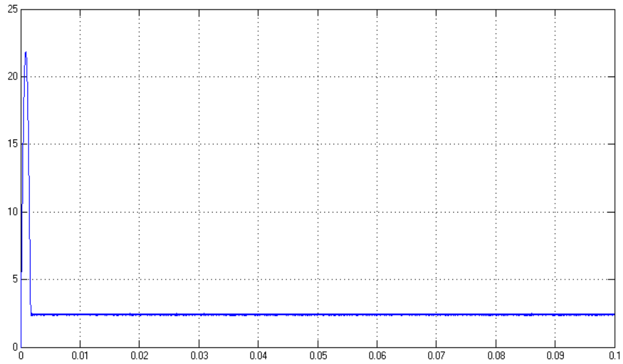


Figure.15 Simulated Dynamic characteristics of inductor current to reach maximum power point

Using the control technique discussed in previous sections the simulated waveforms of the integrated dc shunt motor for Torque and speed under no-load and load conditions are shown in fig.16 & fig.17.

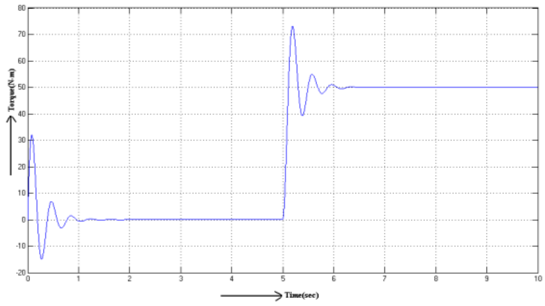


Figure 16 Torque waveform with load of 50 N-m applied at t=5 sec

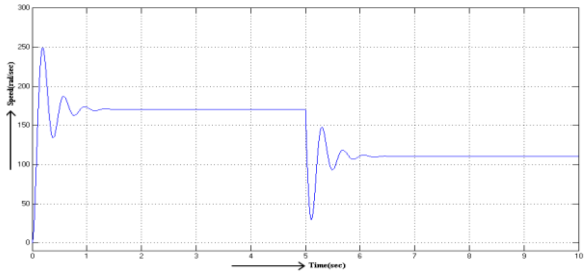


Figure 17 speed waveform with load applied at t=5 sec

VI. CONCLUSION

A Neural network based MPPT algorithm has been developed in this paper for the boost converter supplied PV system. The efficiency of the proposed neural network has been presented for identifying the optimal operating point for the maximum power tracking control of the PV modules. Despite the small set of patterns utilized for the training of the neural network, the network gives accurate predictions over a wide variety of operating modes. The accuracy is not degraded following the seasonal variations of insolation and temperature.

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