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Research paper

A GA trained ANN model for maximum power point tracking in solar photo voltaic systems

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Abstract

Sunlight based vitality is one of the imperative segment of sustainable power source assets and reaping of sun oriented vitality is an actually difficult assignment. Sunlight based PV cells display non liner conduct and their execution is affected by an assortment of components. Fluctuating insolation and temperature assumes a critical part in characterizing the working purpose of the PV cell. Most extreme Power Point Tracking (MPPT) calculations are important to amplify the yield control. The target of getting MPP in PV frameworks is to manage the real working voltage of PV boards. The fundamental reason for acquiring MPP in PV frameworks is to direct the real working voltage of PV boards. In this paper a Genetic Algorithm (GA) –Artificial Neural Network (ANN) MPPT approach is presented. GA is employed to adaptively change the weights during the course of ANN training. The proposed approach is validated by comparing its performance against a data set which contains voltages forecast by ANN approach, Adaptive Neuro Fuzzy (ANFIS) approach and reference voltage obtained through mathematical modeling. The results demonstrate the suitability of the proposed approach in maximum power point tracking through its better performance when compared to the other two approaches. Pearson product-moment correlation has also been calculated to compare the correlation between the predicted voltage and the reference voltage.

Keywords: *MPPT; GA-ANN; ANN; ANFIS; Insolation; Temperature; Solar PV Cell.*

1. Introduction

One of the quickest developing nations on the planet, India is the fifth biggest purchaser of vitality on the planet. It is expected to wind up the third biggest by 2030 [1]. Notwithstanding, India relies upon the fossils for greatest of its vitality sources. Thinking about the present status of vitality utilization, the nation is bit by bit concentrating on its sustainable power source assets. An objective of 20GW by 2022 [2] has been advanced by India, inferable from the consistently expanding power request that has prompted augmenting hole amongst request and supply. Since PV board is a variable power source, it represents the primary test in sun oriented vitality reaping by coordinating them with framework or notwithstanding when utilized as an independent framework. Hypothetically, the components impacting the result of these sun based plants include: temperature, mugginess, wind speed, pneumatic stress, air temperature, sun based authority territory and so forth. The collaborations of these parameters together with their individual impacts on the power age utilizing PV, add to the multifaceted nature of the PV control age. Since the greatest power point (MPP) of a sunlight based board differs with the light and temperature, makes the utilization of MPPT calculation basic to get the most extreme power from a sun oriented cluster. Numerous techniques to discover the MPP have been produced in the course of recent decades. Every one of these methods are one of a kind regarding the quantity of sensors required, trouble, cost, scope of viability, meeting speed and appropriate following of a change in either light or temperature(or both). For a power framework plan with a variable power source, following the most extreme power point is a vital viewpoint.

The MPPT calculation gives a present reference (CMPPT) or a voltage reference (VMPPT), for a given working condition, to the converter controller that is working in shut circle. The situation of the MPP is spoken to by the reference gave by the MPPT piece. Coordinate obligation cycle control is one of the conceivable design, where the switch turn on/off is straightforwardly controlled by the MPPT. Numerous MPPT techniques have been specified in the literatures[3-8] The writings from [9] to [13] talk about the decision between the voltage and current to track the MPP. In [10], the analysts have specified that since PV cluster voltage remains moderately contant over an extensive variety of sun powered radiations, picking voltage control is better. Additionally, in [11] it is said that present very differs with radiation. Along these lines, the transient reactions of the MPPT calculation can cause immersion of the PV exhibit amid cut off, may bring about a sudden voltage drop in voltage and removed power [11], [12].

In this work a novel MPPT following technique in light of GA-ANN is portrayed. The Proposed strategy tracks the greatest voltage through the GA-ANN approach. The GA is utilized to alter the weights by lessening the mean square blunder amid the preparation period of the neural system. After presentation a concise survey of the issue articulation is clarified in segment 2 took after by a point by point clarification about demonstrating of PV cell in area 3. A concise diagram about various MPPT approaches is given in segment 4. The proposed technique for GA-ANN MPPT is clarified in area 5, trailed by results and talk in segment 6. Conclusions and references are given in segment 7 and area 8 separately

2. Problem statement

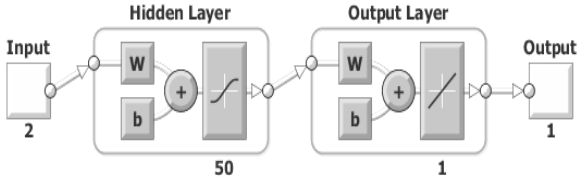

Fig. 1: ANN Configuration Used in the Proposed Work.

