Genetic Algorithm Trained Artificial Neural Network Maximum Power Point Tracking of PV Cells

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Abstract- **The Tracking of maximum power point is an important aspect in any power system, design involving any variable power source. The complexity of the problem in the case of PV cells is compounded by the presence of nonuniform insolation and partial shading. The presence of nonuniform shadow gives rise to multiple peaks. The presences of multiple peaks under partially shadowed conditions are well represented by the proposed modelled systems. The results are also presented. This paper presents a genetic algorithm function to extract maximum power point.. The proposed constraints are the maximum voltage and maximum current under different conditions of varying temperature and varying insoltaion.The required data is obtained from the designed models. Optimized power point values are used to train a neural network system designed for tracking the maximum power point.**

Key words- **Photovoltaic Cells, PV-IV Curves, Modeling, Simulation, Matlab/Simulink.**

I. INTRODUCTION

The successful implementation of any evolutionary approaches depends the way the systems are provided targets to achieve optimum solution. These targets shall be in the form of constraints, bounds etc... The Performance of Artificial Neural Networks is highly influenced by the quality and quantity of the training data. Large Training data sets though may result in accurate prediction, they increases the computational time and hence computational complexity. There has to be a fine balance between the quality and the volume of the training data. In this proposed work. Genetic Algorithm is used to provide the training data, so that the predictions of Artificial Neural Networks converge easily towards the required target outputs.

Genetic Algorithm is a method for solving both constrained and unconstrained optimization problems that are based on natural selection, the process that drives biol biological evolution. The genetic algorithm has repeatedly modified a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution (1). One can apply the genetic algorithm to solve a variety of optimization problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, non - differentiable, stochastic, or highly nonlinear.

II. REVIEW OF THE TWO-DIODE MODEL

In this model, an extra diode is attached in parallel to the circuit of single-diode model. This diode is included to provide a more accurate I-V characteristic curve that considers for the difference in the flow of circuit at low current values due to charge combination in the semiconductor's depletion. The mathematical form of the model is shown in Figure-1. The terminal current I of the cell can be divided into four components, as shown in Equation. (3.10): the photo generated current (IPH), the current through the shunt resistance (IP), the diffusion-diode current (ID1), and the recombination-diode current (ID2).

$$I_L = -I_{ph} + I_{D1} + I_{D2} + I_{sh} \quad \text{---} \qquad (1)$$

Where, I_{ph} is the cell-generated photocurrent,

$$I_{D1} = I_{SD1}[\exp (q (V_L - I_L Rs)/n_1 K_t)] - 1 \text{-(2)}$$

$$I_{D2} = I_{SD2} [\exp\_ (q (V_L - I_L Rs)/n_2 k_T)] - 1 \quad \text{--} \quad (3) \text{ and}$$

$$I_{sh} = V_L - I_L Rs/R_{sh}. \quad \text{---} \qquad (4)$$

$$(V)=I_{PH}-I_P-I_{D1}-I_{D2} = I_{PH}-V+I\, R_{S/RP}-I_{01}\left[\exp^{V+I\, R_S/n_1 V_r} - 1\right] - I_{02}\left[\exp^{V+I\, R_S/n_1 V_r} - 1\right] \quad \text{-------} \qquad (5)$$

The seven unknown parameters in the model are: the photo generated current I_{PH}; the series resistance R_S; the shunt (or parallel) resistance R_P; the reverse saturation current I_{01} and the ideality factor n_1 of the diffusion diode; and the reverse saturation current I_{02} and the ideality factor n_2 of the recombination diode. n_1 is assumed to be equal to one by many authors, in accordance with the diffusion theory of p-n junctions [8], whereas n_2 is sometimes set equal to two, in accordance with the theory of recombination via traps.

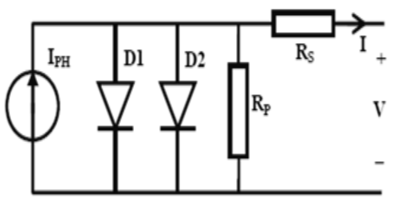

Fig-1: Lumped-circuit, two-diode model of a PV cell.

The thermal voltage $V_T=k_BT/qe$, where T is the p-n junction temperature (considered to be a known or controlled quantity), k_B is Boltzmann's constant, and qe is the elementary charge .The parameters in the two-diode model depend on the irradiance and cell temperature [10]. With reference to Figure-3.13, the current–voltage relation of a two diode model for a silicon solar cell may be expressed as, In the above equations, R_s and R_{sh} are the series and shunt resistances respectively, I_{SD1} and I_{SD2} are the diffuse and saturation currents respectively, n_1 and n_2 are the diffusion and recombination diode ideality factors, k is Boltzmann's constant, q is the electronic charge and T is the temperature in Kelvin [12]. From the above equations, it is seen that the solar cell parameter extraction problem reduces to the determination of the seven parameters (R_s, R_{sh}, I_{ph}, I_{SD1}, I_{SD2}, n_1 and n_2) from the I–V characteristics.

