

A Novel Two Diode Model of Pv Module for MPPT with Neural Compensator

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ABSTRACT

This paper deals with the improved model(Two Diode Model) of solar photovoltaic (SPV) module and back propagation neural network based maximum power point tracking (MPPT) for boost converter in a standalone photovoltaic system under variable temperature and insolation conditions. ie. The proposed model is robust to environment changes and load variations. Unlike Conventional solar-array mathematical model, Neural network modeling does not require any physical definitions for a photovoltaic array, hence they have a potential to provide a superior method of deriving non-linear models than the already established conventional techniques. In this paper back-propagation neural network trained model is employed to simulate and predict the maximum power point of a Photo Voltaic array using a random set of data collected from a real photovoltaic array. In order to validate the developed simulation model, simulated results from the proposed model under standard conditions are compared with specifications of commercially available USL Solar PV module (USP-75) and BP-350U PV Modules. There is a very good agreement between the results. And the functioning of the proposed model and predicted maximum power point of the photo-voltaic array are evaluated by simulation using Matlab/simulink GUI environment.

Keywords: PV module, MPPT, Back Propagation Algorithm.

1. INTRODUCTION

Generation of electricity from sun light is a direct means of obtaining power for low and medium level energy generation is one of the methods of harnessing solar energy. This method comprises of cells arranged in a specific fashion, commercially called as PV system. A PV system is made of a group of arrays connected in series and parallel combinations depending on the required voltage and current levels as specified by the loads. PV systems along with the electronic converters are predominant to handle domestic/industrial loads or to interconnect it to the grid [1]. For effective utilization of tapped solar energy, it requires the knowledge of both PV system design/modeling and electronic converter design, the former aspect is considered in this paper.

The modeling of PV system attached to an electronic converter plays a vital role in order to characterize the practical PV system. The performance of PV depends on solar insolation, ambient temperature, and load impedance. As PV devices have non linear V-I characteristics with various parameters that are influenced by the external causes, it requires effective methods to account and quantify them in modeling the PV

devices. Also a PV system is a power source having nonlinear internal resistances that varies corresponding to the variation in light intensity falling on it. Different models have been proposed in the literature accounting various causes in [2 - 5]. In this paper a precise method of modeling the PV system is proposed that can handle all factors which cause to affect its performance such as its non linear internal resistances, recombination loss in PV cell, etc., that provides an accurate model for simulation [6].

The amount of power that can be trapped from the PV system depends upon various factors listed above and in addition to that it depends on the Tracking phenomenon implemented for power trapping. To extract maximum power from the panel, various approaches for tracking maximum power point (MPP) have been addressed in literature. The general requirements for maximum power point tracker (MPPT) are simple, low cost, quick tracking under dynamic atmospheric conditions and small output power fluctuations. Hence more efficient method for better tracking becomes crucially important. So far many tracking control strategies have been proposed such as perturb and observe, incremental conductance, parasitic capacitance, constant voltage and fuzzy logic strategies which have some disadvantages such as costly, difficulty, complexity and non-stability [7 - 10]. In the present context, Artificial Neural Network (ANN) technology has attracted widespread interest in electrical engineering because of its adaptability, accuracy and as a realistic method of solving inters disciplinary problems [11]. This paper presents idea of adopting neural network technology which provides efficient method for better tracking of MPP of PV system under dynamic atmospheric conditions and small output power fluctuations.

2. MODELING OF PV DEVICE

The mathematical modeling of PV device is necessary to analyze the electronic converters that are used in building a entire PV generation module. As the manufactures provide set of data at different operating conditions that can be used to develop a mathematical model for the PV device. The process of mathematical modeling of PV device provides the initial step in obtaining the final model of PV generation system.