The essential goal of the proposed work is to outline an ANN based MPPT calculation in which the weights of the neuron are balanced with the assistance of GA. The weights are adjusted to the point that the mean square mistake (mse) is improved with the assistance of GA amid the preparation of ANN. The GA based weight enhancement takes after two stages amid preparing of an ANN. Encoding strings to speak to the association weights is the initial step. The transformative procedure reproduced by GA is the second step, which incorporates execution of inquiry administrators in conjunction with the portrayal conspire. Once the populace has joined, the development stops. This happens when 95% of the people constituting the populace share same wellness esteem. In the proposed work an encourage forward neural is utilized, it has three layers with one shrouded layer having 50 neurons. The neural system is prepared with the assistance of an informational indexes which sustains the insolation and temperature as the information and yield voltages as the objective. The consequences of the proposed approach are approved by contrasting the aftereffects of voltage got through a deterministic model in view of two diode detailing. The relationship between's the estimate and the reference voltage is contrasted and the assistance of Pearson item minute connection .

3. Modeling of PV cell

The mathematical model of the solar cell taking into account the effect of breakdown voltage is given by the equation.

$$I=\left(I_{ph}-I_{o}\cdot\left(\exp\left(\frac{V}{mV_{t}}\right)-1\right)\right)M(V)-\frac{V}{R_{p}} \quad (1)$$

Where the effect of the avalanche effect is denoted by multiplication factor M (V). The expression of M (V) is:

$$M(V)=\frac{1}{\left(1-\left(|V|/V_{b}\right)^{n}\right)} \quad (2)$$

Where Vb is the breakdown voltage in invert predisposition and n is the Miller consistent. The proposed display is given by Equation (3) and the relating equal circuit is appeared in Figure-2.

$$I=I_{ph}-I_{o}\left[\exp\left(\frac{V+R_{s}I}{mV_{t}}\right)-1\right]-\left(\frac{V+R_{s}.I}{R_{p}}\right)\left[1+a\left(1-\frac{V+R_{s}I}{V_{b}}\right)^{-n}\right] \quad (3)$$

Where, Vb is the breakdown voltage, 'an' and 'n' are constants. The extra term, E (V), is added to the spillage current into the shunt protection term displayed as a controlled current source:

$$E(V)=1+a\left(1-\frac{V+IR_{s}}{V_{br}}\right)^{-n} \quad (4)$$

Applications for crystalline Si command writing the two-diode demonstrate has principally been connected to Mono crystalline-Si PV cells [16],

The single diode condition accept a consistent incentive for the ideality factor n. In all actuality the ideality factor is an element of the voltage over the gadget. At high voltage, when the recombination in the gadget is commanded by the surfaces and the mass areas the ideality factor is near one. In Two diode demonstrate, an additional diode is connected in parallel to the circuit of single-diode show. This diode is incorporated to give a more precise I-V trademark bend that considers for the distinction in the stream of circuit at low current esteems because of charge mix in the semiconductor's consumption. The scientific type of the model is given by Eq. (5).

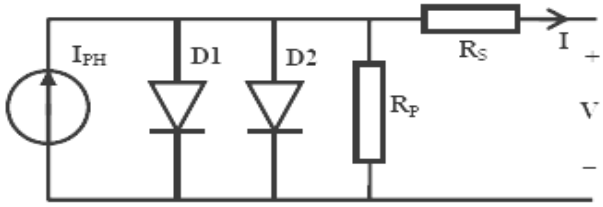

Fig. 2: Lumped-Circuit, Two-Diode Model of A PV Cell.