III. MAXIMUM POWER GA FUNCTION

The proposed work uses a Maximum Power GA function to identify and track the maximum power point. The aim of this function is to pick the peaks of PV power curves shown before; as the objective function and out two variables as arguments x (1), and x (2) (V_{mp}, and I_{mp}).

This function is implemented by maximizing the power with the voltage and current as optimizing variables, and with bounds for them by the values of Voc, and I_{sc} from the PV module data sheet. Nonlinear constraints with the aid of Voc, and I_{sc} obtained from I-V curves for each irradiances, and temperature values. The function and its constraints are as mentioned below.

Function

MPP = *f* (x) MPP = x (1) * x (2)

Function Constraints:

The optimizing variable (x (1)) is bounded by [0 Voc Datasheet].

The optimizing variable (x (2)) is bounded by [0 Isc Data Sheet].

The nonlinear constraint:

Function [c, ceq] = *f* (x) c = [z1-Voc Module (For Each Irradiance & Temperature Values);

z_2 – Isc Module (For Each Irradiance & Temperature Values)]

ceq = [ ]

Our genetic trial uses the following MATLAB prescribed terminologies: Population type: Double Vector with Populations size = 20; Creation function, Initial population, Initial Score, and Initial range: Default; Fitness scaling: Rank; Selection function: Stochastic uniform Reproduction; Elite Count: Default (3), Crossover fraction: Default (0.8); Mutation function: Adaptive feasible (due to its benefits); Crossover function: Scattered Migration; Direction: Forward, Fraction: Default (0.2), Interval: Default (20); Stopping criteria (Defaults): Generations: 100, Time limit: Inf., Fitness limit: Inf., Stall generations: 50, Stall time limit: Inf., Function Tolerance: 1e-6, nonlinear constraint tolerance: 1e-6.

IV. ANN PV GA FUNCTION WITH ITS REGRESSION FUNCTION

This model uses the ANN technique with back-propagation technique. This model uses the previous data obtained from GA function for training or learning data for input and desired target. The inputs in this model are the Irradiance and Temperature; the outputs are: Module Voltage, and Current at maximum Power. This model with its hidden and output layers suitable neuron numbers is depicted in fig- 1.

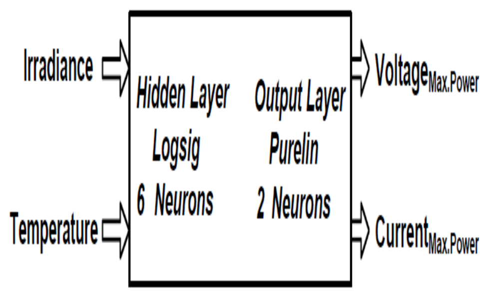

Fig-2: ANN Genetic PV Module for Tracking Maximum Power

The figure-2 depicts the configuration of the Neural Network Used in the proposed work. The network comprises of 2 Layers, one hidden layer and one output layer. The hidden layer has 6 neurons where as the output layer has 2 neurons. Log-sig; Log –Sigmoid transfer function is used in the hidden layer and Purelin a linear transfer is used in the output layer.

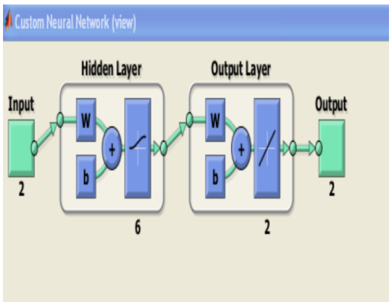

Fig-3: CustomNeuralNetworkView diagram

The training data comprises of targets evolved from GA MPP function, the training data has 2 targets namely the maximum current and the voltage. 140 set of data forms the training data set. The training function employed in the proposed work is trainlm. It is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. Trainlm is the fastest back propagation algorithm in the neural network toolbox of Matlab, and is often recommended as a first-choice supervised algorithm. On the flip side this algorithm requires more memory than other algorithms.

Learn gdm is the gradient descent with momentum weight and bias learning function and this function is used for learning in the proposed work. Learngdm calculates the weight change d_W, for a given neuron from the neuron's input P and error E, the weight (or bias) W, learning rate LR, and momentum constant MC, according to gradient descent with momentum. Mse-Mean squared normalized error performance function is used to analyze the performance of the proposed system. Mse is a network performance function which measures the network's performance according to the mean of squared errors.