2.1. *Single diode model*

The PV cell modeled based on single diode will have current source in parallel with a reverse biased diode and with series/parallel internal resistances, as shown in Figure.1 [12]. The output current (I) can be written as

$$I = I_{PV} - I_o \left[\exp\left(\frac{V + IR_s}{aV_T}\right) - 1 \right] - \left(\frac{V + IR_s}{R_p}\right) \dots (1)$$

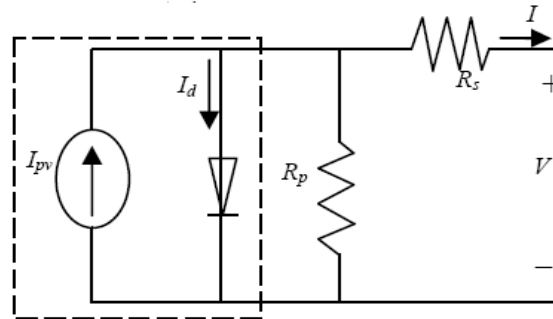


Figure 1. Single Diode Model

where I_{PV} is the current generated by the incidence of light, I_o is the reverse saturation current, V_T is the thermal voltage of the PV module having N_s cells connected in series, q is the electron charge, k is the Boltzmann constant, T is the temperature of PN junction in kelvin and a is the diode ideality factor. This equation originates electrical characteristics of single diode PV cell in the form of V-I curves with the computation of five parameters namely I_{pv} , I_o , R_p , R_s and a , as shown in Figure.2 [12]. This model was extensively used in the literature as this model provides a good compromise between its simplicity and accuracy. But the single diode models were proposed on the assumption that recombination loss in the depletion region is absent. In practice this loss accounts for a substantial amount, which cannot be neglected under extreme working conditions. This is the real basis to work on the alternate model that accounts this aspect [4].

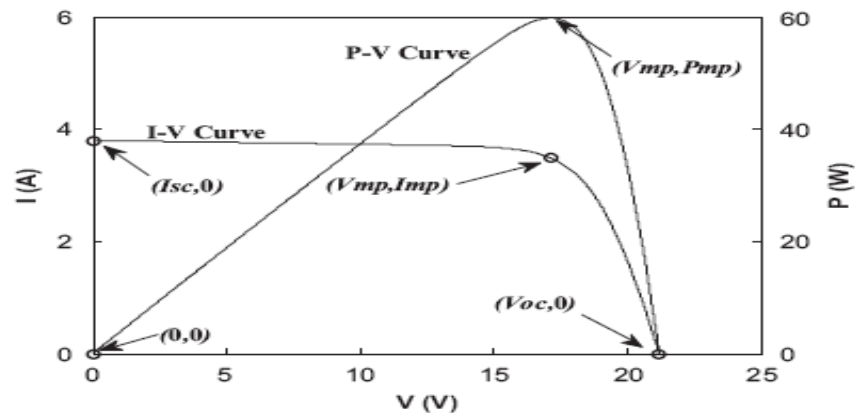


Figure 2. Output characteristics of PV cells

2.2. Two diode model

As mentioned earlier, an alternate model based on Two-diode approach has been proposed [12] to handle the recombination loss. Various methods to analyze the electrical behavior of PV cell based on two diode approach were proposed in the literature [12 - 14], which is based on estimation of model parameters as a function of unknown dynamic values. To evaluate the electrical characteristics of the PV cell on this

approach is a tedious task due to lack of complete information about semi-conductor parameters that are not available in Commercial data sheets of PV cells.

A generalized approach has been proposed to characterize the complete PV cell behavior based on the information readily available on data sheet. The main emphasis on this approach is the simplification of current equation with minimum number of unknown parameters that can be evaluated by both algebraic and iterative manner. The equivalent circuit for the two-diode model proposed in [12] is shown in Figure.3. The simplified current equation for the model is:

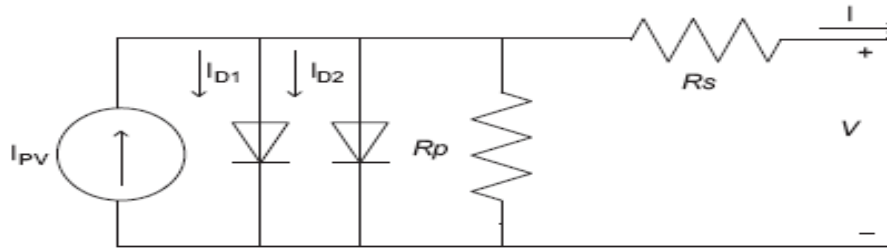


Figure 3. Two Diode Model

$$I = I_{PV} - I_{o1} \left[\exp\left(\frac{V + IR_s}{a_1 V_{T1}}\right) - 1 \right] - I_{o2} \left[\exp\left(\frac{V + IR_s}{a_2 V_{T2}}\right) - 1 \right] - \left(\frac{V + IR_s}{R_p}\right) \dots (2)$$

Where I_{o1} and I_{o2} are the reverse saturation currents of diodes D1 and D2 respectively, V_{T1} and V_{T2} are the thermal voltages of respective diodes, a_1 and a_2 represents ideality constants of respective diodes. The significance of additional diode is to compensate for recombination loss in the depletion region of PV cell.

The simplicity of the two diode model in [12] as compared to the proposed two diode models in the literature [13, 14] can be acceptable with the approach followed in evaluating the model parameters that are discussed in subsequent sections.

2.3. Determination of parameters in two diode model

The two diode model considered in present aspect requires four parameters, compared to six or more in the previously developed two-diode models. The simplified current equation of PV cell for two diode model as described in equation (2) has seven parameters namely I_{PV} , I_{o1} , I_{o2} , R_p , R_s , a_1 and a_2 to be computed, in which the four parameters I_{o1} , I_{o2} , R_p and R_s are evaluated by iterative methods [12].

2.3.1. Simplified current equations

a. Expression for PV current,

The expression for PV current as a function of irradiance and temperature can be written as,

$$I_{PV} = (I_{PV_STC} + K_I \Delta T) \frac{G}{G_{STC}} \dots (3)$$

where I_{PV_STC} is the current generated due to light at STC, $T=T-T_{STC}$, G is the surface irradiance of cell and G_{STC} is the irradiance at STC and K_I is the short circuit current coefficient available in manufacture's datasheet.

b. Simplified expression for saturation current equation,

The expression for saturation current for single diode model considering the temperature variation can be written as,

$$I_o = \frac{(I_{SC_STC} + K_I \Delta T)}{\exp[(V_{oc,STC} + K_V \Delta T) / aV_T] - 1} \dots (4)$$

where K_V is the open circuit voltage coefficient available in manufacture's datasheet.

Now for two diode model, to have simplified expression for saturation currents in two diodes their magnitudes can be made equal to have same computational effort as with simple single diode model. The expression for reverse saturation currents I_{o1} and I_{o2} which are set to be equal can be written as,

$$I_{o1} = I_{o2} = I_o = \frac{(I_{SC_STC} + K_I \Delta T)}{\exp[(V_{oc,STC} + K_V \Delta T) / \{(a_1 + a_2)/p\}V_T] - 1} \dots (5)$$

The diode ideality factors a_1 and a_2 represent diffusion and recombination current components respectively. These ideality factors can be generalized with the following relations, i.e., $(a_1 + a_2)/p = 1$, $a_1 = 1$ and $p \geq 2.2$. Now equation (2) can be simplified in terms of p as

$$I = I_{PV} - I_o \left[\exp\left(\frac{V + IR_s}{V_T}\right) + \exp\left(\frac{V + IR_s}{(p-1)V_T}\right) + 2 \right] - \left(\frac{V + IR_s}{R_p}\right) \dots (6)$$

2.3.2. Evaluating R_s and R_p values

The simplified current equation of PV cell as stated in equation (6) above, when evaluated for practical condition still remains with unknowns of R_s and R_p . Many articles reported in the literature were based on independent evaluation of R_s and R_p values, which results much deviation in its electrical performance when compared to practical values. Hence a simultaneous evaluation of R_s and R_p with iterative approach, was taken to bring the two-diode model in close with the practical PV model.