$$V=\sum_{i=1}^{35}V_{ill\ cell}+V_{sh_{cell}} \quad (5)$$

Where, V is the aggregate PV module voltage, and Vill_cellandVsh_cellare the voltages over the enlightened cells and the shaded one, individually. Eq. (6) shows the terminal current I of the cell, isolated into four portions to be particular: the photo made current (IPH), the current through the shunt assurance (IP), the dispersal diode current (ID1), and the recombination-diode current (ID2). The photo made current IPH; the course of action security RS; the shunt (or parallel) insurance RP; the pivot drenching current I01 and the ideality factor n1 of the dispersal diode; and the switch inundation current I02 and the ideality factor n2 of the recombination diodeare the dark parameters in the model. A couple of makers have anticipated that n1 would be equal to 1, according to the dispersal speculation of p-n convergences [17], however a couple of makers set n2to 2, as showed by the theory of recombination through traps. The warm voltage VT is given by the condition VT =kBT/qe where T levels with the p-n crossing point temperature (generally a known or controlled sum), kB is Boltzmann's reliable, and qe is the simple charge.The irradiance and cell temperature [18] impact the parameters of the two diode appear. The current– voltage association of a two diode appear for a silicon sun based cell in reference to figure 2, may be conveyed as,

$$I_L=-I_{ph}+I_{D1}+I_{D2}+I_{sh} \quad (6)$$

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

$$I_{D1}=I_{SD1}[\exp(q(V_L-I_LRs)/n_1K_t)]-1 \quad (7)$$

$$I_{D2}=I_{SD2}[\exp\_(q(V_L-I_LRs)/n_2k_T)]-1 \quad (8)$$

And

$$I_{sh}=V_L-I_LRs/R_{sh}. \quad (9)$$

$$I(V)=I_{PH}-I_p-I_{D1}-I_{D2}=$$

$$I_{PH}-V+IR_{S/RP}-I_{01}\left[\exp^{V+IR_S/n_1V_t}-1\right]-I_{02}\left[\exp^{V+IR_S/n_1V_t}-1\right] \quad (10)$$

In the conditions above, RsandRshare the arrangement and shunt protections individually, ISD1 and ISD2 are the diffuse and immersion streams separately, n1 and n2 are the dispersion and recombination diode ideality factors, k is Boltzmann's steady, q is the electronic charge and T is the temperature in Kelvin [19].

4. Maximum power point tracking

Greatest Power Point Tracking (MPPT) calculations are important in PV applications in light of the fact that the MPP of a sun based board differs with the illumination and temperature, so the utilization of MPPT calculations is fundamental keeping in mind the end goal to get the most extreme power from a sun based cluster. Over the previous decades numerous techniques to discover the MPP have been produced and accessible. These strategies vary in numerous perspectives, for example, required sensors, trouble, cost, scope of adequacy, meeting speed; remedy following when illumination or potentially temperature change.Among these methods, the Perturb and watch and the Incremental conductance calculations are the most regular. Different strategies in light of various standards are fluffy rationale control, neural system, partial open circuit voltage or short out present, current breadth, etc.The P&O calculation is additionally called "slope climbing", yet the two names allude to a similar calculation relying upon how it is actualized. Slope climbing includes an irritation on the obligation cycle of the power converter and P&O an annoyance in the working voltage of the DC connect between the PV cluster and the power converter. On account of the Hill-climbing, irritating the obligation cycle of the power converter infers altering the voltage of the DC interface between the PV exhibit and the power converter, so the two names allude to a similar strategy. In this technique, the indication of the last irritation and the indication of the last augmentation in the power are utilized to choose what the following annoyance. In the event that there is an addition in the power, the annoyance ought to be kept a similar way and if the power diminishes, at that point the following bother ought to be the other way. In view of these actualities, the calculation is actualized. The procedure is rehashed until the MPP is come to [20]. At that point the working point sways around the MPP.

The incremental conductance calculation depends on the way that the incline of the bend control versus voltage (current) of the PV module is zero as the MPP, positive (negative) on its left and negative (positive) on the right.

$\Delta V/\Delta P = 0$ ($\Delta I/\Delta P = 0$) at the MPP

$\Delta V/\Delta P > 0$ ($\Delta I/\Delta P < 0$) at the Left

$\Delta V/\Delta P < 0$ ($\Delta I/\Delta P > 0$) at the Right

By looking at the addition of the power versus the addition of the voltage (current) between two successive examples, the adjustment in the MPP voltage can be In both P&O and Incremental Conductance plans, how quick the MPP is come to relies upon the span of the augmentation of the reference voltage. Fragmentary open circuit voltagemethod utilizes the roughly straight relationship between the MPP voltages (VMPP) and the open circuit voltage (VOC), which fluctuates with the irradiance and temperature [21]:

$$V_{MPP} \approx K_1 V_{OC} \quad (11)$$

Where, k1 is a consistent relying upon the qualities of the PV exhibit and it must be resolved before by developmental the VMPPandVOCfor diverse levels of light and distinctive temperatures. As per [21] the consistent k1 has been accounted for to be in the vicinity of 0.71 and 0.78.