V. TRAINING ERROR COURSES

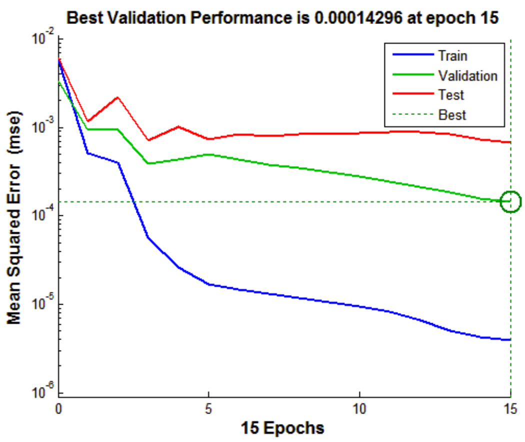

Fig-4: Training Error courses

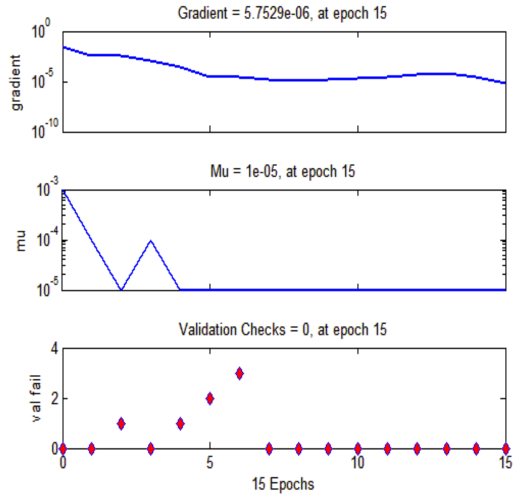

Fig-5: Training Number of Iterations

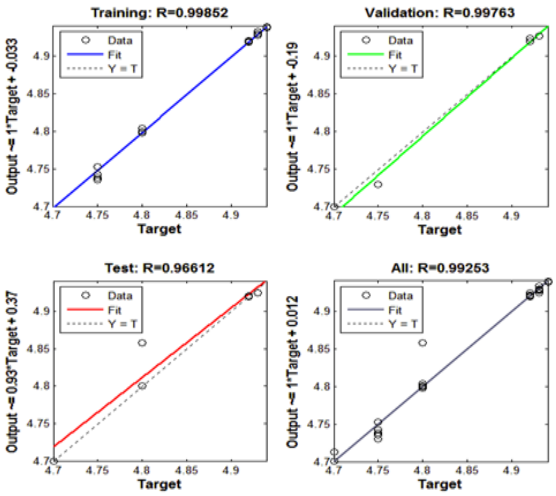

Fig-6: Regression Plots

VI. SIMULATION RESULTS OF MPPT UNDER PARTIAL SHADOW CONDITIONS AT DIFFERENT ISOLATION

The following shows the results of maximum power point tracking under the neural network approach .The system is tested for different grouping of insolation values like 6 modules are subjected to an irradiance of 1000 W/m^2 and the remaining 4 modules subjected to an irradiance of 1000 W/m^2. and Two panels which are subjected to variable insolation are tested for different insolation values like , 800 W/m^2 and 600 W/m^2.The results clearly point to the fact the reference value of the current being DC To AC converter varies as the insolation varies and the system is able to operate at its maximum power point.