The method of evaluating R_s and R_p is shown in the pseudo code, however initialization of this resistances can be made as follows:

$$R_p = \frac{V_{mp} + I_{mp} R_s}{\left\{ I_{PV} - I_0 \left[\exp\left(\frac{V_{mp} + I_{mp} R_s}{V_T}\right) + \exp\left(\frac{V_{mp} + I_{mp} R_s}{(p-1)V_T}\right) + 2 \right] - p_{max,E}/V_{mp} \right\}} \dots (7)$$

$$R_{s0} = 0; R_{p0} = \frac{V_{mp}}{I_{scn} - V_{mp}} - \frac{V_{ocn} - V_{mp}}{I_{mp}} \dots (8)$$

Solving Algorithm: In what follows, the algorithm in pseudo code is given:

Step1: Inputs $T, G, K_v, a_1, a_2, p, P_{max,exp}, R_s=0, R_p=R_{p(min)}$ (Eqn (8))

Step2: Evaluate I_0 ($=I_{o1} = I_{o2}$), Eqn (5), P_{max} (from Eqn (6))

Step3: Compute ε ($=P_{max} - P_{max,exp}$)

Step4: If $\varepsilon > tolerance$, go to Step5, If not *end*

Step5: Increment R_s , Solve Eqn (7), & go to Step2.

The two diode model, stated above is well accepted because of its coincidence with various practical PV models under dynamic irradiance and temperatures. In particular this model exhibits an excellent correlation at lower irradiance levels that makes this model a suitable design tool for PV system designers [12].

3. PRACTICAL VALIDATION OF TWO DIODE MODEL

The two diode model discussed above, was validated by implementing it in MATLAB R2009b/SIMULINK GUI (Graphical User Interface) Environment as shown in Figure.4, and by conducting suitable tests on the experimental setup shown in Figure.7.

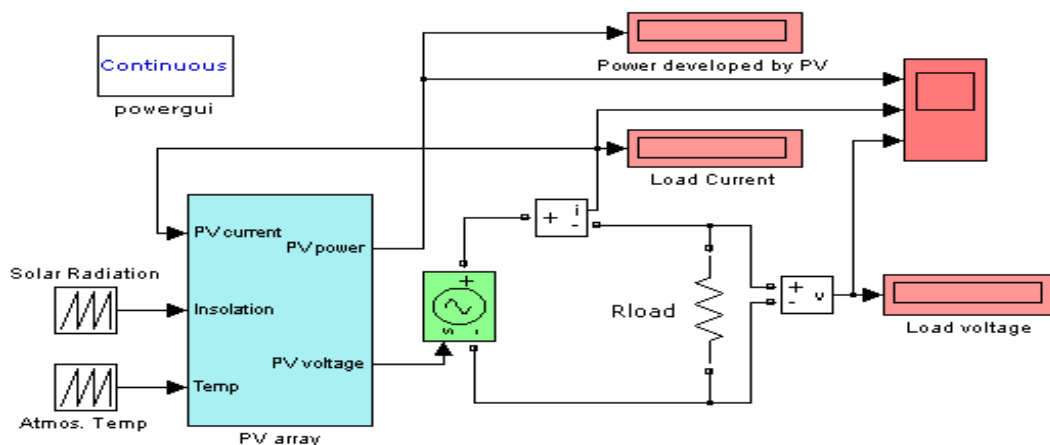


Figure 4. GUI block of the Complete PV cell Simulink diagram

USP 75 M5C01 Solar Panel PV module is chosen for the validation of the developed model in MATLAB. The USP-75 module provides 75 watt of maximum power, and has 36 series connected polycrystalline silicon cells and the simulated results are validated against the practical results obtained from the experimental setup at standard test conditions of sun radiation: 1000 watt/sq.m and 25 deg C temperature as tabulated in Table 1. The MATLAB model I-V and P-V characteristics for different insulations and at 25 deg C temperature are shown in Figure.5 and Figure.6

TABLE - I Validation between practical and simulated models

Standard parameters	P_{max}	V_{max}	I_{max}	V_{oc}	I_{sc}
USP-75	75.00W	17.1V	4.39A	21.5V	4.90A
MATLAB Model	75.55W	17.16V	4.40A	21.5V	4.90A