Once the consistent of proportionality, k1, is known, the MPP voltage VMPPcan be resolved occasionally by estimating VOC. To quantify VOCthe control converter must be closed down quickly so in every estimation lost power happens. Another issue of this strategy is that it is unequipped for following the MPP under light slants, on the grounds that the assurance of VMPP isn't steady.

$$IMPP = K2\ ISC \quad (12)$$

The coefficient of proportionality k2 must be resolved by each PV cluster, as in the past strategy occurred with k1. As per [21] the steady k2 has been accounted for to be in the vicinity of 0.78 and 0.92.Measuring the short out current while the framework is working is an issue. It generally requires adding an additional change to the power converter to occasionally short the PV exhibit and measure ISC. In ISCis estimated by arranging the PV exhibit with a supplementary field-impact transistor included between the PV cluster and the DC interface capacitor.

5. Maximum power point tracking using GA - ANN

In this work the network is created with two neurons in the input layer, 50 neurons in the hidden layer and one neuron in the output layer. The two inputs to the network are the insolation and the temperature. Totally 23 sets of input data samples are given to the network for training. The targets of the network are specified to be the values of voltages that are obtained from modeling for a particular input set among training sets. The weights are optimized through GA as explained before. The details of the ANN used this work is list in the table 1 and the training details for the ANN is listed in table 2 and The data set used for training the ANN is described in the table 3

Table 1: Details about the ANN Model Used in the Proposed Work

1	Number of Neurons in the Input	2 (1 for Insolataion and 1 for Temperature inputs)
2	Number of Neurons in the Hidden Layer	50
3	Type of Neural Network	Feed Forward Back Propagation
4	Activation function used for the input layer	tansig
5	Activation function used for the output layer	purelin
6	Training function	trainlm Levenberg-Marquardt (LM) optimization.

Table 2: Details about Training Parameters Used for Training the ANN

1	Performance goal	0,20
2	Maximum number of epochs	60
3	Maximum validation failure	10
4	Mu decrease factor	0.01

Table 3: Training Data Set for ANN

Insolation (Watts)	Temperature (C)	Voltage (Volts)
50	50	16.15
100	-40	7.95
100	0	11.82
180	30	15.69
200	10	13.75
220	40	17.04
600	52	19.45
700	42	18.58
770	47	19.15
830	35	18
850	50	19.68
900	10	15.41
910	12	15.6
920	13	18.17
950	23.75	16.96
955	23.87	16.97
960	24	16.96
965	24.12	16.96
970	24.25	17.02
975	24.3	17.02
980	24.5	17.08
985	24.62	17.13
995	24.87	17.14

In regard Genetic Algorithm (GA), the GA function available in the Matlab optimization tool box is used .The population size is fixed at 20. The elite count used is fixed at 10 % of the population

which 2. The selection is based on ranking. The cross over fraction is fixed at 0.2 and the adaptive feasible mutation function is used. The migration of the population is fixed as forward with a forward fraction of 0.2. The maximum number of generations is fixed at 100.

6. Results and discussion

In order to model the PV cell Solarex MSX 60 is considered, its specification (1KW/m^2, 25^{0}C) is illustrated in the

Table 4: 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

A generalized PV model is built using Matlab/Simulink to illustrate and verify the nonlinear I-V and P-V output characteristics of PV module.