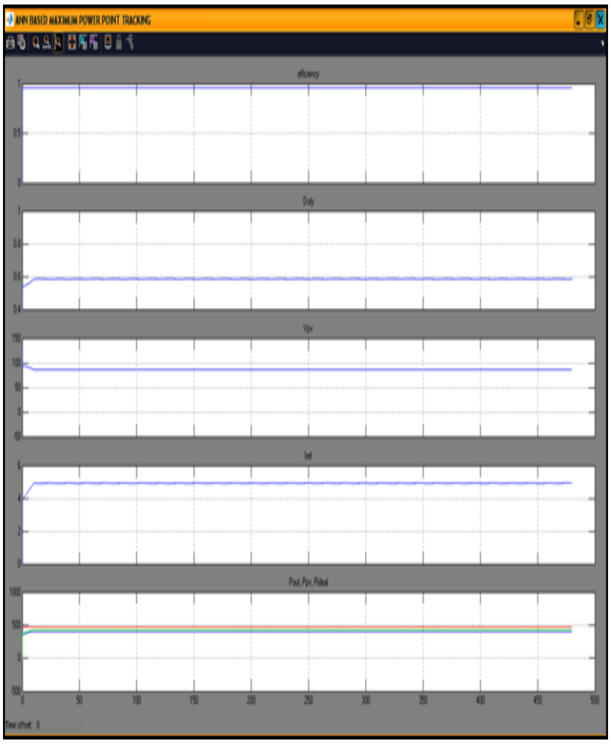

Fig-7: PV Characteristics under constant isolations, 6modules 1000 W/m^2

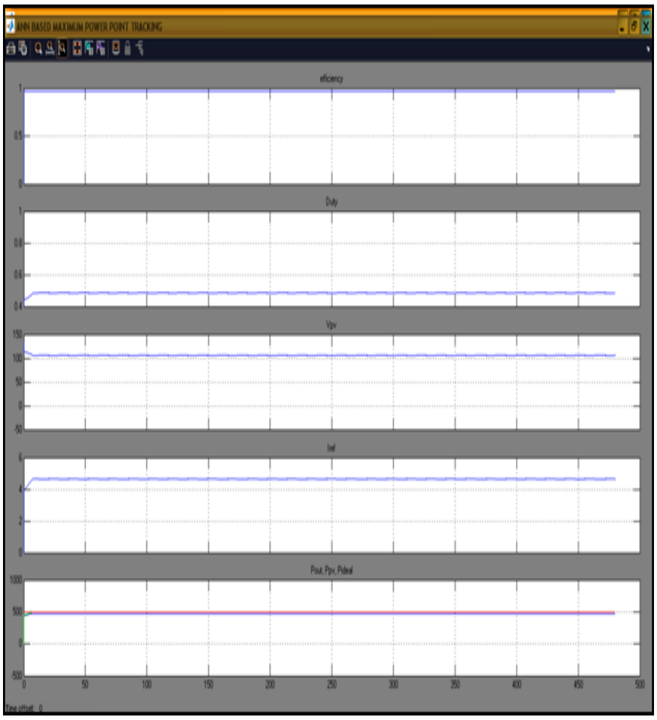

Fig-8: PV Characteristics under different isolations, 4 modules 1000 W/m^2, 2 module 800W/m^2

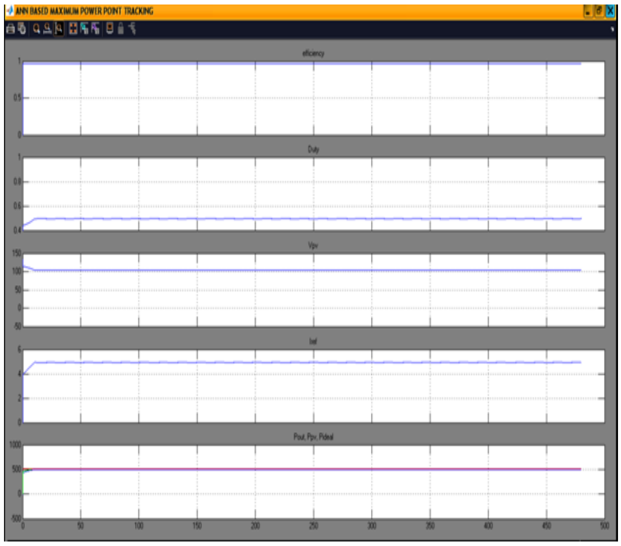

Fig-9 PV Characteristics under different isolations, 4 modules 1000 W/m^2, 2 modules 600W/m^2

VII. CONCLUSION

A detailed analysis of Maximum Power Point tracking methods was presented in this chapter. One conventional method based on a short circuit and Incremental conductance with direct control and the proposed method using an ANN PV GA function were simulated and the results presented for different insolation values including non uniform insolation of PV panels. The data needed to train the ANN was obtained using the maximum power GA function. The results were presented in comparison with the ideal power, the output power and the maximum power tracked for different scenarios.

APPENDICES

Table-1:Specifications of solarex MSX 60

Characteristics	Specification
Typical peak power (P_p)	60W
Voltage at peak power (V_{PP})	17.1V
Current at peak power (I_{PP})	3.5A
Short-circuit current (I_{sc})	3.8A
Open-circuit voltage (V_{oc})	21.1V
Temperature coefficient of open-circuit voltage	-73mV/^{0}C
Temperature coefficient of Short-circuit current	3mA/^{o}C
Approximate effect of temperature on power	-0.38W/^{0}C
Normal operating temperature of cell	49^{0}C

ACKNOWLEDGEMENTS

The great work of Mr. G.Venkateswarlu, that was a Doctoral Thesis and other parts for Power research at S.V. University, Tirupati, A.P, India, was a great help for developing this paper. With the cooperation of my Ph.D. thesis's supervisor Prof. P. S. Raju that spent a valuable part of his time for the paper.

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