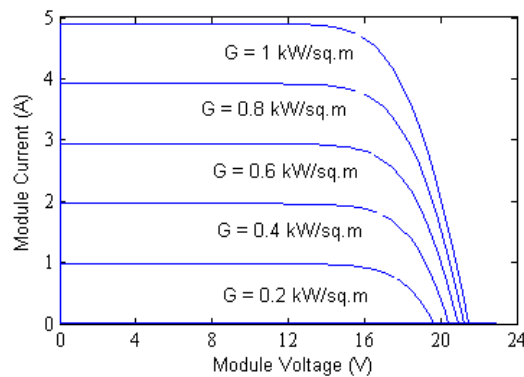


Figure 5. I-V characteristics

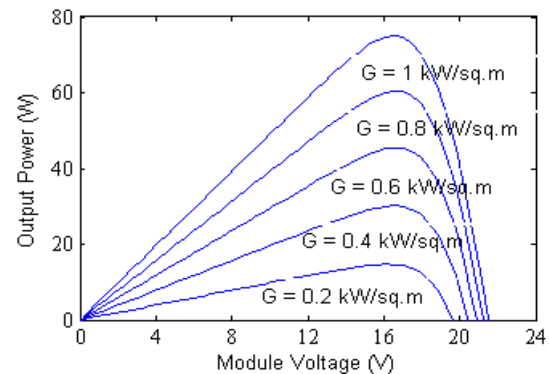


Figure 6. P-V characteristics



Figure 7. Experimental setup

4. PROPOSED MPPT TECHNIQUE

To extract maximum power from the panel, various approaches for tracking maximum power point (MPP) but it lacks with practical implementation, due to its

mismatch with the general requirements for maximum power point tracker (MPPT) such as simplicity, low cost, quick tracking under dynamic atmospheric conditions and small output power fluctuations [7 -10].

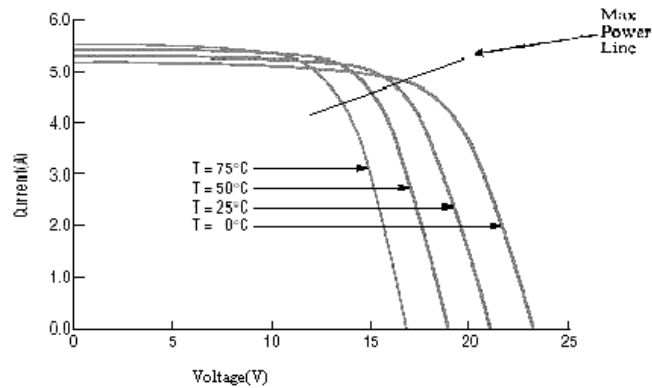


Figure 7. Maximum Power Line with varying weather condition

The typical variations of output voltage versus current for various temperatures of USP 75 M5C01 Solar Panel PV module are shown in Figure.7 [15], as the output voltage rises, the PV produces significant less current. The I-V curve will change depending on the temperature and illumination. The operating voltage or current needs to be carefully controlled so that the maximum power from the array can be obtained.

Also, in order to minimize the long-term system losses, it is required that converter output current has very small ripple and conversion efficiency is very high even at part load [16]. Therefore the installation of a boost type converter is advised and the same is adopted in this paper. The block diagram of the proposed MPPT scheme is shown in Figure. 8.

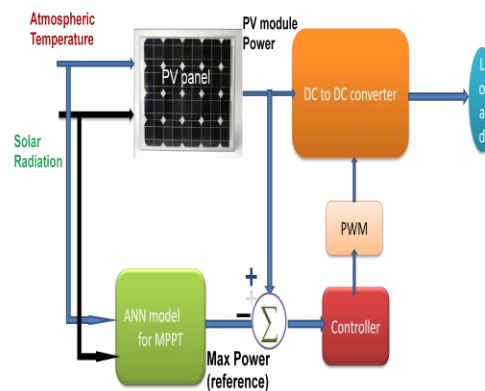


Figure 8. Block diagram of the proposed MPPT scheme

The conventional solar-array mathematical model will give satisfactory result, provided with the physical parameters relating to solar-cell material, weather condition, solar trajectory, illumination factor and temperature. At times due to lack of this information, the derived mathematical model may be inaccurate [2-5]. Neural network modeling does not require any physical definitions for a photovoltaic array, hence they have a potential to provide a superior method of deriving non-linear models than the already established conventional techniques. The Solar array was modeled using artificial intelligence technique, ANN namely Back Propagation [17].