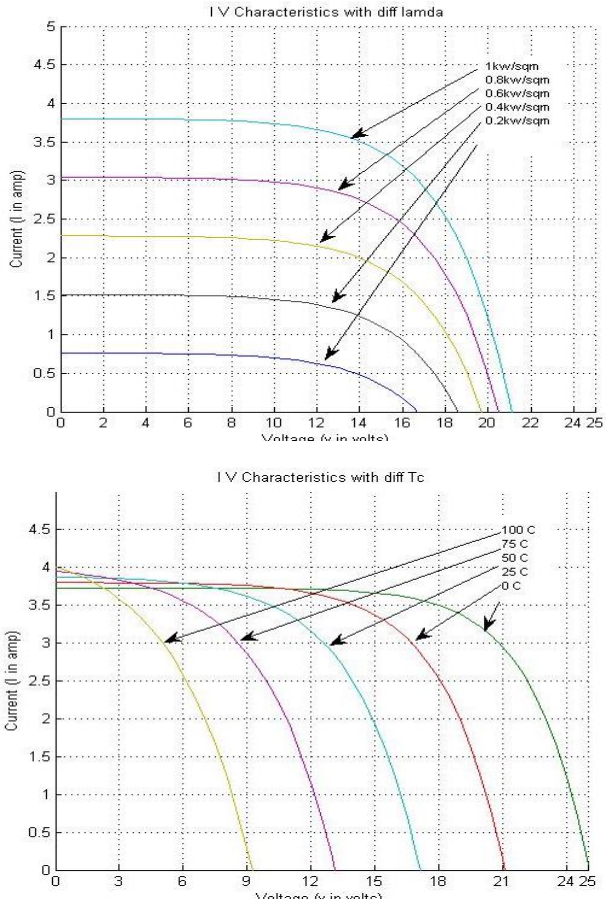

Fig. 3: IV Qualities for Changes in Temperature and Insolation.

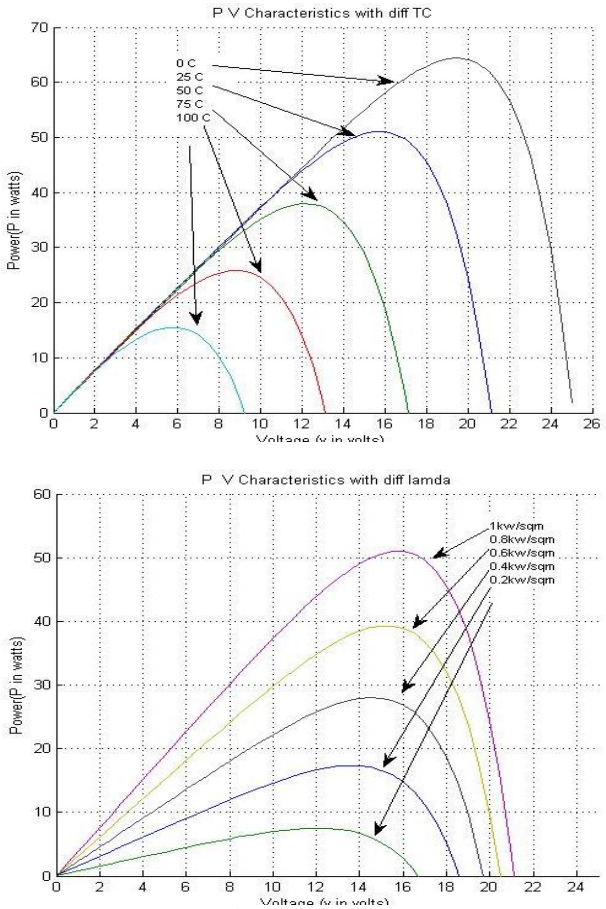

Fig. 4: PV Characteristics for Changes in Temperature and Insolation.

The proposed GA-ANN show is prepared utilizing the information outlined in Table 3. Relapse plot, which demonstrates the connection between the yields of the system and the objectives, is delineated in Figure 5(a) while the execution plot is portrayed in Figure 5(b). The dashed line in every hub speaks to the ideal outcome – yields = targets. The strong line speaks to the best fit direct relapse line amongst yields and targets. The R esteem means that the connection between the yields and targets. In the event that R = 1, this shows there is a correct straight connection amongst yields and targets. On the off chance that R is near zero, at that point there is no straight connection amongst yields and targets. From Figure 5(a) it can be watched that R esteems are over 0.9 and near 1 showing a liner relationship indicating a precise fit and along these lines better expectation.

The consequences of the proposed GA-ANN MPPT is introduced in the Table 5 alongside the forecast give by ANN based model. Keeping in mind the end goal to approve the execution of the proposed following its yield is contrasted and the voltages got through numerical demonstrating reproduced utilizing the Matlab display composed as a piece of this work. It can saw from the Table 5 the execution conveyed by the GA-ANN is better in contrast with the execution conveyed by ANN and unites intently to the qualities got through the model. The test information covers an extensive variety of insolation and temperature inputs. It can be watched that the GA-ANN predicts esteem nearer to that determined utilizing the model for most the test inputs.

The rate blunder between forecasts in light of ANN and GA – ANN is given in the Table 6. It can be surmised from the table that both the techniques have similarly higher level of blunder when the temperature is less of high. This implies the basic factor of temperature in foreseeing the MPPPT and the impact displayed by it in deciding the operational purpose of PV cell. Indeed, even in the high/low temperature test cases the mistake created by proposed GA-ANN technique is nearly less. The legitimacy of the proposed strategy is likewise approved through Pearson item minute correlation between the voltages created by the conjecture models and numerical reproduction.

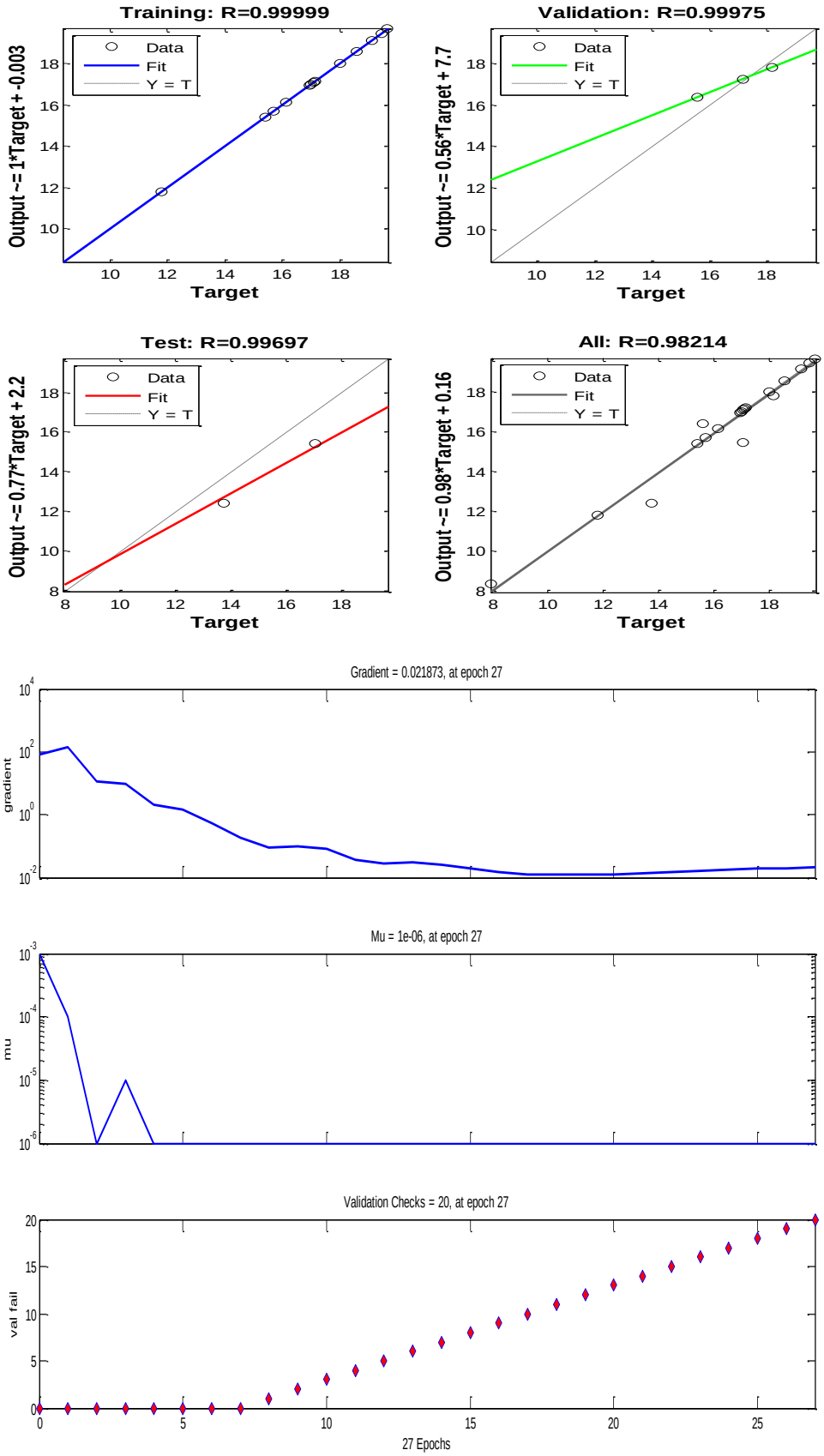

Fig. 5: (A) Regression Plot of ANN, (B) Performance Plot of ANN.