4.1 Back propagation neural network

The general requirements for maximum power point tracker (MPPT) are simple and low cost, quick tracking under condition change, and small output power fluctuation. A more efficient method to solve this problem becomes crucially important. Neural network technology has attracted widespread interest in electrical engineering even many tracking control strategies have been proposed such as perturb and observe, incremental conductance, parasitic capacitance, constant voltage and fuzzy logic strategies have some disadvantages such as costly, difficulty, complexity and non-stability [7 - 10].

As Artificial Intelligence Technique evolved for modeling of non-linear systems, a model based on Fuzzy Logic was suggested for modeling of MPPT. However, the limitation of this technique was that the maximum power point was based on the short circuit current measured on the load side of the system and this current cannot be measured continuously; hence this technique lacks the ability of continuous tracking [10].

Back-propagation is a multilayer feed forward network and it was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions [17]. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. The term back-propagation refers to the manner in which the gradient is computed for nonlinear multilayer networks, it involves performing computations backwards through the network [17].

4.2 Architecture of network for MPPT

In the basic back-propagation training algorithm the weights are moved in the direction of the negative gradient. The training process requires a set of examples of proper network behavior - network inputs and target outputs. During training the weights and biases of the network are iteratively adjusted to minimize the network

performance function. The architecture of proposed neural network for tracking MPPT is shown in Figure.9. The proposed architecture of ANN (Artificial Neural Network) for modeling consists of four layer structure as shown in Fig.9 combines source modeling and MPPT by providing only one ANN model for Maximum Current (I_{max}), Maximum Voltage (V_{max}) and Maximum Power (P_{max}).The input to the ANN is a linear layer consisting of two neurons whose inputs are radiation and temperature. The output layer of the ANN consists of three linear neurons with purelin function which is a linear transfer function and it gives the values of maximum power, maximum voltage and maximum current of PV array at specified input radiation and atmospheric temperatures.

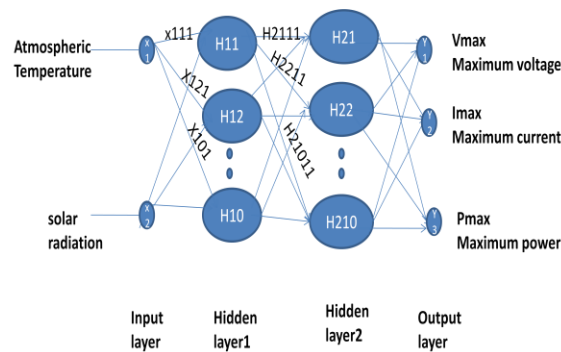


Figure 9. Architecture of Back Propagation Neural Network for PV array Modeling and MPPT tracking having 3 inputs 2 hidden layers (10 neurons in each layer) and 3 outputs

5. SIMULATION MODEL

MATLAB R2009b/SIMULINK is used for the modeling of solar cell. Simulation model is developed for one cell of the PV module using the mathematical equations discussed above as shown in Figure. 4 and is modified to give the proposed Solar MPPT scheme (shown in Figure. 8.) as illustrated in the Graphical User Interface (GUI) block in Figure. 10.