In order to further validate the proposed approach with another famous MPPT approach ANFIS, an ANFIS system isimplemented. In ANFIS the forecast is arrived at by having Hybrid optimization .The ANFIS system for solar forecast considers temperature and insolation as inputs. ANFIS has 101 nodes with 108 linear parameters and 36 nonlinear parameters. The ANFIS is trained using 23 pairs of training data. Triangular membership function is used to create a total of 36 fuzzy rules. The output voltage plotted for different insolation and training is illustrated in the figure (6)

Table 5: Results of the GA- ANN MPPT Tracking

Insolation	Temperature (c)	Voltage Calculated using the Model	Voltage -ANN MPPT Method	Voltage - GA-ANN MPPT Method
960	24	16.96	16.96	16.96
1000	25	17.1	17.25	17.09
700	42	18.52	18.58	18.58
965	24.12	16.96	16.97	16.98
995	24.87	17.14	17.26	17.14
820	40	18.46	14.12	19.35
980	24.5	17.08	17.07	17.08
600	52	19.45	19.4	19.45
765	46	18.6	18.68	18.59

Table 6: Error Percentage on Comparison between the Model Voltage and the Forecast

Insolation	Temperature (c)	% Error ANN MPPT Method	% Error GA- ANN MPPT Method
960	24	0	0
1000	25	-0.87719	0.05848
700	42	-0.32397	-0.32397
965	24.12	-0.05896	-0.11792
995	24.87	-0.70012	0
820	40	23.51029	-4.82124
980	24.5	0.058548	0
600	52	0.257069	0
765	46	-0.43011	0.053763

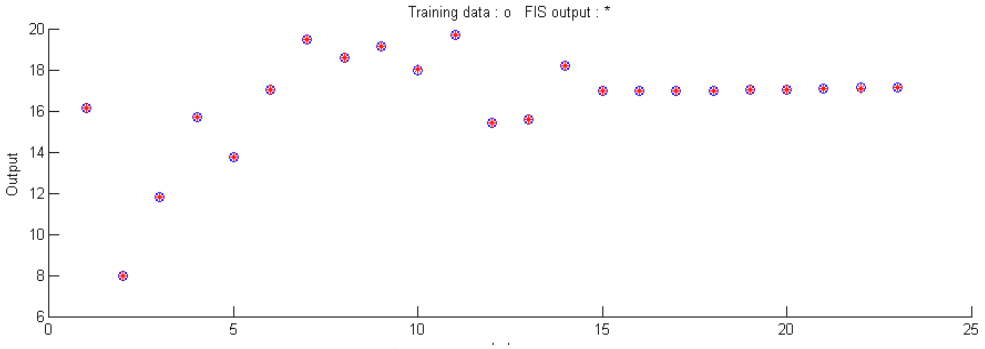

Fig. 6: Plot of Training Data against Actual Output.

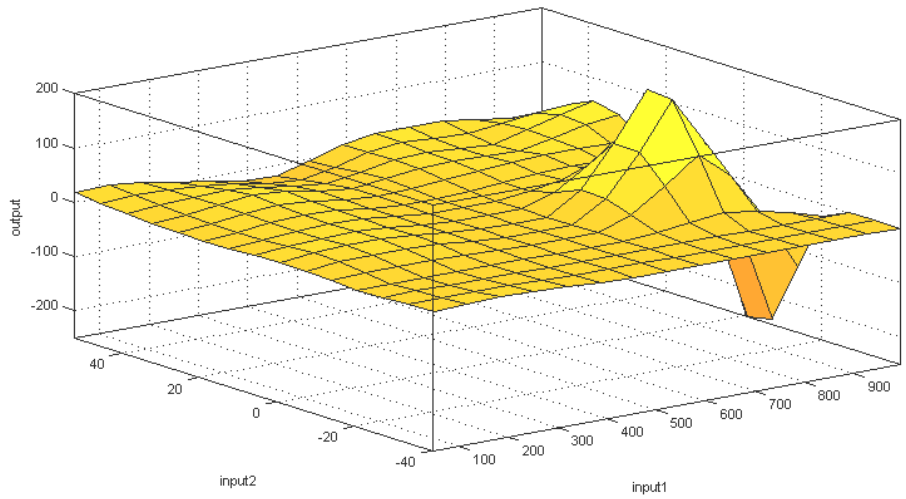

Fig. 7: Surface View of the ANFIS System.

The surface plot illustrating 3 parameters, 2 inputs in the form of insolation and temperature and one output in the form of temperature is illustrated in the figure (7). The Surface Viewer, helps in visualizing a three-dimensional curve that represents the mapping between the inputs and the outputs.

It can be inferred from the Table 7, the voltage produced by GA-ANN MPPT approach is closer to the model voltage considered as reference when compared to the voltage produced by the ANFIS MPPT approach. It can be observed that even though both the methods produce outputs closer to the reference voltage, the voltage produced by ANFIS is consistently on the higher side.

The execution of the proposed MPPT approach is assessed utilizing Pearson connection coefficient (r) Correlation – frequently estimated as a relationship coefficient – shows the quality and heading of a straight connection between two factors (for instance demonstrate yield and watched esteems). The Pearson item minute connection coefficient (additionally called Pearson relationship coefficient or the example relationship coefficient), is gotten by separating the covariance of the two factors by the result of their

standard deviations. The Pearson item minute relationship coefficient can be utilized to appraise the connection amongst's model and perceptions.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})\cdot(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

If there is a perfect increasing linear relationship the correlation is +1, and -1 in case of a decreasing linear relationship. The values that lies in between this range is indicative of the degree of linear relationship between example model and observations. A correlation coefficient of 0 indicates that there is no linear relationship between the variables. The figure 10 shows the Pearson product-moment for the three methods presented here. From the figure (10) we can infer that the Pearson product-moment correlation is higher for the proposed method validating the veracity of the proposed approach in producing the output that correlates well will the reference voltage.

Table 7: Results of the GA- ANN MPPT Tracking Compared with ANFIS MPPT

Insolation	Temperature (c)	Voltage Calculated using the Model	Voltage - GA-ANN MPPT Method	Voltage - ANFIS MPPT Method
960	24	16.96	16.96	16.98
1000	25	17.1	17.09	17.30
700	42	18.52	18.58	18.58
965	24.12	16.96	16.98	16.99
995	24.87	17.14	17.14	17.16
820	40	18.46	19.35	15.82
980	24.5	17.08	17.08	17.07
600	52	19.45	19.45	19.45
765	46	18.6	18.59	18.42

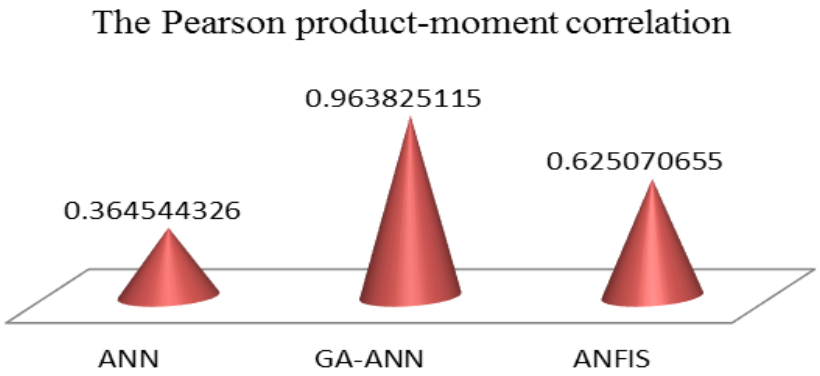

Fig. 10: Pearson Product-Moment Correlation for Different MPPT Approaches.

7. Conclusion

MPPT plays a very crucial role in efficient operation of the PV systems. In this paper a GA- ANN based MPPT approach has been designed and presented. The results of the proposed approach is validated by comparing it with ANN based MPPT and an ANFIS based MPPT. The result demonstrates the ability of the proposed approach to track the voltage close to the reference value. The proposed approach has been observed to produce a more accurate forecast of MPPT by having a reduced error percentage. The correlation between the forecast done by different approaches is also evaluated using Pearson product-moment correlation. The proposed approach has found to exhibit higher degree of correlation than ANN based approach and ANFIS based approach for MPPT.

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