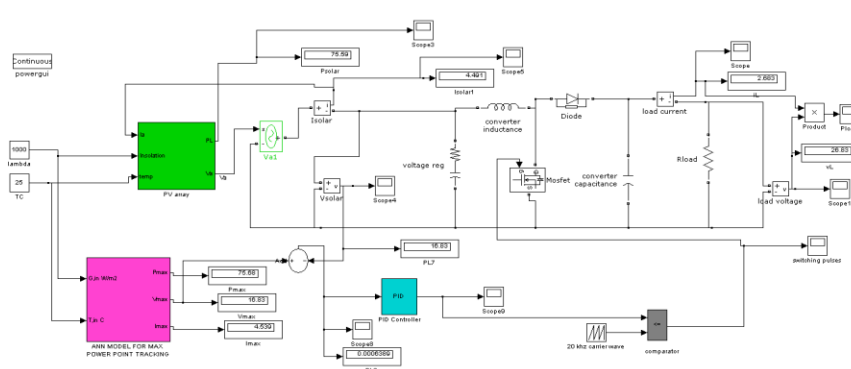


Figure 10. MATLAB R2009b/Simulink model of the proposed Solar MPPT scheme

In this MPPT simulink model the neural network is trained using the data of maximum current, maximum voltage and maximum power of solar array at various radiation (insolation level) level, and temperature levels. The Usp-75 PV Module is used to collect the required data.

6. SIMULATION RESULTS

The simulation of system use following parameters:

TABLE - II Key specifications of USL Solar PV module (USP-75)

Typical Electrical Characteristic of Usp-75 PV Module		
Parameter	Variable	Value
<i>Maximum Power</i>	P_m	75W
<i>Voltage@ Pm</i>	V_m	17.1V
<i>Current @ Pm</i>	I_m	4.39A
<i>Short circuit current</i>	I_{SC}	4.90A
<i>Open-circuit voltage</i>	V_{OC}	21.5.V
Cell temperature in STC	$T_{1,norm}$	25 deg C
Solar insolation	G_{norm}	1000 W/sq.m
<i>Area of one module = 12.5cm x 12.5cm x 36 solar PV cell</i>		

The 1172 data points are collected from the improved model for training the neural network based MPPT. For training back - propagation neural network, the error goal has set as 1×10^{-4} and maximum epochs of 2,000 was used. The following table shows the error of predicted maximum current and voltage of MPPT using back propagation neural network.

TABLE - III The error of predicted maximum current and voltage of maximum power point tracking using back propagation neural

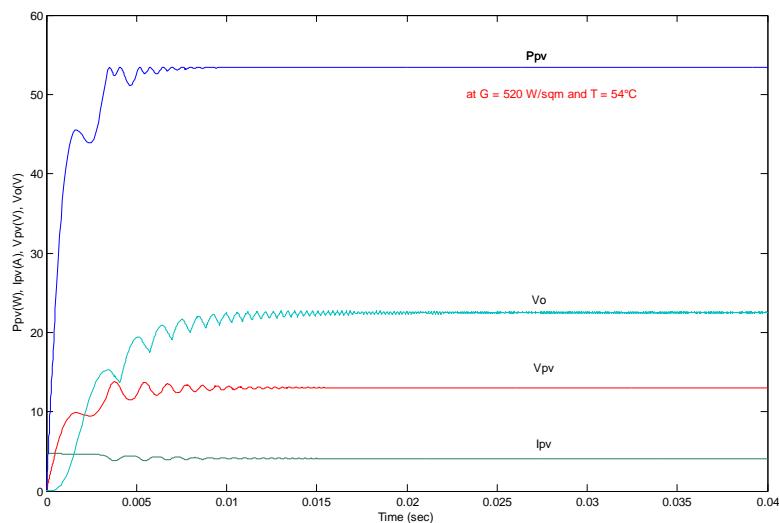
Error (%)	Number of data for training (1172 samples)		
	Pmax	Imax	Vmax
<1	1136	942	454
1-10	29	227	712
11-20	4	1	6
21-30	3	2	0
31-40	0	0	0
41-50	0	0	0

51-60	0	0	0
61-70	0	0	0
71-80	0	0	0
81-90	0	0	0
91-100	0	0	0

The output power obtained from the boost converter is equal to the maximum power excluding the converter losses. The converter has operating at switching frequency $f_s = 20$ kHz and the simulation results are tabulated in TABLE III and Figures 11& 12.

TABLE - III

Insolation (w/sqrm)	Temperature (°C)	V _{pv} (max), in V	I _{pv} (max), in A	P _{pv} (max), in W
520	54	13.8	3.98	54.92
1000	25	17.1	4.39	75

Figure 11. Simulation with load resistance 10Ω (at $I_{rr} = 520$ W/m², temperature = 54°C)

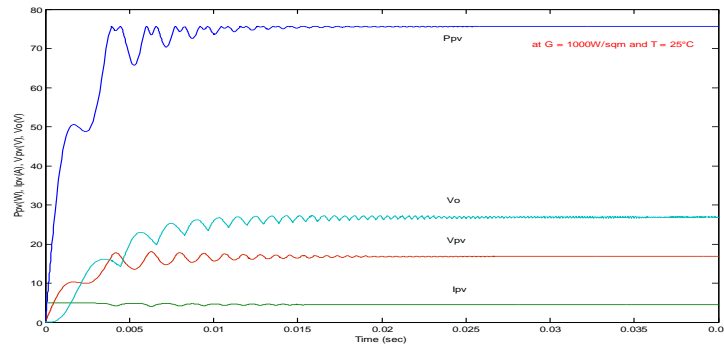


Figure 12.Simulation with load resistance 10 Ω (at Irr = 1000 W/m², temperature = 25°C)

Typical Electrical Characteristic of BP-350U Module		
Parameter	Variable	Value
Maximum Power	P_m	50W
Voltage@ P_m	V_m	17.3V
Current @ P_m	I_m	2.89A
Short circuit current	I_{SC}	3.17A
Open-circuit voltage	V_{OC}	21.8.V
Cell temperature in STC	$T_{1,norm}$	25 deg C
Solar insolation	G_{norm}	1000 W/sq.m
Area of one module = 12.5cm x 12.5cm x 36 solar PV cell		

TABLE - IV Key specifications of BP Solar PV module (BP-350U)

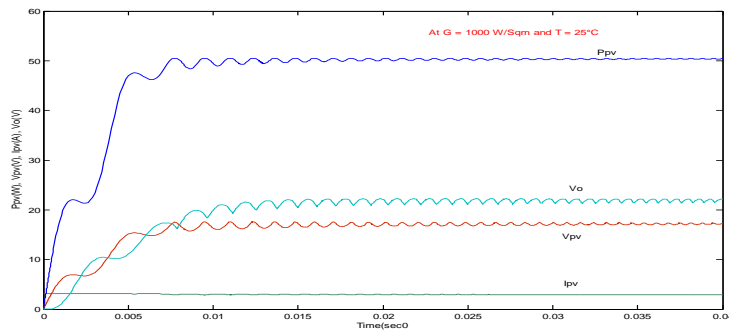


Figure 13.Simulation with load resistance 10 Ω (at Irr = 1000 W/m², temperature = 25°C)

Figure 13 shows the simulation results of BP – 350U PV panel accompanied with boost converter and the proposed MPPT method which are having very good agreement with the Typical Electrical Characteristic of BP-350U Module at practical standard conditions listed in Table IV, It proves that the proposed model can be used as simulation model for predicting the required panel specifications as demanded by the consumer.

7. CONCLUSION

An exact SPVA electrical model is presented in this paper which accounts the recombination loss in the depletion region of PV array to track the robust MPPT. The developed model for solar photovoltaic power electronic conversion system is simulated in MATLAB/Simulink GUI environment. MATLAB model is validated using the data of commercially available Solar PV module USP-75 and BP-350U. This paper has represented the application of back propagation neural network for maximum power point tracing of solar array. Results of comparison verify the accuracy of the developed Simulink model and it show excellent correspondence to manufacturer's data. As the developed model takes care about the variations of all the parameters with respect to environmental conditions, it can be used to predetermine the SPV characteristics. Finally the model development is used to show the Robust maximum power point tracking method for photovoltaic cells in MATLAB/Simulink GUI Environment using neural network the developed MATLAB model can be utilized for dynamic analysis of solar PV based generation system.

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